Weathering Poverty *

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Abstract

The global overlap between poverty and climate damages raises the question of how poverty shapes responses to weather shocks. To examine the causal mechanisms that link individual poverty to climate vulnerability, this paper exploits two independent sources of variation: the randomized roll-out of BRAC's graduation program in Bangladesh, which generates variation in the incidence of extreme poverty, and high-resolution satellite images, which allow us to identify unpredictable variation in floods and droughts. We find that poverty shapes adaptation to these shocks via asset and labor market channels. The poorest households draw down savings, liquidate assets, and sacrifice consumption. In contrast, households randomly lifted out of poverty diversify sources of earnings, rely on more resilient income sources, and protect their wages from less resilient sources by landowners' more limited ability to pass through shocks. Programs that expand access to otherwise unavailable occupations thus both lift households out of poverty and serve as effective ex-ante adaptation investments in the face of unfolding climate change.

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1 Introduction

"Disasters don't kill people: poverty does"
— Fazle Hasan Abed, Founder of BRAC

Climate change stands out as one of the greatest challenges that humanity faces. Its consequences are widely recognized to be unequal, with poorer countries disproportionately affected by large and persistent aggregate effects from climate shocks (Carleton et al., 2022; Gilli et al., 2024; Hsiang et al., 2017; Burgess et al., 2024). Much less is known, however, about the causal mechanisms that link individual poverty to climate vulnerability.

Our goal is to understand how poverty shapes strategies that individuals use to adapt to climate shocks. We distinguish the impacts of poverty on two broad classes of adaptation strategies: ex-post mechanisms via which those affected respond after a shock has occurred, and ex-ante actions undertaken before a shock strikes (Carleton et al., 2024).

This distinction is crucial in understanding how poverty undermines individuals' ability both to avert and to recover from the consequences of shocks. It also has important implications for the sustainability of gains from social protection programs in the face of worsening climate vulnerability. While existing programs focused on ex-post responses play an important role in helping households to smooth consumption losses following shocks, addressing the root causes of vulnerability depends on how far poverty reduction strategies are also able to shield recipients from future shocks.

Our empirical setting in rural Bangladesh is ideal for examining how poverty affects vulnerability to shocks for three reasons.

First, this is a setting where both extreme poverty and weather shocks are prevalent. As is true for millions across the world, rural Bangladesh is a place where the extreme poor both (i) have limited assets and rely on insecure casual wage labor for their livelihoods, and (ii) are increasingly buffeted by environmental shocks such as droughts and floods. Understanding whether and how the poor can adapt to these shocks as they become more frequent and intense is a first-order question.

Second, we are able to combine advances in satellite measurement of shocks with the randomized evaluation of an asset transfer program to test causally how reducing poverty reduces vulnerability to shocks. To do this we overlay household survey panel data covering 23,000 households from the randomized evaluation of a large anti-poverty program, BRAC's graduation program, with new high-resolution, satellite-based data capturing droughts and floods over 20 years. A key feature of the empirical strategy is to separate baseline climate risk from unpredictable weather shocks using villages' long-run shock histories garnered from satellite imagery. Combined with the random assignment of the program, this approach allows us to cleanly identify how extreme weather affects the welfare of the extreme poor and whether an exogenous improvement in households' economic positions mitigates these impacts.

Third, rich data on consumption, assets, labor hours and earnings from our household surveys allow us to study the mechanisms linking poverty to vulnerability. The simplicity of this labor market, where just three occupations — agricultural labor, domestic service and animal husbandry — dominate female labor supply, means that we can cleanly trace out how adding productive assets (which enable new occupations) affects consumption and labor outcomes. This provides us with novel insights into how the poor adapt to shocks. The fact that we survey households right across the wealth distribution means that we can contrast ultra-poor and near-poor household reactions to shocks and examine outcomes for both employers and employees in the casual labor markets which constitute the cornerstone of ultra-poor subsistence.

We begin by documenting that receipt of the program offsets the damaging impacts of climate shocks on household consumption almost entirely. The analysis focuses on the impacts of the unpredictable component of weather shocks — controlling for weather history in each location — in order to isolate exogenous variation in floods and droughts. In control villages, where poverty remains high, unpredictable drought and flood shocks lead to sizable declines in overall and food consumption among households at the bottom of the income distribution. Among this group, exposure to an additional day of unpredictable extreme weather (equivalent to all of the 2.5-km-radius buffer surrounding a village experiencing an unpredictable shock, or a more enduring shock affecting a commensurately smaller area) reduces food consumption by 1.5%. Being lifted out of poverty by the program significantly attenuates this effect: for treated beneficiaries, the impact of unpredictable weather shocks is offset by +1.4%, such that the net effect is statistically indistinguishable from zero.

Effects are driven by *negative* weather shocks, where outcomes are worse than expected. An additional specification that compares 'ultra-poor' beneficiaries to slightly wealthier, non-eligible 'near-poor' individuals within the same village finds that the ultra-poor are worse affected by weather shocks in control but not treatment villages, allaying concerns that results are contaminated by unobservable village-level risk.

We turn next to understanding the mechanisms underlying the resilience of households lifted out of poverty in the face of these shocks. The graduation program affects households along several dimensions that could plausibly reduce vulnerability to shocks (Bandiera et al., 2017). First, it raises savings, thereby increasing households' capacity to buffer income losses and smooth consumption. Second, it enables beneficiaries to acquire productive assets and increase and diversify their labor supply, especially in livestock rearing occupations. Our analysis of mechanisms therefore centers on how assets, investment and occupational choice respond to weather shocks, and how far the program alters these responses among treated beneficiaries.

While the program increases savings and holdings of productive assets, we do not find that treated households are more likely to use savings or assets to smooth consumption in the face of shocks. On the contrary, neither savings nor productive asset holdings decline among treated households hit by shocks, while in control villages an additional day of exposure to an unpredictable weather shock is associated with declines of 16.3% in productive assets and 21.6% in savings.

The results point instead to differences in vulnerability to shocks operating through local labor markets. Two channels appear key: the program allows beneficiaries to rely on more resilient income sources, and their income from less resilient sources is protected as a result of occupational diversification improving their outside options and thus increasing the elasticity of labor supply. While an additional day of unpredictable weather shocks reduces the probability of control households devoting any time to more stable and remunerative livestock rearing by 2.6 percentage points, this effect is entirely offset for treated households. This is crucial given that the transition from casual labor to entrepreneurial livestock husbandry activities is central to being able to move out of poverty in this setting. In addition to increasing the level of productive assets and entrepreneurship hours, households exogenously lifted out of poverty diversify both productive assets and labor occupations, even beyond the mechanical diversification arising from receiving the transfer.

The second key implication of treated households diversifying their income sources is an ability to leverage this improvement in outside options to increase the elasticity of their labor supply, which reduces the sensitivity of casual labor wages to weather shocks. In more unequal villages, climate shocks are transmitted disproportionately to casual workers. Richer landowners are relatively insulated: they 'adapt' to weather shocks by reducing the wages they pay to casual workers, who have no choice but to accept. In control villages, an additional day of weather shock depresses the casual labor wage by 3.1%, driven entirely by more unequal villages (measured using either land concentration or the share of assetless households), while landlords in these villages see *increases* in their earnings and hiring. In stark contrast, the program entirely offsets the negative impact of unpredictable shocks on the casual labor wage in treated villages (again driven by high-inequality villages), while the positive effects for landlords are no longer statistically different from zero.

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; Bandiera et al., 2026). 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 impacts of unpredictable weather shocks are significantly amplified by poverty, but that large-scale anti-poverty programs, underpinned by beneficiaries' ability to maintain and diversify assets and occupations, can be effective in ameliorating these impacts. The returns to scaling up such programs are likely to exceed estimates from individual evaluations both because of this additional value from increased resilience to climate shocks and because lifting the extreme poor out of poverty strengthens their outside options in labor markets, putting upward pressure on casual wages and amplifying aggregate impacts.

This paper contributes to a growing climate adaptation literature that studies how policies that relax household constraints shape the welfare costs of climate risk (Carleton et al., 2024). Our results complement those of Pople et al. (2024), who show that anticipatory cash transfers approximately five days before an extreme flood attenuate impacts on welfare and asset loss by facilitating evacuation and food stockpiling. We build on this work by showing that adaptation is intrinsically tied to poverty: large asset transfer programs that lift households out of poverty, expand access to otherwise unavailable occupations, and improve the outside options of the poor can serve as ex-ante adaptation investments that shield their consumption and assets from the effects of weather shocks.

Estimated impacts on wages connect to a broader literature on how asset ownership shapes the division of surplus in agricultural labor markets. In settings with high inequality, asset-poor households often depend exclusively on casual wage labor. This renders them particularly vulnerable following aggregate shocks, as their subsistence needs create a highly inelastic labor supply precisely when demand falls, amplifying fluctuations in wages (Jayachandran, 2006). Our results indicate that treated households not only benefit from maintaining diversified income sources, but also experience smaller casual labor wage declines following shocks. This is consistent with labor supply being more elastic, as treated households' ability to work in livestock husbandry provides them with a better outside option. This mechanism aligns with theoretical and empirical studies highlighting how asset and land ownership can lead to higher equilibrium wage levels (Mookherjee and Ray, 2002; Eswaran and Kotwal, 1986; Bardhan, 1979; Besley and Burgess, 2000).

The findings are particularly relevant given the earlier literature documenting how household strategies to smooth consumption following shocks — such as self-insurance (Paxson, 1992; Deaton, 1997), informal risk sharing (Townsend, 1994; Coate and Ravallion, 1993), and income or asset diversification (Rosenzweig and Stark, 1989; Rosenzweig and Binswanger, 1993) — offer only partial protection, especially against large covariate shocks.

Our 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).

The rest of the paper is structured as follows. Section 2 describes the background and data. Section 3 presents our empirical strategy and discusses the identifying assumptions. Section 4 documents our main results on how the graduation program influences the impact of unpredictable weather shocks on household welfare. Section 5 investigates mechanisms underpinning these results by examining the impact of weather shocks on labor activities and assets. Section 6 concludes.

2 Background and Data

The context and data we exploit allow us to make progress on long-standing questions about how poverty shapes household vulnerability and resilience to shocks. This section first introduces the household data and BRAC's Targeting the Ultra-Poor program, and then describes our measurement of floods and droughts.

2.1 Household Data

In 2007, BRAC selected 1309 villages in the 13 poorest and most food-insecure districts of Bangladesh to take part in a randomized evaluation of their graduation program, also known as "Targeting the Ultra-Poor" (TUP) (Bandiera et al., 2017). Participatory methods were used to identify the ultra-poor, who were illiterate, assetless, and largely engaged in casual wage labor as agricultural laborers or domestic servants. In half of the villages, ultra-poor households were offered a menu of feasible income-generating activities and received assets, training, and other forms of support such as weekly visits to support occupational change toward their chosen activity. In practice nearly all beneficiaries chose animal husbandry, which was practiced by wealthier women in the village and seen as both secure and high return relative to casual labor. The program was designed to enable the poorest women to take on occupations which had been the preserve of richer women.

In this paper, we leverage the household-level data collected to evaluate BRAC's graduation program, covering 23,000 households. Of these households, over 6000 are considered extremely poor. In a randomly selected half of the villages, all ultra-poor households received the graduation program after the baseline survey in 2007.

Table 1 presents descriptive statistics for this sample of ultra-poor households, and contrasts them with those of households classified as near-poor, middle-rich, and rich[1] in the

[1]Pre-randomization, BRAC officers classify poorer households into two groups: the ultra-poor, who

Table 1: Descriptive statistics

	Ultra-poor	**Near-poor**	**Middle Rich**	**Rich**
Total Consumption	11,598	11,891	14,023	22,708
Food Consumption Share	0.76	0.75	0.73	0.66
Protein Intake	3.58	3.93	5.51	9.79
Total Assets	5,513	14,109	147,808	817,504
Productive Assets	4,843	12,863	142,604	786,753
Savings	139	409	1,569	8,832
Loans	616	1,876	4,918	11,324
Husbandry Hours	269	396	628	733
Casual Labor Hours	648	396	93	4
Illiterate Share	0.93	0.83	0.74	0.49

Notes: This table reports baseline descriptive statistics by BRAC wealth class. All variables are measured in 2007, prior to treatment. Monetary variables are measured in Bangladeshi taka: consumption is annual and per capita; assets, savings, and loans are stock values. Food consumption share is measured as the ratio of food consumption to total consumption. Protein intake is the monthly frequency of consuming eggs, fish, or meat. Hours are annual hours worked. The sample includes 6075 ultra-poor households, 5920 near-poor households, 5466 middle-rich households, and 1782 rich households.

same communities at baseline. 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. Indeed what is most striking about Table 1 is the inequality in productive assets,[2] which are the main focus of the graduation program — rich households have 162 times, and even near-poor households 3 times, the value of ultra-poor households, such that asset inequality far outstrips consumption inequality. Table A1 shows that 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.

Graduation Program Design. 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 source of regular earnings for poor women who are mostly engaged in irregular and insecure casual labor at baseline. Beneficiaries are offered a choice

qualify for the TUP program, and the near-poor, who do not.

[2]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.

from several asset bundles, all of which are valued at around $490 USD in PPP and can be used for income-generating activities (e.g., 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 and 2024. 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]

2.2 Weather Shock Data

Flood data. Flood data were 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-meter resolution, including the start and end dates of a flood and the number of days that each pixel is flooded.[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.

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 kilometers 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-kilometer-radius buffers, are pictured as red circles

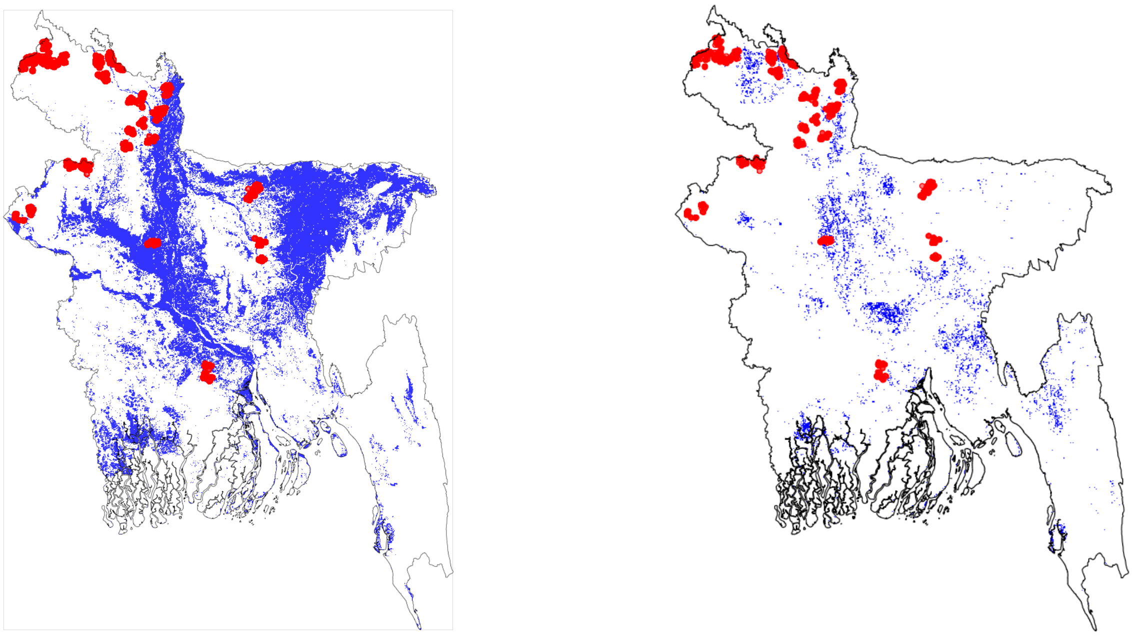
[3]For more details on the program and household survey, see Bandiera et al. (2017).

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

[5]For each recorded flood event, information regarding the start and end 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 start date of the inundated pixel as June 8th and the end date as June 13th.

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

(a) Flood (b) Drought



Notes: This figure shows illustrative satellite-based measures of flood and drought exposure in Bangladesh. Panel (a) shows flood exposure on September 2, 2007. Panel (b) shows drought exposure during the first 10 days of June 2007. White pixels indicate unaffected areas, and blue pixels indicate areas affected by flooding in Panel (a) or severe drought in Panel (b). Red circles show sample villages and their 2.5-kilometer-radius buffers. Flood data are measured at 250 × 250-meter resolution. Drought data are measured at 1 × 1-kilometer resolution and classified as severe drought when the Vegetation Health Index is below 0.15.

in Figure 1. We consider all flood events that affected Bangladesh between January 2000 and December 2011. A total of 78 floods were recorded during this period, with an average of 6.5 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 4.51 days, with significant variability (25th percentile of 2.33 days and 75th percentile of 6.33 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 can also determine how many days of flooding 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 are 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 1×1 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]

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 flood 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.

Combined shock measure. Our preferred specifications consider a *combined* shock that

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

[7]The data are 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 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.

measures the cumulative exposure of a village to both floods and droughts over a one-year period. We pool these two types of extreme events for two reasons. First, although physically distinct, droughts and floods affect ultra-poor households through similar economic channels: both generate negative agricultural income shocks and local consumption goods price shocks, which may trigger coping responses such as cutting consumption or selling assets. Second, extreme events are rare at fine geographic scales, so that combining flood and drought effects improves statistical power. While the central specifications consider the combined shock measure, we also present results separately for flood and drought shocks and find qualitatively similar results.

To construct this composite extreme climate shock measure, we first align the spatio-temporal resolution of the flood and drought data. We aggregate the daily 250-meter-resolution flood data to a 10-day (dekad) frequency and 1-km resolution. A 1-km grid cell is considered "flooded" in a given dekad if any of its constituent 250-meter pixels were flooded on any day within that period. For each dekad, we then calculate the share of each village that experienced (i) a flood and (ii) a drought, and sum the two to obtain the total share of the village that experienced a weather shock during each dekad.[11] Our final measure of the combined shock, $\mathbf{C}_{v(i),t}$, is the sum of these affected shares across all $T = 36$ dekads in a year.[12] This continuous variable measures the exposure of village $v(i)$ to extreme weather events in year t.[13] Appendix Figures E1 and E2 provide a detailed illustration of the methodology, along with descriptive statistics.

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. 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 2009 to control for baseline risk and for additional identification checks, as described in the next section.

[11] While drought and flood shocks may overlap in principle because they are measured using different spatial units and frequencies, this overlap is extremely rare in practice. In 2011, only 23 out of 44,064 village $\times$ dekad observations, or 0.052%, experienced both a drought and a flood shock. Additionally, the combined climate shock is never larger than 1. Our results are robust to excluding observations with overlapping drought and flood shocks.

[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 ($T = 36$ dekads).

[13] To aid interpretation of our results, we note that our shock variable is measured in dekads (10-day periods). One unit of the shock measure corresponds to one dekad in which 100% of the village area (the 2.5-km-radius buffer around the village center) experiences extreme weather. Thus, a shock value of 0.1 represents either (i) the entire village experiencing extreme weather for one day within a dekad, or (ii) 10% of the village area experiencing extreme weather for a full dekad. Throughout the paper, "an additional day of weather shock" refers to one day of complete village-wide exposure, equivalent to approximately 0.3 standard deviations.

3 Empirical Strategy

To identify how poverty shapes adaptation to climate shocks we combine variation in poverty from the randomized roll-out of BRAC's ultra-poor graduation program with variation in floods and droughts.

To isolate exogenous variation in floods and droughts we adapt recent methods to address bias from non-random exposure by controlling for the expected (predictable) component of shock exposure and using residual variation around that expectation for identification (Borusyak and Hull, 2023; Jones et al., 2026; Wooldridge, 2015).

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:

$$\hat{\mathbf{C}}_{v(i),2011} = f\Big(\mathbf{C}_{v(i),2000}, \ldots, \mathbf{C}_{v(i),2009}\Big) \tag{1}$$

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:

$$\mathbf{S}_{v(i)} = \mathbf{C}_{v(i),2011} - \hat{\mathbf{C}}_{v(i),2011} \tag{2}$$

Our methodology builds on an intuition similar to identification 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 are unavailable, as in this setting. The core idea is 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.

Positive values of $\mathbf{S}_{v(i)}$ indicate cases where the actual weather outcomes exceeded the baseline risk (a negative surprise), while negative values of $\mathbf{S}_{v(i)}$ indicate cases where the actual weather outcomes were milder than predicted (a positive surprise).

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 estimate the following model:

$$\begin{aligned} Y_i = \alpha + \beta T_{v(i)} + \gamma^B \hat{\mathbf{C}}_{v(i)} + \gamma^U \mathbf{S}_{v(i)} \\ + \delta^B T_{v(i)} \hat{\mathbf{C}}_{v(i)} + \delta^U T_{v(i)} \mathbf{S}_{v(i)} + \eta_{s(i)} + \varepsilon_i \end{aligned} \tag{3}$$

where Y_i is the outcome of interest for household i in 2011; $T_{v(i)}$ is an indicator for villages assigned to the treatment; and we add fixed effects at the sub-district level $\eta_{s(i)}$ in order to compare villages with similar geography and micro-climate.

β identifies the intent-to-treat impact of the program on household i, comparing outcomes among ultra-poor households residing in treated villages with those among counterfactual ultra-poor households in control villages in the same sub-district. Our analysis focuses on γ^U and δ^U. γ^U captures the impact of experiencing an unpredictable weather shock during the year 2010–2011 for control households. 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 being lifted out of poverty helps households to protect themselves against the damaging effects of an unexpected shock.

γ^B and δ^B capture the effect of baseline risk, and differential program response by baseline risk, respectively. 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. Our measure of baseline risk is likely confounded with other factors affecting the outcome, such as local geography. We therefore interpret any effects of baseline risk as merely suggestive evidence of households' adaptation to previous weather shocks (discussed further in Section 6).

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.

The exponential decay model underpinning our main specifications captures the idea that households react most strongly to recent shocks, while the salience of earlier events diminishes over time. 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 sum that gives a higher weight to more recent years:

$$\hat{\mathbf{C}}_{v(i),2011,d} = \sum_{t=1}^{10} \exp(-t \cdot \lambda) \cdot \mathbf{C}_{v(i),2010-t,d} \tag{4}$$

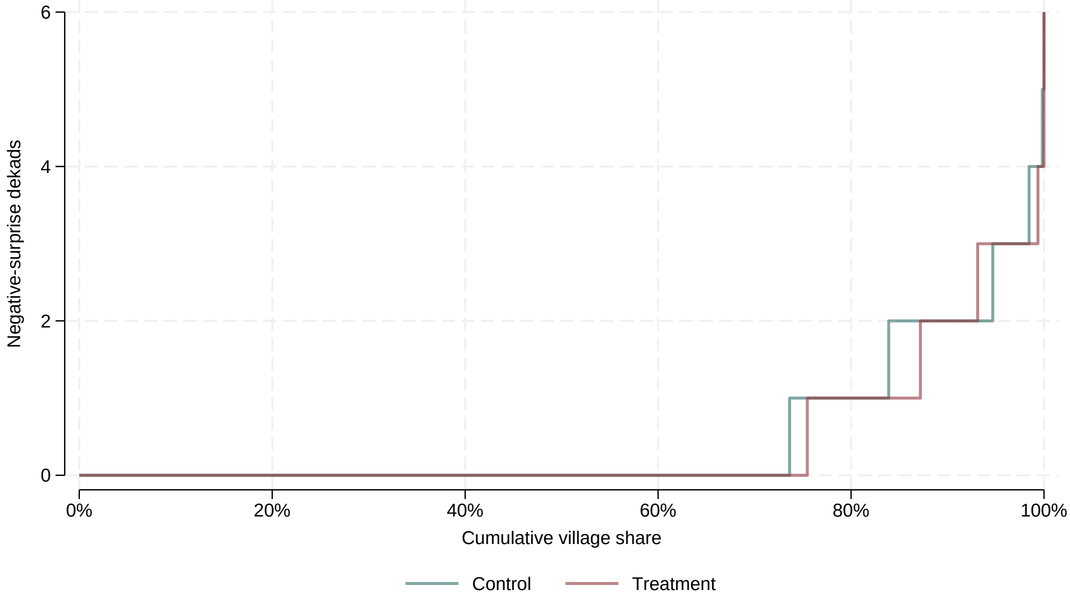
where $\mathbf{C}_{v(i),2010-t,d}$ is our shock variable measuring the exposure to floods and droughts for village $v(i)$ in dekad d and year $2010 - t$ ranging from 2000 to 2009. The dekad-level unpredictable shock (or weather surprise) $\mathbf{S}_{v(i),d}$ is the difference between the actual shock and the baseline risk for dekad d in the 36-dekad pre-survey window preceding the 2011 survey wave, i.e., $\mathbf{C}_{v(i),2011,d} - \hat{\mathbf{C}}_{v(i),2011,d}$. We sum these components over the same 36-dekad pre-survey window, 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 across the year is as predicted.[15]

Panel A of Table E1 presents descriptive statistics for the baseline risk and unpredictable shock components of the weather shock. The unpredictable component is roughly as large as the baseline risk, indicating that substantial variance in experienced shocks remains even after conditioning on a village's weather history. This pattern holds across floods and droughts separately (Figure E4) and across the majority of BRAC branches (Figure E5).

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

[15] In our data, we find that most surprises are driven by the intensive margin, with only a few occurrences of shocks during a dekad that had never been impacted by extreme weather before.

Figure 2: Cumulative distribution of dekads with any negative surprise by treatment status



Notes: This figure plots empirical cumulative distribution functions for treatment and control villages, using village-level negative-surprise exposure over the 36 pre-survey dekads preceding the 2011 wave. A negative surprise is defined as a dekad in which realized combined shock exposure exceeds the village-dekad-specific expected exposure by a strictly positive amount. For each exposure threshold on the vertical axis, the horizontal axis reports the share of villages in the corresponding treatment arm with weakly fewer negative-surprise dekads.

Figure 2, together with Panels B and C of Table E1, further decomposes the unpredictable component by sign. Positive surprises denote dekads in which weather was less severe than predicted; negative surprises denote dekads in which it was more severe; and zero surprises denote dekads in which weather was exactly as predicted. The figure shows that negative surprises impact a substantial share of villages in our sample (36%), with affected villages experiencing up to 60 days of unexpected severe weather. The relative infrequency reflects both the inherent nature of the events we study, which capture unexpected *extreme* floods or drought exposure, and the fact that 2011 was a relatively mild year, so that the typical village experienced less severe weather than its historical decay average would predict. When negative surprises do occur, however, they are severe. Conditional on experiencing a negative surprise, the average share of a village impacted by drought or flooding is 8%, rising to 21% at the 90^{th} percentile. In Section 4, we test whether the welfare results are driven entirely by these infrequent but severe 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 in Appendix A. In the first check, we use outcome data for the same households before the program was announced in 2007. This allows us to test whether, conditional on baseline risk, future 2011 weather surprises are correlated with pre-treatment heterogeneity in observed household outcomes. 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*. We then verify that this conclusion is unchanged when we re-estimate the baseline model with treatment interactions. 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 3) with both outcomes and shocks measured before treatment in 2007. In this specification, the coefficient of interest, δ^U, captures how the response to unpredictable weather shocks differs between eligible households in treatment and 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 δ^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 δ^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.

Finally, we can identify the effects of interest from within-village variation only by using data on near-poor households, that is, poor households who did not qualify for the program. We estimate triple-difference specifications to compare how ultra-poor households respond to weather shocks relative to near-poor households in the same village, conditional on the treatment status of their village, using the following model:

$$\begin{aligned} Y_i = \alpha &+ \beta UP_i + \delta UP_i T_{v(i)} \\ &+ \delta^B UP_i \hat{\mathbf{C}}_{v(i)} + \delta^U UP_i \mathbf{S}_{v(i)} \\ &+ \gamma^B UP_i T_{v(i)} \hat{\mathbf{C}}_{v(i)} \\ &+ \gamma^U UP_i T_{v(i)} \mathbf{S}_{v(i)} \\ &+ \zeta_{v(i)} + \varepsilon_{i,v(i)} \end{aligned} \tag{5}$$

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. As before, $T_{v(i)}$ is an indicator for villages assigned to treatment, and $\hat{\mathbf{C}}_{v(i)}$ and $\mathbf{S}_{v(i)}$ denote baseline risk and the unpredictable weather shock, respectively. Comparing the two groups of households within the same village allows us to include village fixed effects, $\zeta_{v(i)}$, in the model. This is a useful identification check, since these absorb all time-invariant, village-level heterogeneity, such as differences in local geography. With village-fixed effects, we cannot estimate the main effects of the weather shock or the treatment, as both are measured at the village level.

4 Weather Shocks and Poverty

In this section, we leverage our weather shock decomposition and empirical setup to study how weather shocks affect household consumption and how poverty shapes these effects. Our core interest is whether lifting households out of extreme poverty through a policy intervention changes their ability to maintain consumption when they experience severe unpredictable weather shocks, compared to ex-ante similar ultra-poor households who did not receive the treatment. We test this by considering three complementary measures of household consumption: total consumption, food consumption, and protein intake. Total and food consumption are measured as the logarithm of per capita expenditure in Bangladeshi taka. Protein intake is captured by the monthly frequency with which households consume protein-rich foods such as eggs, fish, and meat.

4.1 Baseline Results

Table 2 reports the estimates for β, γ and δ from Equation 3 for our three consumption 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. Relative to households in control villages, treated households spend 13.2% more on total consumption, 8.8% more on food, and consume protein-rich foods 0.9 more times per month — equivalent to roughly 29% of mean monthly protein intake.

The main coefficients of interest are γ, which captures the direct impact of unpredictable weather shocks on the consumption of ultra-poor households, and δ, which measures whether households that escaped extreme poverty were differentially affected by these shocks relative to those that remained ultra-poor — that is, the extent to which poverty status shapes the severity of the impact of shocks. Unpredictable shocks are measured in units of dekads during which all of a village's 2.5-kilometer-radius buffer is affected by an unpredictable shock.[16] Given that one of these units represents an extremely large

[16]Given that this measure combines shock severity measured in terms of both area affected and duration,

Table 2: Impact of weather shocks on poverty

	Log Total Consumption (1)	Log Food Consumption (2)	Protein Intake (3)
Treated (β)	0.124***	0.084***	0.868***
	(0.022)	(0.018)	(0.255)
Unpredictable Shock (γ^U)	-0.136	-0.154*	-3.307***
	(0.097)	(0.082)	(1.201)
Treated × Unpredictable Shock (δ^U)	0.143**	0.135**	2.760***
	(0.057)	(0.062)	(0.711)
Baseline Risk (γ^B)	-0.023	-0.005	-1.745**
	(0.062)	(0.064)	(0.716)
Treated × Baseline Risk (δ^B)	0.102	0.091	2.294***
	(0.076)	(0.066)	(0.782)
Mean Dependent Variable (in levels)	10896.1	7814.9	3.0
P-val: $\gamma^U + \delta^U = 0$	0.931	0.761	0.626
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0516	0.0246	0.2257

Notes: This table reports estimates of Equation 3 for ultra-poor households in 2011. Total consumption and food consumption are annual per capita values, measured in Bangladeshi taka and transformed using the natural logarithm, $\ln(x)$. Protein intake is the monthly frequency of consuming eggs, fish, or meat. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

shock (2.5 standard deviations) in this context, far outside observed severity in the sample, we interpret coefficient magnitudes based on one day during which all of a village's 2.5-kilometer-radius buffer is affected by an unpredictable shock (hereafter "an additional day of unpredictable weather shocks") under the assumption of a linear damage function.

We find that ultra-poor households suffer significant consumption losses from unpredictable weather shocks. Our estimates imply that exposure to an additional day of unpredictable weather shocks (γ^U) reduces total consumption by 1.4% (not statistically significant), food consumption by 1.5%, and protein intake by 0.3 meals including protein per month for ultra-poor households in control villages.

Does escaping extreme poverty cushion households against the consumption effects of weather shocks? The estimate for the interaction coefficient δ^U is positive and significant for all outcomes, suggesting that households lifted out of poverty are more resilient to unpredictable weather shocks. The magnitudes of the estimates for total consumption (+1.5%), food consumption (+1.4%), and protein intake (+0.3 meals per month) indicate that these households are able to offset almost entirely the negative impact of an

this can equivalently be interpreted as more enduring shocks covering a smaller area (for instance, two dekads during which 50% of the village's 2.5-kilometer-radius buffer experiences an unpredictable shock).

unpredictable shock (γ^U), compared to households located in control villages.

To shed further light on the consumption effects of unpredictable shocks, we decompose unpredictable shocks into positive and negative deviations from baseline risk. We define a *negative* weather surprise $\mathbf{S}^-_{v(i)}$ as any instance where the realized shock $\mathbf{C}_{v(i),d}$ exceeds the baseline risk $\hat{\mathbf{C}}_{v(i),d}$. This captures situations when there is more flooding or more drought than historically typical for that village. Conversely, a *positive* weather surprise, $\mathbf{S}^+_{v(i)}$, arises when the realized shock is smaller than the baseline risk, meaning that the weather conditions are better than expected. For example, if a village typically experiences complete flooding during dekad d but faces only mild or no flooding in a given year, this constitutes a positive surprise. This measure ensures that positive unpredictable shocks in one dekad cannot be offset by negative unpredictable shocks in another dekad during the same year.

This decomposition allows us to test for asymmetric responses to positive and negative surprises by estimating a modified version of our baseline specification (Equation 3):

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

where $\mathbf{S}^+_{v(i)}$ and $\mathbf{S}^-_{v(i)}$ are the unpredictable shock components, both measured in absolute value, and other terms are as previously defined.

The results in Table 3 suggest that the negative consumption effects documented in Table 2 are driven by negative weather surprises. The estimates for γ^{U-} are all negative, large, and statistically significant. These results suggest that households do not significantly adjust their consumption when weather conditions are more favorable than expected, but are forced to do so when facing unexpected negative shocks. The interaction term coefficients again suggest that escaping extreme poverty can largely alleviate the impact these negative shocks have on households' consumption.

To explore shock heterogeneity further, we investigate how the impact on consumption varies with the magnitude of negative climate surprises. We classify *large* negative shocks as unpredictable realizations above the median of non-zero negative surprises, and *mild* negative shocks as those below it. Appendix Figure B3 shows that control households experience only modest losses in response to mild shocks, but suffer significantly larger losses under extreme shocks. Strikingly, the evidence suggests that households lifted out of extreme poverty remain fully protected even when facing the large negative weather shocks.

Finally, Appendix Table E4 compares estimates of our baseline specification for the combined shock with separate estimates for droughts and floods. The coefficients on unexpected shocks (γ^U) and the interaction term (δ^U) for both droughts and floods are qualitatively similar to those from the pooled specification, but are less precise given lower power when splitting rare, noisy events at fine geographic scales. The estimates also point to larger effects of droughts than floods on productive assets and labor-market outcomes, consistent with wider evidence that droughts may lead to more persistent reductions in fodder availability, water access, animal nutrition, productivity and fertility (Rodziewicz et al., 2023; Thornton et al., 2022), and increased distress sales and mortality risk (Toulmin, 1987).[17]

Table 3: Impact of weather shocks on consumption: positive vs. negative surprises

	Log Total Consumption (1)	Log Food Consumption (2)	Protein Intake (3)
Treated (β)	0.119***	0.081***	0.895***
	(0.022)	(0.018)	(0.245)
Negative Unpredictable Shock (γ^{U-})	-0.417***	-0.387**	-3.131*
	(0.150)	(0.151)	(1.731)
Treated × Neg. Unpredictable Shock (δ^{U-})	0.439***	0.343**	1.828
	(0.130)	(0.135)	(1.914)
Positive Unpredictable Shock (γ^{U+})	-0.393	-0.285	3.593
	(0.257)	(0.342)	(2.361)
Treated × Pos. Unpredictable Shock (δ^{U+})	0.354	0.193	-4.794
	(0.295)	(0.349)	(3.244)
Baseline Risk (γ^B)	0.480*	0.405	-2.158
	(0.251)	(0.339)	(1.855)
Treated × Baseline Risk (δ^B)	-0.395	-0.242	4.186
	(0.308)	(0.353)	(3.278)
Mean Dependent Variable (in levels)	10896.1	7814.9	3.0
P-val: $\gamma^{U-} + \delta^{U-} = 0$	0.874	0.643	0.537
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0523	0.0248	0.2260

Notes: This table reports estimates of the positive/negative surprise specification for ultra-poor households in 2011. Total consumption and food consumption are annual per capita values, measured in Bangladeshi taka and transformed using the natural logarithm, $\ln(x)$. Protein intake is the monthly frequency of consuming eggs, fish, or meat. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3; positive and negative shocks are measured in absolute value. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[17] Climate projections suggest that flood frequency and intensity will increase more sharply in South Asia than droughts (Hirabayashi et al., 2021; IPCC, 2023), which may be expected to attenuate these differences.

4.2 Within-Village Results

As a complementary test, we employ the alternative empirical strategy that exploits within-village variation described in Equation 5. This triple-differences approach compares how ultra-poor households respond to weather shocks relative to near-poor households in the same village, conditional on the treatment status of their village. 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, and the coefficient on treatment δ to be positive. The coefficient δ^U captures the interaction of ultra-poor status with weather shocks, which will be negative if the ultra-poor in control villages are more severely affected by extreme weather than their richer counterparts. The key parameter of interest is the triple-interaction coefficient, γ^U. If, relative to the near-poor, the ultra-poor are less impacted by weather shocks in treatment villages, we expect this coefficient to be positive.

Table 4: Impact of weather shocks on consumption: within-village estimate

	Log Total Consumption (1)	Log Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.070**	-0.049**	-0.633***
	(0.026)	(0.020)	(0.141)
Ultra-poor × Treated (δ)	0.137***	0.117***	0.825***
	(0.032)	(0.025)	(0.189)
Ultra-poor × Unpredictable Shock (δ^U)	-0.183	-0.290**	-0.804**
	(0.138)	(0.140)	(0.329)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.280*	0.372**	0.915*
	(0.140)	(0.144)	(0.466)
Ultra-poor × Baseline Risk (δ^B)	-0.118	-0.194	-0.062
	(0.138)	(0.139)	(0.298)
Ultra-poor × Treated × Baseline Risk (γ^B)	0.123	0.207	-0.205
	(0.139)	(0.140)	(0.332)
Mean Dependent Variable (in levels)	11302.9	7892.6	3.2
P-val: $\delta^U + \gamma^U = 0$	0.001	0.021	0.738
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1048	0.0502	0.4088

Notes: This table reports triple-difference estimates comparing ultra-poor households with near-poor households in the same village in 2011. Total consumption and food consumption are annual per capita values, measured in Bangladeshi taka and transformed using the natural logarithm, $\ln(x)$. Protein intake is the monthly frequency of consuming eggs, fish, or meat. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include village fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results in Table 4 confirm and extend our baseline findings. In the absence of shocks, ultra-poor households exhibit lower total consumption (-6.8%), food consumption (-4.8%), and protein intake (-0.6 meals per month) relative to their near-poor counterparts. Program participation substantially improves these outcomes for participants, who increase total consumption (+14.7%), food consumption (+12.4%), and protein intake (+0.8 meals per month) — again relative to the near-poor. In other words, the program allows the poorest households in the village to catch up with their slightly richer neighbors, and in some cases surpass them.

Exposure to an additional day of unpredictable weather shocks, on the other hand, exacerbates the underlying poverty gap in control villages, reducing total consumption by 1.8%, food consumption by 2.9%, and protein intake by 0.1 meals per month relative to the near-poor. However, this is not the case for program-eligible households in treatment villages, who are no longer poorer than the non-eligible. There is no detectable differential response to a shock between the treated ultra-poor and the non-eligible near-poor. Overall, these results suggest that program participants have reached a standard of living similar to the slightly less poor in the village, and that this living standard allows them to respond to shocks in a similar way. Note that if there are positive spillover effects of the program on the near-poor, these coefficients would be downward biased and thus they provide a lower bound for the true protective effect of the program. We discuss possible wage spillovers on the casual labor market in Section 5.3.

The results so far indicate that unpredictable weather shocks significantly reduce the consumption of households trapped in poverty. In contrast, households exogenously lifted out of extreme poverty by the program are better able to absorb such shocks and maintain their consumption levels. This highlights a strong link between poverty and the capacity to cope with climate change. In the following sections, we explore the mechanisms underlying this resilience.

5 How Does Poverty Shape Adaptation?

Our analysis so far suggests that being lifted out of poverty improves the resilience of ultra-poor households to adverse effects of weather shocks. We now investigate *how* this happens. Previous research suggests that the graduation program works by enabling beneficiaries to accumulate productive assets and move into more profitable occupations (Bandiera et al., 2017).

We start by investigating whether the program's protection stems from short-term coping strategies, primarily the ability to draw down the initial asset transfer. We show that this is not the case. In fact, it is the ultra-poor who use assets to buffer the effects of weather shocks, while richer households can keep productive assets intact. We then study how they achieve this, documenting that the program led to long-term improvements in labor outcomes, likely by allowing participants to diversify productive assets and income sources.

In particular, richer households are less reliant on casual wage labor — protecting them from volatile wages as weather risks are passed on to casual workers. When these richer treated households do work in casual labor, however, they have higher wages than their control group counterparts. In the final subsection, we explore this wage protection and argue that the program increased the elasticity of labor supply for casual jobs in treatment villages.

5.1 Asset Liquidations and Diversification

The graduation program enables ultra-poor households to accumulate productive assets. Therefore, a first plausible explanation for the consumption effects documented in Section 4 is that treated households cope with weather shocks by liquidating the productive assets provided by the program. Such distress sales would force households to revert to lower-paying occupations, thereby undermining the program's core objectives in the longer run. Under this scenario, the observed resilience would mask a deteriorating economic situation, with households eroding their productive capacity and risking reversion into poverty.

To test this hypothesis, we estimate the effect of weather shocks on asset accumulation, following the specification in Equation 3. Our asset measures include physical assets (productive assets, and total assets also including non-business assets[18]) and financial assets (savings and loans). All asset variables are measured in Bangladeshi taka and estimated in levels using Poisson pseudo-maximum likelihood to account for the presence of zeros in the outcome variables. Table 5 presents the results.

We find that the impact of an unpredictable weather shock (γ^U) is negative and statistically significant across all asset categories. In control villages, an additional day (0.1 dekad) of unpredictable weather shock is associated with decreases of 13.0% in total assets, 16.3% in productive assets, 21.6% in savings, and 25.6% in loans.[19] Being lifted out of poverty builds significant resilience against these shocks. The positive interaction term (δ^U) implies treatment differentials of 15.4% for total assets, 20.1% for productive assets, 29.1% for savings and 30.9% for loans. Combining the shock and interaction coefficients, the net effect of an additional day of unpredictable shock on treated households is close to zero: +0.4% for total assets, +0.5% for productive assets, +1.2% for savings and -2.5% for loans. Figure B1 decomposes these effects by shock magnitude, and shows that the impacts are driven by above-median severity shocks.

[18]Total assets include all productive assets as well as the following: 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.

[19]Similar to Section 4, we decompose unpredictable shocks into positive and negative weather surprises. Figure F2 suggests that both negative and positive surprises matter, with positive shocks prompting households to increase investment.

Table 5: Impact of weather shocks on assets

	Physical Assets		Financial	
	Total (1)	Productive (2)	Savings (3)	Loan (4)
Treated (β)	1.014***	1.064***	1.748***	-0.079
	(0.201)	(0.217)	(0.145)	(0.221)
Unpredictable Shock (γ^U)	-1.388*	-1.775**	-2.435***	-2.951**
	(0.717)	(0.884)	(0.457)	(1.287)
Treated $\times$ Unpredictable Shock (δ^U)	1.429***	1.829***	2.558***	2.694***
	(0.516)	(0.676)	(0.447)	(0.917)
Baseline Risk (γ^B)	-1.136*	-1.511**	-1.852***	-2.855***
	(0.602)	(0.759)	(0.497)	(1.026)
Treated $\times$ Baseline Risk (δ^B)	1.357**	1.754**	1.806***	2.802***
	(0.625)	(0.785)	(0.493)	(1.012)
Mean Dependent Variable (in levels)	10375.3	9090.7	264.7	1257.6
P-val: $\gamma^U + \delta^U = 0$	0.903	0.885	0.579	0.733
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Pseudo R-square	0.1460	0.1444	0.2190	0.1311

Notes: This table reports estimates of Equation 3 for ultra-poor households in 2011. All physical and financial assets are in Bangladeshi taka and estimated in levels using PPML to account for zeros. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These results suggest that treated households are largely able to mitigate the effects of weather shocks without materially reducing their productive assets or savings. This is a central finding: the graduation program's success in protecting consumption does not come at the expense of its long-term goal of sustainably lifting participants out of poverty by accumulating productive assets. However, the question of how this protection is achieved remains. If it does not come from the depletion of assets or savings, it must reflect income streams that are less affected by shocks. To investigate this mechanism, the next subsection examines labor outcomes.

5.2 Ex-ante Adaptation: The Labor Market Channel

In order to test whether the observed resilience among households lifted out of poverty arises from improved labor outcomes, we examine whether households lifted out of poverty secure a more diverse and remunerative set of occupations, thereby raising and stabilizing income and enhancing resilience to shocks.

To test this hypothesis, we estimate the effect of weather shocks on four labor market outcomes, following the specification in Equation 3. We consider hours worked in husbandry activities (poultry and livestock) and casual labor (maid and agricultural day labor), as well as hourly income from these activities. We analyze hours worked along two complementary margins. First, we estimate hours in levels using Poisson pseudo-maximum likelihood, which accounts for zeros in the hours variables. Second, we estimate an extensive-margin specification, where the dependent variable is an indicator equal to one if the household reports any positive hours in the relevant activity. Hourly income is defined as the natural logarithm of annual labor income divided by annual hours worked in the corresponding activity, estimated conditional on strictly positive labor income and hours worked.

Table 6: Impact of weather shocks on labor

	Number of Hours		Any Hours Worked		Log Income per Hour	
	Husbandry (1)	Casual Labor (2)	Husbandry (3)	Casual Labor (4)	Husbandry (5)	Casual Labor (6)
Treated (β)	0.959***	-0.485***	0.364***	-0.186***	0.922***	0.133***
	(0.077)	(0.085)	(0.037)	(0.032)	(0.121)	(0.029)
Unpredictable Shock (γ^U)	-0.378	0.617*	-0.256**	0.183	-0.326	-0.396***
	(0.289)	(0.375)	(0.104)	(0.114)	(0.533)	(0.105)
Treated × Unpredictable Shock (δ^U)	0.351*	-0.342	0.268***	-0.148*	0.107	0.323***
	(0.198)	(0.238)	(0.090)	(0.080)	(0.429)	(0.084)
Baseline Risk (γ^B)	-0.063	0.153	-0.153**	0.049	0.071	-0.219***
	(0.250)	(0.249)	(0.069)	(0.087)	(0.442)	(0.072)
Treated × Baseline Risk (δ^B)	0.003	-0.470**	0.138*	-0.062	0.102	0.370***
	(0.226)	(0.237)	(0.069)	(0.082)	(0.465)	(0.056)
Mean Dependent Variable (in levels)	364.0	734.8	0.6	0.6	2.7	8.0
P-val: $\gamma^U + \delta^U = 0$	0.875	0.269	0.890	0.689	0.342	0.495
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123	2771	3076
Adjusted R-square	0.1903	0.1211	0.1540	0.1026	0.1068	0.1657

Notes: This table reports estimates of Equation 3 for ultra-poor households in 2011. Hours are total annual hours worked in each activity. Columns (1)–(2) estimate hours in levels using PPML to account for zeros. Columns (3)–(4) estimate linear probability models, where the dependent variable is an indicator equal to one if the household reports positive hours in the activity. Income per hour is annual labor income divided by annual hours worked in the corresponding activity, transformed using the natural logarithm, $\ln(x)$, and estimated conditional on strictly positive labor income and hours worked. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 presents the results. Consistent with the decline in productive assets documented above, an additional day (0.1 dekad) of unpredictable weather shock affecting control households reduces the probability of engaging in any husbandry activity by 2.6 percentage points, while the PPML estimate for total annual husbandry hours implies a 3.7% decline in husbandry hours worked (not statistically significant). Furthermore, the unpredictable shock lowers the casual labor wage by 3.9%. These findings suggest a dual impact of shocks on households in extreme poverty. On the one hand, the reduction in productive assets limits their capacity for self-employed husbandry, resulting in fewer hours worked. On the other hand, if households shift toward casual wage labor, they face reduced earnings due to lower wages.[20] These results are consistent with an asset-based poverty trap, in which weather shocks force vulnerable households to liquidate productive assets, pushing them out of higher-return husbandry activities and into casual labor markets where wages are both lower and more volatile.

Being lifted out of poverty again builds significant resilience against these effects. The interaction term (δ^U) suggests that, on average, treated households fully offset the negative impact of one additional day of unpredictable weather shocks on labor outcomes. Specifically, treatment offsets the declines in the probability of any husbandry activity by 2.7 percentage points, total husbandry hours by +3.6%, and hourly income from casual labor by +3.3%. Figure B2 decomposes these effects by shock magnitude. Consistent with the consumption and assets results, adverse impacts are most severe among control households experiencing above-median unpredictable shocks, while treated households remain protected.

Taken together, these results suggest that treated households are able to mitigate the effects of weather shocks without depleting their productive assets, accepting lower wages, or shifting to lower-return and more vulnerable occupations. On the contrary, the benefits of the program are cumulative. Poverty reduction appears to offer comprehensive protection across multiple economic dimensions, safeguarding both the consumption and the productive capacity of ultra-poor households.[21]

The finding that households lifted out of poverty are able to maintain their casual labor wages during weather shocks is noteworthy for two key reasons. First, labor income is the cornerstone of ultra-poor subsistence, and stability along this margin suggests more than short-run protection. Second, the stability of casual wages, which are typically highly responsive to local labor market conditions, points toward the possibility that the availability of alternative sources of earnings makes the supply of casual labor more elastic to the wage.

One striking pattern in our data lends credibility to this mechanism. Table G1 in Appendix G shows that the program increases both asset portfolio diversification and the va-

[20] Figure F3 shows that labor outcomes are primarily affected by negative shocks.

[21] Figure B8 in the Appendix reveals heterogeneity in the program's protective effects. While treated households in the upper tail of the asset distribution are fully resilient to shocks, those who possessed few productive assets continue to suffer from the shocks. This is consistent with a poverty threshold as discussed in Balboni et al. (2022), which may be reinforced by severe weather shocks.

riety of labor occupations, even after accounting for the mechanical effect of the program's transfers. While households likely do not diversify explicitly to hedge against weather shocks, this shift toward a broader mix of productive assets and labor activities provides two potential advantages during crises. First, diversification itself yields a more stable income stream, reducing vulnerability to any single shock.[22] Second, and perhaps more importantly for understanding wage stability, this diversification increases the elasticity of labor supply to any given sector. We test this in the next section.

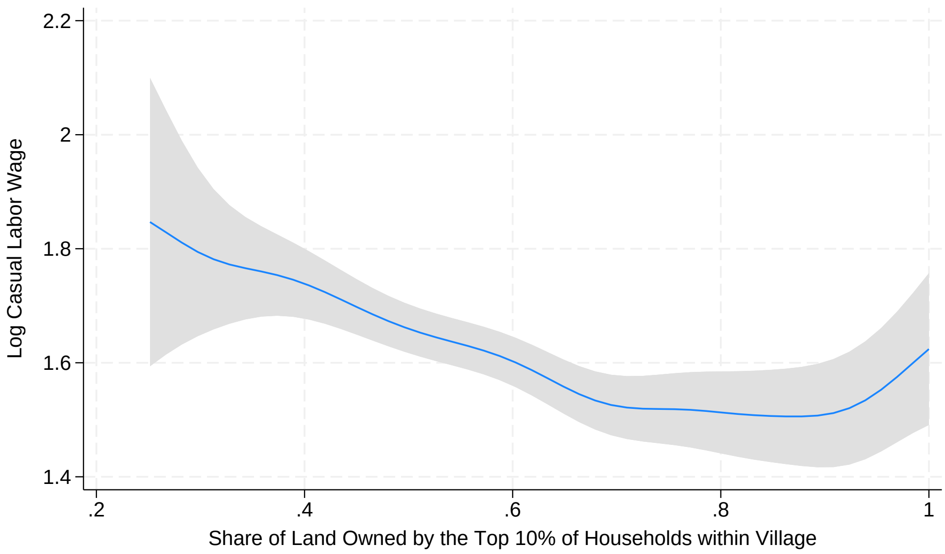
5.3 Resilience and Dependence on Casual Labor Wages

In this subsection, we examine the mechanism behind the differential impact of weather shocks on casual labor wages between treated and untreated households, as presented in Table 6, column (6). Casual labor constitutes the primary income source for ultra-poor households: as shown in Figure B4, casual labor accounts for 67% of hours worked and over 90% of income for households that remain ultra-poor, compared with 35% of hours and 58% of income for households lifted out of extreme poverty. This dependence makes ultra-poor households particularly vulnerable to weather shocks, since their need to meet subsistence creates a highly inelastic labor supply precisely when demand for labor falls, amplifying fluctuations in wages (Jayachandran, 2006).

A possible explanation for this wage protection is that the program increases the elasticity of labor supplied to local markets. A large body of literature suggests that asset and land ownership can raise equilibrium wages by improving a worker's outside options (Mookherjee and Ray, 2002; Eswaran and Kotwal, 1986; Bardhan, 1979; Besley and Burgess, 2000). This theory implies that the effects of lifting households from poverty should be strongest in villages with high baseline inequality, where the market power of landowners is strongest in the absence of the program. Correlational evidence is consistent with this: Figure 3 shows that villages with more concentrated land ownership (measured as the within-village share of land held by the top 10% of households) exhibit lower casual labor wages for ultra-poor households. Figure B5 documents a similar pattern for baseline asset inequality (measured as the within-village share of households with no assets).

[22]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.

Figure 3: Initial Level of Land Ownership Inequality and Casual Labor Wage



Notes: This figure plots the relationship between baseline land ownership inequality and casual labor wages earned by ultra-poor households. Land ownership inequality is measured as the share of village land held by the top 10 percent of households in 2007, prior to treatment. The vertical axis reports the village-level log casual labor wage in 2007. The figure displays a local polynomial fit with 90 percent confidence intervals.

Table 7 formally tests the labor supply elasticity mechanism by examining how the wage effects of weather shocks vary with baseline village inequality. Column (1) presents a village-level analog of our main household-level regression. Columns (2)–(5) split the sample by baseline inequality, using median thresholds for (i) land concentration (columns (2)–(3)), and (ii) the share of households with no assets (columns (4)–(5)). The results show that the adverse wage effect of a weather shock is concentrated entirely in villages with high baseline inequality. In these same villages, however, the program fully mitigates this negative effect for treated households.

Table 7: Impact of weather shocks on casual labor wage

	Log Ultra-poor Casual Labor Wage				
		Top 10% Land Share		Assetless Share	
	Combine	*Below Median*	*Above Median*	*Below Median*	*Above Median*
	(1)	(2)	(3)	(4)	(5)
Unpredictable Shock (γ^U)	-0.318**	-0.051	-0.533***	0.122	-0.798***
	(0.157)	(0.274)	(0.165)	(0.200)	(0.273)
Treated × Unpredictable Shock (δ^U)	0.266***	-0.097	0.591***	-0.133	0.730***
	(0.082)	(0.183)	(0.109)	(0.132)	(0.200)
Baseline Risk (γ^B)	-0.148	0.066	-0.307***	0.147	-0.409**
	(0.090)	(0.185)	(0.098)	(0.157)	(0.167)
Treated × Baseline Risk (δ^B)	0.334***	0.168	0.491***	0.124	0.584***
	(0.076)	(0.173)	(0.095)	(0.123)	(0.162)
Treated (β)	0.140***	0.111***	0.168***	0.102***	0.179***
	(0.028)	(0.036)	(0.051)	(0.022)	(0.061)
Mean Dependent Variable (in levels)	7.8	8.4	7.2	8.7	6.9
P-val: $\gamma^U + \delta^U = 0$	0.740	0.510	0.770	0.954	0.739
Number of obs.	887	443	444	443	444
Adjusted R-square	0.217	0.252	0.169	0.225	0.168

Notes: This table reports village-level analogs of Equation 3 for ultra-poor casual labor wages in 2011. The outcome is the log village-level casual labor wage, defined as annual casual labor income divided by annual casual labor hours, transformed using the natural logarithm, $\ln(x)$, and estimated conditional on strictly positive labor income and hours worked. Column (1) estimates the pooled village-level specification. Columns (2)–(3) split villages by whether the baseline share of land held by the top 10 percent of households is below or above the median. Columns (4)–(5) split villages by whether the baseline share of assetless households is below or above the median. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We also examine outcomes on the landlord/employer side of the labor market, following village-level analogs of the specification in Equation 3. If the program strengthens workers' outside options, treated households should be less willing to supply labor at low wages, limiting employers' ability to shift the income losses from climate shocks onto workers. Table 8 tests these implications using two employer-reported outcomes: earnings per acre and hired labor for land. Earnings per acre is defined as annual land-related earnings divided by land acreage, aggregated at the village level, and transformed using the natural logarithm. Hired labor for land is defined as total annual hired labor used for land-related activities, aggregated at the village level and estimated in levels using Poisson pseudo-maximum likelihood.

Consistent with the mechanism discussed above, the interaction term is negative for both outcomes, but only in high-inequality villages. This asymmetry suggests that employers in ex-ante high-inequality areas, where workers initially had weaker outside options, absorb a larger share of the shock once ultra-poor workers have been lifted out of poverty. No comparable effects appear in low-inequality villages, where employers have low market power from the start. Taken together, the symmetry between worker-side wage protection and employer-side income adjustments provides consistent evidence that the program operates by improving workers' outside options and increasing the elasticity of their labor supply.

Table 8: IMPACT OF WEATHER SHOCKS ON LANDLORD OUTCOMES

	Log Earnings per Acre		Hired Labour for Land	
	Low Landless	**High Landless**	**Low Landless**	**High Landless**
	(1)	(2)	(3)	(4)
Unpredictable Shock (γ^U)	-1.196***	1.399**	-0.557	4.340***
	(0.369)	(0.620)	(1.210)	(0.836)
Treated × Unpredictable Shock (δ^U)	-0.358	-1.690**	1.116	-3.890***
	(0.248)	(0.625)	(0.859)	(1.322)
Baseline Risk (γ^B)	-0.777**	1.068**	-1.071	3.369***
	(0.300)	(0.518)	(0.920)	(1.006)
Treated × Baseline Risk (δ^B)	0.015	-1.671***	1.236	-2.938***
	(0.243)	(0.493)	(0.878)	(1.023)
Treated (β)	-0.057	0.196*	-0.087	-0.029
	(0.125)	(0.108)	(0.271)	(0.446)
Mean Dependent Variable (in levels)	250.6	281.9	32.2	18.7
P-val: $\gamma^U + \delta^U = 0$	0.000	0.553	0.609	0.739
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	211	214	211	214
Adjusted R-square	0.088	0.030	0.350	0.368

Notes: This table reports village-level analogs of Equation 3 for landlord outcomes in 2011. The landlord sample is defined as households in the top 15 percent of the within-village baseline land-size distribution. Earnings per acre is annual land-related earnings divided by land acreage, aggregated at the village level and transformed using the natural logarithm, $\ln(x)$. Hired labor for land is total annual hired labor used for land-related activities, aggregated at the village level, and estimated in levels using PPML to account for zeros. Columns split villages by whether the baseline share of landless households is below or above the median. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusions

As studies of climate damages have evolved, it has become ever more apparent that these are most keenly felt in the areas of the world where extreme poverty is most pronounced. The focus of this paper is the relationship between climate change and poverty — the two main foci of current development economics.

Two fundamental questions emerge when we examine this relationship. First, does poverty amplify vulnerability to environmental shocks? Second, can poverty-reduction programs provide protection against them? We tackle both questions directly in rural Bangladesh, a setting where both extreme poverty and weather shocks are prevalent, and where we can combine rich data from the randomized evaluation of a large anti-poverty program with satellite-derived shock measures.

Our first contribution is to show that poverty is a key determinant of vulnerability to weather shocks. Unpredictable weather shocks have substantial negative impacts on the consumption of poor households, but those randomized into a large-scale anti-poverty program are successfully shielded from these adverse effects. Reducing poverty is thus central to improving resilience to droughts and floods, which will become both more frequent and intense as climate change unfolds.

Our second contribution is to shed light on the mechanisms through which poverty reduction enhances resilience to environmental shocks. Households that receive the program diversify their productive assets and labor activities which, in turn, enables them to build resilience through two complementary channels.

First, diversified income sources — particularly from livestock enterprises and small businesses — confer additional and more stable earnings which remain resilient in the face of droughts and floods. Households use these alternative income sources to smooth consumption and reduce their overall exposure to earnings fluctuations. In contrast, control households are forced to run down savings and assets. We find that these new income sources fully protect treated households from above-median negative drought and flood shocks and confer a similar level of resilience to that enjoyed by near-poor households in the village.

Second, the improvement in workers' outside options raises their elasticity of casual labor supply, helping to maintain wage income in the face of a shock. Underpinning this effect is a weakening of landlords' market power in treated villages, where they are no longer able to pass through the full incidence of shocks onto workers by lowering wages. This effect is most pronounced in villages with severe land inequality, where landlords had enjoyed more market power in the absence of the program. In such settings, possessing an asset that simultaneously generates an additional, more stable income stream and reduces dependence on the lowest-paid, least secure forms of employment during climate shocks turns out to be critical.

The results therefore point to the importance of occupational change in protecting poor households from droughts and floods. Adding a new business activity is shown to be important both for reducing poverty and increasing resilience to shocks. A key implication for policy design is that poverty reduction is a key form of climate adaptation. Interventions that lift households from the bottom of the wealth distribution can protect against extreme weather precisely because they expand the set of feasible occupations and strengthen outside options. Our results thus point to the adaptation value of big-push asset transfer programs that are substantial enough to relax binding constraints on occupational change and generate durable additional income streams.

Much policy has focused on ex-post adaptation, where relief is provided after shocks occur. The contrast between households that receive the program and those that do not in our setting instead points to the central role that ex-ante adaptation might play in climate policy. Households that receive assets that enable them to take on new occupations are found to mitigate the effects of weather shocks without depleting their productive assets, accepting lower wages, or shifting to more vulnerable occupations. As such, safeguarding both consumption and productive capacity of poor households appears to be key to effective ex-ante policy design.

This paper helps to connect the poverty and climate agendas, and to explain why extreme poverty and climate damages overlap so tightly across the globe. Large populations still depend on informal, weather-dependent casual labor and face substantial barriers to occupational mobility. As droughts and floods grow more frequent and severe, these constraints leave such populations increasingly vulnerable — underscoring the urgency of building resilience before environmental conditions deteriorate further.

Policies that enable households to move up the occupational ladder will therefore be critical to protecting people from the rising damages from climate change. The graduation program we study is one effective means of achieving this, particularly for the large poor populations engaged in subsistence agriculture.

The paper opens up a broader research agenda focused on identifying policy interventions that can simultaneously lift populations out of poverty and provide them with durable protection against climate change. Policies that facilitate diversification or provide individuals with credible outside options — investments in infrastructure that expand access to non-local labor markets, job protection and wage stabilization schemes during shocks, and interventions that reduce barriers to occupational change and migration — may be powerful in this regard. Unlocking such routes to occupational mobility for the world's poorest people is likely to be central to this research program.

References

Balboni, C., O. Bandiera, R. Burgess, M. Ghatak, and A. Heil (2022). Why do people stay poor? *The Quarterly Journal of Economics 137*(2), 785–844.

Bandiera, O., R. Burgess, N. Das, S. Gulesci, I. Rasul, and M. Sulaiman (2017). Labor markets and poverty in village economies. *The Quarterly Journal of Economics 132*(2), 811–870.

Bandiera, O., R. Burgess, A. Heil, and M. Sulaiman (2026). Poverty traps. In P. Dupas, P. K. Goldberg, and R. Pande (Eds.), *Handbook of Development Economics*, Volume 6, Chapter 11. Elsevier. Forthcoming.

Banerjee, A., R. Banerji, J. Berry, E. Duflo, H. Kannan, S. Mukerji, M. Shotland, and M. Walton (2017). From proof of concept to scalable policies: Challenges and solutions, with an application. *Journal of Economic Perspectives 31*(4), 73–102.

Bardhan, P. K. (1979). Labor supply functions in a poor agrarian economy. *American Economic Review 69*(1), 73–83.

Besley, T. and R. Burgess (2000). Land reform, poverty reduction, and growth: Evidence from India. *The Quarterly Journal of Economics 115*(2), 389–430.

Borusyak, K. and P. Hull (2023). Nonrandom exposure to exogenous shocks. *Econometrica 91*(6), 2155–2185.

Burgess, R., O. Deschênes, D. Donaldson, and M. Greenstone (2024). Weather, climate change and death in India. Working paper.

Cai, J. (2016). The impact of insurance provision on household production and financial decisions. *American Economic Journal: Economic Policy 8*(2), 44–88.

Carleton, T., E. Duflo, B. K. Jack, and G. Zappalà (2024). Adaptation to climate change. In L. Barrage and S. Hsiang (Eds.), *Handbook of the Economics of Climate Change*, Volume 1, Chapter 4, pp. 143–248. North-Holland.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics 137*(4), 2037–2105.

Coate, S. and M. Ravallion (1993). Reciprocity without commitment: Characterization and performance of informal insurance arrangements. *Journal of Development Economics 40*(1), 1–24.

Deaton, A. (1997). *The analysis of household surveys: A microeconometric approach to development policy.* Johns Hopkins University Press.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–798.

Duflo, E. (2017). The economist as plumber. *American Economic Review 107*(5), 1–26.

Eswaran, M. and A. Kotwal (1986). Access to capital and agrarian production organisation. *The Economic Journal 96*(382), 482–498.

Gilli, M., M. Calcaterra, J. Emmerling, and F. Granella (2024). Climate change impacts on the within-country income distributions. *Journal of Environmental Economics and Management 127*, 103012.

Hirabayashi, Y., M. Tanoue, O. Sasaki, X. Zhou, and D. Yamazaki (2021). Global exposure to flooding from the new CMIP6 climate model projections. *Scientific Reports 11*(1), 3740.

Hirvonen, K., D. O. Gilligan, J. Leight, H. Tambet, and V. Villa (2023). Do ultra-poor graduation programs build resilience against droughts? Evidence from rural Ethiopia. IFPRI Discussion Paper 2206, International Food Policy Research Institute, Washington, DC.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics 8*(1), 43–75.

Hsiang, S., R. E. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, et al. (2017). Estimating economic damage from climate change in the United States. *Science 356*(6345), 1362–1369.

IPCC (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.

Jayachandran, S. (2006). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy 114*(3), 538–575.

Jones, B. F., J. Moscona, B. A. Olken, and C. von Dessauer (2026). With or without U? Binning bias and the causal effects of temperature extremes. Working Paper 34671, National Bureau of Economic Research.

Kahana, M. J. (2012). *Foundations of human memory*. Oxford University Press.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics 129*(2), 597–652.

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research 15*(11), 91–100.

Macours, K., P. Premand, and R. Vakis (2022). Transfers, diversification and household risk strategies: Can productive safety nets help households manage climatic variability? *The Economic Journal 132*(647), 2438–2470.

Michler, J. D. and A. L. Josephson (2017). To specialize or diversify: Agricultural diversity and poverty dynamics in Ethiopia. *World Development 89*, 214–226.

Mookherjee, D. and D. Ray (2002). Contractual structure and wealth accumulation. *American Economic Review 92*(4), 818–849.

Mullainathan, S. (2002). A memory-based model of bounded rationality. *The Quarterly Journal of Economics 117*(3), 735–774.

Mulwa, C. K. and M. Visser (2020). Farm diversification as an adaptation strategy to climatic shocks and implications for food security in northern Namibia. *World Development 129*, 104906.

Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in Thailand. *American Economic Review 82*(1), 15–33.

Pople, A., R. Hill, S. Dercon, and B. Brunckhorst (2024). The importance of being early: Anticipatory cash transfers for flood-affected households. CSAE Working Paper Series, Centre for the Study of African Economies.

Rodziewicz, D., J. Dice, and C. Cowley (2023). Drought and cattle: Implications for ranchers. Research Working Paper 23-06, Federal Reserve Bank of Kansas City.

Rosenzweig, M. R. and H. P. Binswanger (1993). Wealth, weather risk and the composition and profitability of agricultural investments. *The Economic Journal 103*(416), 56–78.

Rosenzweig, M. R. and O. Stark (1989). Consumption smoothing, migration, and marriage: Evidence from rural India. *Journal of Political Economy 97*(4), 905–926.

Tellman, B., J. A. Sullivan, C. Kuhn, A. J. Kettner, C. S. Doyle, G. R. Brakenridge, T. A. Erickson, and D. A. Slayback (2021). Satellite imaging reveals increased proportion of population exposed to floods. *Nature 596*(7870), 80–86.

Thornton, P., G. Nelson, D. Mayberry, and M. Herrero (2022). Impacts of heat stress on global cattle production during the 21st century: a modelling study. *The Lancet Planetary Health 6*(3), e192–e201.

Toulmin, C. (1987). Drought and the farming sector: Loss of farm animals and post-drought rehabilitation. *Development Policy Review 5*(2), 125–148.

Townsend, R. M. (1994). Risk and insurance in village India. *Econometrica 62*(3), 539–591.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources 50*(2), 420–445.

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 diversification results.
- Appendix D presents other decomposition methods.
- Appendix E presents details on floods and droughts measurement.
- Appendix F presents additional evidence on positive vs. negative surprises.

A Descriptive Statistics and Identification Tests

A.1 Additional Descriptive Statistics

Table A1: Additional Descriptive Statistics for Ultra-Poor

	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. Monetary values are in Bangladeshi taka over the last year; hours worked are annual hours; protein intake is the number of meals per month including eggs, fish, or meat. Food consumption and total consumption are measured per capita. The sample includes N=6075 observations for the ultra-poor and N=5920 for the near-poor.

In Section 2, 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 contrasts them with households classified as near-poor, middle-rich, and rich, for comparison. In this appendix section, we provide additional descriptive statistics about our household data. Table A1 zooms in on the ultra-poor and near-poor groups, with detailed statistics on the distribution of key outcomes. 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 Bangladeshi taka 100, corresponding to only $4 USD PPP. Table A2 shows similar statistics as Table 1 but for 2011, five years after treatment.

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

[23]The total annual hours spent on husbandry are 269, less than half the hours spent on casual labor (maid and agricultural day labor).

Table A2: Descriptive statistics for survey wave 3

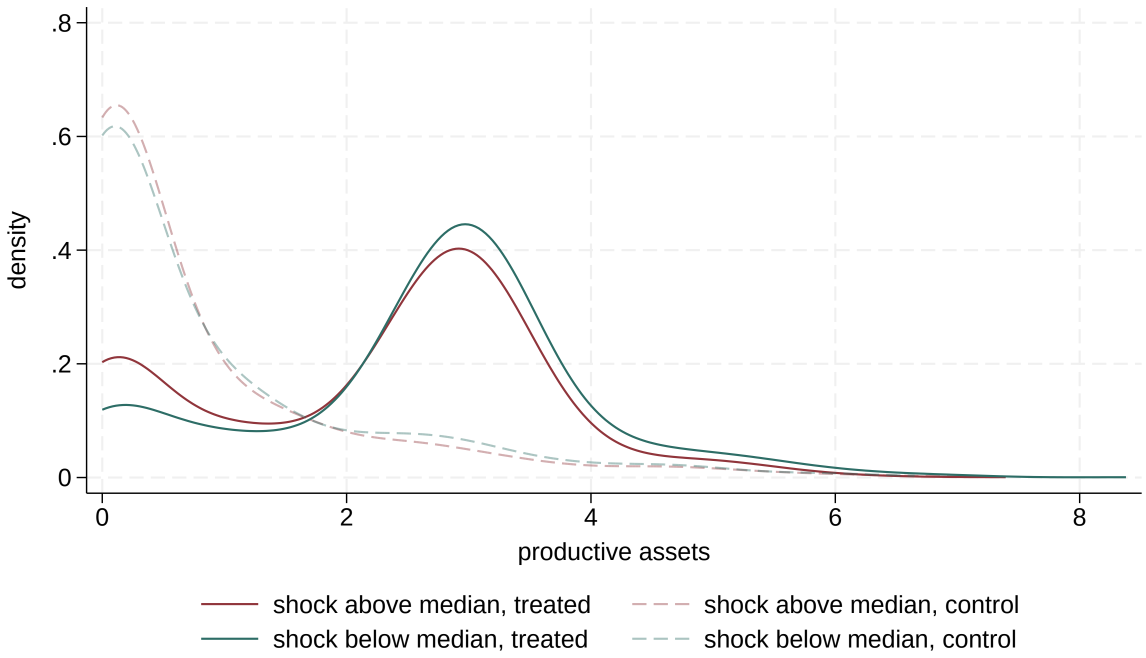
	Ultra-poor		**Near-poor**	**Middle Rich**	**Rich**
	Control	Treated			
Total Consumption	10,896	12,161	11,848	13,292	21,994
Food Consumption Share	0.72	0.69	0.69	0.66	0.57
Protein Intake	3.01	3.80	3.56	4.55	7.19
Total Assets	10,375	29,256	30,325	370,672	2,290,845
Productive Assets	9,091	27,288	27,656	362,232	2,246,303
Savings	265	1,283	555	1,555	8,506
Loans	1,258	1,332	2,709	9,686	31,499
Husbandry Hours	364	816	475	694	798
Casual Labor Hours	735	442	430	132	10
Illiterate Share	0.94	0.91	0.83	0.74	0.50

Notes: All variables are measured in 2011. Monetary values are in Bangladeshi taka over the last year; hours worked are annual hours; protein intake is the number of meals per month including eggs, fish, or meat. Food consumption and total consumption are measured per capita. The sample includes N=6123 observations for the ultra-poor, N=6043 for the near-poor, N=5567 for the middle-rich, and N=1817 for the rich.

defined as high weather shock zones, i.e., villages where ex-ante combined flood and drought exposure over 2000–2006 is greater than the median across villages, versus villages classified as low weather shock zones. The dotted lines represent control households who did not receive the program, and the solid lines represent treated households. The emerald 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, emerald 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 dashed emerald 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

Figure A1: Distribution of productive assets in 2011



Notes: This figure shows the distribution of productive assets in 2011, five years after treatment, in high-shock versus low-shock villages, and in treated versus control villages. High-shock villages are defined as villages with ex-ante combined flood and drought exposure over 2000–2006 above the median across villages; low-shock villages are below the median. The red curves represent high-shock villages and the emerald curves represent low-shock villages. The dashed lines are the control group and the solid lines are the treatment group.

in terms of consumption, assets and labor market outcomes.

A.2 Identification Tests

In this section, we conduct two identification tests. The first is a pre-treatment balance test: conditional on baseline risk, it asks whether villages that later experience larger 2011 weather surprises already differed in 2007. The second is a placebo exercise using only pre-program outcomes and shocks.

For the first identification test, we use outcome data for the same households before the program was announced, in 2007. This allows us to test whether, conditional on baseline risk, future 2011 weather surprises are correlated with pre-treatment heterogeneity in observed household outcomes. 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*. We then verify that this conclusion is unchanged when we re-estimate the baseline model with treatment interactions. Since our weather shock measure is a continuous variable rather than binary, we cannot split the sample and perform a t-test,[24] so instead we regress the 2007 outcome variables on the continuous 2011 shock variable, expecting coefficients close to zero and statistically insignificant. We first estimate the following linear model that accounts for weather shocks only, without the interaction with the treatment $T_v(i)$:

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

Results are presented in columns (1) and (2) of Table A3. For all the outcome variables (productive assets, loan, savings, etc.), we do not observe significant associations between 2007 outcomes and exposure to the 2011 weather surprise once we control for baseline risk. This suggests that the residual 2011 shock is not systematically related to pre-treatment differences in observed baseline outcomes. We verify this by re-estimating our baseline Equation 3, still measuring outcomes in 2007. Figure A2 plots the coefficient γ^U for

Table A3: Balance test

	Weather Shocks		**Baseline Model**	
	β	p-value	β	p-value
Total Consumption	0.08	0.160	-0.05	0.320
Food Consumption	0.05	0.345	-0.06	0.279
Protein Consumption	-0.02	0.966	-1.00	0.177
Total Assets	0.14	0.310	-0.14	0.447
Productive Assets	0.09	0.495	0.01	0.957
Savings	-0.03	0.360	-0.03	0.570
Loan	-0.03	0.679	-0.02	0.808
Husbandry Hour	0.06	0.166	0.13	0.209
Casual Labor Hour	-0.07	0.120	-0.00	0.973

Notes: Outcome variables are measured in 2007, while shocks are measured in 2011. Monetary values are in Bangladeshi taka over the last year; hours worked are annual hours; protein intake is the number of meals per month including eggs, fish, or meat. Food consumption and total consumption are measured per capita. The Weather Shocks columns estimate $Y_{i,2007} = \alpha + \gamma^B \hat{\mathbf{C}}_{v(i),2011} + \gamma^U \mathbf{S}_{v(i),2011} + \varepsilon_i$. The Baseline Model columns report the coefficient γ^U from Equation 3 estimated with 2007 outcomes and the 2011 combined (flood and drought) weather shock. Standard errors are clustered at the branch level.

the weather surprise. Columns (3) and (4) of Table A3 show the corresponding Baseline Model 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 were balanced at baseline with respect to future unpredictable 2011 shocks.

[24] 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 statistically significant differences exist.

In the second identification test, we re-estimate our baseline model (Equation 3) with both outcomes and shocks measured before treatment, in 2007. The coefficient of interest is δ^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 do not 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 δ^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 generate differential responses to surprise shocks in treatment and control villages before the program begins.

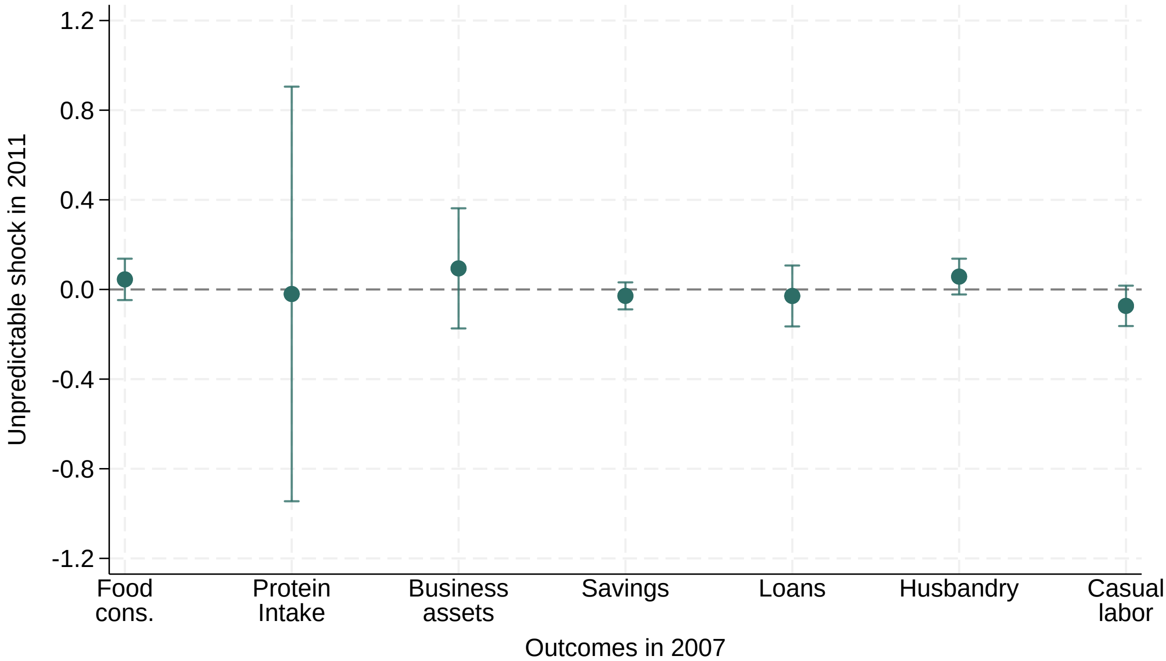
Table A4 and Figure A3 show the results. Overall, they do not show any systematic pattern. Taken together, they lend support to our empirical strategy and suggest that our identifying assumptions are reasonable.

Table A4: Placebo test

	Unpredictable Shock × Treat		**Baseline Risk × Treat**	
	β	p-value	β	p-value
Total Consumption	0.11	0.108	0.12	0.054
Food Consumption	0.06	0.225	0.08	0.081
Protein Intake	0.19	0.722	0.30	0.568
Total Assets	0.29	0.009	0.29	0.024
Productive Assets	0.11	0.257	0.13	0.314
Savings	-0.01	0.679	0.01	0.841
Loans	0.08	0.205	-0.01	0.895
Husbandry Hours	-0.06	0.414	-0.04	0.656
Casual Labor Hours	-0.06	0.403	0.04	0.556

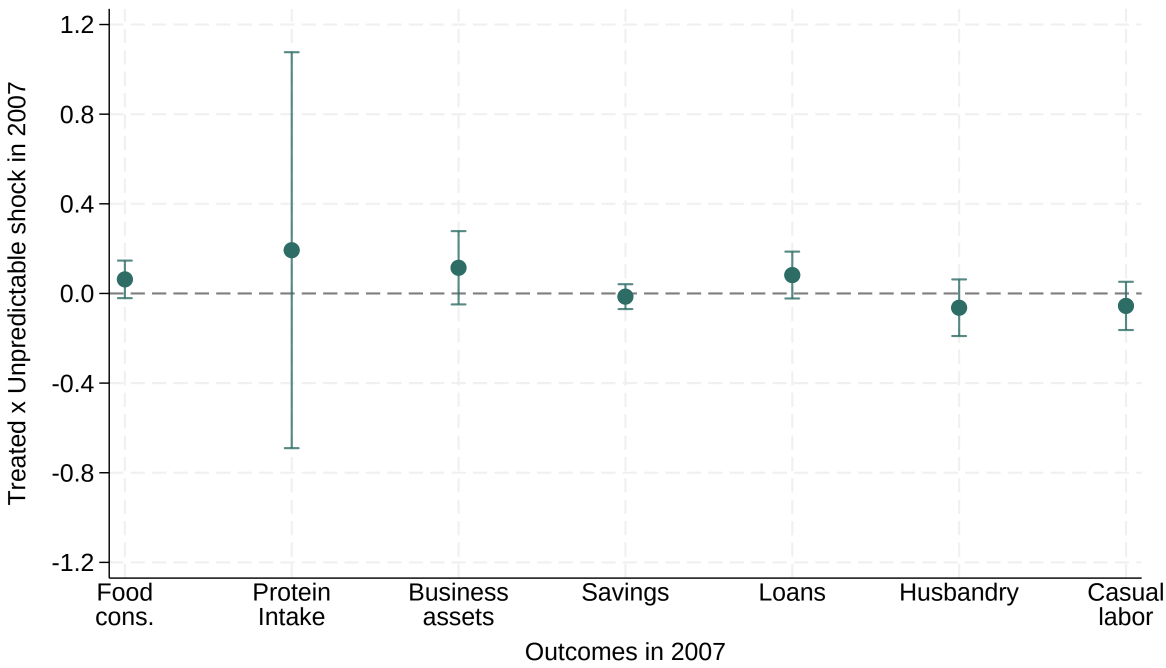
Notes: All variables are measured in 2007. Monetary values are in Bangladeshi taka over the last year; hours worked are annual hours; protein intake is the number of meals per month including eggs, fish, or meat. Food consumption and total consumption are measured per capita. The table reports the interaction coefficients δ^U and δ^B from Equation 3 estimated with 2007 outcomes and the 2007 combined weather shock.

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



Notes: This figure plots the coefficient γ^U from Equation 3 in the balance test, using 2007 outcomes and the 2011 combined (flood and drought) weather shock. Outcome variables are measured in 2007, while shocks are measured in 2011. Monetary values are in Bangladeshi taka over the last year; hours worked are annual hours; protein intake is the number of meals per month including eggs, fish, or meat. Standard errors are clustered at the branch level.

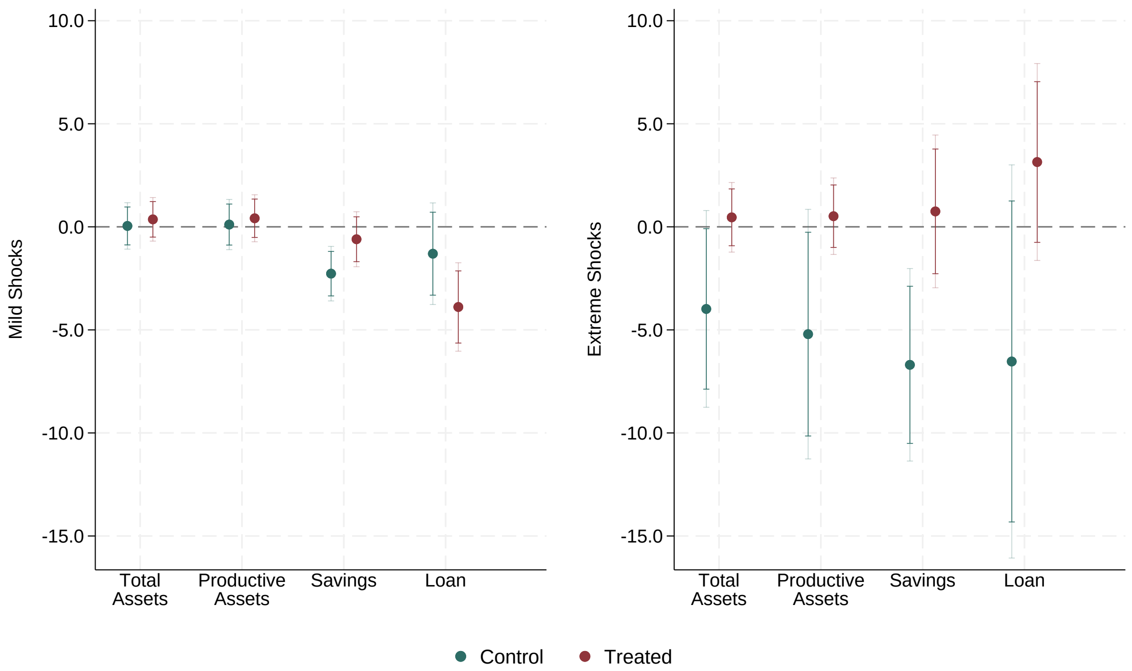
Figure A3: PLACEBO TEST: BASELINE EQUATION BEFORE TREATMENT



Notes: This figure plots the coefficient δ^U from Equation 3 estimated with both outcomes and shocks measured in 2007. Units are Bangladeshi 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 eggs, fish, or meat). Food consumption and total consumption are measured per capita. Standard errors are clustered at the branch level.

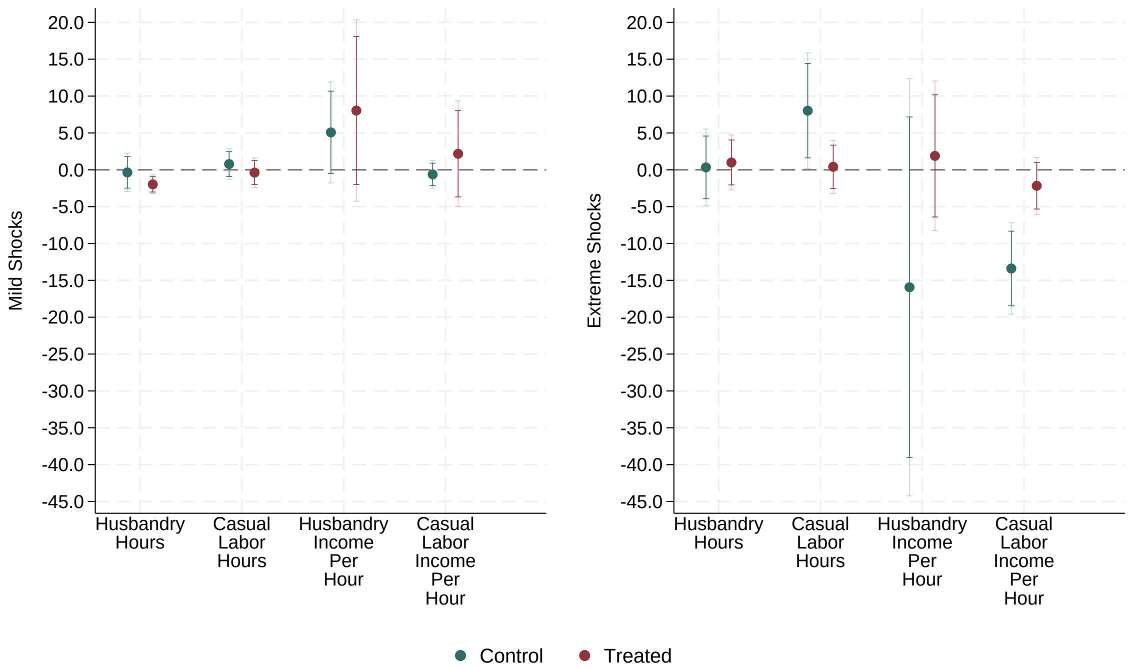
B Additional Results and Robustness Checks

Figure B1: Mild vs. Extreme Weather Shocks: Impact on Asset Holding



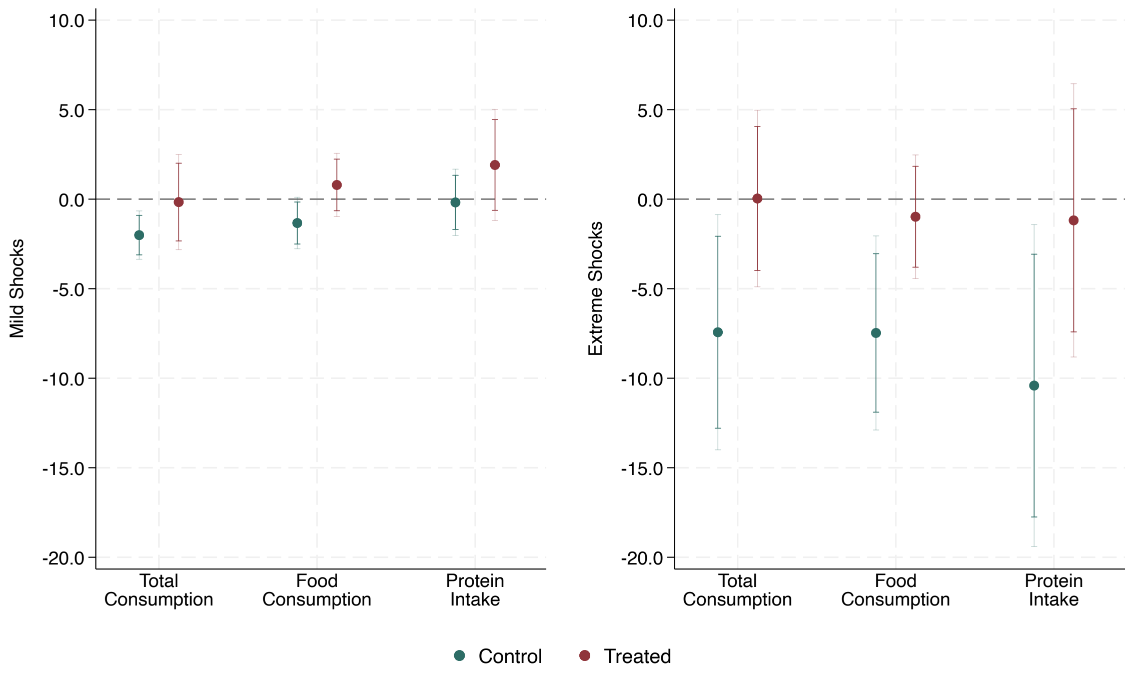
Notes: Each dot represents an estimated treatment effect. Within each group of coefficients, emerald markers correspond to the control group, while red markers correspond to the TUP-treated group. The left-hand panel reports results for mild shocks, and the right-hand panel reports results for extreme shocks. Negative climate shocks are split at the 50th percentile to define mild versus extreme shocks. Total and productive assets are measured in Bangladeshi taka and estimated in levels using PPML, while savings and loans are measured in Bangladeshi taka and estimated as log outcomes. All specifications include sub-district fixed effects, and standard errors are clustered at the branch level.

Figure B2: Mild vs. Extreme Weather Shocks: Impact on Labor Market Outcomes



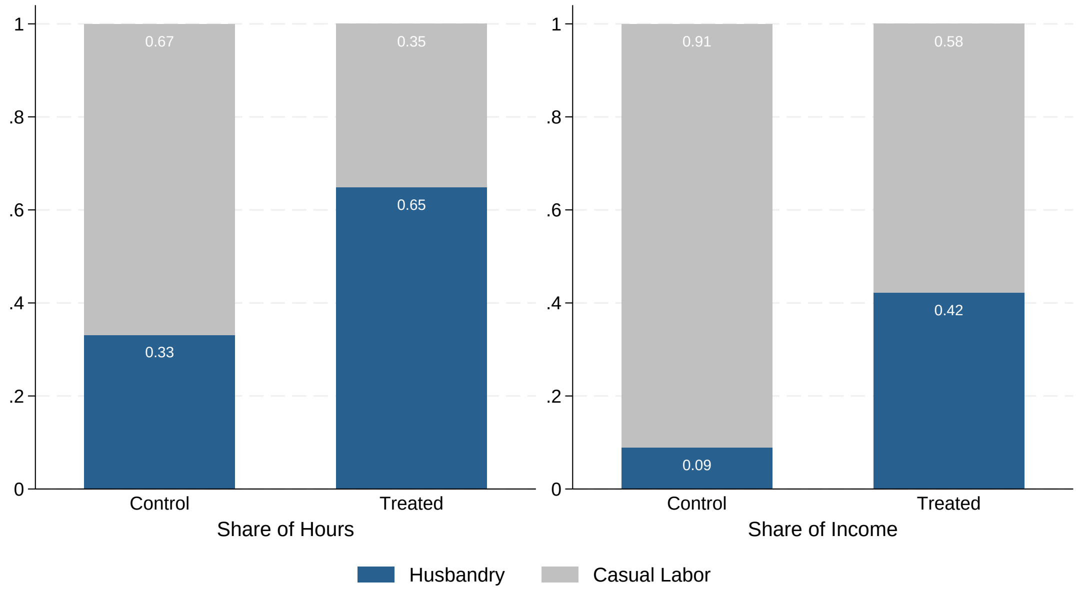
Notes: Each dot represents an estimated treatment effect. Within each group of coefficients, emerald markers correspond to the control group, while red markers correspond to the TUP-treated group. The left-hand panel reports results for mild shocks, and the right-hand panel reports results for extreme shocks. Negative climate shocks are split at the 50th percentile to define mild versus extreme shocks. Both hours and income per hour are expressed in logs. All specifications include sub-district fixed effects, and standard errors are clustered at the branch level.

Figure B3: Mild vs. Extreme Weather Shocks: Impact on Consumption



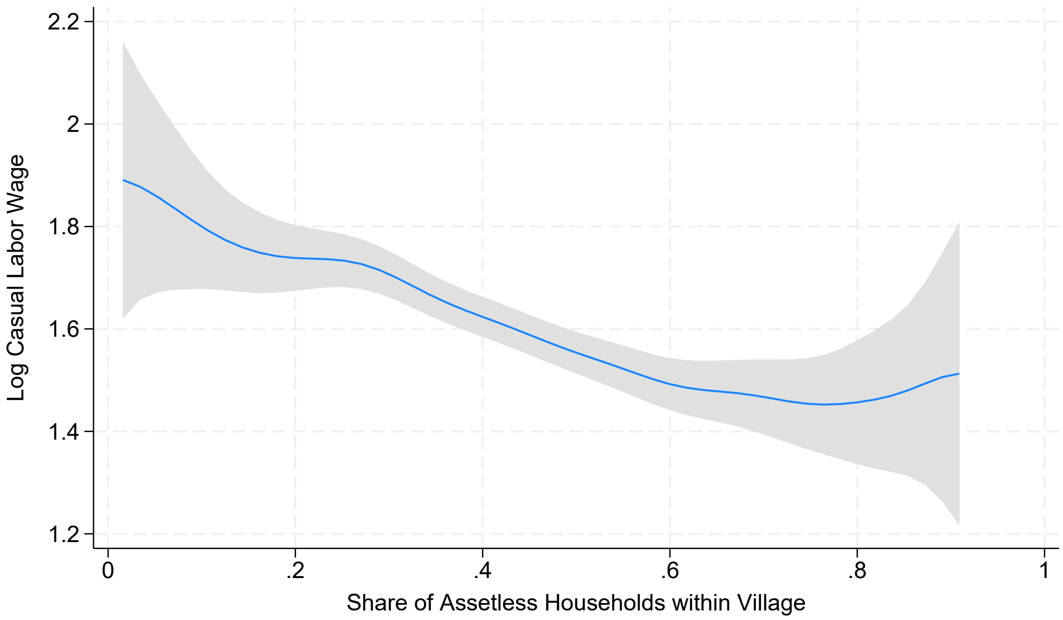
Notes: Each dot represents an estimated treatment effect. Within each group of coefficients, emerald markers correspond to the control group, while red markers correspond to the TUP-treated group. The left-hand panel reports results for mild shocks, and the right-hand panel reports results for extreme shocks. Negative climate shocks are split at the 50th percentile to define mild versus extreme shocks. Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. All specifications include sub-district fixed effects, and standard errors are clustered at the branch level.

Figure B4: Labor income and hours worked



Notes: The figure plots the share of total labor hours and total labor income derived from casual labor (maid and agricultural day labor) versus husbandry activities for control and treated households in 2011. Other activities are excluded. Light blue bars represent casual labor; gray bars represent husbandry.

Figure B5: Initial Level of Asset Holding Inequality and Casual Labor Wage



Notes: This figure plots the relationship between asset-holding inequality — measured as the share of assetless households within a village — and casual labor wages earned by ultra-poor households. The vertical axis reports the village-level log casual labor wage in 2007, and the horizontal axis reports asset inequality in 2007, prior to the intervention. The figure displays a local polynomial fit with 90% confidence intervals.

Table B1: Impact of weather shocks on welfare: near-poor

	Consumption		
	Total (1)	Food (2)	Protein (3)
Near-poor	0.071***	0.041**	0.575***
	(0.024)	(0.017)	(0.154)
Unexpected Shock	0.013	-0.118	-0.800
	(0.068)	(0.073)	(0.585)
Near-poor × Unexpected Shock	0.138	0.202	0.832*
	(0.125)	(0.122)	(0.424)
Expected Shock	0.014	-0.063	-0.428
	(0.065)	(0.064)	(0.394)
Near-poor × Expected Shock	0.073	0.122	0.143
	(0.125)	(0.122)	(0.414)
Sub-district FE	Yes	Yes	Yes
Number of obs.	5738	5738	5738
Adjusted R-square	0.0510	0.0196	0.2998

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 weather shocks on assets and labor: near-poor

	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)
Near-poor	1.271***	1.681***	0.115***	0.335***	1.115***	-1.350***	0.317***	0.093***
	(0.125)	(0.188)	(0.021)	(0.046)	(0.180)	(0.192)	(0.090)	(0.018)
Unexpected Shock	-0.029	-1.408	-0.064	-0.183	-2.611***	-0.636	1.082**	-0.204*
	(0.405)	(0.887)	(0.124)	(0.296)	(0.683)	(0.956)	(0.471)	(0.100)
Near-poor × Unexpected Shock	0.550*	1.167**	0.021	-0.143	1.116**	0.115	-1.469***	0.131
	(0.290)	(0.537)	(0.088)	(0.169)	(0.522)	(0.494)	(0.333)	(0.119)
Expected Shock	0.177	-0.537	-0.039	0.018	-1.069**	-0.835	0.933**	-0.153**
	(0.222)	(0.491)	(0.086)	(0.214)	(0.439)	(0.595)	(0.335)	(0.071)
Near-poor × Expected Shock	0.039	0.547	-0.017	-0.163	0.471	0.104	-1.412***	0.125
	(0.253)	(0.428)	(0.090)	(0.163)	(0.537)	(0.516)	(0.351)	(0.117)
Number of obs.	5738	5738	5738	5738	5738	5738	1762	2841
Adjusted R-square	0.1361	0.1127	0.0414	0.1353	0.0649	0.1372	0.0415	0.2171

Notes: Physical assets and financial outcomes are denominated in Bangladeshi 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 outcome variables are in logs. 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 B3: IMPACT OF WEATHER SHOCKS ON WELFARE, WITHOUT SUB-DISTRICT FE

	Consumption			
	Total	Food	Calories	Protein
	(1)	(2)	(3)	(4)
Treated (β)	0.116***	0.090***	0.136**	0.806
	(0.034)	(0.032)	(0.065)	(0.606)
Unexpected Shock (γ^U)	-0.108	-0.102*	-0.151	-2.087***
	(0.077)	(0.055)	(0.100)	(0.605)
Treated × Unexpected Shock (δ^U)	0.225**	0.193***	0.144	2.855***
	(0.093)	(0.071)	(0.142)	(0.739)
Expected Shock (γ^E)	-0.152*	-0.085	-0.129	-1.537**
	(0.078)	(0.053)	(0.104)	(0.724)
Treated × Expected Shock (δ^E)	0.157*	0.091	0.164	1.864**
	(0.081)	(0.055)	(0.109)	(0.790)
Number of obs.	6123	6123	6484	6484
Adjusted R-square	0.0242	0.0075	0.0082	0.0148

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Calorie intake is measured as household calories and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Standard errors are clustered at the branch level.

Table B4: Impact of weather shocks on welfare with different decay parameter: food consumption

	Food Consumption			
Decay Rate	20%	40%	60%	80%
	(1)	(2)	(3)	(4)
Treated (β)	0.095***	0.089***	0.081***	0.078***
	(0.019)	(0.018)	(0.017)	(0.016)
Unpredictable Shock (γ^U)	-0.180**	-0.178**	-0.119	-0.043
	(0.071)	(0.078)	(0.082)	(0.068)
Treated × Unpredictable Shock (δ^U)	0.173***	0.156**	0.114*	0.084
	(0.057)	(0.058)	(0.066)	(0.071)
Baseline Risk (γ^B)	-0.013	-0.019	0.013	0.042
	(0.060)	(0.061)	(0.066)	(0.074)
Treated × Baseline Risk (δ^B)	0.107*	0.101	0.079	0.055
	(0.060)	(0.063)	(0.067)	(0.065)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.0248	0.0248	0.0243	0.0237

Notes: Food consumption is expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Baseline risk and unpredictable risk are decomposed following the decay decomposition, with four alternative decay parameters. Decay parameters have been further rescaled to sum to one. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

Table B5: IMPACT OF WEATHER SHOCKS ON WELFARE: PROTEIN INTAKE DECOMPOSITION

	Eggs (1)	Big Fish (2)	Small Fish (3)	Meat (4)
Treated (β)	0.142***	0.125***	0.083**	0.054**
	(0.034)	(0.037)	(0.031)	(0.024)
Unexpected Shock (γ^U)	-0.502***	-0.164	-0.448**	-0.214**
	(0.146)	(0.103)	(0.214)	(0.088)
Treated × Unexpected Shock (δ^U)	0.396***	-0.038	0.476***	0.196***
	(0.051)	(0.054)	(0.173)	(0.049)
Expected Shock (γ^E)	-0.250***	-0.086	-0.234	-0.145***
	(0.058)	(0.056)	(0.177)	(0.051)
Treated × Expected Shock (δ^E)	0.277***	0.132**	0.345**	0.156**
	(0.084)	(0.064)	(0.151)	(0.066)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6206	6206	6206	6206
Adjusted R-square	0.2169	0.1588	0.2089	0.1672

Notes: This table reports estimates of Equation 3 for ultra-poor households in 2011, separately for each component of protein intake. The outcomes are the monthly frequencies of consuming eggs, big fish, small fish, and meat, which together form the protein intake measure used in the main welfare tables. Realized weather shocks are decomposed into baseline risk and unpredictable shocks as described in Section 3. All specifications include sub-district fixed effects. Robust standard errors clustered at the BRAC branch level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B6: Impact of weather shocks on assets: $\log(1+x)$

	Physical Assets		Financial Assets	
	Total	Productive	Savings	Loan
	(1)	(2)	(3)	(4)
Treated (β)	2.492***	4.420***	0.576***	0.133***
	(0.168)	(0.306)	(0.034)	(0.043)
Unpredictable Shock (γ^U)	-0.123	-1.497*	-0.189**	-0.150
	(0.400)	(0.760)	(0.085)	(0.171)
Treated × Unpredictable Shock (δ^U)	0.536*	2.195***	0.214***	0.232
	(0.283)	(0.628)	(0.073)	(0.157)
Baseline Risk (γ^B)	0.176	-1.025**	-0.085	-0.183
	(0.317)	(0.438)	(0.052)	(0.141)
Treated × Baseline Risk (δ^B)	-0.216	1.072**	0.113**	0.132
	(0.304)	(0.450)	(0.055)	(0.129)
Mean	10375.3	9090.7	264.7	1257.6
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.288	0.281	0.326	0.072

Notes: Physical assets and financial outcomes are measured in Bangladeshi 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.

Table B7: Impact of weather shocks on assets: Comparing Different Estimators

	Physical Assets		Financial	
	Total	Productive	Savings	Loan
	(1)	(2)	(3)	(4)
Panel (a): Baseline results (PPML estimator)				
Unpredictable Shock (γ^U)	-1.388*	-1.775**	-2.435***	-2.951**
	(0.717)	(0.884)	(0.457)	(1.287)
Treated × Unpredictable Shock (δ^U)	1.429***	1.829***	2.558***	2.694***
	(0.516)	(0.676)	(0.447)	(0.917)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.1460	0.1444	0.2190	0.1311
Panel (b): OLS: $\ln(1+\text{X})$				
Unpredictable Shock (γ^U)	-0.123	-1.497*	-0.189**	-0.150
	(0.400)	(0.760)	(0.085)	(0.171)
Treated × Unpredictable Shock (δ^U)	0.536*	2.195***	0.214***	0.232
	(0.283)	(0.628)	(0.073)	(0.157)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.2879	0.2811	0.3258	0.0724
Panel (c): OLS: $\mathbb{1}\{X > 0\}$				
Unpredictable Shock (γ^U)	-0.008	-0.224***	-0.025	-0.100
	(0.015)	(0.081)	(0.107)	(0.099)
Treated × Unpredictable Shock (δ^U)	0.023*	0.279***	0.152	0.183**
	(0.013)	(0.084)	(0.093)	(0.087)
Sub-district FE	Yes	Yes	Yes	Yes
Number of obs.	6123	6123	6123	6123
Adjusted R-square	0.0245	0.1585	0.3941	0.0675

Notes: Physical assets and financial outcomes are measured in Bangladeshi taka. The three blocks report, from top to bottom, estimates using log(1+x) outcomes, PPML estimates in levels, and extensive-margin estimates where the outcome is an indicator for holding a positive value. 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 B8: Impact of weather shocks on labor: Comparing Different Estimators

	Hours	
	Husbandry (1)	Casual Labor (2)
Panel (a): Baseline results (PPML estimator)		
Unpredictable Shock (γ^U)	-0.377	0.615
	(0.289)	(0.375)
Treated $\times$ Unpredictable Shock (δ^U)	0.352*	-0.342
	(0.199)	(0.238)
Sub-district FE	Yes	Yes
Number of obs.	6123	6123
Adjusted R-square	0.1903	0.1210
Panel (b): OLS: $\ln(1+\mathrm{X})$		
Unpredictable Shock (γ^U)	-1.469**	1.467*
	(0.712)	(0.808)
Treated $\times$ Unpredictable Shock (δ^U)	1.543***	-1.167**
	(0.540)	(0.554)
Sub-district FE	Yes	Yes
Number of obs.	6123	6123
Adjusted R-square	0.1915	0.1130
Panel (c): OLS: $\mathbb{1}\{X > 0\}$		
Unpredictable Shock (γ^U)	-0.254**	0.184
	(0.103)	(0.114)
Treated $\times$ Unpredictable Shock (δ^U)	0.267***	-0.148*
	(0.090)	(0.080)
Sub-district FE	Yes	Yes
Number of obs.	6123	6123
Adjusted R-square	0.1540	0.1026

Notes: Hours are total annual hours worked in each activity. 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 B9: Impact of weather shocks, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.111***	0.071***	0.714***
	(0.019)	(0.016)	(0.207)
Unpredictable Shock (γ^U)	-0.212	-0.282	-4.229*
	(0.213)	(0.208)	(2.229)
Treated $\times$ Unpredictable Shock (δ^U)	0.226	0.282	3.768
	(0.194)	(0.197)	(2.266)
Baseline Risk (γ^B)	0.048	0.095	-0.807
	(0.084)	(0.100)	(0.667)
Treated $\times$ Baseline Risk (δ^B)	0.046	0.010	1.616
	(0.107)	(0.102)	(1.135)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0509	0.0238	0.2237

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 B10: Impact of weather shocks: positive vs. negative surprises, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.119***	0.087***	0.867***
	(0.021)	(0.018)	(0.202)
Negative Unpredictable Shock (γ^U)	-0.081	-0.033	-3.819
	(0.184)	(0.155)	(2.919)
Treated × Neg. Unpredictable Shock (δ^U)	0.102	0.026	2.065
	(0.182)	(0.147)	(3.143)
Positive Unpredictable Shock (γ^U)	0.505	0.825**	4.397*
	(0.403)	(0.403)	(2.361)
Treated × Pos. Unpredictable Shock (δ^U)	-0.493	-0.843**	-7.864***
	(0.396)	(0.395)	(2.338)
Baseline Risk (γ^B)	-0.055	-0.103**	-1.240
	(0.068)	(0.048)	(0.932)
Treated × Baseline Risk (δ^B)	0.147	0.214***	2.706*
	(0.110)	(0.069)	(1.462)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0507	0.0240	0.2255

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 B11: Impact of weather shocks: within-village estimate, linear decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.055**	-0.027	-0.436***
	(0.022)	(0.017)	(0.134)
Ultra-poor × Treated (δ)	0.103***	0.082***	0.559***
	(0.028)	(0.023)	(0.170)
Ultra-poor × Unpredictable Shock (δ^U)	-0.309	-0.517	-1.354
	(0.295)	(0.328)	(2.115)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.462	0.663*	1.796
	(0.299)	(0.334)	(2.150)
Ultra-poor × Baseline Risk (δ^B)	-0.057	-0.094	0.404
	(0.156)	(0.166)	(0.486)
Ultra-poor × Treated × Baseline Risk (γ^B)	0.004	0.057	-0.946*
	(0.158)	(0.168)	(0.517)
Mean	13141.8	8303.4	4.2
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1044	0.0497	0.4080

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 B12: Impact of weather shocks 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)	2.321***	4.217***	0.551***	0.109***	2.559***	-1.286***	0.915***	0.139***
	(0.138)	(0.252)	(0.030)	(0.038)	(0.198)	(0.165)	(0.100)	(0.030)
Unpredictable Shock (γ^U)	-0.056	-2.763***	-0.305**	-0.012	-1.673	2.932**	0.480	-0.305**
	(0.856)	(0.828)	(0.147)	(0.236)	(1.207)	(1.223)	(0.850)	(0.126)
Treated × Unpredictable Shock (δ^U)	0.704	4.294***	0.335*	0.080	2.564**	-3.629***	-0.198	0.323**
	(0.922)	(0.969)	(0.182)	(0.232)	(1.179)	(1.219)	(0.851)	(0.126)
Baseline Risk (γ^B)	0.364	-0.326	-0.001	-0.226	-0.330	-0.520	0.065	-0.149**
	(0.405)	(0.528)	(0.060)	(0.138)	(0.599)	(0.802)	(0.519)	(0.069)
Treated × Baseline Risk (δ^B)	-0.667	-0.228	0.025	0.139	-0.333	0.622	-0.029	0.336***
	(0.463)	(0.667)	(0.082)	(0.122)	(0.668)	(0.849)	(0.538)	(0.072)
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	0.2863	0.2813	0.3248	0.0722	0.1907	0.1126	0.1058	0.1635

Notes: Physical assets and financial outcomes are denominated in Bangladeshi 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 outcome variables are in logs. 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 B13: Impact of weather shocks, history decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.133***	0.095***	0.917***
	(0.025)	(0.021)	(0.326)
Unpredictable Shock (γ^U)	-0.129	-0.131*	-2.910***
	(0.093)	(0.071)	(1.025)
Treated × Unpredictable Shock (δ^U)	0.163**	0.159**	2.795***
	(0.063)	(0.066)	(0.737)
Baseline Risk (γ^B)	-0.001	0.024	-1.423**
	(0.063)	(0.068)	(0.691)
Treated × Baseline Risk (δ^B)	0.101	0.088	2.237***
	(0.076)	(0.064)	(0.733)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0513	0.0241	0.2242

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 B14: Impact of weather shocks: within-village estimate, history decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Ultra-poor (β)	-0.065*	-0.047*	-0.743***
	(0.035)	(0.027)	(0.173)
Ultra-poor × Treated (δ)	0.133***	0.114***	0.909***
	(0.039)	(0.032)	(0.218)
Ultra-poor × Unpredictable Shock (δ^U)	-0.154	-0.266	-1.038*
	(0.167)	(0.177)	(0.593)
Ultra-poor × Treated × Unpredictable Shock (γ^U)	0.234	0.328*	0.977
	(0.170)	(0.182)	(0.644)
Ultra-poor × Baseline Risk (δ^B)	-0.113	-0.188	-0.064
	(0.143)	(0.145)	(0.367)
Ultra-poor × Treated × Baseline Risk (γ^B)	0.110	0.196	-0.234
	(0.144)	(0.147)	(0.401)
Mean	13141.8	8303.4	4.2
Village FE	Yes	Yes	Yes
Number of obs.	12161	12161	12161
Adjusted R-square	0.1043	0.0497	0.4086

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. 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 B15: Impact of weather shocks 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)	2.679***	4.675***	0.585***	0.169***	2.917***	-1.452***	0.944***	0.105***
	(0.177)	(0.327)	(0.038)	(0.048)	(0.261)	(0.255)	(0.142)	(0.030)
Unpredictable Shock (γ^U)	-0.660	-2.137**	-0.199**	-0.388**	-1.769**	1.277	-0.117	-0.275**
	(0.413)	(0.914)	(0.098)	(0.190)	(0.773)	(0.834)	(0.584)	(0.129)
Treated × Unpredictable Shock (δ^U)	1.051***	2.860***	0.230**	0.365*	1.939***	-1.313**	0.120	0.237*
	(0.359)	(0.736)	(0.098)	(0.185)	(0.617)	(0.643)	(0.493)	(0.122)
Baseline Risk (γ^B)	0.130	-1.091***	-0.071	-0.198	-0.786*	0.263	0.159	-0.165**
	(0.268)	(0.377)	(0.050)	(0.131)	(0.437)	(0.602)	(0.445)	(0.068)
Treated × Baseline Risk (δ^B)	-0.149	1.138**	0.115*	0.179	0.631	-0.590	0.024	0.362***
	(0.304)	(0.481)	(0.057)	(0.126)	(0.473)	(0.579)	(0.481)	(0.062)
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	0.2901	0.2823	0.3255	0.0731	0.1922	0.1123	0.1059	0.1653

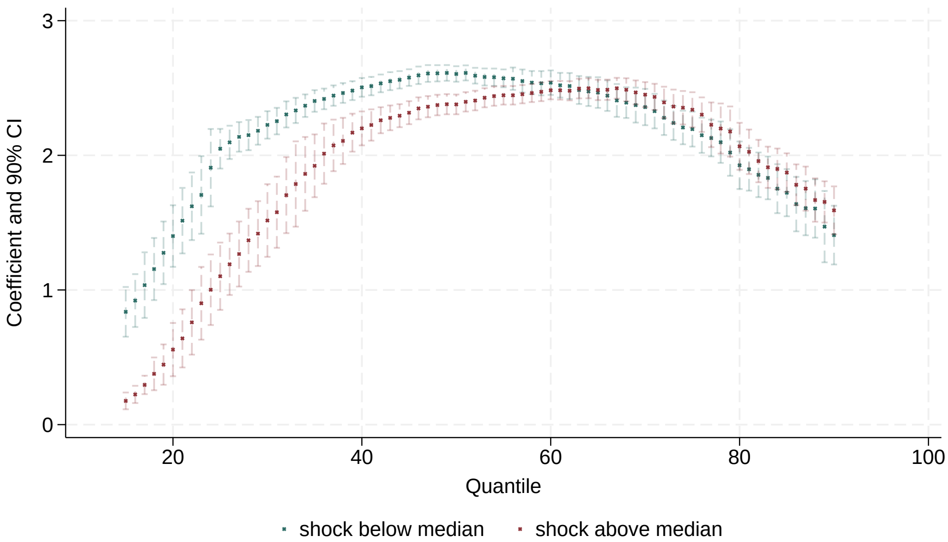
Notes: Physical assets and financial outcomes are denominated in Bangladeshi taka. Hours are measured as the number of hours worked a year. Income per hour is the annual labor income divided by the number of hours worked a year. All outcome variables are in logs. Baseline risk and unpredictable risk are decomposed following the *history* decomposition. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

Table B16: Impact of weather shocks: positive vs. negative surprises (counts), decay decomposition

	Total Consumption (1)	Food Consumption (2)	Protein Intake (3)
Treated (β)	0.188***	0.174***	0.802*
	(0.040)	(0.044)	(0.470)
Negative Unpredictable Shock (γ^{U-})	-0.017**	-0.011	-0.127
	(0.008)	(0.008)	(0.082)
Treated $\times$ Neg. Unpredictable Shock (δ^{U-})	0.043***	0.037***	0.577***
	(0.011)	(0.009)	(0.163)
Positive Unpredictable Shock (γ^{U+})	0.013***	0.012***	0.031
	(0.003)	(0.003)	(0.023)
Treated $\times$ Pos. Unpredictable Shock (δ^{U+})	-0.010**	-0.012**	-0.007
	(0.004)	(0.005)	(0.048)
Baseline Risk (γ^{B})	0.017	0.029	0.401
	(0.033)	(0.041)	(0.426)
Treated $\times$ Baseline Risk (δ^{B})	0.004	0.014	-0.712
	(0.033)	(0.040)	(0.424)
Mean	11655.8	8141.3	3.5
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0543	0.0261	0.2280

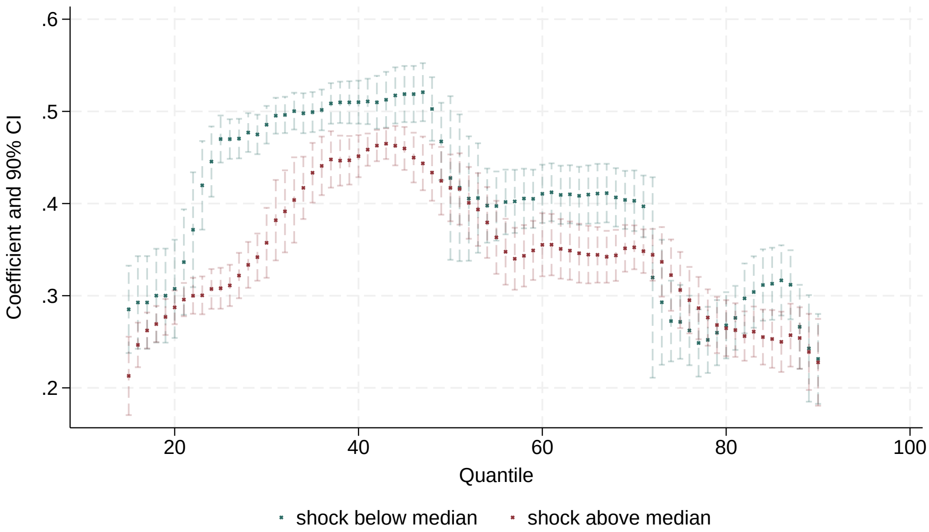
Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. Protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. Baseline risk and unpredictable risk are decomposed following the decay decomposition. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

Figure B6: Impacts of the graduation program on productive assets, historical exposure



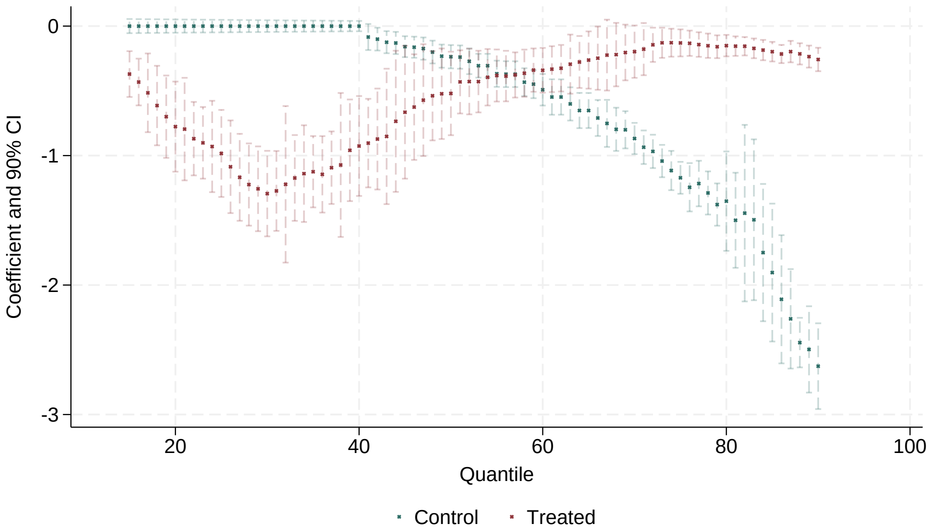
Notes: Quantile regression estimates of treatment effects on log productive assets (2011). Each dot represents the treatment effect at a different quantile (15th–90th). Red dots indicate villages with above-median historical weather shock exposure before 2007 (combining floods and droughts); emerald dots indicate villages with below-median historical exposure. Bars indicate 90% confidence intervals.

Figure B7: Impacts of the graduation program on husbandry hours



Notes: Quantile regression estimates of treatment effects on log husbandry hours (2011). Each dot represents the treatment effect at a different quantile. Red dots indicate villages with above-median weather shock exposure before 2007 (for either unpredictable or baseline shocks, combining floods and droughts); emerald dots indicate villages with below-median weather shock exposure. Bars indicate 90% confidence intervals.

Figure B8: Impacts of weather shocks on productive assets



Notes: Quantile regression estimates of weather shock effects on log productive assets (2011), combining floods and droughts. Each dot represents the shock effect at a different asset quantile. Red dots indicate treated villages; emerald dots indicate control villages. Bars indicate 90% confidence intervals.

Table B17: Impact of weather shocks on casual labor wage: dummy version

	Ultra-poor Casual Labor Wage		
		Top 10% Land Share	Assetless Share
	(1)	(2)	(3)
Unpredictable Shock (γ^U)	-0.318**	0.016	0.037
	(0.157)	(0.237)	(0.190)
Baseline Risk (γ^B)	-0.148	0.105	0.126
	(0.090)	(0.167)	(0.137)
High Inequality		-0.014	-0.089**
		(0.049)	(0.043)
Treated × High Inequality		0.071	0.078
		(0.070)	(0.062)
High Inequality × Unpredictable Shock		-0.559**	-0.850***
		(0.217)	(0.309)
High Inequality × Baseline Risk		-0.385*	-0.583*
		(0.211)	(0.306)
Treated × Unpredictable Shock (δ^U)	0.266***	-0.208	-0.250*
	(0.082)	(0.181)	(0.146)
Treated × Baseline Risk (δ^B)	0.334***	0.060	0.044
	(0.076)	(0.170)	(0.141)
Treated × High Inequality × Unpredictable Shock		0.818***	1.067***
		(0.244)	(0.341)
Treated × High Inequality × Baseline Risk		0.432*	0.609*
		(0.228)	(0.315)
Treated (β)	0.140***	0.109***	0.105***
	(0.028)	(0.037)	(0.025)
Mean Baseline Control			
Number of obs.	887	887	887
Adjusted R-square	0.217	0.219	0.229

Notes: Casual labor wage is measured as the average income per hour worked. All outcome variables are in logs. Column (1) replicates our baseline household-level regression at the village level. Columns (2)–(3) interact treatment and weather shocks with above-median baseline inequality indicators: top 10% land share and assetless share. 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 B18: Impact of weather shocks on casual labor wage: continuous version

	Ultra-poor Casual Labor Wage		
		Top 10% Land Share	Assetless Share
	(1)	(2)	(3)
Unpredictable Shock (γ^U)	-0.318**	0.880	1.038
	(0.157)	(0.622)	(0.744)
Baseline Risk (γ^B)	-0.148	0.669	0.949
	(0.090)	(0.558)	(0.721)
Inequality		-0.167	-0.231
		(0.141)	(0.152)
Treated × Inequality		0.292	0.201
		(0.280)	(0.269)
Inequality × Unpredictable Shock		-1.959**	-3.310*
		(0.939)	(1.765)
Inequality × Baseline Risk		-1.273	-2.545
		(0.891)	(1.711)
Treated × Unpredictable Shock (δ^U)	0.266***	-1.696**	-1.563*
	(0.082)	(0.698)	(0.796)
Treated × Baseline Risk (δ^B)	0.334***	-0.600	-0.871
	(0.076)	(0.574)	(0.740)
Treated × Inequality × Unpredictable Shock		3.149***	4.234**
		(1.125)	(1.877)
Treated × Inequality × Baseline Risk		1.458	2.761
		(0.914)	(1.736)
Treated (β)	0.140***	-0.029	0.063
	(0.028)	(0.156)	(0.099)
Mean Baseline Control			
Number of obs.	887	887	887
Adjusted R-square	0.217	0.220	0.225

Notes: Casual labor wage is measured as the average income per hour worked. All outcome variables are in logs. Column (1) replicates our baseline household-level regression at the village level. Columns (2)–(3) interact treatment and weather shocks with continuous baseline inequality measures: top 10% land share and assetless share. 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 B19: Impact of weather shocks on landlord: decomposition

	Earnings per Acre		Hired Labour for Land	
	Low Landless	High Landless	Low Landless	High Landless
	(1)	(2)	(3)	(4)
Treated (β)	-0.050	0.200*	0.423	0.222
	(0.130)	(0.110)	(0.267)	(0.256)
Negative Unpredictable Shock (γ^{U-})	-0.896	2.160***	-2.892*	3.985**
	(0.742)	(0.675)	(1.641)	(1.491)
Treated × Neg. Unpredictable Shock (δ^{U-})	-0.263	-1.805***	1.109	-2.339
	(1.397)	(0.645)	(1.926)	(1.755)
Positive Unpredictable Shock (γ^{U+})	-1.647*	-0.480	5.348*	6.146
	(0.911)	(2.102)	(2.732)	(5.118)
Treated × Pos. Unpredictable Shock (δ^{U+})	-0.690	-1.360	3.369	-8.404*
	(2.549)	(1.972)	(3.070)	(4.929)
Baseline Risk (γ^{B})	-1.197	-0.643	4.242*	5.531
	(0.775)	(1.895)	(2.095)	(4.923)
Treated × Baseline Risk (δ^{B})	-0.331	-1.285	3.040	-7.444
	(2.472)	(1.902)	(2.954)	(4.924)
Mean dep. var.	250.6	281.9	32.2	18.7
P-val: $\gamma^{U-} + \delta^{U-} = 0$	0.318	0.410	0.264	0.070
Number of obs.	211	214	211	214
Adjusted R-square	0.078	0.030	0.213	0.270

Notes: Every observation is a village. All outcome variables are in logs. Different columns split villages according to whether they are above or below the median ex ante in land concentration (landless share). Baseline risk and unpredictable risk are decomposed following the decay decomposition. Unpredictable shocks are further decomposed into negative shocks and positive shocks. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

C Additional Results on Diversification

Table C1: Diversification at the household level (excluding livestock activities and cows)

	Asset Diversification	Labor Diversification	
	# Asset Categories (1)	# Occupations (2)	HHI (3)
Treat	1.586***	0.270***	-0.059***
	(0.105)	(0.067)	(0.016)
Unpredictable Shock	-0.721	-0.458*	0.063
	(0.443)	(0.253)	(0.076)
Treat × Unpredictable Shock	1.195***	0.645***	-0.090*
	(0.322)	(0.181)	(0.053)
Expected Shock	-0.463	-0.594***	0.110**
	(0.293)	(0.114)	(0.045)
Treat × Expected Shock	0.814***	0.705***	-0.137***
	(0.272)	(0.124)	(0.049)
Subdistrict Fixed-effects	Yes	Yes	Yes
Number of obs.	6481	6484	6484
Adjusted R-square	0.1708	0.0546	0.0390

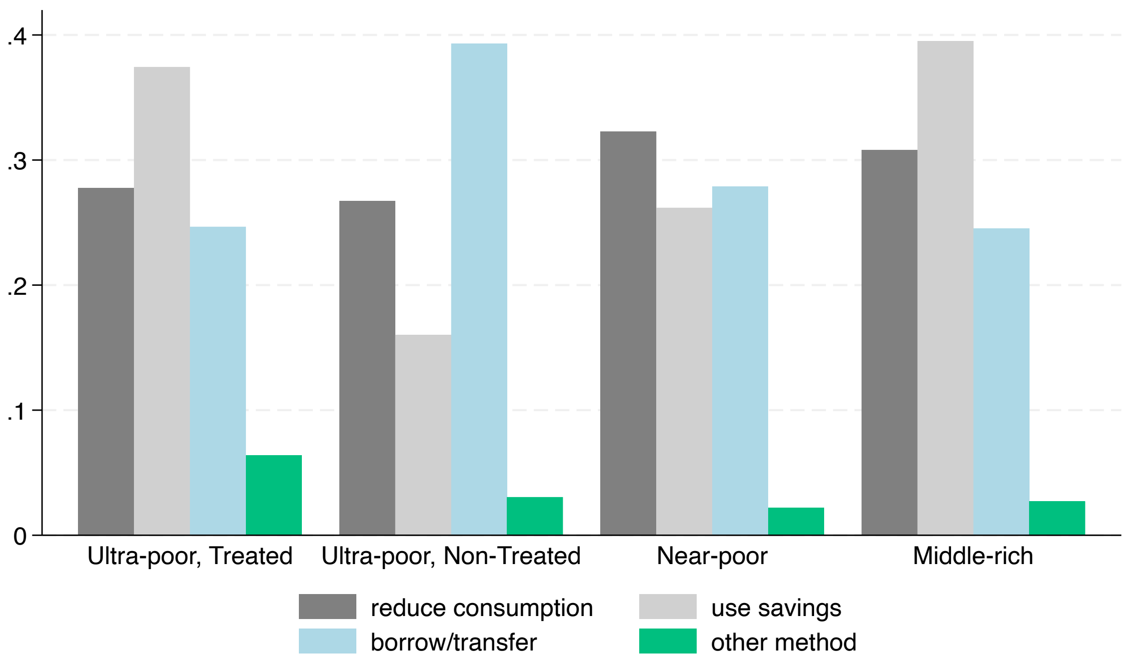
Notes: Asset diversification is the number of distinct asset categories for the household. Labor diversification at the household level is measured in two ways: the number of business activities and the normalized HHI. We remove livestock husbandry (directly related to cows) for labor diversification, and remove cows for asset diversification. Baseline risk and unpredictable shocks 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 (1)	Husbandry (2)	Casual Labor (3)	Husbandry (4)	Casual Labor (5)	Husbandry (6)	Casual Labor (7)	Husbandry (8)
Treated (β)	0.136***	0.909***	0.140***	1.032***	0.052*	0.140*	0.026	-0.084
	(0.029)	(0.123)	(0.028)	(0.106)	(0.031)	(0.082)	(0.036)	(0.094)
Unpredictable Shock (γ^U)	-0.321***	-0.342	-0.318**	0.021	-0.160	-0.630	-0.060	-0.608
	(0.119)	(0.537)	(0.157)	(0.488)	(0.126)	(0.446)	(0.199)	(0.417)
Treated × Unpredictable Shock (δ^U)	0.244***	0.113	0.266***	-0.203	0.134	0.846**	0.070	0.856**
	(0.088)	(0.433)	(0.082)	(0.377)	(0.083)	(0.316)	(0.149)	(0.369)
Baseline Risk (γ^B)	-0.164**	0.062	-0.148	0.221	-0.046	-0.648*	0.046	-0.779**
	(0.074)	(0.447)	(0.090)	(0.361)	(0.083)	(0.349)	(0.144)	(0.334)
Treated × Baseline Risk (δ^B)	0.331***	0.118	0.334***	-0.090	0.229***	0.635*	0.121	0.625*
	(0.057)	(0.470)	(0.076)	(0.392)	(0.078)	(0.343)	(0.151)	(0.370)
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	0.1594	0.1063	0.2170	0.2550	0.2033	0.1047	0.1563	0.0668

Notes: Labor wage is measured as the average income per hour worked. All outcome variables are in logs. Baseline risk and unpredictable shocks are decomposed following the decay decomposition. Fixed effects are at the sub-district level. Standard errors are 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 weather 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 methods for decomposing weather shocks into a 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 exposure to weather shocks, separately for floods, droughts, and their combined measure, 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 $d \in \{1, 2, \ldots, 36\}$ 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 an *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 from either (i) the intensive margin: a village experiencing above-average flooding during a dekad that is usually flooded, or (ii) 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).[25]

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

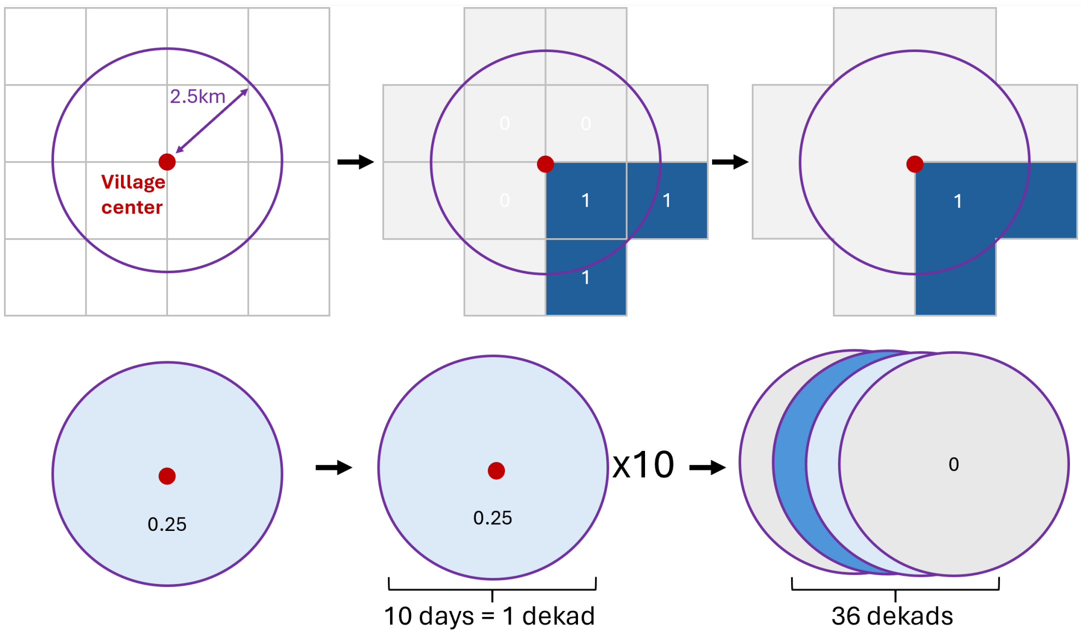
$$\hat{\mathbf{C}}_{v(i),2011,d} = \frac{\sum_{t=1}^{10} \mathbf{C}_{v(i),2011-t,d}}{10}$$

Our regression results are robust to various specifications.

[25]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.

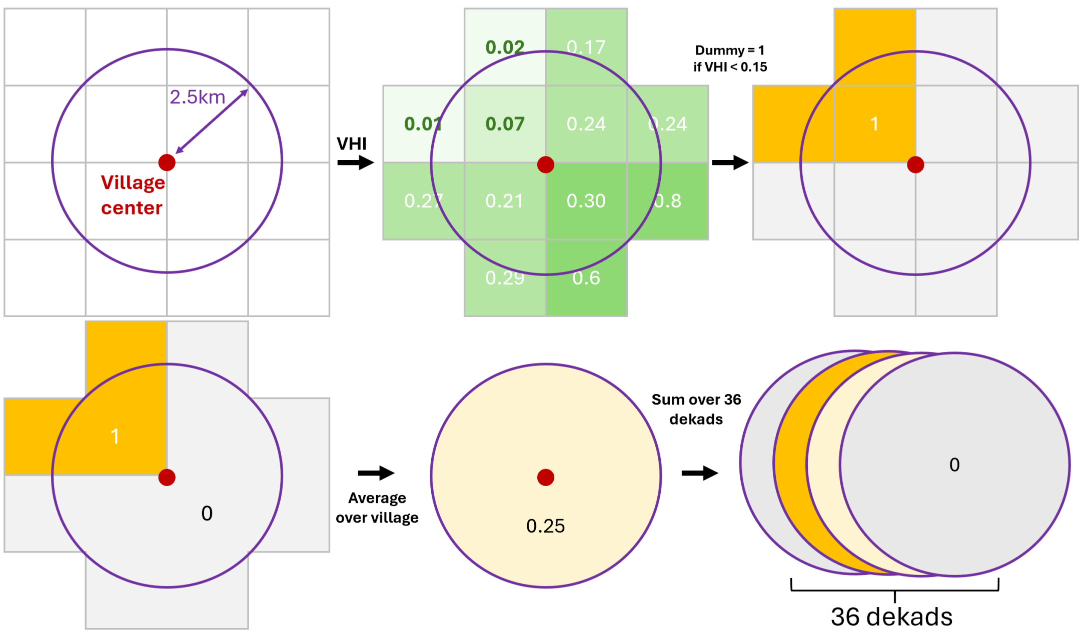
E Measurement

Figure E1: Flood measurement: illustration



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

Figure E2: Drought measurement: illustration



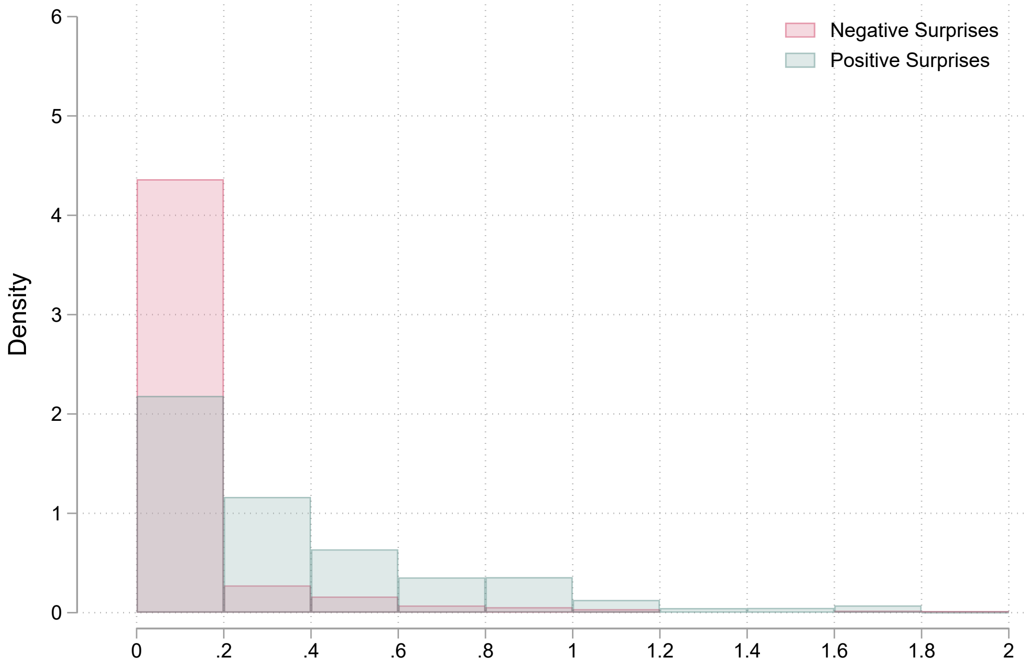
Notes: This diagram illustrates the different steps in the construction of the drought shock, from the VHI satellite data at 1-km resolution to the continuous measure at the village × dekad level.

Table E1: Predictable and Unpredictable Weather Shocks

Variable	Mean	p25	p50	p75	p90	SD
Panel A: Shock Decomposition						
Baseline Risk	0.420	0.114	0.235	0.523	1.019	0.498
Unpredictable Shock	-0.318	-0.404	-0.201	-0.101	-0.054	0.402
Negative Surprise	0.064	0.000	0.000	0.032	0.199	0.171
Positive Surprise	0.382	0.113	0.234	0.497	0.842	0.435
Panel B: Shock Duration (Dekad Distribution)						
Actual Shocks						
Dekads with Zero Shocks	0.967	0.944	1.000	1.000	1.000	0.052
Dekads with Non-Zero Shock	0.033	0.000	0.000	0.056	0.111	0.052
Surprises						
Dekads with Positive Surprises	0.313	0.222	0.306	0.389	0.500	0.114
Dekads with Negative Surprises	0.023	0.000	0.000	0.056	0.083	0.035
Dekads with Zero Surprises	0.664	0.556	0.694	0.778	0.806	0.135
Conditional Surprises						
Dekads with Positive Surprises $\mid > 0$ Positive Surprises	0.313	0.222	0.306	0.389	0.500	0.114
Dekads with Negative Surprises $\mid > 0$ Negative Surprises	0.063	0.028	0.056	0.083	0.111	0.031
Panel C: Shock Intensity (Area Affected)						
Actual Shocks						
Village Area Affected	0.003	0.000	0.000	0.001	0.009	0.008
Village Area Affected | Non-Zero Shock	0.062	0.017	0.042	0.067	0.158	0.070
Conditional Surprises						
Village Area Affected | Positive Surprise	0.001	0.000	0.000	0.000	0.003	0.004
Village Area Affected | Negative Surprise	0.080	0.023	0.052	0.104	0.210	0.085

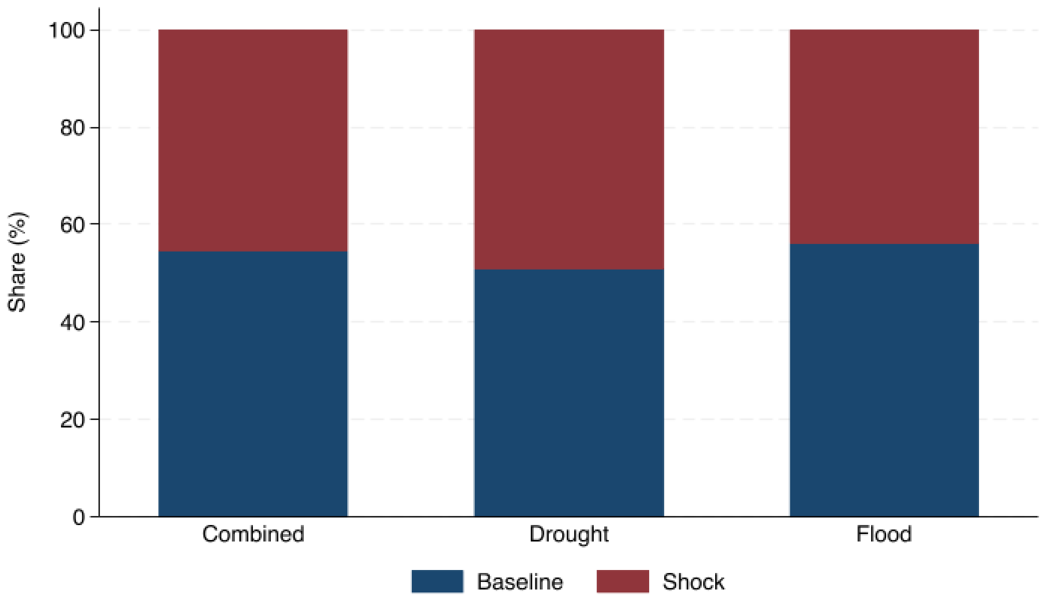
Notes: This table reports village-level descriptive statistics for the decay decomposition of the combined weather shock over the 36 pre-survey dekads preceding the 2011 survey wave. A negative surprise denotes a dekad in which the realized shock exceeds the expected shock; a positive surprise denotes a dekad in which the realized shock is below the expected shock; a zero surprise denotes a dekad in which the realized and expected shocks are equal. Panel A reports village-level sums of baseline risk and unpredictable shock, together with the decomposition of the unpredictable component into negative and positive surprises (measured in absolute value). Panel B reports the share of dekads with zero and non-zero realized shocks and the share with positive, negative, and zero surprises. Panel C reports the average village area share affected, unconditionally, conditional on a non-zero realized shock, and conditional on positive and negative surprises.

Figure E3: Unpredictable Weather Shocks: Negative and Positive Surprises



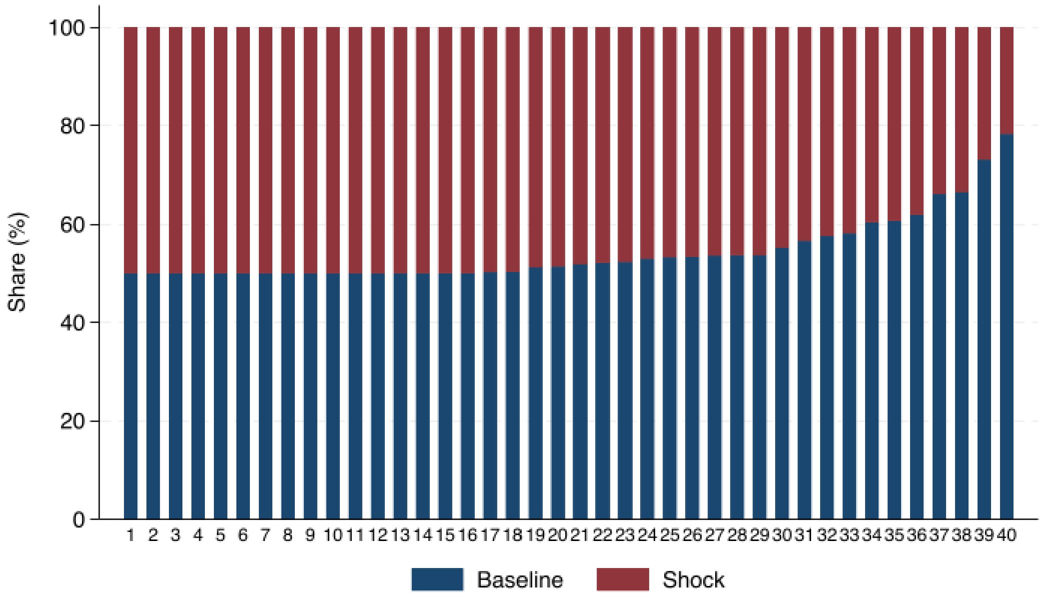
Notes: This histogram shows the distribution of negative and positive weather surprises, measured in absolute value. The unit is the total number of dekads with any weather shock (flood or drought) in 2011. A negative surprise denotes cases where realized weather shock exposure exceeds baseline risk, i.e., $\mathbf{C}_{v(i),2011,d} > \hat{\mathbf{C}}_{v(i),2011,d}$. A positive surprise denotes cases where realized weather shock exposure is below baseline risk, i.e., $\mathbf{C}_{v(i),2011,d} < \hat{\mathbf{C}}_{v(i),2011,d}$.

Figure E4: Unpredictable weather shock decomposition by shock type



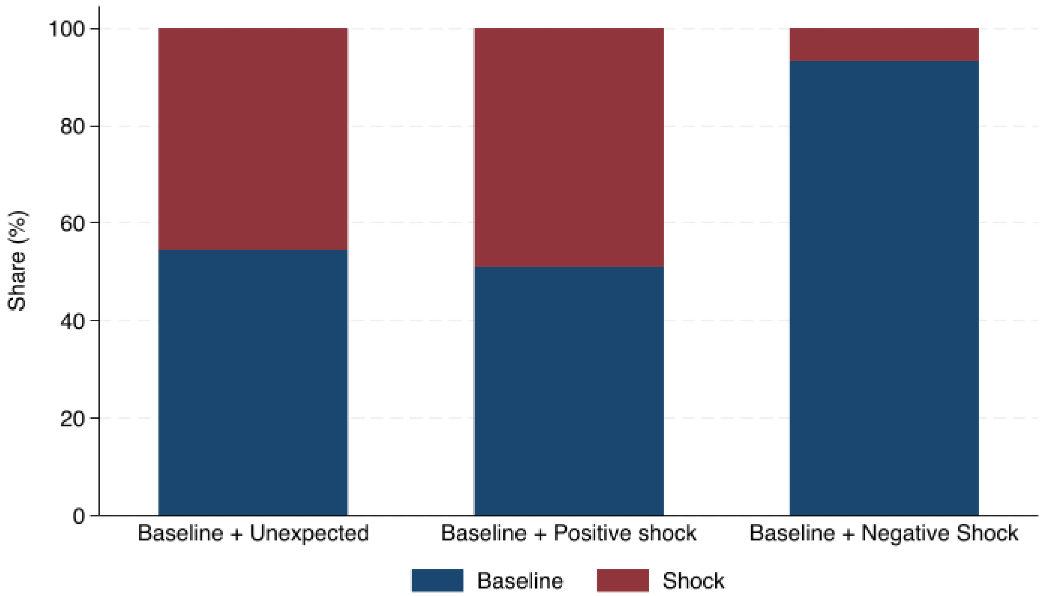
Notes: This figure reports the mean decomposition of village-level weather shocks over the 36 pre-survey dekads preceding the 2011 survey wave. For each shock type, the bars show the share of the total shock attributable to baseline risk and to the unpredictable component, measured in absolute value, so that the two shares sum to 100 percent.

Figure E5: Unpredictable weather shock decomposition by BRAC branch



Notes: This figure reports the mean decomposition of village-level combined weather shocks over the 36 pre-survey dekads preceding the 2011 survey wave, averaged to the BRAC branch level. For each branch, the bars show the share of the total shock attributable to baseline risk and to the unpredictable component, measured in absolute value, so that the two shares sum to 100 percent.

Figure E6: Unpredictable weather shock decomposition by shock sign



Notes: This figure reports the mean decomposition of village-level combined weather shocks over the 36 pre-survey dekads preceding the 2011 survey wave by shock sign. A negative surprise denotes a dekad in which the realized shock exceeds the expected shock; a positive surprise denotes a dekad in which the realized shock is below the expected shock. For the overall unpredictable component and for positive and negative surprises separately, the bars show the share of the baseline-plus-surprise total attributable to baseline risk and to the relevant unpredictable component, measured in absolute value, so that the two shares sum to 100 percent.

Table E2: Compare different weather shocks: food consumption

	Food Consumption (1)	Food Consumption (2)	Food Consumption (3)
Treated (β)	0.073***	0.070***	0.068***
	(0.015)	(0.015)	(0.016)
Unpredictable Shock (γ^U)	-0.138**	-0.128	0.031
	(0.068)	(0.103)	(0.360)
Treated × Unpredictable Shock (δ^U)	0.121**	0.206**	-0.124
	(0.051)	(0.076)	(0.417)
Baseline Risk (γ^B)	-0.008	0.036	0.189
	(0.053)	(0.057)	(0.371)
Treated × Baseline Risk (δ^B)	0.081	0.035	-0.103
	(0.055)	(0.057)	(0.418)
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.0245	0.0234	0.0245

Notes: Food consumption is expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed. 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 E3: Compare different weather shocks: productive assets

	Productive Assets (1)	Productive Assets (2)	Productive Assets (3)
Treated (β)	4.420***	4.340***	4.266***
	(0.306)	(0.258)	(0.285)
Unpredictable Shock (γ^U)	-1.497*	-0.752	-9.044***
	(0.760)	(0.827)	(2.932)
Treated × Unpredictable Shock (δ^U)	2.195***	2.500***	7.611**
	(0.628)	(0.715)	(3.263)
Baseline Risk (γ^B)	-1.025**	-0.536	-7.925***
	(0.438)	(0.596)	(2.824)
Treated × Baseline Risk (δ^B)	1.072**	-0.261	7.014**
	(0.450)	(0.595)	(3.086)
Sub-district FE	Yes	Yes	Yes
Number of obs.	6123	6123	6123
Adjusted R-square	0.2811	0.2817	0.2817

Notes: Productive assets are denominated in Bangladeshi 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.

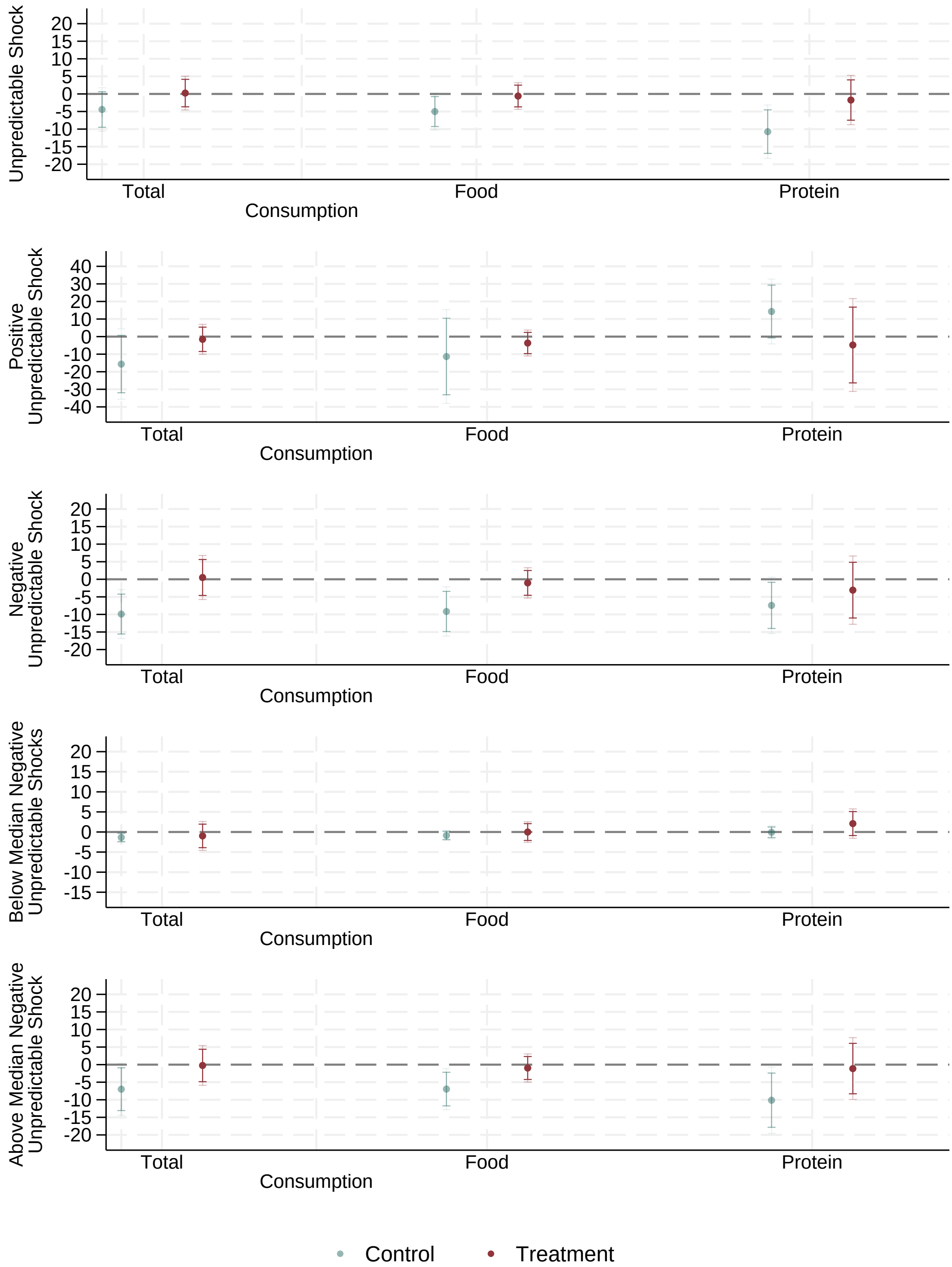
Table E4: Compare different unpredictable weather shocks (γ^U and δ^U): all outcomes

Outcome	Combined		Floods		Droughts	
	γ^U	δ^U	γ^U	δ^U	γ^U	δ^U
Consumption						
Total	-0.044	0.047**	-0.006	0.031	0.007	-0.128
	(0.032)	(0.019)	(0.027)	(0.020)	(0.088)	(0.114)
Food	-0.050*	0.044**	-0.026	0.041**	0.013	-0.044
	(0.027)	(0.020)	(0.021)	(0.016)	(0.114)	(0.133)
Protein	-1.073***	0.900***	-0.411*	0.566***	-0.814	-0.617
	(0.387)	(0.230)	(0.207)	(0.144)	(0.963)	(1.388)
Assets						
Total	-0.040	0.174*	-0.003	0.147***	-1.292***	1.062***
	(0.130)	(0.092)	(0.061)	(0.049)	(0.268)	(0.307)
Productive	-0.486*	0.713***	-0.130	0.432***	-2.435***	2.049**
	(0.247)	(0.204)	(0.143)	(0.124)	(0.789)	(0.878)
Savings	-0.061**	0.069***	-0.049	0.043	-0.118*	0.084
	(0.027)	(0.024)	(0.033)	(0.030)	(0.063)	(0.092)
Loan	-0.049	0.075	-0.031	0.042	-0.158	-0.011
	(0.056)	(0.051)	(0.037)	(0.033)	(0.109)	(0.140)
Labour						
Husbandry Hours	-0.481**	0.501***	-0.228	0.339**	-1.379*	0.795
	(0.232)	(0.176)	(0.195)	(0.151)	(0.696)	(0.883)
Casual Labour Hours	0.475*	-0.379**	0.124	-0.245**	1.128**	-0.179
	(0.263)	(0.180)	(0.140)	(0.118)	(0.489)	(0.640)
Husbandry Income per Hour	-0.106	0.035	-0.243	0.191	0.797***	-0.957***
	(0.173)	(0.139)	(0.178)	(0.136)	(0.253)	(0.290)
Casual Labour Income per Hour	-0.128***	0.105***	-0.060**	0.077***	-0.251***	0.446***
	(0.034)	(0.027)	(0.027)	(0.023)	(0.088)	(0.111)

Notes: Total consumption and food consumption are expressed in per capita terms, denominated in Bangladeshi taka, and log-transformed; protein intake is measured as the monthly frequency of consuming eggs, fish, or meat, ranging from zero to more than four times per week. Physical assets and financial outcomes are measured in Bangladeshi 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 outcome variables are in logs. Baseline risk and unpredictable shocks are decomposed following the decay decomposition. Unpredictable shocks are standardized to have mean zero and unit standard deviation, so the estimated coefficients are directly comparable across shock measures. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

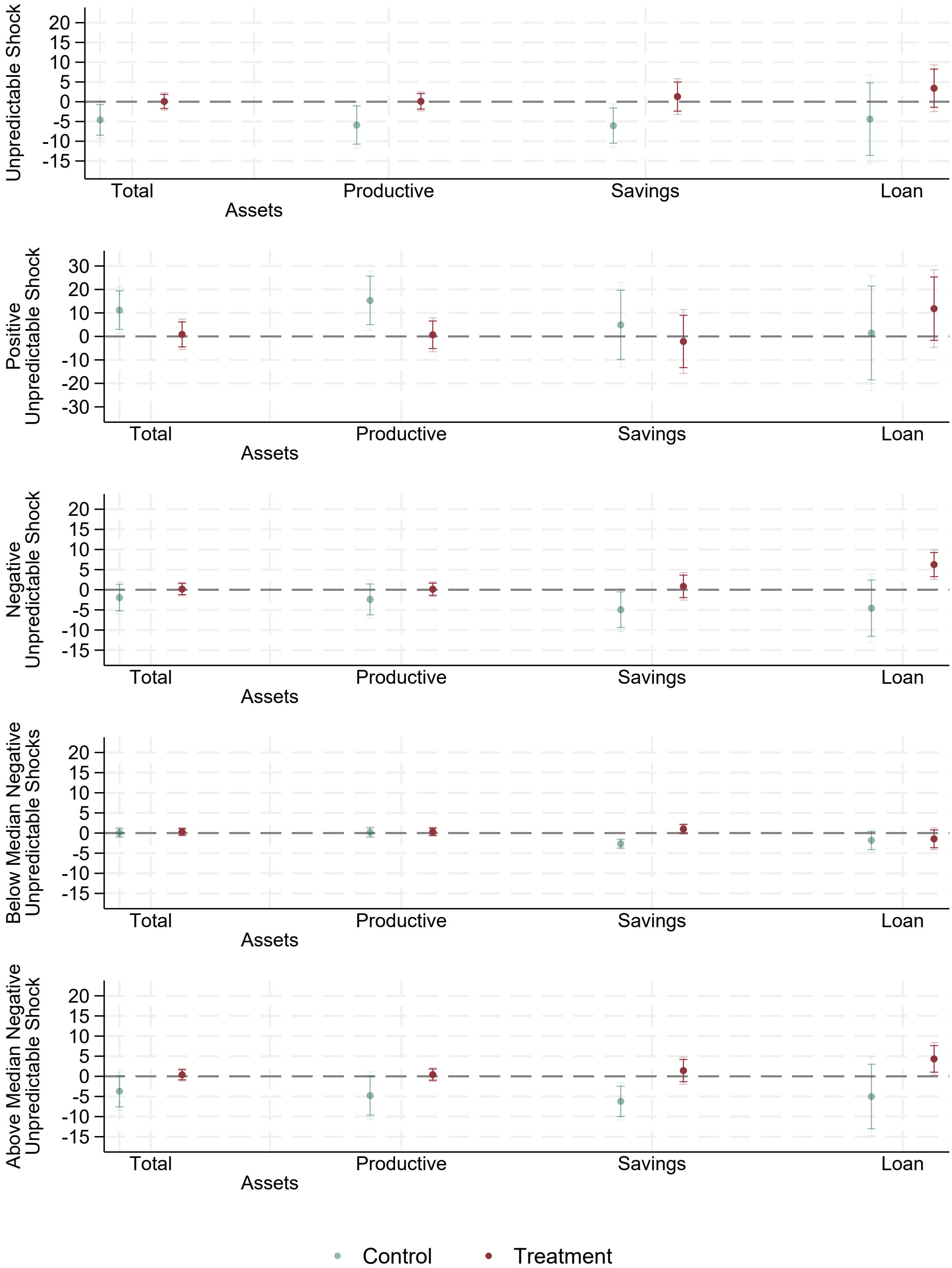
F Positive and Negative Weather Surprises: Graphical Evidence

Figure F1: Impacts of Weather Shocks: Consumption



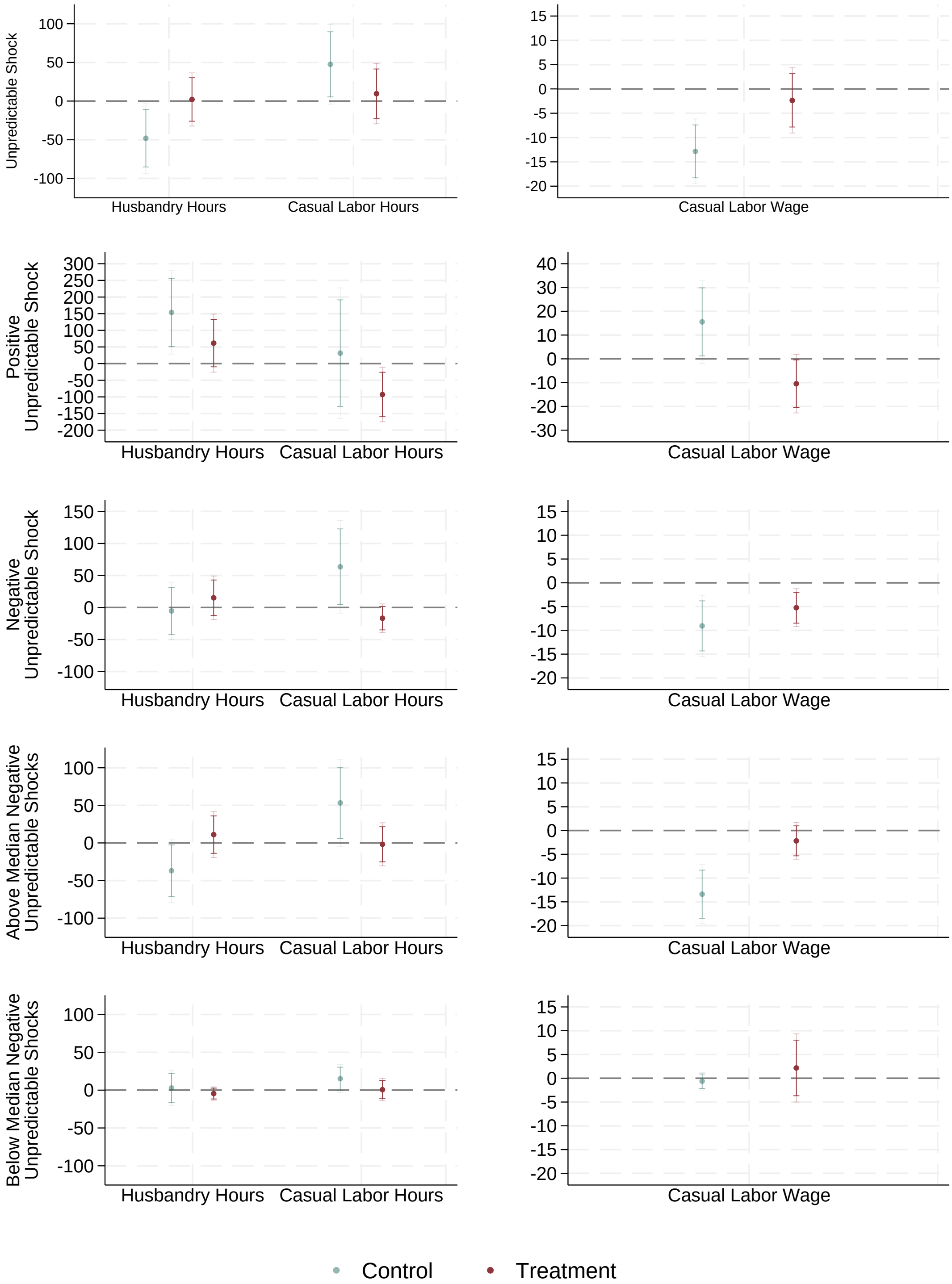
Notes: Each dot represents a treatment effect estimate for either the treated group (exposed to an unpredictable climate shock) or the interaction between treatment and the unpredictable shock (Treatment × Unpredictable Shock). Positive and negative unpredictable shocks are defined by splitting the distribution at the median (50th percentile). Negative shocks are further divided into above-median and below-median values based on the distribution of negative shock magnitudes.

Figure F2: Impacts of Weather Shocks: Assets



Notes: Each dot represents a treatment effect estimate for either the treated group (exposed to an unpredictable climate shock) or the interaction between treatment and the unpredictable shock (Treatment $\times$ Unpredictable Shock). Positive and negative unpredictable shocks are defined by splitting the distribution at the median (50th percentile). Negative shocks are further divided into above-median and below-median values based on the distribution of negative shock magnitudes.

Figure F3: Impacts of Weather Shocks: Labor



Notes: Each dot represents a treatment effect estimate for either the treated group (exposed to an unpredictable climate shock) or the interaction between treatment and the unpredictable shock (Treatment × Unpredictable Shock). Positive and negative unpredictable shocks are defined by splitting the distribution at the median (50th percentile). Negative shocks are further divided into above-median and below-median values based on the distribution of negative shock magnitudes.

G The Broader Role of Diversification

Section 5 demonstrated that being lifted out of extreme poverty builds multidimensional resilience, enabling treated households to protect productive assets, savings, and labor occupations in the face of weather shocks. In particular, the results suggest that the adverse effects of a weather 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 central role of poverty in the vulnerability to weather shocks. 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, thereby ensuring more stable income and food security.

We measure asset diversification by the number of distinct asset types a household owns. Labor diversification is measured in two ways: the number of distinct labor activities a household engages in, and the normalized Herfindahl-Hirschman Index (HHI) of hours worked across distinct occupations, which measures how households concentrate their working hours in distinct activities.[26] 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 linear model linking diversification of assets and labor to program participation:

$$Y_i = \alpha + \beta \times T_{v(i)} + \eta_{s(i)} + \varepsilon_{i,s(i)} \tag{7}$$

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.

Table G1 reports the results. 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 assess the extent of the effect of 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.

[26] The normalized Herfindahl-Hirschman Index is $\frac{\sum_{i=1}^{n} s_i^2 - \frac{1}{n}}{1-\frac{1}{n}}$, 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.

The results in Table G1 provide clear evidence that the program enables household diversification across both assets and labor occupations. Treated households own on average 2.14 more types of assets and engage in 0.85 more labor activities on average. The normalized HHI, which captures concentration of working hours across occupations, is lower by 0.18 for treated households, indicating less reliance on any single occupation. 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.

Table G1: Diversification at the household level

	Panel A: All Activities		
	Asset Diversification	Labor Diversification	
	# Asset Categories (1)	# Occupations (2)	HHI (3)
Treated	2.143***	0.847***	-0.179***
	(0.089)	(0.083)	(0.014)
Sub-district 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)
Sub-district Fixed-effects	Yes	Yes	Yes
Number of obs.	6729	6732	6732
Adjusted R-square	0.1624	0.0524	0.0385

Notes: Asset diversification is the number of distinct asset categories for the household. Labor diversification at the household level is measured in two ways: the number of business activities and the normalized HHI. Panel A uses all labor activities and assets. Panel B excludes cows as an asset and livestock husbandry as a labor activity to isolate non-program-specific diversification. Fixed effects are at the sub-district level. Standard errors are clustered at the branch level.

Finally, we examine how diversification is affected by weather shocks by interacting the treatment with our shock measure, following the specification in Equation 3. Table C1 presents these results, using the more conservative measures of diversification that exclude program-related livestock. The estimates show that while weather shocks reduce asset and labor diversification for control households, being lifted out of poverty fully mitigates this adverse effect for treated households.