Weathering Poverty

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PRELIMINARY, NOT FOR CIRCULATION

Abstract

The overlapping incidence of poverty and climate damages globally raises the question of whether and how poverty makes people more vulnerable to worsening weather shocks. To study this question, we overlay high-resolution, satellite-based drought and flood measures on household survey panel data from the randomized evaluation of a flagship anti-poverty graduation program in Bangladesh. The comparison of households that were equally poor before a randomly chosen group of them were given the graduation program reveals that the poorest bear the brunt of negative consumption impacts from unpredictable weather shocks. Those lifted out of poverty by the program do not reduce consumption and this protection is sustainable because it is achieved by diversifying labor activities rather than divesting assets. Programs that diversify income generating activities are thus a promising means of enhancing the climate resilience of the extreme poor and avoiding adding to their numbers in the future.

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1 Introduction

"Disasters don't kill people: poverty does"

— Fazle Hasan Abed, Founder of BRAC

Climate change and extreme poverty stand out as the two greatest challenges that humanity faces. At the macro level, these two challenges reinforce one another as the poorest suffer disproportionately from climate damages across and within countries (Carleton et al., 2022; Gilli et al., 2024; Hsiang et al., 2017). This paper examines how climate change and extreme poverty interact at the individual level.

Understanding the link between poverty and individuals' ability to confront the impacts of climate change is essential in estimating the aggregate and distributional costs of climate change, which will become more pressing given evidence linking climate change to damages from rising temperatures (Bilal and Känzig, 2024; Deschênes and Greenstone, 2011) and more frequent extreme weather events (Schiermeier, 2018; Philip et al., 2020). This is especially important because the significant changes in the global climate will likely require adjustments to the design of anti-poverty programs to help vulnerable populations confront the effects of these new risks.

To study how poverty affects vulnerability to unpredictable weather shocks, we overlay household survey panel data covering 23,000 households from the randomized evaluation of a flagship big-push anti-poverty program in Bangladesh, BRAC's graduation program, with new high-resolution, satellite-based data capturing droughts and floods over 20 years. This combination of datasets, measured at an extremely fine spatial resolution, allows us to precisely match the geographical extent of each weather shock with the villages where this large-scale poverty alleviation program operates. The rural, agricultural population these data cover is representative of large extreme poor populations across the world who are experiencing the strongest negative effects of climate change (Burgess et al., 2023; Burke et al., 2015).

Identification requires that variation in exposure to both poverty and weather shocks, and hence their interaction, is orthogonal to unobservable determinants of resilience to weather shocks. Variation in poverty comes from the randomized roll-out of BRAC's graduation program, which provided a large transfer of productive assets and complementary training to extremely poor households residing in treatment villages in 2007, without affecting control villages until 2013. Variation in weather shocks comes from a novel method that separates the predictable and unpredictable components of an observed drought or flood shock. Our analysis focuses on the impact of unpredictable weather shocks, and how these interact with poverty, while controlling for baseline risk as captured by the predictable

component of weather shocks. This strategy is thus robust to the fact that weather shocks are correlated over time, and to selection of households into climate-vulnerable regions.

We find that unexpected drought and flood shocks have substantial negative impacts on households' overall and food consumption. The central finding of the paper is that the impact of these shocks is significantly amplified by poverty. While exposure to an additional 10 days of unpredictable extreme weather (equivalent to 2.5 standard deviations) reduces food consumption by 15% among control households, receipt of the graduation program ameliorates this effect considerably, increasing food consumption by 13%. These effects are driven entirely by *negative* unpredictable weather shocks, for which the realized weather shock is larger than the magnitude that would be predicted by baseline risk. Very similar results obtain using a within-village specification that compares how ultra-poor beneficiaries of the program respond to unpredictable weather shocks, relative to near-poor households in the same villages that do not receive the program. The finding that big-push poverty reduction programs can help to support beneficiaries' consumption and keep them out of poverty in the face of these weather shocks suggests that such programs may provide a promising means of protecting the increasing numbers of climate vulnerable households worldwide.

How sustainable the impacts of the program are in increasing climate resilience – and the extent to which this may compromise other program goals – depends on the mechanisms via which it helps households to withstand weather shocks. In particular, we are interested in whether the consumption impacts we estimate reflect long-term reductions in vulnerability, or simply treated households drawing down the assets that the program transfers when hit by a shock. Our original evaluation of BRAC's graduation program (Bandiera et al., 2017) found that the program enables beneficiaries to escape poverty by acquiring productive assets and increasing their labor supply, especially in livestock rearing occupations. This mirrors the correlation between poverty and occupational choice observed worldwide. Motivated by this evidence, we examine how investment and occupational choice respond to weather shocks in order to understand the mechanisms underlying the program's protective impact in the face of these shocks.

The results suggest that treated households' enhanced climate resilience is underpinned by their increased ability to maintain and diversify productive assets and labor activities, rather than resulting from treated households drawing down productive assets. An additional day of an unpredictable weather shock reduces productive assets and hours spent in husbandry activities by 15% among control households, but treated beneficiaries are able to offset these effects entirely. Treated households not only benefit from being able to maintain this diversified income source, but those who continue to work in casual labor occupations also experience lower wage reductions during shock periods, consistent

with an increase in bargaining power. Finally, the graduation program increases diversification of both productive assets and labor occupations, even beyond the mechanical effects driven by the program transferring new types of productive assets to beneficiaries. Taken together, these results suggest that the program's protective impact in the face of weather shocks results from fundamental improvements in beneficiaries' labor market and risk management opportunities. These findings are consistent with emerging evidence in other contexts suggesting that large transfers linked to productive investments may help to ameliorate the negative impacts of droughts, while simple cash transfers do not (Macours et al., 2022; Hirvonen et al., 2023).[1]

We close the paper by considering the potential implications of our results for modifications to the design of anti-poverty programs under climate risk, by examining the impact of a household's history of weather shocks on their investment decisions. If poor households facing climate disasters adopt costly coping strategies to mitigate risk (Carleton et al., 2024) – for instance by diverting their investments towards less risky activities at the expense of reducing their long-term income potential (Karlan et al., 2014; Cole et al., 2017) – this might pose a major challenge to poverty reduction policies, especially those that hinge on large asset transfers (Balboni et al., 2022; Bandiera et al., 2017; Mobarak et al., 2022; Banerjee et al., 2015).

We partition our sample of ultra-poor beneficiaries, all of whom had close to zero productive assets before the program, according to whether their villages suffered above- or below-median levels of drought and flooding before the program began in 2007. We find that households residing in areas *ex-ante* more prone to weather shocks invest less in productive assets, and allocate fewer labor hours to husbandry activities, thus dampening the effect of the program. This suggests that, in order to deal with the increased risks posed by climate change, asset transfers may have to become more generous in vulnerable regions or incorporate insurance products in order to maintain incentives to invest (Lane, 2024; Kousky, 2019).

The search for effective policy instruments to combat extreme poverty has dominated much of the development economics literature over the past two decades, contributing to a significant evidence base on successful approaches (Banerjee et al., 2017; Duflo, 2017). In recent years, the threat of climate change has been emerging as a second, increasingly dominant policy challenge within development economics. This reflects growing evidence that the extreme poor, particularly those reliant on agriculture in rural areas concentrated in South Asia and Africa, are among those most exposed to weather shocks and climate change. The results of this paper suggest that the adverse consumption and poverty

[1]This also relates to an older literature examining the role of saving and consumption smoothing in protecting households against weather shocks (Paxson, 1992; Townsend, 1994; Deaton, 1997; Coate and Ravallion, 1993).

impacts of unpredictable weather shocks, which will become more prevalent as the climate changes, are significantly amplified by poverty. Large-scale anti-poverty programs can be effective in ameliorating these impacts, underpinned by beneficiaries' ability to maintain and diversify more productive and resilient assets and occupations, but may need to be augmented to sustain program effectiveness in the face of changing climate risks.

The rest of the paper is structured as follows. Section 2 describes background and data. Section 3 presents our empirical strategy and discusses the identifying assumptions. Section 4 documents our main results on the impact of unpredictable weather shocks and the graduation program on consumption outcomes. Section 5 investigates mechanisms underpinning these results by examining the impact of weather shocks on labor activities and assets. Section 6 discusses the implications of the paper's results for the design of anti-poverty programs under climate risk. Section 7 concludes.

2 Background and data

We leverage household-level data collected to evaluate BRAC's graduation program (also known as "Targeting the Ultra-poor") in Bangladesh (Bandiera et al., 2017; Balboni et al., 2022). This data covers 23,000 households living in 1,309 villages in the 13 poorest districts of the country. Of these households, over 6,000 are considered extremely poor, half of which are randomly selected to participate in the graduation program.

Table 1 presents descriptive statistics for this sample of ultra-poor households, and contrasts these with those for households classified as near-poor[2] in the same communities. Ultra-poor households concentrate their spending on food, which accounts for over 75% of their total consumption. They have a low intake of protein, which is consumed on average just 3.5 times a month. The ultra-poor possess few or no assets, loans or savings, and are mainly involved in casual labor in agriculture or domestic service, with a smaller share of hours devoted to animal husbandry. The value of productive assets (including land) is very skewed, with a median value corresponding to only $4 USD PPP. Near-poor households are slightly better off than the ultra-poor by these measures, but the descriptive statistics underline that both groups are very poor in absolute terms and strongly dependent on climate-vulnerable agricultural occupations.

BRAC's graduation program consists of a one-off transfer of productive assets, asset-specific training, consumption support, access to healthcare and financial services, and life-skills coaching. Its aim is to simultaneously relax credit and skill constraints and to create a

[2]Pre-randomization, BRAC officers apply inclusion and exclusion criteria to further classify poorer households into two groups: the ultra-poor, who qualify for the TUP program, and the near-poor, who do not—despite possessing very few productive assets and exhibiting similar levels of consumption.

Table 1: Descriptive statistics

	Ultra-poor				Near-poor			
	mean	p25	p50	p75	mean	p25	p50	p75
Total Consumption	11598	8615	10617	13304	11891	8914	10923	13546
Food Consumption Share	0.76	0.71	0.77	0.82	0.75	0.71	0.76	0.82
Protein Intake	3.58	2	2	4	3.93	2	2	6
Total Assets	5513	300	790	2050	14109	650	1710	7362
Productive Assets	4843	0	120	1000	12863	0	500	5200
Savings	139	0	0	50	409	0	10	350
Loans	616	0	0	0	1876	0	0	2000
Husbandry Hours	269	0	0	365	396	0	340	700
Casual Labor Hours	648	0	200	1200	396	0	0	720

Notes: All variables are measured in 2007. Units are Taka in the last year, except for hours worked (number of hours in the last year) and protein intake (total number of meals per month including egg, fish or meat). Food consumption and total consumption are measured per capita. The number of observations for the Ultra-poor group is N=6075 and for Near-poor group is N=5920.

source of regular earnings for poor women who are mostly engaged in irregular and insecure casual labor at baseline. Beneficiaries are offered a choice from several asset bundles, all of which are valued at around $490 USD in PPP and can be used for income-generating activities (i.e., a cow). Respondents are encouraged to retain the asset for at least two years, after which they can liquidate it.

BRAC identifies beneficiaries by running a participatory wealth assessment exercise in every village, yielding a classification of households into three wealth classes (poor, middle and upper class) which forms the sampling frame. The survey covers all of the poor and 10% of the other wealth classes in each village. The group of poor households is further split into program eligibles (ultra-poor) and non-eligibles (near-poor) according to BRAC's eligibility criteria. A baseline survey was conducted before the intervention in 2007, three follow-up surveys were undertaken in 2009, 2011 and 2014, and the initially ultra-poor were again interviewed in 2018. We focus in this paper on the five-year period between the intervention and the second follow-up survey in 2011. By 2014 control households had started to receive the graduation program, precluding direct comparisons between treatment and control groups.[3]

Flood data. Flood data was obtained from the Global Flood Database (Tellman et al., 2021), which employs satellite imagery and state-of-the-art visualization methods (using the MODIS instrument onboard NASA's Terra and Aqua satellites) to detect and measure flood events worldwide.[4] This dataset provides detailed daily flood information at 250-

[3]For more details on the program and household survey see Bandiera et al. (2017).

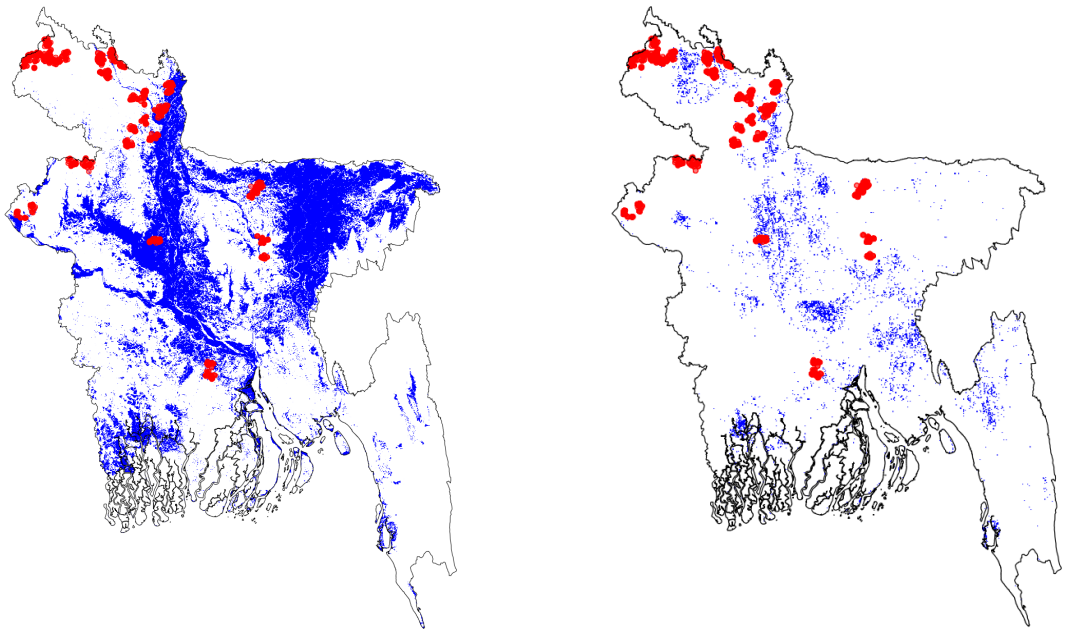
[4]The data is available at https://global-flood-database.cloudtostreet.ai/. Floods included in the Global Flood Database come from the Flood Observatory

meter resolution, including the start and end date of a flood, as well as the number of days of flooding for each pixel.[5] We remove permanent water pixels to avoid false classification of floods. In the left panel of Figure 1, we present an illustrative flood event map on a single day, showing flooded pixels in blue.

Figure 1: Illustrative satellite images of flood and drought in Bangladesh

(a) Flood

(b) Drought



Notes: Panel (a) shows a flood map for September 2nd, 2007. Panel (b) shows a drought map for the first 10 days of June 2007. White pixels indicate no impact, blue pixels represent areas affected by flood (left) on that day or drought (right) in that dekad. Red circles represent the location of sample villages, with a circular area of radius of 2.5 kilometers around the village's center. Flood data is measured at 250 $\times$ 250 meter resolution and drought data is measured at 1 $\times$ 1 kilometer resolution as a VHI value lower than 0.15.

The spatial resolution of our flood data enables us to precisely match each flood event with the geographical location of villages participating in the graduation program. To quantify the extent of flooding affecting a village, we consider a circular area with a radius of 2.5 kilometer around the village's center, remove permanent water pixels, and calculate the share of the remaining area that is flooded every day as a continuous measure of the shock. The study villages including their 2.5 km radius buffers are pictured as red circles in Figure 1. We consider all flood events that affected Bangladesh between January 2000

https://floodobservatory.colorado.edu/.

[5]For each recorded flood event, information regarding the commencement and termination dates of the flood event is available; however, at the pixel level, we only observe the count of days of inundation. To address this data gap, we use the midpoint date of the flood event as an approximation for the midpoint date of the inundated pixel. To illustrate, if a flood event spans from June 1st to June 20th, and a particular pixel experiences flooding for a duration of 6 days, we impute the initiation date of the inundated pixel as June 8th and the cessation date as June 13th.

and December 2011. 108 floods were recorded during this period, with an average of 5.4 events per year. The range of occurrences varied significantly, from a minimum of one flood to a maximum of 16 floods in 2007. We use the duration (number of days of flooding) as an indicator of the severity of each flood event. The average flood duration in Bangladesh over the period is 4.56 days, with significant variability (25th percentile of 2.41 days and 75th percentile of 6.34 days).

We validate this methodology for measuring exposure to floods using follow-up survey data from 2011, wherein households were asked how many floods they experienced in the last 10 years. We code all reported values greater than 0 as having experienced flooding in the past 10 years; 38% of households report facing such a shock. Using floods identified with satellite imagery, we determine how many dekads of flood a household experienced over the same 10-year period. This allows us to compare, for each household, information about their self-reported flood experiences over the past decade with their exposure to floods based on satellite imagery.

Both survey-based and satellite-derived measures are subject to noise and imperfections: memories can fade or become distorted over time, leading households to inaccurately recall the frequency or severity of past floods, while satellite data only capture large floods and our methodology assigns the flood occurrence to the entire village. Despite these limitations, we find a robust positive correlation of 0.54 between the two continuous measures, and a positive correlation of 0.47 between the binary variable for reported floods and a binary variable equal to one if flood intensity determined by satellite imagery is greater than the 50th percentile (since larger floods are most likely to be recalled by respondents). In the latter framework, the classification accuracy[6] approaches 75%, validating the effectiveness of our satellite-based approach in accurately capturing actual flood exposure.

Drought data. Data on droughts in Bangladesh is obtained from the Food and Agriculture Organization's Vegetation Health Index (VHI),[7] for intervals spanning 10 days (a dekad) from 2000 to 2011, at a spatial resolution of 1 x 1 kilometer. The VHI data capture the severity of drought based on the vegetation health and the influence of temperature on plant conditions. For each pixel, it combines data from the Vegetation Condition Index (VCI), a widely-used metric for quantifying the health and density of vegetation using satellite data,[8] and from the Temperature Condition Index (TCI).[9]

[6]Accuracy is defined as the ratio of the number of correct predictions to the total number of input samples.

[7]The data is available here: https://www.fao.org/giews/earthobservation/access.jsp?lang=en

[8]The VCI relates current dekadal Normalized Difference Vegetation Index (NDVI) to its long-term minimum and maximum, normalized by the historical range of NDVI values for the same dekad.

[9]Using AVHRR thermal bands, TCI is used to determine stress on vegetation caused by temperatures and excessive wetness (see FAO - Agricultural Stress Index System (ASIS)). The TCI is calculated using a similar equation to the VCI: it relates the current temperature to the long-term maximum and

The Vegetation Health Index of each pixel spans from 0 to 1, with 0 representing severe droughts and 1 indicating very healthy vegetation. For consistency with the floods data, we discretize this continuous variable into a binary measure of severe drought. We follow the Food and Agriculture Organization in classifying each pixel with a VHI below 0.15 during a 10-day interval as experiencing severe drought conditions.[10] Following the methodology used for floods, we evaluate the severity of drought impacting a village by considering a circular area with a radius of 2.5 kilometers, centered around the village center. We compute the proportion of this area affected by drought during each 10-day interval, providing us with a village-level indicator of drought intensity. The right panel of Figure 1 shows an illustrative drought event map for the first 10-day interval of June 2007.

Our preferred specifications consider a *combined* shock, capturing simultaneously exposure to both floods and droughts.[11] In order to facilitate comparison with the drought data, we first aggregate the daily flood information to the spatial and temporal resolution of the drought data by taking the average flood shock within each 10-day period, and aggregating the 250 $\times$ 250 meters pixels into 1 $\times$ 1 km pixels, defining the entire 1 km pixel as flooded if any of the original 250 meters pixels within it are flooded. We then calculate the share of each village that experienced (i) a flood and (ii) a drought for each dekad, and sum the two to obtain the total share of the village that experienced a weather shock during each dekad. Summing this variable across all dekads in a year yields our measure of *combined shock* $\mathbf{C}_{v(i),t}$, which is a continuous variable measuring the exposure of village $v(i)$ to natural disaster during year t, combining floods and droughts[12].

We choose the timing such that $\mathbf{C}_{v(i),t}$ measures the number of dekads and share of village $v(i)$ area experiencing an extreme weather event in the 36 dekads before the 2011 survey date t.[13] As the duration of the graduation program from its inception in 2007 is two years, our measure thus captures any protective effect on households one to two years after the program ended. We also construct $\mathbf{C}_{v(i),t}$ for all years from 2000 to 2010 to control for baseline risk and for additional identification checks, as described in the next section.

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minimum, as it is assumed that higher temperatures tend to cause a deterioration in vegetation conditions.

[10] In robustness specifications reported at Appendix B, we instead use a cutoff of 0.35 following Kogan (1995), which captures smaller droughts. We prefer the 0.15 threshold in the central specifications as in this case the drought and flood data are more comparable, given that the latter captures only more extreme flood events.

[11] Appendix C shows that results are robust to considering the effects of floods and droughts separately.

[12] Formally, $\mathbf{C}_{v(i),t} = \frac{\sum_{\tau=t-T}^{t-1} \text{affected pixels}_{v(i),\tau}}{\text{total pixels}_{v(i),t}}$ where t is the reference date and T the number of periods before that date (T=360 days for floods and T=36 dekads for droughts)

[13] If the interview date for a household is missing, we use the average interview date in the household's village since interviews are conducted at similar times across households in the same village. If the interview date for all households in a village is missing, we use July 1st to approximate the interview date.

3 Empirical strategy

A key objective of our analysis is to test how far weather shocks reduce the consumption of vulnerable households, and how far poverty affects this relationship. We estimate equations of the form:

$$Y_i = \alpha + \beta \times T_{v(i)} + \gamma \times \mathbf{C}_{v(i)} + \delta \times T_{v(i)} \times \mathbf{C}_{v(i)} + \varepsilon_{v(i)} \tag{1}$$

where Y_i is the outcome of interest of household i in the second follow-up survey in 2011; We drop the notation subscript t because we use only cross-sectional variation. $T_{v(i)}$ is an indicator equal to 1 if i lives in a treated v that received the graduation program starting in 2007; and $\mathbf{C}_{v(i)}$ is the weather shock measure described in Section 2 for the year prior to the 2011 survey. Thus β measures the effect of the program in the absence of weather shocks, γ is the correlation between weather shocks and outcomes in control villages, and δ is the differential effect in treatment villages, our main coefficient of interest. We expect weather shocks to have a negative impact on consumption outcomes ($\beta < 0$) and test whether this is dampened by participation in the program ($\delta > 0$).

Causal identification of the parameters of interest in this specification requires the treatment and the shock to be orthogonal to the error term. That is, the identifying assumptions are (i) $\text{Cov}(\varepsilon_{v(i)}, T_{v(i)}) = 0$ and (ii) $\text{Cov}(\varepsilon_{v(i)}, \mathbf{C}_{v(i)}) = 0$. Assumption (i) holds because treatment is randomized at the village level $v(i)$. Assumption (ii), in contrast, might be subject to several potential sources of bias. First, unobserved village characteristics, such as proximity to a river, can influence both a household's risk of weather shocks and their consumption. Second, because weather is correlated over time, past shocks are likely to impact a household's ability to accumulate assets, their occupational choices, and, consequently, their consumption today. Third, unobservable village characteristics as well as past shocks can affect the type of household that resides in a village, or the set of ultra-poor households that are eligbile for the program in a given village. These factors could bias not only estimates of the direct effect of a shock (γ in Equation 1), but also the treatment effect of the program and thus estimates of the interaction term (δ).

We propose a novel approach to separate the impact of a current weather event from ex-ante differences in impacted households or adaptation to previous shocks. This builds on a similar intuition to strategies that employ location fixed effects to absorb a baseline risk of extreme weather (Dell et al., 2014; Hsiang, 2016) – conditional on which the occurrence of a given weather event in a given year is exogenous – but can be implemented when panel data over a long period is unavailable, as in this setting. This approach relies on the fact that, even in the absence of a long panel of *outcome* data, we can observe the *weather history* of each location. By controlling flexibly for this history, we can account for

all differences in past weather realizations, which by design capture all differences between villages that might link climate risk to outcomes. By holding constant this baseline risk, we then identify the effect of weather shocks from the comparison of outcomes across villages that have the same history of weather shocks (and hence the same predicted shock in 2011) but experience different shock realizations in 2011.

We use high frequency data on weather shocks for the years 2000-2009 to estimate, for each village, a *baseline risk* as the predicted weather shock in 2010-2011, the year prior to our follow-up survey:

$$\hat{\mathbf{C}}_{v(i),2011} = f\Big(\mathbf{C}_{v(i),2000}, ..., \mathbf{C}_{v(i),2009}\Big) \tag{2}$$

where $f(\cdot)$ denotes a general prediction function that can take various forms, as discussed below. We then decompose the actual weather realization in 2011, $\mathbf{C}_{v(i),2011}$, into a predictable component, or *baseline risk*, $\hat{\mathbf{C}}_{v(i),2011}$, and a weather surprise, or *unpredictable shock*, defined as the difference between the observed weather realization and baseline risk:

$$S_{v(i)} = \mathbf{C}_{v(i),2011} - \hat{\mathbf{C}}_{v(i),2011} \tag{3}$$

3.1 Baseline specification

After decomposing the weather shock $\mathbf{C}_{v(i)}$ into a predictable component $\hat{\mathbf{C}}_{v(i)}$ capturing the level of baseline climate risk, and a weather surprise $\mathbf{S}_{v(i)}$ capturing unpredictable shocks, we augment Equation 1 to estimate the following model:

$$\begin{aligned} Y_i = \alpha + \beta \times T_{v(i)} + \gamma^B \times \hat{\mathbf{C}}_{v(i)} + \gamma^U \times \mathbf{S}_{v(i)} \\ + \delta^B \times T_{v(i)} \times \hat{\mathbf{C}}_{v(i)} + \delta^U \times T_{v(i)} \times \mathbf{S}_{v(i)} + \eta_{s(i)} + \varepsilon_i \end{aligned} \tag{4}$$

where Y_i is the outcome of interest for household i in 2011. β identifies the intent-to-treat impact of the program on household i, comparing outcomes among ultra-poor households residing in treated villages to those among counterfactual ultra-poor households in control villages in the same sub-district. γ^U captures the impact of experiencing an unpredictable weather shock during the year 2010-2011. δ^U, the main coefficient of interest, measures how the response to an unpredictable weather shock differs between treatment and control households. We expect γ^U to be negative and δ^U positive, if the treatment helps households to protect themselves against an unexpected shock.

γ^B and δ^B capture the effect of baseline risk, and differential program response by baseline risk, respectively; we return to the interpretation of these baseline risk coefficients in Section 6. These terms control for any differences in outcomes driven by differences in the

underlying frequency of extreme weather, including potential differences due to households' pre-program adaptation to the local climate. Finally, we add fixed-effects at the sub-district level $\eta_{s(i)}$ in order to compare villages located in a similar geography and micro-climate.

3.2 Decomposing weather shocks

There are multiple plausible ways to model extreme weather risk based on past data. Our preferred approach is to model the baseline risk for every dekad as an exponential decay model to account for short-term memory and then sum deviations across dekads to aggregate over the year. This approach is particularly well suited to capturing the possibility that household outcomes after a shock in 2011 may also be affected by previous shocks through adaptation or long run damages. Appendix D details other decomposition methods based on: (i) a simple deviation from the historical average, and (ii) a linear regression model to predict the intensity of floods and droughts at the dekad level. Our main results are robust to these alternative decompositions, as shown in Appendix B.

For the exponential decay model used in our central specifications, we assume that household adaptation reacts more strongly to more recent shocks: households remember and respond to past weather events for some time, but not forever. The particular functional form is motivated by seminal work on memory (Mullainathan, 2002; Kahana, 2012) finding that recall probabilities decay exponentially over time. We use a model with a decay parameter $\lambda = \frac{ln(2)}{t_{1/2}}$ and set $t_{1/2} = 1$ in our preferred specification, so that the memory of past weather shocks halves after a year.[14] Our measure of baseline risk in 2011 for dekad d and village $v(i)$ is thus constructed as a weighted average that gives a higher weight to more recent years:

$$\hat{\mathbf{C}}_{v(i),2011,d} = \sum_{t=1}^{10} \exp(-t \cdot \lambda) \cdot \mathbf{C}_{v(i),2010-t,d} \tag{5}$$

where $\mathbf{C}_{v(i),2011-t,d}$ is our shock variable measuring the exposure to floods and droughts for village $v(i)$ in dekad d and year $2011 - t$ ranging from 2001 to 2010. The dekad-level unpredictable shock (or weather surprise) $\mathbf{S}_{v(i),d}$ is therefore the difference between the baseline risk and the actual shock in dekad d in 2011, i.e. $\mathbf{C}_{v(i),2011,d} - \hat{\mathbf{C}}_{v(i),2011,d}$. We sum these components over all 36 dekads of the year, so that a weather surprise may result from (i) the intensive margin: a village experiencing more flooding (drought) during a dekad when some flooding (drought) is predicted, or (ii) the extensive margin: flooding (drought) occurring during a dekad that is not predicted to have any flooding (drought), even if the total number of flood (drought) days is as predicted.[15] Table E2 in Appendix

[14] We show the robustness of results to alternative choices for this parameter at Appendix B Table B4.

[15] In our data, we find that most surprises are driven by the intensive margin, with only a few occurrences

E shows descriptive statistics for the shock's baseline risk and unpredictable components; while baseline risk has a higher magnitude than unpredictable shocks, they have similar standard deviation (0.5 and 0.4 dekads respectively). Note that weather shocks may be less severe than predicted, in which case the continuous unpredictable shock variable would be below zero. We refer to this case as a positive weather surprise. In section 4, we further split shocks into positive and negative weather surprises and show that the results are driven entirely by negative surprises.

3.3 Identification assumptions and checks

We present a series of checks to confirm that the approach outlined in the previous subsection captures sufficient information about underlying baseline risk to support the central identification assumption. Full details of these additional identification checks are included at Appendix A. In the first check, we use outcome data for the same households measured before the program was announced in 2007; this allows us to test whether there are household-specific, time-invariant characteristics that are different in treatment and control villages, and correlated with weather shocks. The approach is akin to a balance test where we show that, after controlling for baseline risk, villages that receive an unpredictable weather shock in 2011 look similar to those that do not *at baseline*, and this holds across both treatment and control groups. We interpret this as evidence that our model of baseline risk indeed captures all relevant variation and village characteristics that could confound outcomes *after* the program occurred. Table A3 and Figure A2 show the results for this balance test. Systematic differences between villages, if any, disappear once we control for baseline risk.

In the second identification check, we re-estimate our baseline model (Equation 4) with both outcomes and shocks measured before treatment, in 2007. In this specification, the coefficient of interest, γ^U, compares the differential response to unpredictable weather shocks of eligible households in treatment versus control villages before the program has been rolled out. This is akin to a placebo test which ensures that we do not introduce an artificial correlation between receiving a shock and being in the treatment group through a particular pattern of (bad) controls. Absent such correlation, we expect γ^U to be zero, since the program has not yet happened and unpredictable weather shocks should be orthogonal to treatment *assignment*. Table A4 and Figure A3 report the estimates for γ^U in this exercise and confirm that there is no such correlation. Taken together, these two exercises lend support to our empirical strategy and suggest that our identifying assumptions are reasonable.

of shocks during a dekad that had never been impacted by extreme weather before.

4 Weather shocks and poverty

In this section, we leverage our weather shock decomposition and empirical setup to study the impact of severe weather shocks on household welfare. Our core interest is in whether exposure to the graduation program prevents households from falling deeper into poverty when they experience severe weather shocks that they did not anticipate. We focus on three measures of household welfare: total consumption, food consumption, and protein intake. Total and food consumption are measured in Taka and in per capita terms, while protein intake is recorded as the monthly frequency of consuming protein-rich foods, such as eggs, fish, and meat, ranging from zero to more than four times per week.

4.1 Baseline results

Table 2 reports the difference-in-difference estimates for β, γ and δ from Equation 4 for our three welfare measures. As documented in Bandiera et al. (2017), the graduation program has a positive impact on all aspects of the lives of ultra-poor households, allowing them to accumulate productive assets, take on better occupations, generate additional cash flows and, as shown in the first row of Table 2, increase consumption and food security. Treated households spend 11.4% more on total consumption and 7.3% more on food, and they consume protein 10.1% more frequently than households in control villages.

The main coefficients of interest are γ, which captures the direct impact of natural disasters on the consumption of ultra-poor households, and δ, which measures how far program beneficiaries were differentially affected by weather shocks relative to non-beneficiaries. We find that ultra-poor households suffer significant consumption losses from weather shocks, particularly from unpredictable events: our estimates imply that exposure to an additional dekad[16] of unpredicatable weather shocks (γ^U) leads to a large reduction in total consumption (-13.4%, not significant), food consumption (-15.4%), and protein intake (-3.4 meals including protein per month) for ultra-poor households in control villages.

Does the program help households shield themselves from the sharp decline in welfare caused by weather shocks? The estimate for the interaction coefficient δ^U is positive and significant for all outcomes, suggesting that the program does provide strong protection for treated households against unpredictable weather shocks. The magnitudes of the estimates for total consumption (+13.8%), food consumption (+12.7%), and protein intake (+2.8), indicate that treated households are able to offset almost entirely the negative impact of an unpredictable shock (γ^U), compared to households located in control villages. The treatment effect for protein intake appears to be larger in places with higher baseline risk, though we emphasize that this coefficient should be thought of as a control variable, and

[16] One dekad is equivalent to 2.5 standard deviations.

Table 2: Impact of natural disaster on poverty: baseline

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.114***	0.073***	0.872***
	(0.020)	(0.015)	(0.253)
Unpredictable Shock (γ^U)	-0.134	-0.154**	-3.392***
	(0.084)	(0.066)	(1.144)
Treated × Unpredictable Shock (δ^U)	0.138***	0.127**	2.817***
	(0.048)	(0.048)	(0.686)
Baseline Risk (γ^B)	-0.029	-0.019	-1.844**
	(0.054)	(0.050)	(0.700)
Treated × Baseline Risk (δ^B)	0.097	0.089	2.350***
	(0.065)	(0.053)	(0.755)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0513	0.0248	0.2261

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

its interpretation is not straightforward, a point we return to in Section 6.

To shed further light on the negative consumption effects of unpredictable shocks, we split unpredictable shocks into *positive* and *negative* weather surprises. We define a *negative* weather surprise $\mathbf{S}^{-}_{v(i)}$ as a weather shock for which the realized shock $\mathbf{C}_{v(i),d}$ is greater than the baseline risk $\hat{\mathbf{C}}_{v(i),d}$. This captures, for example, the case where a village usually experiences two days of severe drought during a particular dekad d, but in a given year the drought in this dekad is three times as long. The greater the *negative* weather shock, the more severely households are affected. Conversely, when the realized shock is smaller than predicted by the baseline risk level, we refer to this as a *positive* weather surprise $\mathbf{S}^{+}_{v(i)}$, as households experience a less severe shock than anticipated. For example, if a village is usually fully flooded during dekad d, but this year the flood is mild or absent, it would be considered a positive weather surprise.

We aim to understand whether the impact of unpredictable shocks documented above comes from both negative and positive surprises, or if the effect is asymmetric. After splitting the unpredictable shock into positive and negative components, we rewrite Equation

4 as follows:

$$
\begin{aligned}
Y_i = \alpha + \beta \times T_i + \gamma^B \times \hat{\mathbf{C}}_{v(i)} + \gamma^{U+} \times \mathbf{S}^+_{v(i)} + \gamma^{U-} \times \mathbf{S}^-_{v(i)} \\
+ \delta^B \times T_i \times \hat{\mathbf{C}}_{v(i)} + \delta^{U+} \times T_i \times \mathbf{S}^+_{v(i)} + \delta^{U-} \times T_i \times \mathbf{S}^-_{v(i)} \\
+ \eta_{s(i)} + \varepsilon_i
\end{aligned} \tag{6}
$$

where Y_i is again the welfare outcome of interest for household i in 2011, and $\eta_{s(i)}$ is a sub-district fixed-effect. The unpredictable shock is split into negative and positive components, both measured in terms of their absolute value and included simultaneously in the regression. Table 3 shows the results. The estimates for β and γ^B are similar to those presented in Table 2, so we focus here on coefficients γ^{U+}, γ^{U-}, δ^{U+} and δ^{U-}.

Our results suggest that the effects of unpredictable shocks are highly asymmetric: while positive surprises do not significantly affect welfare, the bulk of the effect documented in Table 2 comes from negative weather surprises. The estimates for γ^{U-} are all negative, large, and significant. These results suggest that households do not adjust their consumption when weather conditions are more favorable than expected, but are compelled to do so when they are severely impacted by an unexpected negative shock. The interaction term coefficients suggest that the program is again effective in providing almost complete protection against these negative shocks.[17]

4.2 Within village specification

In a complementary specification, we leverage our detailed data to consider an alternative empirical strategy that exploits within-village variation, as shown in Equation 7. This strategy compares how ultra-poor households respond to weather shocks relative to near-poor households in the same village, depending on the treatment status of their village. We estimate the following differece-in-difference-in-difference model:

$$
\begin{aligned}
Y_i = \alpha + \beta \times UP_i + \delta \times UP_i \times T_{v(i)} \\
+ \delta^B \times UP_i \times \hat{\mathbf{C}}_{v(i)} + \delta^U \times UP_i \times \mathbf{S}_{v(i)} \\
+ \gamma^B \times UP_i \times T_{v(i)} \times \hat{\mathbf{C}}_{v(i)} \\
+ \gamma^U \times UP_i \times T_{v(i)} \times \mathbf{S}_{v(i)} \\
+ \zeta_{v(i)} + \varepsilon_{i,v(i)}
\end{aligned} \tag{7}
$$

[17] In Appendix B, we further investigate the heterogeneity of the protection effect with respect to the magnitude of the negative climate surprise. We define *large* negative climate surprises as unpredictable shocks (normalized by baseline risk) that are above the median, i.e., compared to what is predicted, the surprise is large. Table B14 and Figure B1 present the results, and suggest that the treatment cannot fully protect households when the negative weather surprise is too large.

Table 3: Impact of natural disaster on welfare: positive vs. negative surprises

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.107***	0.069***	0.895***
	(0.020)	(0.016)	(0.244)
Negative Unpredictable Shock (γ^U)	-0.424***	-0.380***	-3.423*
	(0.128)	(0.124)	(1.817)
Treated × Neg. Unpredictable Shock (δ^U)	0.445***	0.331***	2.242
	(0.120)	(0.115)	(1.843)
Positive Unpredictable Shock (γ^U)	-0.367*	-0.240	3.266
	(0.210)	(0.242)	(2.390)
Treated × Pos. Unpredictable Shock (δ^U)	0.341	0.167	-4.166
	(0.227)	(0.244)	(2.650)
Baseline Risk (γ^B)	0.446**	0.346	-1.866
	(0.200)	(0.237)	(1.915)
Treated × Baseline Risk (δ^B)	-0.379	-0.209	3.564
	(0.238)	(0.247)	(2.672)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0522	0.0251	0.2263

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

In this specification, UP_i is an indicator equal to one if individual i belongs to the ultra-poor class, and zero if they belong to the near-poor. $T_{v(i)}$ indicates whether village $v(i)$ is assigned to receive the graduation program in 2007. $\hat{\mathbf{C}}_{v(i)}$ and $\mathbf{S}_{v(i)}$ denote baseline risk and the unpredictable weather shock, respectively. $\zeta_{v(i)}$ is the village fixed effect, added to exploit within-village differences. Since the village fixed effect will absorb all the across-village variation, we cannot estimate the effects of the weather shock or treatment independently, since both are measured at the village level. We expect the coefficient β to be negative given that the ultra-poor are selected to be worse-off than their near-poor counterparts in the same village. The triple-difference coefficients γ^U and γ^B measure the difference in response between treated and untreated ultra-poor households to unpredictable and predictable weather shocks, respectively, relative to near-poor households in the same villages.

The results, shown in Table 4, are very consistent with the baseline findings. The estimates of β indicates that, compared to near-poor households, ultra-poor households have lower

Table 4: Impact of natural disaster on welfare: within village estimate

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.064**	-0.042**	-0.631***
	(0.024)	(0.017)	(0.140)
Ultra-poor × Treated (δ)	0.126***	0.104***	0.828***
	(0.029)	(0.021)	(0.187)
Ultra-poor × Unpredictable Shock (δ^U)	-0.169	-0.260**	-0.823**
	(0.121)	(0.119)	(0.313)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.261**	0.339***	0.959**
	(0.123)	(0.123)	(0.458)
Ultra-poor × Baseline Risk (δ^B)	-0.108	-0.174	-0.101
	(0.121)	(0.118)	(0.283)
Ultra-poor × Treated × Baseline Risk (γ^B)	0.115	0.190	-0.153
	(0.122)	(0.119)	(0.316)
Mean	13141.8	8303.4	4.2
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1047	0.0506	0.4088

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the village level. Standard errors are clustered at the branch level.

total consumption (-6.4%), food consumption (-4.2%), and protein intake (-0.63 meals). When ultra-poor households benefit from the program, their consumption increases by 12.6% (for total consumption), 10.4% (for food), and 0.83 meals (for protein intake). We find that unpredictable weather shocks impact the poorest households the most: compared to near-poor households in the same village, ultra-poor households experiencing such a weather shock reduce their consumption by 16.9% (for total consumption), 26% (for food consumption), and 0.82 meals (for protein intake). However, receiving the graduation program fully offsets these effects, increasing their consumption by 26.1%, food consumption by 33.9%, and protein intake by 0.96 meals.

Taken together, our results suggest that unpredictable weather shocks significantly impact the welfare of poor households, leading to substantial reductions in consumption. However, the graduation program helps these households to shield themselves from such adverse effects, enabling them to maintain their consumption levels in the face of natural disasters. In the following sections, we explore the mechanisms underlying this resilience.

5 Mechanisms

How does the graduation program influence the ability of households to withstand weather shocks and maintain their consumption in the face of natural disasters? Understanding this is central to assessing whether the protective effects on consumption in the face of weather shocks documented in Section 4 are driven by treated households drawing down transferred assets when hit by a shock, or reflect longer-term improvements in labor activities and risk management. While both could be consistent with the results in the previous section, only the latter would imply sustainable reductions in vulnerability to weather shocks.

Previous research suggests that the graduation program works by enabling beneficiaries to accumulate productive assets and move into more profitable labor activities (Bandiera et al., 2017). To investigate mechanisms, we therefore first focus on how these outcomes respond to unpredictable shocks for ultra-poor households with and without the graduation program. Informed by this analysis, we then examine whether the program helps households to diversify labor and business activities, another potential means via which households could maintain consumption levels in the face of weather risk. Finally, we investigate how the returns to different activities (wages) are affected by shocks.

5.1 Labor and assets

The graduation program enables ultra-poor households to accumulate productive assets and secure more remunerative and stable occupations, which ultimately helps them to rise out of poverty. In line with this, a first plausible explanation for the results in Section 4 is that treated households simply cope with weather shocks by selling their productive assets to maintain consumption during periods of natural disasters. The concern is that by doing so, they are forced to revert to lower-paying occupations, potentially undermining the core objectives of the program. If this is the case, a temporary increase in consumption might actually signal a worsening economic situation, with households at risk of falling back into permanent poverty due to the loss of productive assets.

To investigate this, we study how weather shocks affect physical and financial asset accumulation, as well as labor occupations and investigate whether the program's protective effect — documented in Section 4 — extends to these outcomes. Within physical assets, we consider productive assets[18] and total assets, which also comprise non-business assets[19]. To capture financial assets, we consider both savings and loans. When studying labor supply

[18]Productive assets include land, cows, goats, sheep, chickens, ducks, power pump, plough, tractor, mowing machine, unit for keeping livestock, shop premises, boat, fishnet, rickshaw/van, cart, and any "other" productive assets mentioned by the respondent.

[19]Total assets include all productive assets as well as: radio cassette player, television, electric fan, refrigerator, cellular phone, bicycle, motorcycle, sewing machine, chair, table, chouki (bed), sofa, mosquito net, jewelry, ceremonial sarees, and any "other" assets mentioned by the respondent.

Table 5: Impact of natural disaster on assets

	Physical Assets		**Financial**	
	Total	Productive	Savings	Loan
	(1)	(2)	(3)	(4)
Treated (β)	2.488***	4.423***	0.578***	0.135***
	(0.167)	(0.303)	(0.033)	(0.043)
Unpredictable Shock (γ^U)	-0.073	-1.484*	-0.181**	-0.132
	(0.403)	(0.757)	(0.083)	(0.172)
Treated × Unpredictable Shock (δ^U)	0.520*	2.230***	0.220***	0.234
	(0.288)	(0.640)	(0.075)	(0.159)
Baseline Risk (γ^B)	0.179	-1.047**	-0.086	-0.175
	(0.319)	(0.448)	(0.054)	(0.141)
Treated × Baseline Risk (δ^B)	-0.208	1.109**	0.114**	0.128
	(0.305)	(0.450)	(0.055)	(0.129)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.2878	0.2812	0.3259	0.0725

Notes: Both physical assets and financial outcomes are measured with Taka. All of them are in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

outcomes, we focus on the number of hours spent on husbandry activities (poultry and livestock) and casual labor (maid and agricultural day labor), as well as income per hour in these occupations.

Our empirical approach follows the baseline specification detailed in Equation 4. Table 5 shows the results for physical and financial assets, while Table 6 focuses on labor outcomes. We find that γ^U, which measures the impact of a weather shock, is negative across all asset categories and statistically significant for productive assets and savings. An additional day (0.1 dekad) of an *unpredictable* weather shock is associated with a decrease in productive assets (-14.8%) and savings (-1.8%) in control villages. Without the program, extreme weather damages productive assets or forces households to sell them. Accordingly, an additional day of unpredictable weather shock also affects the number of hours worked in husbandry activities (-14.7%). The shock also depresses the casual labor wage (-3.9%), as discussed in more detail in the next subsection.

These results highlight the severe impact that unpredictable weather events have on vulnerable populations beyond consumption. From reduced food consumption and the depletion

Table 6: Impact of natural disaster on labor

	Hours		Income per hour	
	Husbandry	Casual Labor	Husbandry	Casual Labor
	(1)	(2)	(3)	(4)
Treated (β)	2.753***	-1.382***	0.921***	0.128***
	(0.242)	(0.211)	(0.122)	(0.029)
Unpredictable Shock (γ^U)	-1.472**	1.341	-0.324	-0.389***
	(0.703)	(0.818)	(0.532)	(0.104)
Treated × Unpredictable Shock (δ^U)	1.583***	-1.202**	0.118	0.304***
	(0.535)	(0.570)	(0.425)	(0.084)
Baseline Risk (γ^B)	-0.841*	0.450	0.048	-0.225***
	(0.480)	(0.610)	(0.439)	(0.071)
Treated × Baseline Risk (δ^B)	0.646	-0.626	0.114	0.368***
	(0.454)	(0.581)	(0.461)	(0.056)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	2771	3076
Adjusted R-square	0.1917	0.1128	0.1068	0.1659

Notes: Hours are measured as the number of hours worked a year. Income per hour is the annual labor income divided by the number of hours worked a year. All of them are in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

of productive assets to reduced savings and the weakening of livestock practices, the repercussions have a cascading effect on their daily lives. This instability threatens not only their livelihoods, but also their ability to plan for the future. Faced with this uncertainty, people often resort to immediate, albeit precarious, solutions such as seeking casual work opportunities, perpetuating a cycle of economic instability.

Focusing now on the interaction term (δ), the results in Tables 5 and 6 indicate that, on average, program participants are more resilient to unexpected weather shocks. Beneficiaries are again able to entirely offset the negative impact of the one additional day (0.1 dekad) of unpredictable shock on total assets (+5.2%), productive assets (+22.3%), savings (+2.2%), loan(+2.3%), number of hours worked in husbandry (+15.8%), and hourly income from casual labor (+3%), the beneficiaries are again able to perfectly offset the negative impact of the unpredictable shock.

These results suggest that the graduation program sustainably shields beneficiaries, who manage to absorb weather shocks without relinquishing their assets or resorting to distress sales, nor switching from husbandry to lower-earning jobs. This is a central finding: the resilience of treated households to natural disasters in terms of consumption, as documented in Section 4, does not come at the expense of other goals of the graduation program, such

as asset accumulation. On the contrary, the benefits are cumulative, as the program offers comprehensive protection in all aspects of life for ultra-poor households.[20]

5.2 Resilience and dependence on casual labor wage

In this subsection, we delve deeper into the differential impact of weather shocks on casual labor wages for treated and untreated households, as presented in Table 6, column (4). This wage effect is likely to be particularly important for understanding how the program protects consumption given that untreated households are heavily reliant on this income source. Figure 3 highlights that casual labor constitutes 67% of the hours worked and over 90% of income for untreated households. This concentrated reliance creates a double vulnerability: these households are directly affected by weather shocks that limit their ability to work and, even when they do find work, they face reduced wages during these periods.

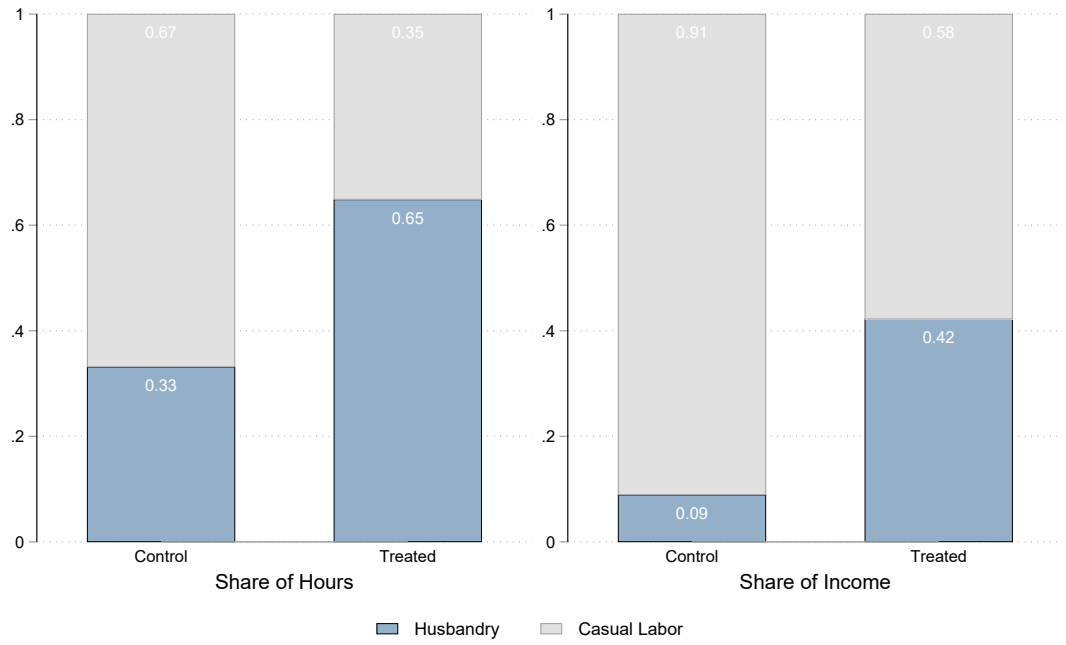
To better understand this wage effect, we investigate whether the decline in casual labor wages in untreated villages impacts all households equally. Specifically, we ask whether this is a broader labor market phenomenon, potentially tied to village-level characteristics, or whether the effect is concentrated among untreated ultra-poor households. If the latter is true, the protective effect of the program on the casual labor wage received by beneficiaries during weather shocks may indicate that treated households have gained stronger bargaining power in the labor market, for instance as a result of enhanced asset positions and diversified income streams.

Table 7 summarizes the results. We first replicate our baseline household-level regression focusing only on near-poor households and find that their casual labor wages are unaffected by weather shocks. Village-level regressions confirm this finding: the negative wage impact is evident only when we isolate ultra-poor households, and disappears when near-poor households are included or when all households in the village are analyzed together. These results suggest that the wage depression during shock periods is particularly severe for untreated ultra-poor households. This vulnerability likely stems from their lack of alternative income sources, which forces them to accept any available wage, even if significantly lower than normal levels.

The resilience of treated households' wages underscores a broader implication about the program's effectiveness. Treated households exhibit enhanced economic resilience through

[20]However, Figure B4 in the Appendix highlights heterogeneity in the program's protective effects: while treated households in the upper tail of the asset distribution achieve full resilience, those who initially possessed few productive assets continue to suffer from the shocks. This is suggestive of a poverty threshold as discussed in Balboni et al. (2022), which in this case would be reinforced by severe weather shocks.

Figure 3: Labor income and hours worked



Notes: Light blue bars represent the share of labor hours and labor income spent on casual labor activities (maid and agricultural day labor). Grey bars represent the share of labor hours and labor income spent on husbandry activities. Each panel plots both the control group and the treated group in 2011, excluding other activities.

two complementary mechanisms. First, they sustain more stable incomes during shock periods, partly due to their ability to secure higher wages in the casual labor market. Second, their diversified income sources reduce their overall exposure to wage fluctuations in any single sector. This diversification ensures that, even when casual labor wages decline, treated households can mitigate losses through other income streams, particularly from livestock enterprises and small businesses.

This dual resilience highlights the program's broader impact on household welfare, extending beyond mere asset transfers to include labor market advantages and risk management capabilities. It also points to the importance of diversification as a strategy for ameliorating the adverse effects of weather shocks. In the next subsection, we further explore the contribution of diversification across all labor occupations and assets.

5.3 The role of diversification

In the previous subsection, we found that the graduation program protects beneficiaries' productive assets, savings and labor occupations in the face of weather shocks. In par-

Table 7: Impact of natural disaster on casual labor wage

	Household-Level Regressions		**Village-Level Regressions**	
	Only Ultra-poor	*Only Near-poor*	*Only Ultra-poor*	*All Households*
	(1)	(2)	(3)	(4)
Treated (β)	0.131***	0.054*	0.137***	0.050
	(0.030)	(0.027)	(0.028)	(0.031)
Unpredictable Shock (γ^U)	-0.322***	0.009	-0.302**	-0.165
	(0.118)	(0.140)	(0.148)	(0.131)
Treated × Unpredictable Shock (δ^U)	0.228**	0.158	0.246***	0.122
	(0.089)	(0.137)	(0.078)	(0.086)
Baseline Risk (γ^B)	-0.171**	0.107	-0.148*	-0.051
	(0.072)	(0.114)	(0.087)	(0.086)
Treated × Baseline Risk (δ^B)	0.332***	0.118	0.326***	0.227***
	(0.057)	(0.114)	(0.073)	(0.081)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	2152	1484	887	1037
Adjusted R-square	0.1599	0.1527	0.2170	0.2039

Notes: Causal labor wage is measured as the average income per hours worked. All of them are in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

ticular, the results suggest that the adverse effects of a climate shock on income streams are mitigated by lower reliance of treated households on a single, fragile source of income: casual labor. In this section, we make the broader case for diversification of assets and labor as an important mechanism underlying the protective effect of the program. Diversification, particularly in agriculture, has been shown to be an important strategy for alleviating the adverse effects of weather shocks (Karlan et al., 2014; Cai, 2016; Michler and Josephson, 2017; Mulwa and Visser, 2020), as it spreads risk across different crops, livestock or activities, reducing dependence on a single source of income. This approach helps buffer against weather shocks, as the failure of one crop, livestock type or activity due to adverse weather can be offset by others, ensuring more stable income and food security.

We measure asset diversification by the number of different types of assets a household owns. On the labor side, we measure diversification by the number of labor activities a household engages in, as well as the normalized Herfindahl-Hirschman Index (HHI) for hours spent on different occupations, which measures how households concentrate their

working hours in different activities.[21] All outcomes are measured at the household level, to capture the potential benefits of the program for other family members, and because diversification is likely to be coordinated within households.

We estimate the following simple linear model linking diversification of assets and labor to program participation:

$$Y_i = \alpha + \beta \times T_{v(i)} + \eta_{s(i)} + \varepsilon_{i,s(i)} \tag{8}$$

where Y_i is a measure of asset or labor diversification for household i in 2011, $T_{v(i)}$ indicates treatment of village $v(i)$ by the graduation program, and $\eta_{s(i)}$ is a sub-district fixed-effect.

The results are presented in Table 8. In Panel A, we consider all types of assets and labor activities, including those directly affected by the program. Since the graduation program involves transferring assets (primarily cows), beneficiaries will naturally report more productive assets and occupations. To consider how far there is evidence for diversification beyond this mechanical effect, Panel B excludes the asset categories related to cows and removes livestock husbandry, which is directly linked to the program's asset transfer.

The results in Table 8 clearly suggest that the program allows households to diversify their assets and labor occupations. Treated households own on average 2.14 more types of assets and increase their number of different labor occupations by 0.85. The normalized HHI, which accounts for the share of labor hours and the number of occupations, is significantly lower (-0.18) for treated households, implying that their labor activities are less concentrated in small number of occupations.

Evidence for diversification among treated households holds even when we eliminate the mechanical effects of the program transfers. In Panel B, when we exclude cows from productive assets and livestock activities from labor occupations, the results remain significant, but of lower magnitude. The total number of assets excluding cows increases by 1.54, the total number of occupations excluding livestock husbandry increases by 0.36, and the HHI without livestock husbandry decreases by 0.09. These results indicate that the program helps households diversify beyond the direct, mechanical effect of the asset transfer. In Table C1, we follow the same identification specification as Equation 4 and interact the treatment status with the decomposed weather shock in 2011. Here, we also remove productive assets labeled as cows and livestock activities. The table shows that the graduation program increases asset and labor diversification. It also shows that, while weather shocks negatively affect diversification, the program restores it.

[21] The normalized Herfindahl-Hirschman Index is $\frac{\sum_n s_i^2 - \frac{1}{n}}{1-\frac{1}{n}}$, where s_i is the share of hours spent on occupation i, and n is the total number of occupations the household has worked in.

Table 8: Diversification at the household level

	Panel A: All Activities		
	Asset Diversification	**Labor Diversification**	
	# Asset Categories	# Occupations	HHI
	(1)	(2)	(3)
Treated	2.143***	0.847***	-0.179***
	(0.089)	(0.083)	(0.014)
Subdistrict Fixed-effects	Yes	Yes	Yes
Number of obs.	6729	6732	6732
Adjusted R-square	0.2077	0.0781	0.0630
	Panel B: Excluding Livestock Activities		
Treated	1.539***	0.360***	-0.089***
	(0.078)	(0.056)	(0.014)
Subdistrict Fixed-effects	Yes	Yes	Yes
Number of obs.	6729	6732	6732
Adjusted R-square	0.1624	0.0524	0.0385

Notes: Assets diversification is the number of different assets categories for the household. Labor diversification at the household level is measured in two different ways: the number of business activities and normalized HHI. Panel A uses all labor activities and assets. Panel B removed livestock husbandry (directly related with cows) for labor diversification, and removed cows for assets diversification. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

6 Lessons for policy design under climate risk

The results in Sections 4 and 5 suggest that BRAC's graduation program enhances ultra-poor households' resilience to weather shocks, and does so by helping them to maintain and diversify productive activities and assets. This throws up two key forward-looking questions for the design of large-scale anti-poverty programs. First, how will households cope with worsening weather risks as the global climate changes? And second, how might big-push anti-poverty programs have to be modified to account for this changing risk profile?

We probe the potential implications of our results for these two questions. While we have so far focused on the impacts of *unpredictable* weather shocks, the results in the penultimate row of Table 5 also suggest that high *baseline* risk reduces the accumulation of productive assets. Motivated by this, we consider evidence for adaptation, i.e. adjustments undertaken by households in anticipation of expected weather shocks. In particular, we study the adaptation strategies of ultra-poor households in our sample by looking at the impact of a household's history of weather shocks on their investment decisions. In this setting, investment behavior and income generation choices are the primary margins via

which households are likely to respond to the risk of weather shocks, given that the study population have very limited access to credit and insurance.

Adaptation strategies undertaken by households may be difficult to identify for three reasons. First, weather shocks are correlated over time, so it is challenging to differentiate adaptive adjustments from the direct impacts of shocks. Second, adaptation strategies may involve forgoing risky activities, which cannot be identified without observing a counterfactual risk level. Third, a location's history of shocks may be correlated with other characteristics (such as geography) that also influence outcomes via other channels.

We present motivating evidence on adaptation strategies drawing on the fact that beneficiaries have close to zero productive assets before the program. As a result, differences in program impacts on asset accumulation and savings across individuals with differential exposure to severe weather shocks before the baseline survey (controlling for shocks experienced thereafter) can help to identify adaptation strategies.

We estimate the following quantile regression model, which also allows us to examine distributional implications:

$$Q_{k_{(i)}}(\tau|e_{2000-2006,v(i)}) = \beta_0(\tau) + \beta_1(\tau) \times e_{2007-2011,v(i)} + \beta_2(\tau) \times T_{v(i)} + u_i \tag{9}$$

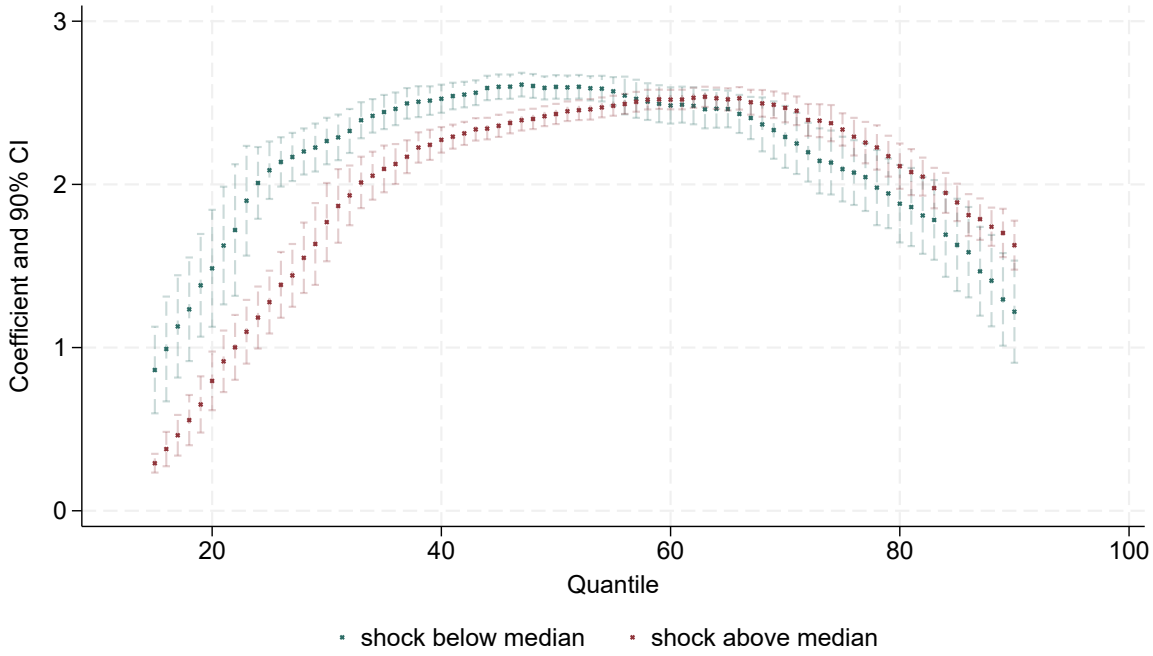
where $\tau = [15, ..., 90]$ are percentiles of the asset (consumption) distribution and $e_{2000-2006,v(i)}$ captures exposure to weather shocks from 2000 up to two years before the treatment. We construct an indicator variable equal to 1 if village v is in the top 50th percentile of the baseline risk distribution, and estimate Q separately for the groups for which $e_{2000-2006,v(i)} = 0$ and $e_{2000-2006,v(i)} = 1$. $e_{2007-2011,v(i)}$ is the exposure to shocks between the first survey wave in 2007 and the third survey wave in 2011. As in Equation 4, $T_{v(i)} = 1$ for households i residing in treated village that receive the graduation program in 2007, and 0 otherwise. The coefficients of interest are the two β_2 coefficients, estimated respectively for the groups for which $e_{2000-2006,v(i)} = 0$ and $e_{2000-2006,v(i)} = 1$. These coefficients capture the treatment effect of the program separately for treated households that are heterogeneous in terms of their ex ante exposure to drought and flood risk. The absence of a significant difference between the two coefficients would imply that the history of weather shocks does not matter for investment decisions, while differences would indicate that prior shock exposure influences these decisions.

Figure 4 presents the results where the log level of productive assets is the dependent variable.[22] The figure indicates that the impact of the graduation program on productive asset accumulation is weaker in villages that experienced above-median weather shocks

[22]We cannot estimate the relationship for quantiles lower than 15 since there are no assets owned by the control households, thus the difference is not defined.

before implementation of the program (shown in red), relative to those that experienced below-median weather shocks (shown in blue), up to the 60th quantile. The effects become indistinguishable across the two groups at higher quantiles of the distribution. Appendix Figure B2 shows a similar pattern when villages' baseline risk is assigned based on a simple historical average rather than using the decomposed shocks.

Figure 4: Impacts of the graduation program on productive assets



Notes: Each dot represents one estimate for the treatment effect for different quantiles. The maroon ones represents high weather shock villages (combine floods and droughts, either unpredictable shock or baseline shock is higher than the 50th percentile of the distribution) before 2007, and the emerald dots represent low weather shock villages. Bars represent 90% confidence interval. The outcome is productive assets in 2011 in log.

Figure B3 offers a complementary perspective in understanding adaptive adjustments by presenting the same figure with the log level of husbandry hours worked as the dependent variable. In villages that are ex-ante more exposed to severe weather shocks, households not only accumulate fewer productive assets, but also turn less to entrepreneurship. The weaker effect of the program is again evident at lower quantiles (up to the 70th quantile), with similar effects across the two groups at higher quantiles of the distribution.

Given evidence that asset accumulation and the transition to entrepreneurial occupations are key factors in escaping poverty in this setting (Balboni et al., 2022), these results suggest that underlying weather risk may undermine the effectiveness of anti-poverty programs for the poorest beneficiaries by reducing productive investment. If households that are more exposed to weather shocks *ex-ante* are more reluctant to invest in profitable activities, this may suggest a case for modifications to program design. This might include, for

instance, increasing the size of the transfer in more vulnerable regions, or incorporating weather-dependent insurance for productive assets to reduce uncertainty. Evidence from other settings suggests that such approaches can result in both faster, more certain, and larger payouts to households after a disaster (Kousky, 2019), and higher production and investment ex-ante (Cole et al., 2017; Karlan et al., 2014; Lane, 2024).

7 Conclusions

There is growing evidence that the extreme poor are most acutely exposed to current weather shocks, and will be hardest hit by climate change. However we are still in the infancy of designing effective programs to protect the most vulnerable from these changing risks. In this paper, we aim to shed light on the following key questions. First, how do extreme weather events such as droughts and floods affect the vulnerable, and how does poverty interact with this vulnerability? Second, do existing anti-poverty programs offer protection against these events and, if so, how? Finally, how might these programs be augmented to become more effective in the face of these new climate risks? To consider these questions, we bring to bear detailed household survey panel data from the randomized evaluation of a poverty alleviation program in Bangladesh with granular satellite data on exposure to floods and droughts.

We find that droughts and floods have significant negative impacts on households' consumption, but that a large-scale asset transfer scheme – BRAC's graduation program – successfully shields beneficiary households from these effects. Importantly, the protective effects of the program are not driven by beneficiaries drawing down the assets that the program transfers, but instead by helping them to maintain and diversify their productive assets and activities. This finding that 'big push' poverty reduction programs can also increase resilience to climate change is important as it suggests that such approaches may play a key role in protecting the increasing numbers of climate-vulnerable households worldwide.

Estimates of quantile treatment effects for those in villages with higher versus lower levels of ex-ante weather risk before receiveing the transfer suggest that the protective impact of the program for productive asset holdings may be muted for beneficiaries who are exposed to higher levels of baseline weather risk. The finding that ex-ante risk exposure can influence program impacts may point to ways that anti-poverty programs might be modified in the face of changing climate risks. For instance, integrating conditional loans or weather-dependent insurance into poverty alleviation programs might help to make their protective impacts more resilient to a worsening trajectory of climate risks. Taken together, the paper's findings underline the importance of further research to understand and adapt

poverty reduction strategies to meet the unique challenges of climate change.

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Appendix

Outline

- Appendix A presents additional descriptive statistics and the placebo test
- Appendix B presents additional empirical results and robustness checks
- Appendix C presents additional empirical results for mechanisms
- Appendix D presents other decomposition method
- Appendix E presents details on floods and droughts measurement

A Descriptive statistics and identification tests

A.1 Additional descriptive statistics

Table 1 presents descriptive statistics for a sample of ultra-poor households among whom 50% are targeted by the graduation program in 2007, measured before treatment and contrast it with households classified as near-poor, for comparison. Table A2 shows similar statistics but for 2011, five years after treatment. It confirms that ultra-poor households concentrate their spending on food. Food consumption accounts for over 70% of their total consumption, but with little protein intake, consumed on average just 3.5 times a month. They possess few or no assets, loans or savings, and are mainly involved in casual labor, rather than husbandry.[23] Importantly, the value of productive assets (including land) is very skewed, and the median barely exceeds Taka 100, corresponding to only $4 USD in PPP.

Table A1: Descriptive statistics for survey wave 3

	Ultra-poor				**Near-poor**			
	mean	p25	p50	p75	mean	p25	p50	p75
Total Consumption	11656	8000	10663	13845	11848	8256	10716	13804
Food Consumption Share	0.70	0.62	0.72	0.80	0.69	0.61	0.71	0.79
Protein Intake	3.48	2	2	4	3.56	2	2	4
Total Assets	21714	1127	7548	20865	30325	1323	3568	12205
Productive Assets	20019	135	4957	19078	27656	0	1127	8262
Savings	876	0	486	1155	555	0	23	282
Loans	1302	0	0	451	2709	0	0	1945
Husbandry Hours	635	30	660	1035	475	0	350	720
Casual Labor Hours	559	0	50	960	430	0	0	840

Notes: All variables are measured in 2011. Units are Taka in the last year, except for hours worked (number of hours in the last year) and protein intake (total number of meals per month including egg, fish or meat). Food consumption and total consumption are measured per capita. The number of observations for the ultra-poor group is N=6123 and the number of observations for near-poor group is N=6043.

In Figure A1, we focus on the accumulation of productive assets after the initial transfer, and its interaction with weather shocks. We plot the distribution of productive assets in 2011, five years after the treatment, for the treatment and control groups, in villages defined as high weather shock zones, i.e. regions where ex-ante exposure to weather shocks between 2000 and 2006,[24] is greater than the 50th percentile, versus villages classified as low weather shock zones. The dotted lines represent control households who did not receive

[23] The total annual hours spent on husbandry are 268, almost two times less than on casual labor (maid and agricultural day labor).

[24] Defined as the number of days of severe weather event

Table A2: Descriptive statistics for survey wave 1, rich households

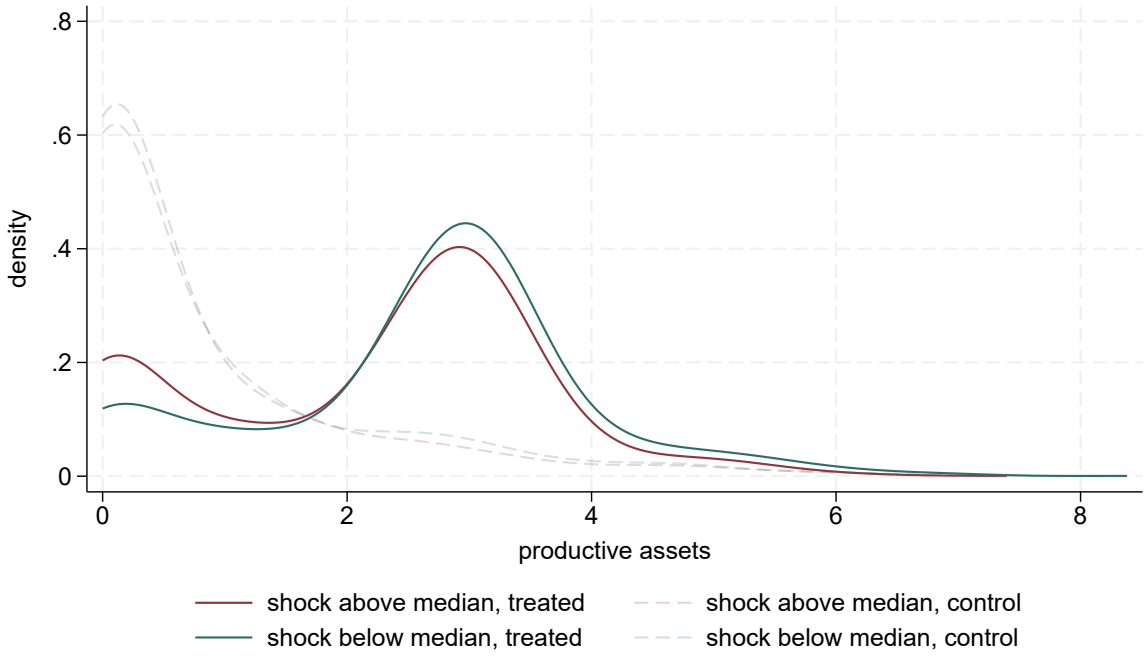
	Middle-rich				Rich			
	mean	p25	p50	p75	mean	p25	p50	p75
Total Consumption	14023	9899	12294	15918	22708	13451	18332	25695
Food Consumption Share	0.73	0.69	0.76	0.81	0.66	0.58	0.69	0.77
Protein Intake	5.51	2	4	8	9.79	4	8	14
Total Assets	147808	4630	34775	169100	817504	259250	564075	1070000
Productive Assets	142604	1700	30375	162500	786753	236700	544150	1036600
Savings	1569	0	200	1000	8832	10	700	4500
Loans	4918	0	50	5000	11324	0	0	10000
Husbandry Hours	628	320	640	1000	733	360	700	1050
Casual Labor Hours	93	0	0	0	4	0	0	0

Notes: All variables are measured in 2007. Units are Taka in the last year, except for hours worked (number of hours in the last year) and protein intake (total number of meals per month including egg, fish or meat). Food consumption and total consumption are measured per capita. The number of observations for the Middle-rich group is N=5567 and the number of observations for Rich group is N=1817.

the program, and the solid lines represent treated household. The blue line represents households living in villages located in low weather shock zones (shock = 0) and the red line represents high weather shock zones (shock = 1).

Comparing the treatment group with the control group (solid versus dashed lines) confirms that the graduation program leads to a substantial increase in productive assets (Bandiera et al., 2017). When we turn to the differences between the areas most exposed to weather shocks (shock = 1, red solid line) and those less exposed (shock = 0, blue solid line) within the treatment group, the figure shows a substantial disparity between the distributions of the two groups, which suggests a negative impact of weather shocks on the accumulation of productive assets. In contrast, in the control group, while there is some contrast between the dotted blue and red lines, the difference is relatively minor. There is, of course, an obvious reason for this: the control group is made up of ultra-poor households that own few or no productive assets and receive no transfers, so weather shocks cannot damage anything. Within the control group, the difference might also come from the ex-ante heterogeneity in households living in exposed versus non exposed villages. Within the control group, this difference may not be due to exposure to weather shocks, but to the fact that households living in exposed or unexposed villages are different ex-ante in term of consumption, assets and labor market outcomes.

Figure A1: Distribution of the productive assets in 2011



Notes: This figure shows the distribution of the productive assets in 2011, five years after treatment, in the high shock areas versus low shock areas, and in treated villages versus control villages. The maroon curves represents high shock areas, defined as the number of weather shock days (both flood and drought) between 2000 and 2006 being above the 50th percentile in all the villages. The emerald curve is below the 50th percentile. The dashed line is the control group and the solid line is the treatment group.

A.2 Identification tests

In this section, we conduct two identification tests. Each of the identification checks presents a counterfactual scenarios in which the same confounding factors, if relevant, are present but the program is not.

For the first identification, we use outcome data for the same households at the time before the program was announced (2007); this will allow us to test whether there are household specific, time invariant, characteristics that are different in treatment and control villages, and correlated to weather shocks. The approach is akin to a balance test where we show that after controlling for baseline risk, villages that receive an unpredictable weather shock in 2011 look similar to those that don't *at baseline*, and this holds across both treatment and control group. Since our weather shock measure is a continuous variable not a dummy, we cannot split the sample and perform a t-test,[25] so instead we regress the 2007 outcome variables on the continuous 2011 shock variable, expecting coefficients close to zero and

[25]Ideally, we would like to split our sample based on whether households experienced a shock in 2011 and then perform a t-test on the outcomes observed in 2007 to investigate whether a statistically significant differences exist.

statistically insignificant. We first estimate the following linear model that accounts for weather shocks only, without the interaction with the treatment $T_v(i)$:

$$Y_{i,2007} = \alpha + \gamma^B \times \hat{\mathbf{C}}_{v(i),2011} + \gamma^U \times \mathbf{S}_{v(i),2011} + \varepsilon_i$$

Results are presented in columns (1) and (2) of Table A3. For more all the outcome variables (productive assets, loan, savings, etc.), we do not observe any significant difference between villages: exposure to climate surprise in 2011, controlling for baseline risk, is not correlated to ex-ante village characteristics. We verify this by re-estimating our baseline Equation 4, still measuring outcomes in 2007. Figure A2 plots the coefficient δ^U for the cli-

Table A3: Balance test

	Climate Shocks		**Baseline Model**	
	γ^U	p-value	γ^U	p-value
Total Consumption	0.07	0.160	-0.05	0.308
Food Consumption	0.03	0.406	-0.06	0.194
Protein Consumption	-0.01	0.838	-0.11	0.118
Total Assets	0.16	0.243	-0.12	0.522
Productive Assets	0.11	0.416	0.04	0.844
Savings	-0.03	0.326	-0.03	0.504
Loan	-0.02	0.754	-0.01	0.883
Husbandry Hour	0.06	0.112	0.13	0.173
Casual Labor Hour	-0.07	0.108	0.01	0.936

Notes: All variables are measured in 2007, and are measured with Taka, except the hours worked and protein intake. The coefficient is from regressing the 2007 values on the 2011 combined (flood and drought) weather shock, with standard error clustered at the branch level. The weather shocks only equation estimated is: $Y_{i,2007} = \alpha + \gamma^B \times \hat{\mathbf{C}}_{v(i),2011} + \gamma^U \times \mathbf{S}_{v(i),2011} + \varepsilon_i$ and Baseline Model is our baseline Equation 4.

mate surprise, and columns (3) and (4) show the results: coefficients are all non-significant after controlling for baseline risk, and the magnitudes of these coefficients are small relative to the mean values of the outcome variables. This suggests that households in 2007 are balanced in terms of the *unpredictable* 2011 weather shocks, which we take into account in our empirical approach.

In the second counterfactual, we re-estimate our baseline model (Equation 4) with both outcomes and shocks measured before treatment, in 2007. The coefficient of interest is γ^U, comparing the differential shock-response to unpredictable weather shocks of eligible households in treatment vs. control villages. This approach is akin to a placebo-test which ensures that we don't artificially introduce a correlation between having a shock and being in the treatment group through a particular pattern of (bad) controls. Absent

such correlation, we expect γ^U to be zero, since the program has not yet happened and unpredictable weather shocks should be orthogonal to treatment *assignment*. Put simply, this allows us to test whether there are village specific, possibly time varying, unobservables that create differences in surprise shocks in treatment and control villages.

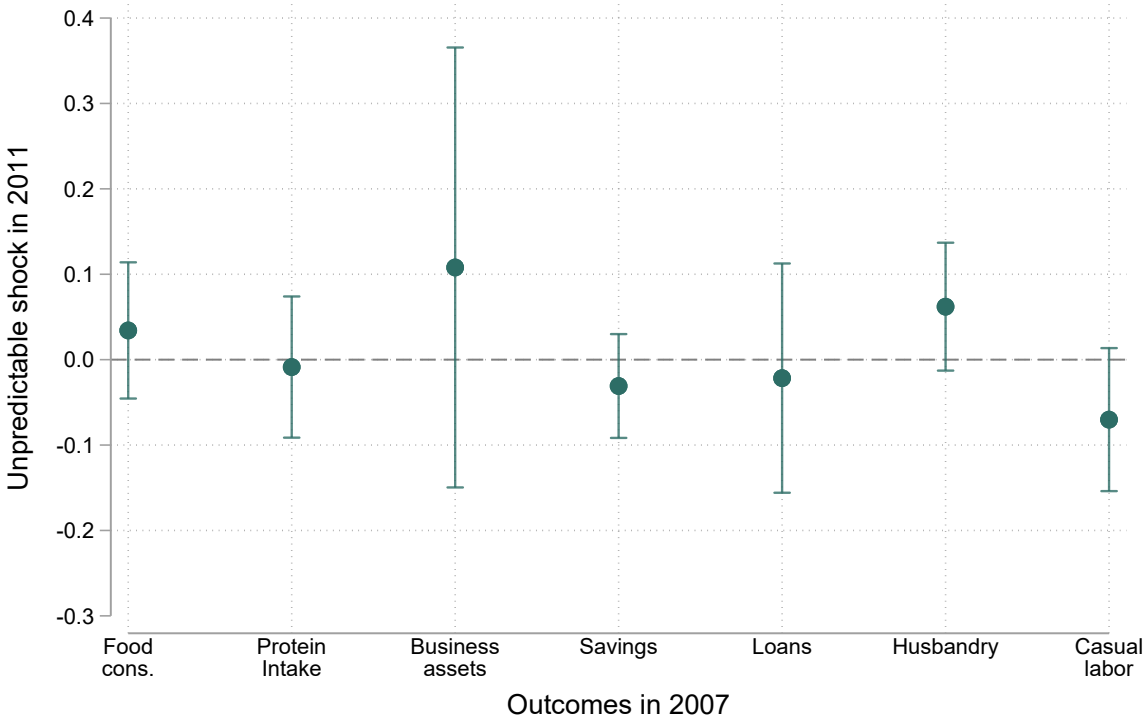
Table A4 and Figure A3 show the results. and don't show a systematic pattern of results. Taken together, they lend support to our empirical strategy and suggest that our identifying assumptions are reasonable.

Table A4: Placebo test

	$\mathbf{S}_v(i) \times T_v(i)$		$\hat{\mathbf{C}}_v(i) \times T_v(i)$	
	δ^U	p-value	δ^B	p-value
Total Consumption	0.10	0.122	0.10	0.061
Food Consumption	0.05	0.281	0.07	0.081
Protein Intake	0.02	0.631	0.03	0.540
Total Assets	0.29	0.008	0.29	0.024
Productive Assets	0.11	0.264	0.12	0.318
Savings	-0.01	0.698	0.01	0.818
Loans	0.08	0.206	-0.01	0.887
Husbandry Hours	-0.06	0.410	-0.04	0.650
Casual Labor Hours	-0.06	0.385	0.03	0.597

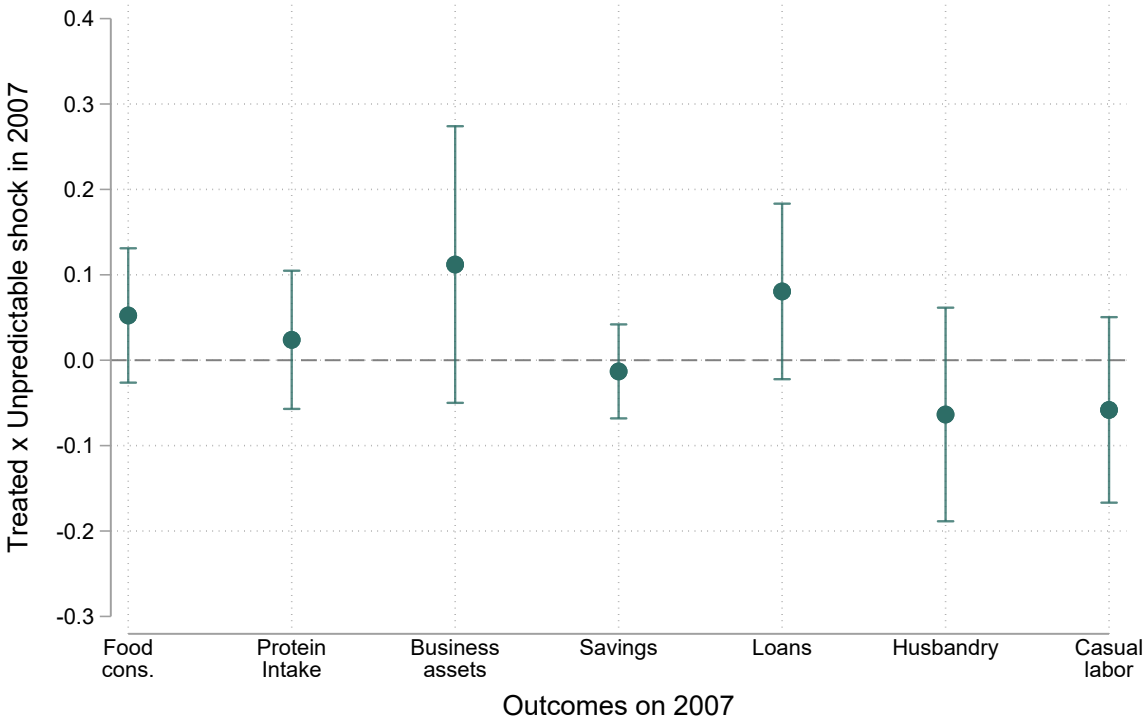
Notes: All variables are measured in 2007, and are measured with Taka, except the hours worked and protein intake. The coefficient is from regressing the 2007 values on the 2007 weather shock, with standard error clustered at the branch level.

Figure A2: Balance test: shock in 2011 vs. outcomes in 2007



Notes: This figure plots the beta coefficients for our placebo test. All variables are measured in 2007, and are measured with Taka, except the hours worked and protein intake. Coefficients are from regressing the 2007 values on the 2011 combined (flood and drought) weather shock, with standard error clustered at the branch level. The regression model is our baseline Equation 4

Figure A3: Placebo test: baseline equation before treatment



Notes: This figure plots the beta coefficients for our placebo test. All variables are measured in 2007, and are measured with Taka, except the hours worked and protein intake. Coefficients are from regressing the 2007 values on the 2007 combined (flood and drought) weather shock, with standard error clustered at the branch level.

B Additional results

Table B1: Impact of natural disaster on welfare: near-poor

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Near-poor	0.083***	0.050***	0.583**
	(0.022)	(0.015)	(0.211)
Unexpected Shock	-0.109	-0.104*	-2.150***
	(0.078)	(0.055)	(0.560)
Near-poor × Unpredictable Shock	0.155	0.204*	0.903
	(0.117)	(0.116)	(0.607)
Expected Shock	-0.149*	-0.086	-1.540**
	(0.079)	(0.053)	(0.697)
Near-poor × Baseline Risk	0.088	0.123	0.258
	(0.117)	(0.117)	(0.633)
Mean	11303.7	7893.4	3.2
Number of obs.	5738	5738	5738
Adjusted R-square	0.0187	0.0037	0.0090

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table B2: Impact of natural disaster on asset and labor: near-poor

	Physical Assets		Financial		Hours		Income per hour	
	Total	Productive	Savings	Loan	Husbandry	Casual Labor	Husbandry	Casual Labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Near-poor	1.268***	1.682***	0.115***	0.335***	1.109***	-1.349***	0.318***	0.092***
	(0.125)	(0.187)	(0.021)	(0.046)	(0.180)	(0.191)	(0.090)	(0.017)
Unexpected Shock	-0.000	-1.400	-0.054	-0.135	-2.552***	-0.640	1.133**	-0.177*
	(0.395)	(0.877)	(0.122)	(0.295)	(0.662)	(0.950)	(0.460)	(0.096)
Near-poor × Unpredictable Shock	0.560*	1.224**	0.024	-0.139	1.147**	0.111	-1.472***	0.126
	(0.287)	(0.537)	(0.087)	(0.171)	(0.498)	(0.489)	(0.328)	(0.115)
Expected Shock	0.182	-0.579	-0.036	0.020	-1.132**	-0.832	0.976**	-0.146**
	(0.228)	(0.504)	(0.087)	(0.219)	(0.418)	(0.604)	(0.342)	(0.069)
Near-poor × Baseline Risk	0.065	0.602	-0.015	-0.159	0.522	0.100	-1.418***	0.125
	(0.254)	(0.415)	(0.088)	(0.164)	(0.525)	(0.508)	(0.345)	(0.115)
Number of obs.	5738	5738	5738	5738	5738	5738	1762	2841
Adjusted R-square	0.1361	0.1127	0.0414	0.1350	0.0647	0.1373	0.0416	0.2170

Notes: Both physical assets and financial outcomes are measured with Taka. Hours are measured as the number of hours worked a year. Income per hour is the annual labor income divided by the number of hours worked a year. All of them are in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

Table B3: Impact of natural disaster on welfare, w/o subdistrict FE

	Total Consumption	Food Consumption	Protein Intake
	(1)	(2)	(3)
Treated (β)	0.115***	0.089***	0.952
	(0.034)	(0.032)	(0.639)
Unpredictable Shock (γ^U)	-0.109	-0.104*	-2.150***
	(0.077)	(0.054)	(0.553)
Treated × Unpredictable Shock (δ^U)	0.221**	0.191***	3.087***
	(0.094)	(0.070)	(0.728)
Baseline Risk (γ^B)	-0.149*	-0.086	-1.540**
	(0.078)	(0.053)	(0.688)
Treated × Baseline Risk (δ^B)	0.157*	0.093*	1.909**
	(0.081)	(0.055)	(0.766)
Mean	11655.8	8141.3	3.5
Sub-district FE	NO	NO	NO
Number of obs.	6123	6123	6123
Adjusted R-square	0.0238	0.0073	0.0186

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Standard errors are clustered at the branch level.

Table B4: Impact of natural disaster on welfare with different decay parameter: food consumption

	Food Consumption			
Decay Rate	20%	40%	60%	80%
	(1)	(2)	(3)	(4)
Treated (β)	0.082***	0.077***	0.070***	0.068***
	(0.016)	(0.015)	(0.015)	(0.014)
Unpredictable Shock (γ^U)	-0.175***	-0.174***	-0.124*	-0.052
	(0.057)	(0.062)	(0.068)	(0.057)
Treated × Unpredictable Shock (δ^U)	0.159***	0.145***	0.107**	0.079
	(0.044)	(0.045)	(0.052)	(0.057)
Baseline Risk (γ^B)	-0.024	-0.031	-0.001	0.031
	(0.047)	(0.048)	(0.052)	(0.059)
Treated × Baseline Risk (δ^B)	0.102**	0.098*	0.078	0.056
	(0.048)	(0.050)	(0.055)	(0.053)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.0250	0.0250	0.0245	0.0238

Notes: Food consumption is measured with Taka, in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition, with 4 alternative decay parameters. Decay parameters have been further re-scaled to sum up to one. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

Table B5: Impact of natural disaster on welfare: decompose food consumption

	Eggs (1)	Big Fish (2)	Small Fish (3)	Meat (4)
Treated (β)	0.143***	0.125***	0.079**	0.056**
	(0.034)	(0.037)	(0.031)	(0.024)
Unexpected Shock (γ^U)	-0.502***	-0.171*	-0.484**	-0.212**
	(0.138)	(0.099)	(0.213)	(0.084)
Treated × Unexpected Shock (δ^U)	0.403***	-0.033	0.478***	0.201***
	(0.049)	(0.053)	(0.171)	(0.048)
Expected Shock (γ^E)	-0.261***	-0.094	-0.255	-0.146***
	(0.059)	(0.056)	(0.173)	(0.051)
Treated × Expected Shock (δ^E)	0.282***	0.132**	0.364**	0.156**
	(0.081)	(0.064)	(0.148)	(0.065)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6206	6206	6206	6206
Adjusted R-square	0.22	0.16	0.21	0.17

Notes: Protein intake is decomposed into four categories: eggs, big fish, small fish and meat consumption. Each category is measured as the number of meals including this specific protein per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Standard errors clustered at the branch level.

Table B6: Impact of natural disaster, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.102***	0.062***	0.711***
	(0.017)	(0.014)	(0.204)
Unpredictable Shock (γ^U)	-0.265	-0.317*	-4.534**
	(0.183)	(0.177)	(2.091)
Treated × Unpredictable Shock (δ^U)	0.276	0.309*	3.963*
	(0.164)	(0.166)	(2.049)
Baseline Risk (γ^B)	0.058	0.092	-0.790
	(0.072)	(0.079)	(0.622)
Treated × Baseline Risk (δ^B)	0.025	0.001	1.628
	(0.094)	(0.080)	(1.062)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0507	0.0241	0.2241

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the linear model decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table B7: Impact of natural disaster: positive vs. negative surprises, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.105***	0.073***	0.836***
	(0.020)	(0.016)	(0.207)
Negative Unpredictable Shock (γ^U)	-0.181	-0.119	-4.652
	(0.151)	(0.129)	(2.798)
Treated × Neg. Unpredictable Shock (δ^U)	0.203	0.108	3.001
	(0.147)	(0.120)	(2.869)
Positive Unpredictable Shock (γ^U)	0.430	0.694**	3.674*
	(0.338)	(0.325)	(2.139)
Treated × Pos. Unpredictable Shock (δ^U)	-0.405	-0.696**	-7.037***
	(0.329)	(0.317)	(2.163)
Baseline Risk (γ^B)	-0.001	-0.053	-0.825
	(0.067)	(0.043)	(0.928)
Treated × Baseline Risk (δ^B)	0.080	0.147**	2.209
	(0.103)	(0.060)	(1.323)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0505	0.0242	0.2258

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the linear model decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table B8: Impact of natural disaster: within village estimate, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.050**	-0.022	-0.430***
	(0.020)	(0.014)	(0.131)
Ultra-poor × Treated (δ)	0.094***	0.071***	0.554***
	(0.026)	(0.020)	(0.168)
Ultra-poor × Unpredictable Shock (δ^U)	-0.317	-0.487*	-1.056
	(0.260)	(0.287)	(2.250)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.458*	0.615**	1.527
	(0.263)	(0.291)	(2.279)
Ultra-poor × Baseline Risk (δ^B)	-0.041	-0.075	0.317
	(0.140)	(0.144)	(0.517)
Ultra-poor × Treated × Baseline Risk (γ^B)	-0.006	0.046	-0.857
	(0.142)	(0.145)	(0.542)
Mean	13141.8	8303.4	4.2
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1043	0.0501	0.4080

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the linear model decomposition. Fixed effects are at the village level. Standard errors are clustered at the branch level.

Table B9: Impact of natural disaster on assets and labor, linear decomposition

	Physical Assets		**Financial**		**Hours**		**Income per hour**	
	Total (1)	Productive (2)	Savings (3)	Loan (4)	Husbandry (5)	Casual Labor (6)	Husbandry (7)	Casual Labor (8)
Treated (β)	2.322***	4.219***	0.551***	0.110***	2.558***	-1.281***	0.914***	0.138***
	(0.138)	(0.251)	(0.030)	(0.038)	(0.198)	(0.164)	(0.099)	(0.029)
Unpredictable Shock (γ^U)	-0.052	-2.901***	-0.290**	0.050	-1.900	2.698**	0.353	-0.362***
	(0.883)	(0.859)	(0.143)	(0.239)	(1.191)	(1.131)	(0.877)	(0.133)
Treated × Unpredictable Shock (δ^U)	0.723	4.482***	0.330*	0.052	2.753**	-3.419***	-0.126	0.347***
	(0.930)	(0.952)	(0.173)	(0.230)	(1.148)	(1.134)	(0.875)	(0.128)
Baseline Risk (γ^B)	0.377	-0.296	-0.005	-0.233*	-0.279	-0.453	0.117	-0.133*
	(0.402)	(0.509)	(0.060)	(0.134)	(0.574)	(0.785)	(0.510)	(0.066)
Treated × Baseline Risk (δ^B)	-0.680	-0.261	0.024	0.134	-0.356	0.556	-0.050	0.332***
	(0.449)	(0.639)	(0.080)	(0.117)	(0.646)	(0.831)	(0.529)	(0.067)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123	6123	6123	2771	3076
Adjusted R-square	0.2864	0.2815	0.3248	0.0724	0.1907	0.1125	0.1057	0.1639

Notes: Both physical assets and financial outcomes are measured with Taka. Hours are measured as the number of hours worked a year. Income per hour is the annual labor income divided by the number of hours worked a year. All of them are in log. Baseline risk and unpredictable risk are decomposed following the linear model decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

Table B10: Impact of natural disaster, history decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.112***	0.076***	0.785**
	(0.025)	(0.020)	(0.339)
Unpredictable Shock (γ^U)	-0.049	0.032	-0.158
	(0.110)	(0.106)	(1.770)
Treated × Unpredictable Shock (δ^U)	0.081	0.067	0.312
	(0.146)	(0.147)	(2.383)
Baseline Risk (γ^B)	0.041	0.118	0.270
	(0.101)	(0.115)	(1.615)
Treated × Baseline Risk (δ^B)	0.068	0.042	0.518
	(0.125)	(0.136)	(2.025)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0503	0.0238	0.2205

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the *history* decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table B11: Impact of natural disaster: positive vs. negative surprises, history decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.113***	0.079***	0.904***
	(0.024)	(0.019)	(0.320)
Negative Unpredictable Shock (γ^U)	-0.021	0.144	4.292**
	(0.193)	(0.194)	(1.849)
Treated × Neg. Unpredictable Shock (δ^U)	-0.241	-0.290	-7.849*
	(0.385)	(0.261)	(4.264)
Positive Unpredictable Shock (γ^U)	0.174	0.239	9.431**
	(0.381)	(0.399)	(4.078)
Treated × Pos. Unpredictable Shock (δ^U)	-0.510	-0.580	-12.919**
	(0.437)	(0.397)	(5.047)
Baseline Risk (γ^B)	-0.064	-0.125	-8.214**
	(0.354)	(0.390)	(3.684)
Treated × Baseline Risk (δ^B)	0.484	0.536	12.567**
	(0.445)	(0.392)	(4.894)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0506	0.0239	0.2237

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the *history* decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table B12: Impact of natural disaster: within village estimate, history decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.058*	-0.037	-0.721***
	(0.031)	(0.024)	(0.176)
Ultra-poor × Treated (δ)	0.117***	0.095***	0.909***
	(0.036)	(0.028)	(0.224)
Ultra-poor × Unpredictable Shock (δ^U)	-0.313	-0.406	-1.148
	(0.250)	(0.244)	(1.527)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.498*	0.578**	1.325
	(0.259)	(0.271)	(1.660)
Ultra-poor × Baseline Risk (δ^B)	-0.275	-0.351	-0.323
	(0.242)	(0.230)	(1.329)
Ultra-poor × Treated × Baseline Risk (γ^B)	0.403	0.483*	0.184
	(0.247)	(0.246)	(1.410)
Mean	13141.8	8303.4	4.2
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1043	0.0499	0.4085

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the *history* decomposition. Fixed effects are at the village level. Standard errors are clustered at the branch level.

Table B13: Impact of natural disaster on assets and labor: history decomposition

	Physical Assets		**Financial**		**Hours**		**Income per hour**	
	Total (1)	Productive (2)	Savings (3)	Loan (4)	Husbandry (5)	Casual Labor (6)	Husbandry (7)	Casual Labor (8)
Treated (β)	2.613***	4.486***	0.568***	0.156***	2.829***	-1.437***	0.935***	0.107***
	(0.168)	(0.320)	(0.036)	(0.043)	(0.253)	(0.244)	(0.140)	(0.030)
Unpredictable Shock (γ^U)	-1.652***	-3.142*	-0.371**	-0.778***	-1.754	3.049***	-0.824	-0.301
	(0.570)	(1.777)	(0.158)	(0.248)	(1.437)	(0.906)	(0.680)	(0.248)
Treated × Unpredictable Shock (δ^U)	2.109***	3.214	0.156	0.582**	2.009	-3.417***	0.120	0.516*
	(0.647)	(1.955)	(0.223)	(0.253)	(1.540)	(0.930)	(0.707)	(0.269)
Baseline Risk (γ^B)	-0.815	-2.174	-0.224*	-0.609***	-1.128	2.148**	-0.347	-0.295
	(0.529)	(1.486)	(0.117)	(0.215)	(1.334)	(0.800)	(0.605)	(0.175)
Treated × Baseline Risk (δ^B)	1.146*	2.289	0.114	0.446**	1.129	-2.713***	0.041	0.638***
	(0.580)	(1.751)	(0.172)	(0.208)	(1.468)	(0.927)	(0.661)	(0.216)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123	6123	6123	2771	3076
Adjusted R-square	0.2898	0.2806	0.3256	0.0737	0.1906	0.1131	0.1066	0.1650

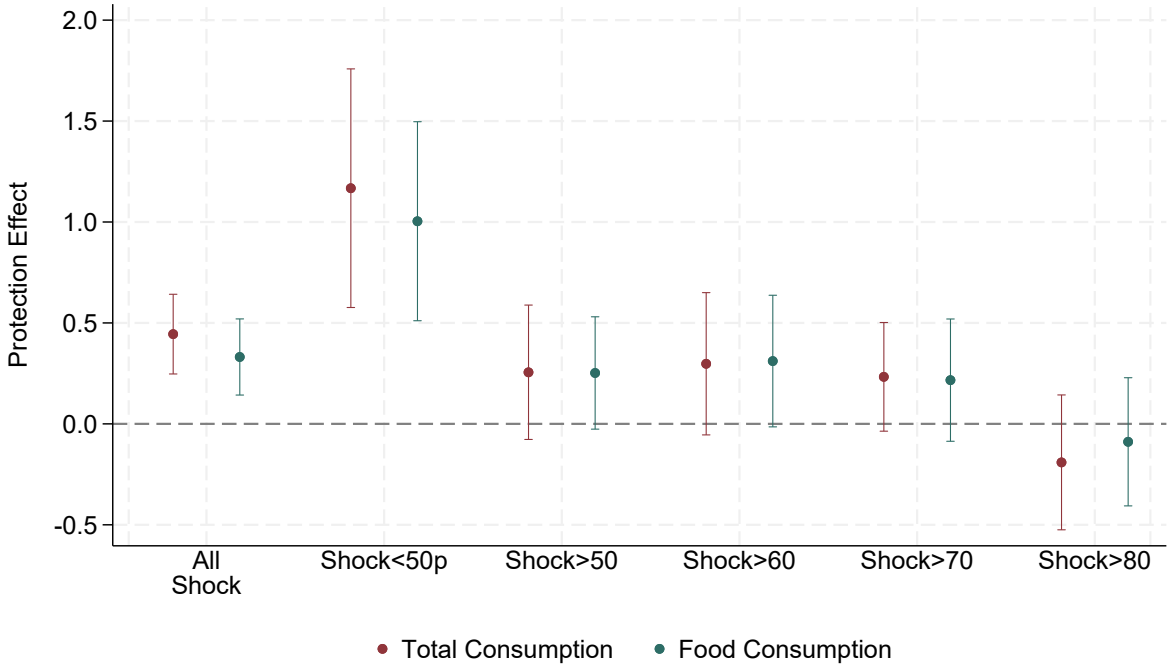
Notes: Both physical assets and financial outcomes are measured with Taka. Hours are measured as the number of hours worked a year. Income per hour is the annual labor income divided by the number of hours worked a year. All of them are in log. Baseline risk and unpredictable risk are decomposed following the *history* decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

Table B14: Impact of Large vs. Small natural disasters on welfare

	Total Consumption		Food Consumption		Protein Intake	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated (β)	0.107***	0.100***	0.069***	0.065***	0.101***	0.100***
	(0.020)	(0.019)	(0.016)	(0.016)	(0.024)	(0.022)
Negative Unpredictable Shock (γ^U)	-0.424***	-1.013***	-0.380***	-0.745**	-0.443**	-0.246
	(0.128)	(0.309)	(0.124)	(0.280)	(0.172)	(0.368)
Treated × Neg. Unpredictable Shock (δ^U)	0.445***	1.168***	0.331***	1.004***	0.295*	0.282
	(0.120)	(0.359)	(0.115)	(0.300)	(0.170)	(0.439)
Treated × Neg. Unpredictable Shock × Large Shock		-0.912**		-0.752**		-0.030
		(0.390)		(0.368)		(0.498)
Positive Unpredictable Shock (γ^U)	-0.367*	-0.295	-0.240	-0.224	0.167	0.157
	(0.210)	(0.242)	(0.242)	(0.255)	(0.217)	(0.243)
Treated × Pos. Unpredictable Shock (δ^U)	0.341	0.317	0.167	0.153	-0.253	-0.243
	(0.227)	(0.243)	(0.244)	(0.250)	(0.255)	(0.257)
Baseline Risk (γ^B)	0.446**	0.381	0.346	0.329	-0.036	-0.040
	(0.200)	(0.228)	(0.237)	(0.246)	(0.175)	(0.190)
Treated × Baseline Risk (δ^B)	-0.379	-0.366	-0.209	-0.210	0.214	0.196
	(0.238)	(0.250)	(0.247)	(0.252)	(0.258)	(0.249)
Neg. Unpredictable Shock × Large Shock		0.759**		0.439		-0.155
		(0.364)		(0.359)		(0.359)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123	6123	6123
Adjusted R-square	0.0522	0.0529	0.0251	0.0249	0.2723	0.2722

Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Figure B1: Impact of Large vs. Small natural disasters on welfare



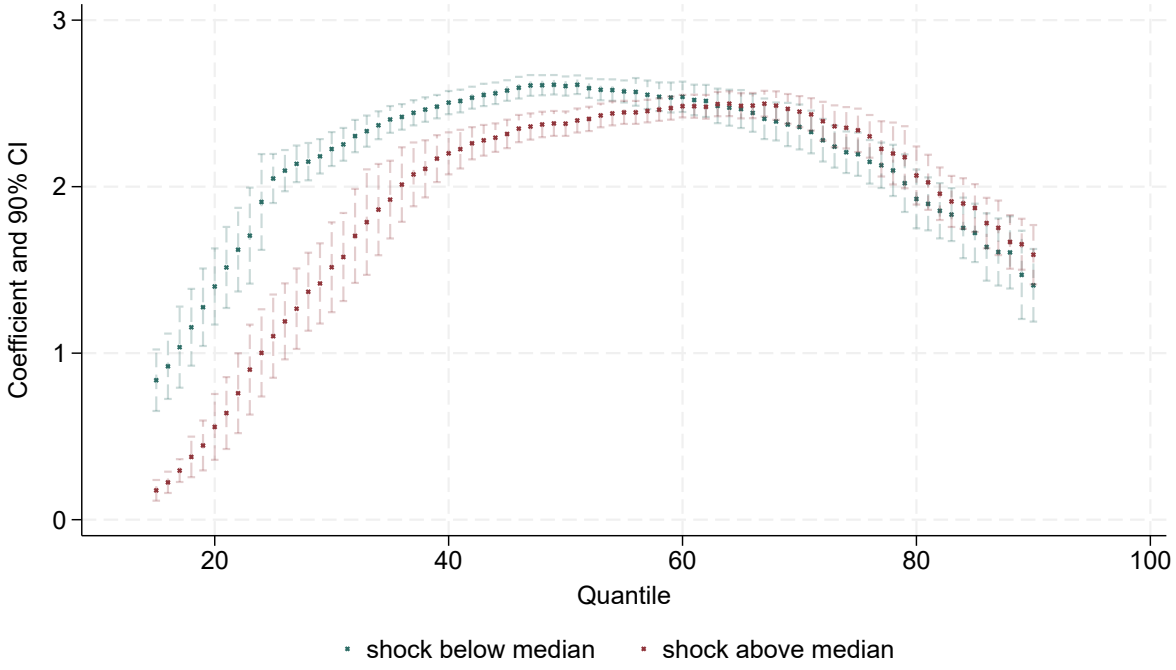
Notes: Each dot represents the estimate for the protection effect of the treatment for different magnitude of unpredictable weather event (normalized by the level of baseline risk): shock below median are considered as *small* compare to baseline, while shocks respectively above p50, p60, p70 and p80 are *large* shocks. The maroon ones represents effect on total consumption, and the green dots represent effect on food consumption. Bars represent 90% confidence interval. Outcome variables are in log.

Table B15: Impact of nature disaster on the number of meals

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)	Number of Meals (4)
Treated (β)	0.114***	0.073***	0.872***	3.880***
	(0.020)	(0.015)	(0.253)	(0.706)
Unpredictable Shock (γ^U)	-0.134	-0.154**	-3.392***	-1.392
	(0.084)	(0.066)	(1.144)	(3.466)
Treated × Unpredictable Shock (δ^U)	0.138***	0.127**	2.817***	2.669
	(0.048)	(0.048)	(0.686)	(2.224)
Baseline Risk (γ^B)	-0.029	-0.019	-1.844**	-2.869
	(0.054)	(0.050)	(0.700)	(2.535)
Treated × Baseline Risk (δ^B)	0.097	0.089	2.350***	2.720
	(0.065)	(0.053)	(0.755)	(2.412)
Mean	11655.8	8141.3	3.5	28.0
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6120
Adjusted R-square	0.0513	0.0248	0.2261	0.0283

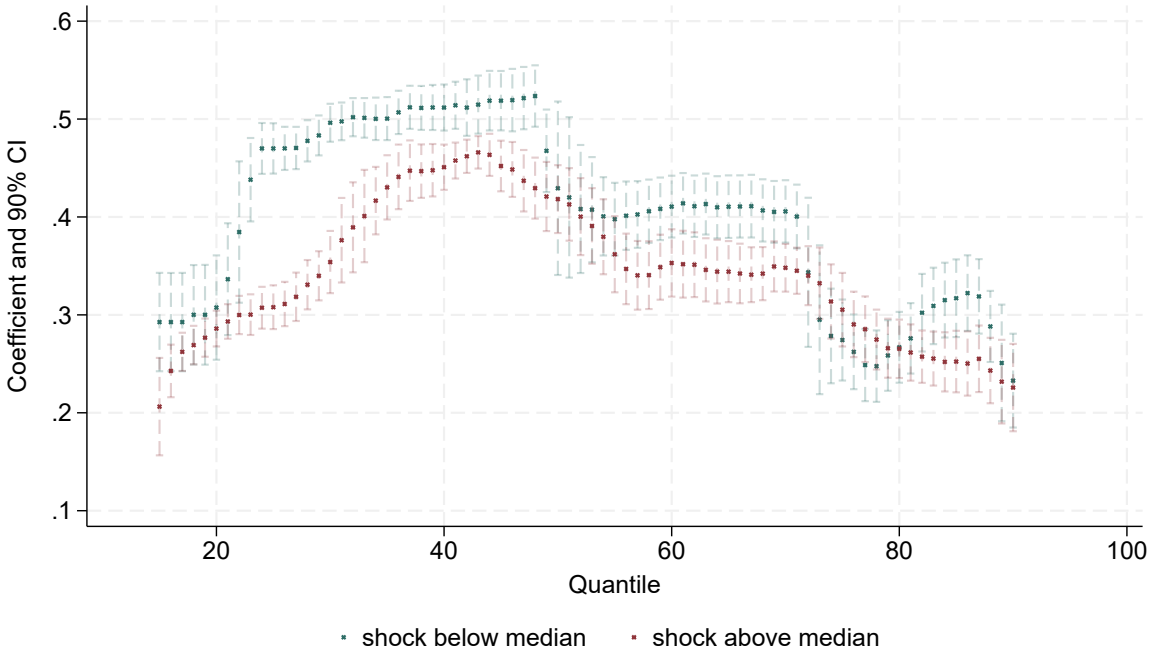
Notes: Total consumption and food consumption are measured with Taka in per capita terms with log transformation. Protein intake is measured as the total number of meals including protein (egg, fish or meat) per month. Number of meals measures the meals consumed by adults over the past 3 days. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Figure B2: Impacts of the graduation program on productive assets, historical exposure



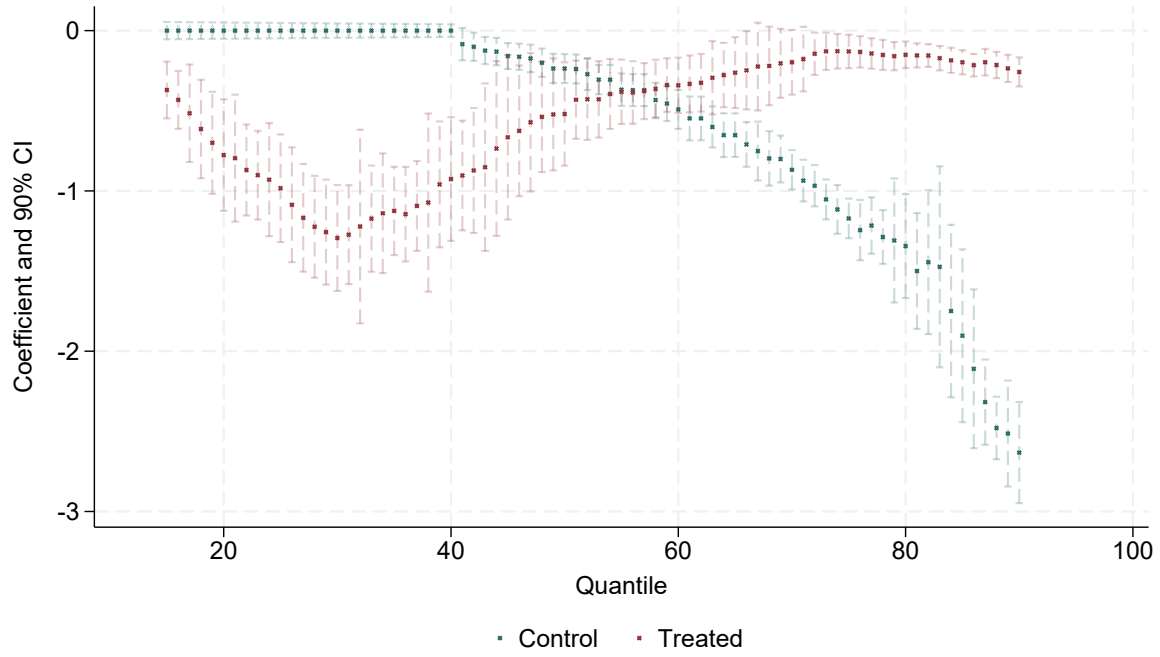
Notes: Each dot represents one estimate for the treatment effect for different quantiles. The maroon ones represents high weather shock villages (combine floods and droughts, higher than the 50th percentile of the historical exposure distribution) before 2007, and the emerald dots represent low weather shock villages. Bars represent 90% confidence interval. The outcome is productive assets in 2011 in log.

Figure B3: Impacts of the graduation program on husbandry hour



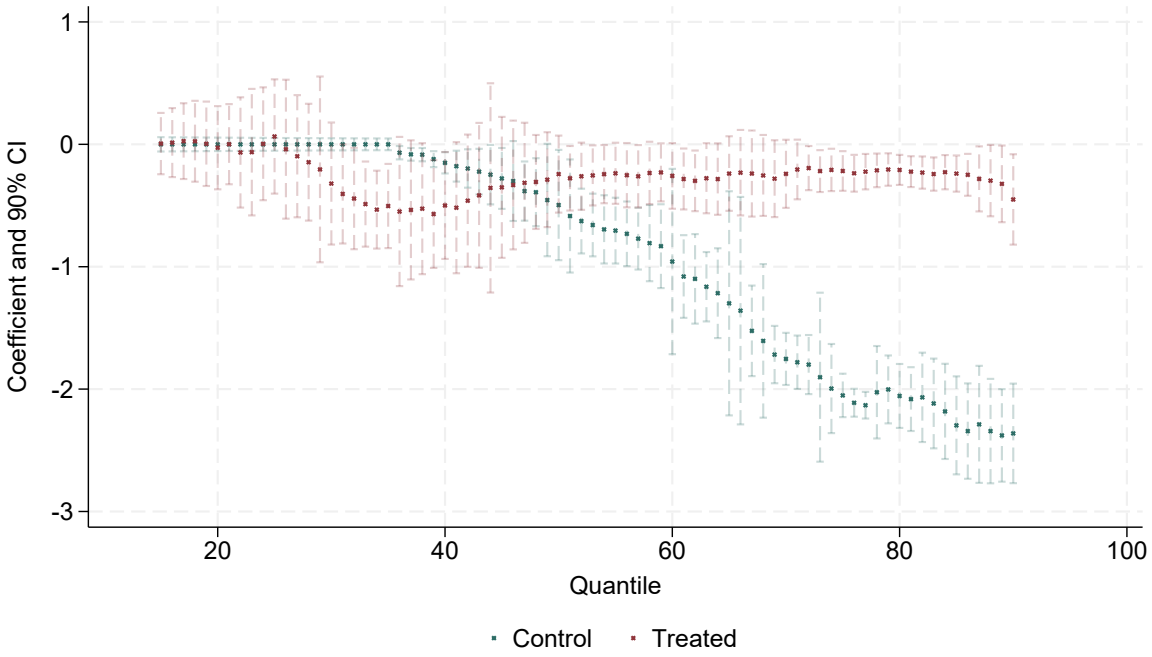
Notes: Each dot represents one estimate for the treatment effect for different quantiles. The maroon ones represents high weather shock villages (combine floods and droughts, either unpredictable shock or baseline shock is higher than the 50th percentile of the distribution) before 2007, and the emerald dots represent low weather shock villages. Bars represent 90% confidence interval. The outcome is husbandry hour in 2011 in log.

Figure B4: Impacts of weather shock on productive assets



Notes: Each dot represents one estimate for the weather shock effect (combine floods and droughts) for different quantiles of productive assets at baseline. The maroon ones represents treated villages in 2011, and the green dots represent control villages in 2011. Bars represent 90% confidence interval. The outcome is productive assets in 2011 in log.

Figure B5: Impacts of unpredictable weather shock on productive assets



Notes: Each dot represents one estimate for the unexpected weather shock effect (combine floods and droughts, with decay decomposition) for different quantiles of productive assets at baseline. The maroon ones represents treated villages in 2011, and the green dots represent control villages in 2011. Bars represent 90% confidence interval. The outcome is productive assets in 2011 in log.

C Mechanism

Table C1: Diversification at the household level (exclude livestock activities)

	Asset Diversification	**Labor Diversification**	
	# Asset Categories	# Occupations	HHI
	(1)	(2)	(3)
Treat	1.593***	0.276***	-0.060***
	(0.105)	(0.068)	(0.017)
Unpredictable Shock	-0.687	-0.420*	0.053
	(0.454)	(0.249)	(0.076)
Treat × Unpredictable Shock	1.221***	0.640***	-0.088
	(0.333)	(0.183)	(0.054)
Expected Shock	-0.467	-0.567***	0.103**
	(0.304)	(0.119)	(0.046)
Treat × Expected Shock	0.818***	0.682***	-0.130**
	(0.282)	(0.127)	(0.050)
Subdistrict Fixed-effects	Yes	Yes	Yes
Number of obs.	6481	6484	6484
Adjusted R-square	0.1709	0.0546	0.0390

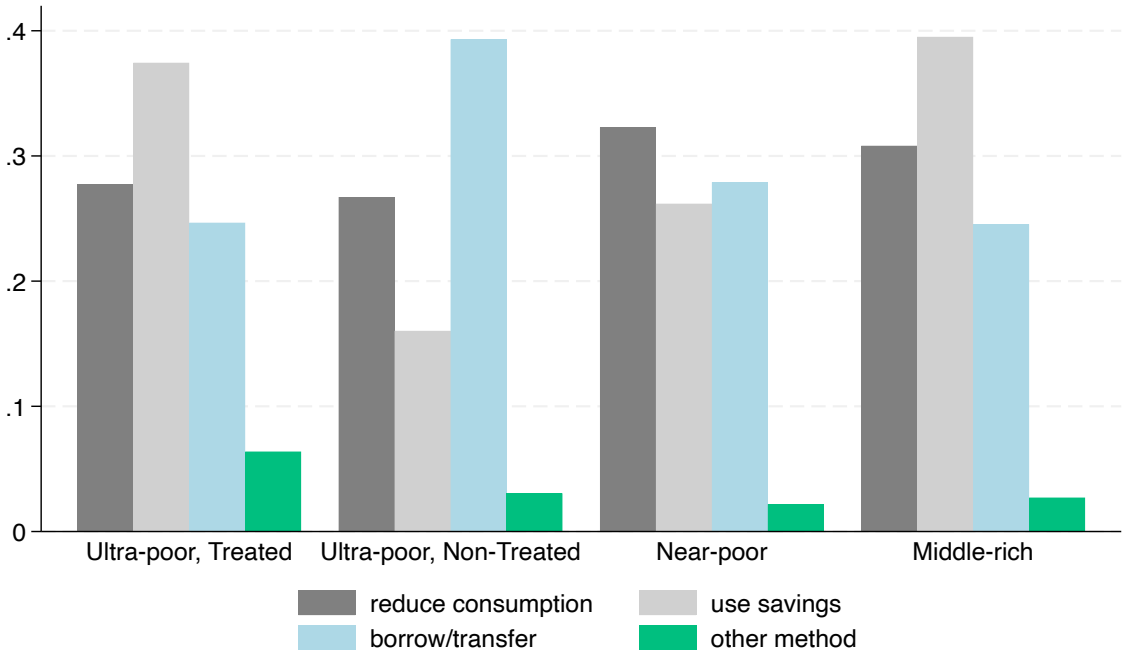
Notes: Assets diversification is the number of different assets categories for the household. Labor diversification at the household level is measured in two different ways: the number of business activities and normalized HHI. Panel A uses all labor activities and assets. Panel B removed livestock husbandry (directly related with cows) for labor diversification, and removed cows for assets diversification. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table C2: Mechanism: wage and climate shocks

	HH-Level		Village: UP		Village: ALL		Village: Ex. UP	
	Casual Labor	Husbandry	Casual Labor	Husbandry	Casual Labor	Husbandry	Casual Labor	Husbandry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated (β)	0.131***	0.909***	0.137***	1.037***	0.050	0.141*	0.024	-0.083
	(0.030)	(0.124)	(0.028)	(0.108)	(0.031)	(0.083)	(0.036)	(0.094)
Unpredictable Shock (γ^U)	-0.322***	-0.340	-0.302**	0.061	-0.165	-0.592	-0.070	-0.579
	(0.118)	(0.536)	(0.148)	(0.502)	(0.131)	(0.447)	(0.192)	(0.411)
Treated × Unpredictable Shock (δ^U)	0.228**	0.124	0.246***	-0.201	0.122	0.831**	0.067	0.846**
	(0.089)	(0.428)	(0.078)	(0.388)	(0.086)	(0.309)	(0.149)	(0.363)
Baseline Risk (γ^B)	-0.171**	0.038	-0.148*	0.227	-0.051	-0.624*	0.037	-0.756**
	(0.072)	(0.444)	(0.087)	(0.377)	(0.086)	(0.349)	(0.144)	(0.331)
Treated × Baseline Risk (δ^B)	0.332***	0.131	0.326***	-0.106	0.227***	0.619*	0.125	0.614
	(0.057)	(0.466)	(0.073)	(0.405)	(0.081)	(0.338)	(0.150)	(0.365)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	2152	2764	887	925	1037	1194	789	1173
Adjusted R-square	0.1599	0.1063	0.2170	0.2549	0.2039	0.1046	0.1567	0.0669

Notes: Labor wage is measured as the average income per hours worked. All of them are in log. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors clustered at the branch level.

Figure C1: Coping strategies by social class



Notes: Each bar represents the share of respondents reporting the type of coping strategy they use when facing a natural disaster shock. Different colors indicate different coping strategies. Households are divided into treated ultra-poor, control ultra-poor, near-poor, and middle-rich groups. The survey was conducted in 2011.

D Other decomposition methods

In this section, we describe other decomposition methods of the weather shocks into an predictable (baseline risk) and unpredictable (weather surprise) component. The baseline risk component captures the part of the shock that is predictable using past data, while the unpredictable component captures a real weather surprise, that is, a deviation from the baseline risk. The first alternative decomposition is a linear model as follows:

$$\mathbf{C}_{v(i),2011,d} = \alpha_{2011,d} + \sum_{t=1}^{10} \beta_{t,d} \cdot \mathbf{C}_{v(i),2011-t,d} + \varepsilon_{v(i),2011,d}$$

where $\mathbf{C}_{v(i),2011,d}$ is a variable measuring the exposure to natural disasters, separately for flood, drought, and then combined, for village $v(i)$ in dekad d. $\mathbf{C}_{v(i),2011-t,d}$ are the historical weather shocks measured for the same village and the same dekad, for each year from 2001 to 2010. Therefore, $\beta_{t,d}$ captures to what extent past weather shocks predict the 2011 weather shock. We estimate this regression for each dekad $d \in [1, 2, ..., 36]$ separately. Using the estimates for $\hat{\alpha}_{2011,d}$ and $\hat{\beta}_{t,d}$ we compute a *predictable* component ($\hat{\alpha}_{2011,d} + \sum_{t=1}^{10} \hat{\beta}_{t,d} \times \mathbf{C}_{v(i),2011-t,d}$) and *unpredictable* component (the weather *surprise*, $\hat{\varepsilon}_{v(i),2011,d}$) for each village and dekad. We then sum those two components over all 36 dekads of the year. In this framework, a weather surprise may result (i) from the intensive margin: a village experiencing above-average flooding during a dekad that is usually flooded, or (ii) from the extensive margin: flooding occurring during a dekad that is not usually flooded (even if the total number of flood days is similar to previous years).[26]

The second alternative decomposition method relies on a simple historical exposure to weather shocks. $\hat{\mathbf{C}}\{\text{Natural disaster}\}_{v(i),2011,d}$, the predictable component, is therefore the average of the past weather shocks, and the unpredictable component is the deviation of the current shock to the historical average shock. The exact specification is as follows.

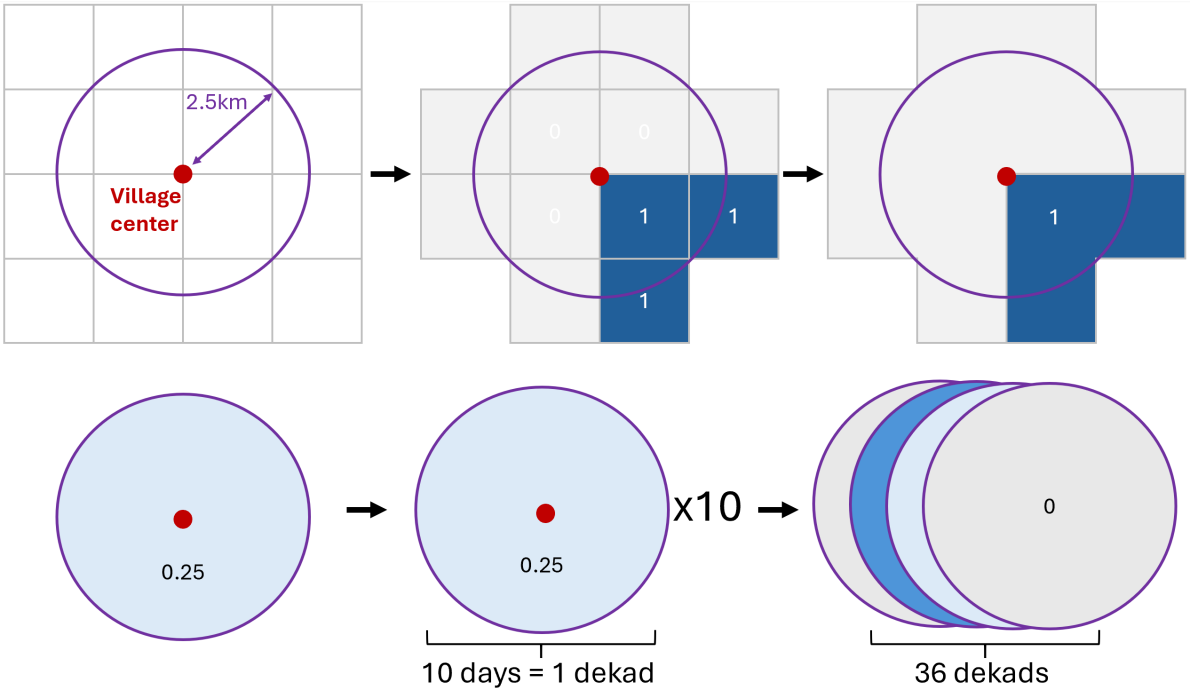
$$\hat{\mathbf{C}}_{v(i),2011,d} = \frac{\sum_{t=1}^{10} \mathbf{C}_{v(i),2011-t,d}}{10}$$

Our regression results are robust to various specifications.

[26] In our data, we find that most surprises are from the intensive margin, with only a few occurrences of shocks during a dekad never impacted before

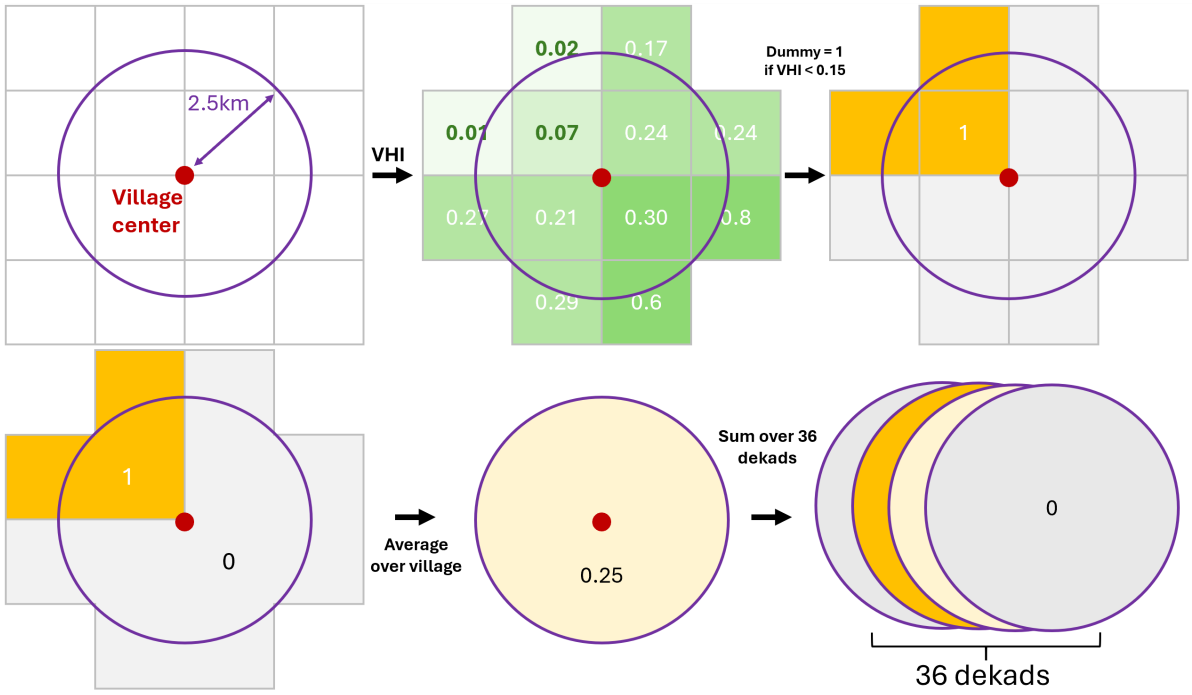
E Measurement

Figure E1: Flood measurement: illustration



Notes: This diagram illustrates the different steps in the construction of the flood shock, from the satellite data at the 250-meters resolution to the continuous measure at the village × dekad level.

Figure E2: Flood measurement: illustration



Notes: This diagram illustrates the different steps in the construction of the drought shock, from the VHI satellite data at the 1-km resolution to the continuous measure at the village × dekad level.

Table E1: Expected and unexpected shocks

Variable	Mean	p25	Median	p75	SD
Baseline Risk	0.420	0.114	0.235	0.523	0.498
Unpredictable Shock	-0.318	-0.404	-0.201	-0.101	0.402
Pos. Unpredictable Shock	0.064	0.000	0.000	0.032	0.171
Neg. Unpredictable Shock	0.382	0.113	0.234	0.497	0.435

Notes: Descriptive statistics for the baseline and unpredictable shock, following the decay decomposition for the combine shock. The unit is the total dekads of any weather shock (flood or drought) in 2011. Neg. Unpredictable Shock corresponds to *positive* (good) weather surprises only (i.e., $\mathbf{C}_{v(i),2011,d} < \hat{\mathbf{C}}_{v(i),2011,d}$) and Pos. Unpredictable Shock using only *negative* (bad) weather surprises (i.e., $\mathbf{C}_{v(i),2011,d} > \hat{\mathbf{C}}_{v(i),2011,d}$).

Table E2: summary statistics for weather shocks

Variable	Mean	p25	Median	p75	SD
Flood Shock	0.068	0.000	0.000	0.010	0.200
Drought Shock	0.014	0.000	0.000	0.000	0.045
Combined Weather Shock	0.082	0.000	0.000	0.033	0.226

Notes: Descriptive statistics for flood, drought and combined weather shocks. The unit is the total dekads of weather shock in 2011.

Table E3: Compare different climate shocks: food consumption

	Combine (1)	Flood (2)	Drought (3)
Treated (β)	0.073***	0.070***	0.068***
	(0.015)	(0.015)	(0.015)
Unpredictable Shock (γ^U)	-0.154**	-0.125	-0.032
	(0.066)	(0.103)	(0.334)
Treated × Unpredictable Shock (δ^U)	0.127**	0.204**	-0.140
	(0.048)	(0.076)	(0.391)
Baseline Risk (γ^B)	-0.019	0.035	0.130
	(0.050)	(0.057)	(0.341)
Treated × Baseline Risk (δ^B)	0.089	0.036	-0.116
	(0.053)	(0.057)	(0.389)
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0248	0.0234	0.0249

Notes: Food consumption are measured with Taka in per capita terms with log transformation. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.

Table E4: Compare different climate shocks: productive assets

	Combine	Flood	Drought
	(1)	(2)	(3)
Treated (β)	4.423***	4.338***	4.270***
	(0.303)	(0.258)	(0.281)
Unpredictable Shock (γ^U)	-1.484*	-0.657	-9.376***
	(0.757)	(0.793)	(2.974)
Treated × Unpredictable Shock (δ^U)	2.230***	2.440***	7.999**
	(0.640)	(0.701)	(3.392)
Baseline Risk (γ^B)	-1.047**	-0.576	-8.304***
	(0.448)	(0.597)	(2.866)
Treated × Baseline Risk (δ^B)	1.109**	-0.254	7.377**
	(0.450)	(0.600)	(3.177)
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.2812	0.2817	0.2818

Notes: Productive assets are measured with Taka. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the Sub-district level. Standard errors are clustered at the branch level.