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Weathering challenges

Distributional impacts of climatic shocks on household consumption in Mozambique

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Abstract: Mozambique is highly vulnerable to climate change. It faces frequent cyclones, floods, and droughts while having limited revenue collection capacity and social protection programmes. This paper assesses the distributional effects of climate shocks on household consumption and explores adaptation strategies using consumption survey data from 2008 to 2022, combined with district-level climate data. We find that extreme rainfall and dryness shocks during the growing season significantly reduce household expenses for essential goods, with impacts most pronounced at the bottom to the middle of the consumption distribution. However, we found that the consumption of self-produced goods mitigates the expense losses. Our findings suggest that the main social protection programme in the country, PSSB, also helps mitigate these negative effects. We do not find evidence that domestic family transfer and international remittances cushion consumption losses because of climate shocks. This study underscores the importance of developing targeted policies to protect households in vulnerable regions as climate risks intensify.

Key words: Mozambique, consumption, inequality, climate shocks, poverty

JEL classification: Q54, I30, Q56

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1 Introduction

Developing countries are expected to experience disproportionately severe impacts from climate change compared to developed nations (R. S. J. Tol 2009, 2018). Many of these countries have limited adaptive capacity, primarily due to low revenue collection and weak state institutions. Mozambique exemplifies this challenge, ranking 5th on the global climate risk index (Germanwatch 2021). It is one of the most vulnerable countries worldwide, regularly facing intense climate shocks such as cyclones, floods, and droughts. Its weak domestic revenue collection, limited institutional capacity, and lack of robust social protection programmes make its population especially vulnerable to climate change, even in comparison to other developing nations. Understanding the distributional effects of climate shocks on household consumption is thus crucial for designing effective interventions to improve welfare.

This paper examines the distributional effects of climate shocks in Mozambique and explores potential household adaptation strategies. Our analysis draws on four waves of a nationwide consumption survey conducted between 2008 and 2022, which provides detailed information on individuals' district of residence and interview dates. We combine these data with district-level historical records of temperature, rainfall, and the Standardized Precipitation-Evapotranspiration Index (SPEI). Using unconditional quantile regressions, we estimate the impacts of temperature and rainfall shocks on household consumption, controlling for a wide range of observable characteristics, as well as district and quarter-by-year fixed effects. Our identification strategy leverages variations in the timing and geographic distribution of climate shocks across districts and quarters over the 14-year period in Mozambique.

The main results indicate that elevated temperatures and precipitation levels during the growing season (November to April) reduce household expenditures on non-durable essential goods by 17.7% and 7.3%, respectively. However, self-production for own consumption helps mitigate these shocks, as we find no significant effect of extreme weather events on total consumption, which includes both household expenses and the consumption of self-produced goods. In contrast, droughts, as indicated by low SPEI levels, decrease both expenditures and total consumption by 10%.

Next, we estimate the distributional effects of climate shocks using re-centred influence regressions. Our findings reveal that households below the median of the consumption distribution are disproportionately affected by climate shocks in Mozambique, particularly during episodes of extreme precipitation and high temperatures. We show that extremely high temperatures during the previous growing season reduce the share of households with expenditures exceeding the full, half, and quarter value of the basic food basket by 3.7, 6.2, and 7.5 percentage points (p.p.), respectively. Similarly, high rainfall during the previous growing season reduces the share of households with expenditures above a quarter of the food basket's value by 3 p.p.

We explore some potential coping mechanisms despite being constrained by data limitations. First, our analysis shows that families in rural areas rely more heavily on self-production, a reliance that increases during climate shocks characterized by high temperatures and low rainfall. Second, data from the 2019–20 and 2022 survey waves enable us to identify households benefiting from social protection programmes. We find that social protection policies help mitigate the impact of climate shocks on household consumption. Specifically, households enrolled in Mozambique's flagship social protection programme, PSSB, have higher levels of expenses and consumption during climate shocks compared to those not receiving any social protection support. Third, the nationwide consumption surveys allow us to robustly examine the role of informal transfers in attenuating the effects of climate shocks across a broad swath of the consumption distribution. Contrary to findings in many low-income countries, however, domestic and international family transfers do not seem to mitigate the adverse effects of climate shocks in Mozambique.

This paper's contribution is threefold. First, we contribute by measuring the impacts of climate shocks on consumption poverty and inequality in one of the world's poorest countries. Prior work for developed and upper-middle-income countries has shown systematic negative impacts of climatic shocks on economic activity but mixed evidence on income inequality (R. S. J. Tol 2018; R. S. Tol 2022; Dang et al. 2024). Measuring welfare using consumption is also important because *consumption inequality* estimates may be more stable because consumption usually depends more on permanent rather than current (possibly transitory) income. Second, consumption goes beyond income as an indicator of well-being, which is better measured in surveys in low-income countries. Rather, prior work focused on gross domestic product (GDP) per capita, income, productivity,[1] and mortality (Deschenes and Moretti 2009; Deschênes and Greenstone 2011; Heutel et al. 2021; Barreca et al. 2016; Kahn 2005).

Third, we contribute to the literature on mechanisms attenuating climate impacts.[2] We provide some evidence that beneficiaries of the unconditional cash transfer may suffer less from climate shocks, contributing to the literature of government programmes as coping mechanisms (Garg et al. 2020; Premand and Stoeffler 2022). This is even more important considering a context where cash transfers are very small and cannot satisfy even the basic consumption needs, trans-

[1] See R. S. J. Tol (2018); Burke and Emerick (2016); Adhvaryu et al. (2020); Somanathan et al. (2021).

[2] For technology adoption, see: *irrigation*: Schlenker et al. (2005); *AC*: Barreca et al. (2016); Park et al. (2020); Somanathan et al. (2021), *mobile money*: Riley (2018); Batista and Vicente (2023); *LED lighting*: Adhvaryu et al. (2020). For infrastructure build-out, see Da Mata et al. (2023); Mullins and White (2020). For mobility and migration, see: Colmer (2021); Gröger and Zylberberg (2016); Liu et al. (2023).

fers suffer with high delays, and sometimes beneficiaries spend months without receiving it (Almeida et al. 2024).

This paper is structured as follows. In Section 2, we contextualize Mozambique's vulnerability to climate shocks. In Section 3, we describe our data and the construction of our climate shock variables. In Section 4, we explain the methodology. Results are presented in Section 5.1. Section 6 concludes.

2 Vulnerability to climate shocks

Mozambique ranks 5th in the climate risk index (Germanwatch 2021), facing frequent natural disasters, including cyclones, floods, and droughts. According to data from the Climate Change Knowledge Portal (World Bank 2024), in the period from 1980 to 2020, Mozambique had, at least, 21 years with the presence of floods, 14 with storms, and 11 with droughts. The country's long coastline along the Indian Ocean makes it particularly susceptible to tropical cyclones, which have increased in intensity due to changing climate patterns. Mozambique's vulnerability is further compounded by widespread poverty, limited infrastructure, and a heavy reliance on climate-sensitive sectors like agriculture and fisheries. These factors significantly increase the country's exposure to natural disasters, threatening the livelihoods of millions and hampering economic development.

Using data from the Calamities Questionnaire of the *Inquerito de Orcamentos Familiares* (IOF) from 2019–20 and 2022, we present contextual information on climate vulnerability in Table 1. This section of the survey conducted by Mozambique's Statistical Institute (INE) asks household heads if they have had losses due to calamities in the past 12 months and dissects its consequences among the impacted population. Interviewees are expected to indicate up to three calamities that impacted them the most. Calamities are broadly defined in the questionnaire, including weather shocks, diseases, and loss of family members.[3] We focus on weather shocks, grouping them into drought and rainfall categories that include rainfall, floods, storms, and cyclones. Among the whole sample, we observe that 37% of individuals were impacted by at least one type of calamity, 14% suffered from drought, and 22% from high rainfall-related shocks.

[3] Calamities in the context of the questionnaire encompass: droughts, excessive rainfall/floods, rainy season, storms/cyclones, animal diseases, fires, agricultural pests, acute and chronic diseases, loss of a family member, and COVID-19.

Table 1: Self-reported impacts of weather shocks from the IOF's calamities questionnaire, 2019–20 and 2022

	Constant	Drought	Rainfall
Panel A: Direct losses of			
Food	0.080***	0.028	0.090***
	(0.013)	(0.019)	(0.019)
Animals	0.060***	0.047**	0.014
	(0.011)	(0.020)	(0.019)
Crops or seeds	0.178***	0.643***	0.517***
	(0.022)	(0.030)	(0.039)
Panel B: Negative impact on			
Access to potable water	0.086***	0.092***	0.073***
	(0.012)	(0.024)	(0.018)
Access to energy sources	0.047***	-0.011	0.036***
	(0.007)	(0.011)	(0.012)
Capacity to obtain food	0.126***	0.283***	0.130***
	(0.013)	(0.041)	(0.027)
Panel C: Adaptation strategies			
Increase foraging	0.025***	0.035**	0.060***
	(0.008)	(0.015)	(0.014)
Reduce food consumption	0.130***	0.086***	0.031
	(0.023)	(0.030)	(0.023)
Consume less expensive food items	0.078***	0.001	-0.015
	(0.012)	(0.016)	(0.014)
	Any calamity	Drought	Rainfall
Total share impacted (all households)	0.371***	0.145***	0.223***
	(0.035)	(0.015)	(0.024)

Note: this table displays estimates capturing correlations between being affected by a climate shock and vulnerability indices. The data are the 2019–20 and 2022 waves of the IOF. We estimate linear regressions with format $Y_i = \beta_0 + \beta_1 \text{Drought}_i + \beta_2 \text{Rainfall}_i + \varepsilon_i$. Each Y_i is displayed in the table rows, while the shocks are a self-reported indication of being affected by a drought or rainfall/cyclone-related calamity. Standard errors are clustered at the district level. Regressions in Panels A and B have a sample of 5,811 households that were impacted by some calamity, and Panel C has a sample of 4,518 households that declared loss of access to an essential service. Total shares impacted were calculated based on the full sample of 17,481 households. All regressions are weighted according to household sample weights. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

In Panel A of Table 1, we see that households that experienced rainfall shocks had direct losses of food more often (9 p.p.) than households impacted by other types of calamities. On the other hand, losses of animals (e.g., chicken, pigs, or cows) were more common among households that faced drought (4.7 p.p.). Losses of crops and seeds were much more frequent among households impacted by weather shocks than other calamities, being 64.3 p.p. higher for drought and 51.7 p.p. higher for floods.

Besides direct losses, calamities—and weather shocks in particular—have negative impacts on access to essential services and fulfilling basic needs, as we see in Table 1 Panel B. Both drought and high rainfall negatively impact access to potable water compared to other calamities, and rainfall is also correlated with less access to energy sources (e.g., firewood, coal, electricity). Households also indicate more frequently a negative impact on the capacity to obtain food when they experience drought (28 p.p. more often) and rainfall (13 p.p. more).

Households were asked to indicate their main adaptation strategies in case they had declared any negative impacts of calamities on access to essential services and basic needs. We see in Panel C in Table 1 that households are more likely to adapt by increasing foraging when they are impacted by drought (3.5 p.p.) or by a high rainfall shock (6 p.p.) than for other calamities. Reducing food consumption is more common among households that faced drought compared to other calamities by 8.6 p.p. However, weather calamities do not show a disproportional relation to consuming less expensive food items, presenting the same rate for this strategy as the other calamities.

3 Data

3.1 IOF surveys: household consumption

The main dataset in our analysis is the *Inquerito de Orcamentos Familiares* (IOF), a nationwide consumption survey conducted by the Mozambique Statistical Institute (INE). This survey aims to identify the consumption of durable and non-durable goods by Mozambican families. We utilize three waves of the survey: 2008–09, 2014–15, 2019–20, and 2022. From the survey, we are able to observe the household's district and the quarter of the year of the interview. Quarters of the year are divided as: from August to October (Q1), from November to January (Q2), from February to April (Q3), and from May to June (Q4).

The first wave in our sample, IOF 2008–09, was conducted between September 2008 and August 2009, crossing through five quarters. The IOF 2014–15 had interviews between August 2014 and July 2015, with observations for three quarters. The IOF 2019–20 was in camp from November 2019 to December 2020, with interviews conducted through four quarters and including periods impacted by the COVID-19 pandemic. Our last wave, IOF 2022 had interviews from January 2022 to January 2023, encompassing five quarters. While the IOF 2008–09, 2019–20, and 2022 are organized as cross-sections of different households interviewed through the cycle, the IOF 2014–15 was structured as a panel following the same households in different quarters.

Table 2: Summary statistics

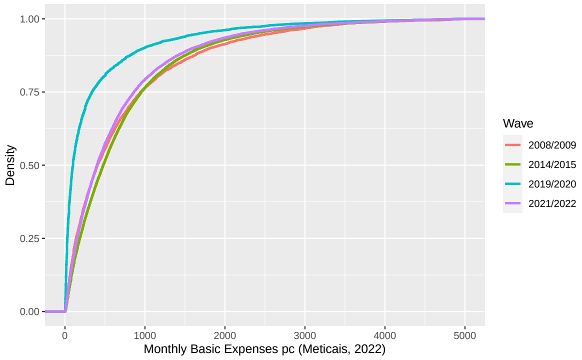
Variables	All surveys	2019/20–2022
Panel A: Household head characteristics		
Woman	0.215	0.218
	(0.011)	(0.009)
Age	44.1	46.4
	(0.458)	(0.969)
Single	0.027	0.023
	(0.003)	(0.002)
Literacy	0.708	0.706
	(0.021)	(0.024)
Panel B: Household characteristics		
Rural	0.609	0.574
	(0.060)	(0.060)
Household size	6.17	5.88
	(0.064)	(0.065)
Received family transfer	0.170	0.221
	(0.006)	(0.010)
Had self-production	0.794	0.805
	(0.045)	(0.038)
Total expenses per capita	481.2	408.2
	(59.4)	(49.3)
Total consumption per capita	910.2	833.5
	(30.8)	(26.0)
Received PSSB	-	0.015
		(0.002)
Received any social programme	-	0.032
		(0.003)

Note: information on social programmes is only available for waves 2019–20 and 2022. Expenses and consumption values refer to 'daily goods', which are composed by essential non-durable goods, like food, beverages, and vice goods (alcohol and tobacco). Social programmes are: i) PSSB – Basic Social Assistance , ii) PASP – Productive Social Assistance, and iii) PASD – Direct Social Assistance (for Emergency Response).
Source: authors' compilation based on data.

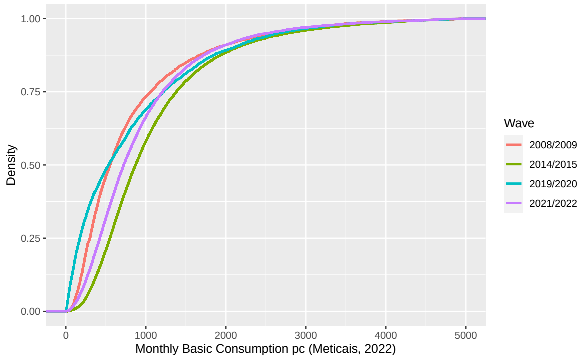
The main variables of interest in our analysis are per capita household consumption and expenses on essential non-durable goods, referred to as daily household expenses (*Despesas Diarias do Agregado Familiar*) within the survey. This category is comprised of food items, beverages, and also vice goods such as alcohol and tobacco. We aggregate the total consumption of the household on these essential non-durable goods and divide it by the number of individuals in the household. We also break down the value of consumed goods into purchased goods (expenses) and estimated value of self-produced items.

In Table 2, we show statistics on the households in our sample. Approximately 21.5% of the households are headed by a woman, the average age of the head is 44 years, and less than 3% of household heads are single. Among household heads, 70.8% are literate, above the overall national literacy rate of 45%. Most households are in rural areas (60.9%), and even more consume self-produced goods at some level (79.4%). While the average total consumption per capita stands at 910 *Meticais* (MT) at 2022 values, total expenses per capita are much lower, on average, at 481 MT, emphasizing the importance of self-production for Mozambicans. Coverage of governmental assistance programmes is very limited, with only 3.2% of households in the last two surveys being served by any social programme—a much smaller share than households receiving family transfers (17% in the total sample, and 22% in the last two surveys).

Figure 1: Non-durables expenses and consumption per capita by wave



(a) Expenses



(b) Consumption

Source: authors' compilation based on data.

We observe in Figure 1 the cumulative distribution of monthly household expenses and consumption per capita on essential non-durable goods. Comparing the distribution of expenses (Panel A) and consumption (Panel B), we can observe that accounting for only expenses would lead to severely underestimate consumption levels. For example, considering the per capita value of the 2020 Basic Food Basket—MZN470 in 2022 prices, or approximately US$7.40—we find in 2022 close to 60% of households with expenses below this threshold but actually only around 30% consuming below this value.[4] The distribution of expenses and consumption in the wave 2019–20 were impacted by the COVID-19 pandemic.

3.2 Climate data

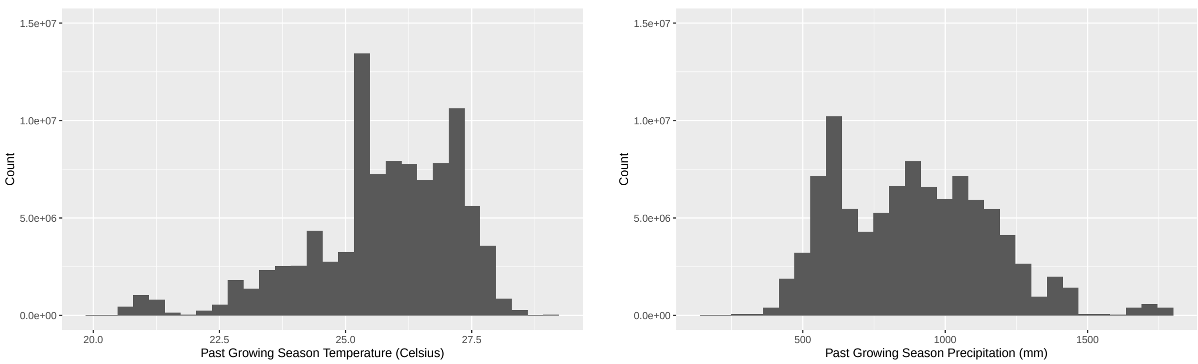
The study utilizes mainly historical data on average temperature (in Celsius) and monthly cumulative precipitation (in millimetres) spanning from 1980 to 2022. The temperature data were sourced from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2) provided by NASA, which offered daily mean air temperatures measured at a height of 2 meters. These data were represented on a grid with a spatial resolution of 0.5 x 0.625 degrees. Precipitation data were obtained from the Global Precipitation Climatology Centre (GPCC) of NOAA, featuring monthly cumulative precipitation based on global station data, organized on a grid with a 1 x 1 degree resolution. All datasets were aggregated at the district level to facilitate analysis.

[4] The 2020 Basic Food Basket was calculated by the *Centro de Estudos de Economia e de Gestão* at 24,026 Meticais per year for a five-person family (Marrengula et al. 2021). We adjust this value for 2022 Meticais and calculate the monthly value of the basic food basket per capita.

Additionally, we make use of Standardized Precipitation-Evapotranspiration Index (SPEI) data in alternative specifications. We obtain monthly SPEI data by the Global SPEI database from the *Consejo Superior de Investigaciones Cientificas* (CSIC). The SPEI data cover the period from 1901 to 2022 and are organized on a grid of 0.5 x 0.5 degree of resolution. This measure takes into account both precipitation and potential evapotranspiration, which incorporates impacts of temperature, in determining drought (Vicente-Serrano et al. 2010). The index is normalized with a mean of zero and standard deviation of one, with lower levels being associated with dryer periods.

Mozambique has a tropical to subtropical climate, with agro-climatic zones ranging from semi-arid to humid and exposure to cyclones and tropical storms. Figure 2 shows the distribution of precipitation and temperature levels during the growing season in Mozambique faced by individuals in our sample. Each bin represents the (survey-weighted) number of persons that experienced the referred weather in the past growing season (November–April). While average temperatures range between 20^oC and 30^oC, precipitation shows a wider variation, from less than 500 mm to more than 1,500 mm. The distribution of SPEI is available in Appendix Figure A2.

Figure 2: Past growing season weather histogram



(a) Temperature

(b) Precipitation

Note: growing season average temperature (Celsius) and accumulated precipitation (millimetres) levels are on the horizontal axis. Vertical axis measures are the number of persons (using survey weights) under each weather bin. Source: authors' compilation based on data.

In this study, we identify climate shocks as events in which temperature or precipitation is below the 20th percentile or above the 80th percentile of the district weather distribution, considering all periods from 1980 to 2022. Approximately 16.7% of individuals were impacted by a high growing season temperature and 3.2% faced low temperature, as observed in Appendix Table A1. Furthermore, 18.5% of individuals faced high precipitation in the past growing season, and 10.1% were in districts with low precipitation. However, weather circumstances are not spread evenly across the years, as Appendix Figure A1 illustrates. For example, the period covered by the waves 2019–20 and 2022 had concomitantly higher temperatures and lower precipitation in growing seasons than previous periods.

4 Methodology

In this paper, we are interested in capturing the impacts of climate shocks on household consumption on average and at different points of the consumption distribution in Mozambique. To estimate the distributional effects of climate shocks we follow a RIF-OLS approach, following Firpo et al. (2009).

We define climate shocks as events on the tail of each district's distribution of precipitation and temperature, using weather from 1980 to 2022. We focus on analysing growing season events of precipitation and temperature that are in the first and last quintile (below the 20th percentile and above the 80th percentile) of the distribution. Our main specifications for capturing precipitation and temperature shocks follows the general form described in Equation 1.

$$Y_{idt} = \beta_T Temp_{dt} + \beta_P Prcp_{dt} + \theta_X X_{idt} + \mu_d + \varphi_t + \eta_{rt} + {}_{idt}, \tag{1}$$

The dependent variable Y_{idt} is a measure of consumption per capita of household i, in district d, at the year-quarter t. When analysing the average effects of shocks, the dependent variable is the logarithm of household consumption (as well as expenses or self-produced consumption) per capita on essential non-durable items. When analysing the impacts on different points of the consumption distribution, our Y_{idt} variable of interest is the re-centred influence function of log-consumption or log-expenses per capita at a given decile of the distribution.

Our identification strategy explores variations in the time and district of the climate shocks to identify the parameters β_P and β_T, representing the impacts of extreme rainfall and temperature episodes. X_{idt} is a vector of demographic and socio-economic characteristics that include dummies for rural area, female head of household, single marital status, schooling level, receiving family transfers, having self-production, a quadratic polynomial for household head age, and an interaction of rural dummy with a year-level time trend. Our main specification includes district, year-quarter, and region-year fixed effects.

5 Results

5.1 Main results

In Table 3 we present the average effects of different extreme weather shocks in the past growing season (November–April) on households' expenses and consumption per capita for non-durable essential goods. We consider the within-district lowest and highest quintile weather as growing season shocks and estimate average medium-term impacts under four different specifications. In columns (1) and (2), we present the results of a simplified specification without region-year fixed effects or control for sector-specific time trends. This specification indicates that high temperature shocks reduce households' expenses on essential items by 15.6%, without significant effects on final consumption, suggesting substitution via self-produced goods, a pattern repeated in the following specifications.

Table 3: Impacts of extreme weather in the past growing season on household expenses and consumption

	Log household non-durables per capita							
Dependent variables:	Expenses	Consumption	Expenses	Consumption	Expenses	Consumption	Expenses	Consumption
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High temperature (80p)	-0.156**	0.024	-0.177***	0.004	-0.171***	0.009	-0.186***	-0.002
	(0.062)	(0.082)	(0.061)	(0.063)	(0.060)	(0.053)	(0.061)	(0.062)
Low rain (20p)	0.042	-0.020	0.018	-0.021	0.025	0.012	0.039	-0.001
	(0.062)	(0.056)	(0.060)	(0.060)	(0.055)	(0.045)	(0.058)	(0.053)
High rain (80p)	-0.029	0.090*	-0.073*	0.026	-0.072*	0.041	-0.088**	-0.010
	(0.041)	(0.046)	(0.042)	(0.041)	(0.042)	(0.040)	(0.043)	(0.041)
Low SPEI (20p)							-0.105*	-0.100*
							(0.056)	(0.053)
High SPEI (80p)							0.005	0.058*
							(0.037)	(0.032)
Rural × Linear time trend			Yes	Yes			Yes	Yes
Rural × Year					Yes	Yes		
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-year FE			Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,499	45,499	45,499	45,499	45,499	45,499	45,499	45,499
R^2	0.4296	0.2072	0.4338	0.2262	0.4361	0.2603	0.4340	0.2273
Within R^2	0.1481	0.0837	0.1502	0.0957	0.1537	0.1356	0.1506	0.0970

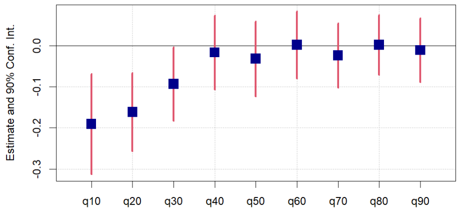
Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

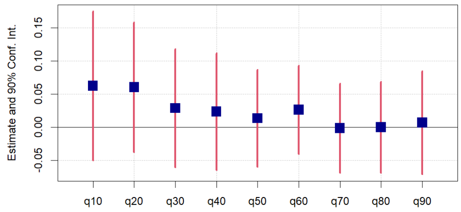
The results of our preferred specification are presented in columns (3) and (4), with high temperatures in the growing season reducing expenses by 17.7% and high rain reducing expenses by 7.3%—but no effects on final consumption. We prefer this specification as it permits accounting for regional and sector trends, since we are observing the Mozambique society over a relatively long period. Results are similar in columns (5) and (6), where we let rural time trends follow any arbitrary pattern, suggesting the linear time trend assumption for rural areas is not too constraining. Finally, in columns (7) and (8) we return to our main specification but add SPEI extreme events controls. Similar to past specifications, we observe negative impacts of high temperatures and high rainfall on expenses, but we also find that low SPEI levels (abnormally dry growing seasons) reduce both expenses and final consumption by 10%.

In Figure 3 we present the impacts of weather shocks during the growing season at different points of the distribution of expenses and consumption of essential non-durable goods, with all regressions following our main specification. The overall results mirror the average effects, with high rain and high temperature impacting negatively parts of the expenses distribution but having effects muted in total consumption. Extreme high rain in the growing season has significant negative impacts for the lowest third of the distribution and reduces expenses of the lowest decile by 19%. Extreme high temperature, in contrast, does not significantly impact the lowest decile, but it reduces expenses from the 20th quantile (by 31%) until the 70th quantile (by 14%), fading for the highest parts of the distribution. No effects are found on total consumption, indicating households are adjusting via self-production.[5]

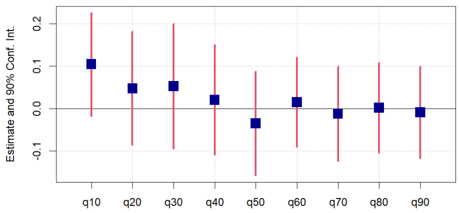
Figure 3: Unconditional quantiles analysis—impact of weather shocks on household expenses and consumption per capita



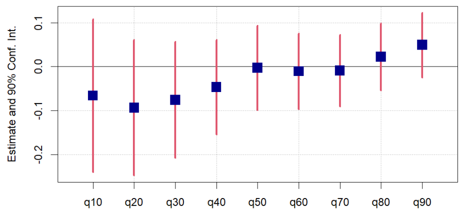
(a) High rain – expenses



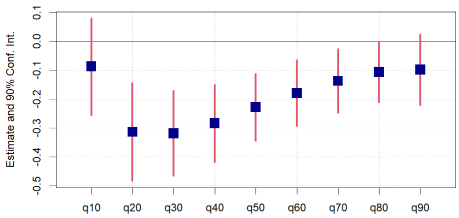
(b) High rain – consumption



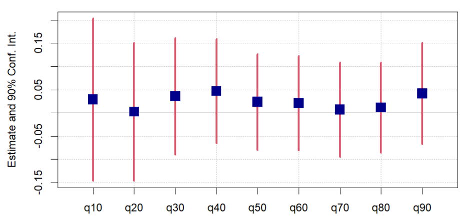
(c) Low rain – expenses



(d) Low rain – consumption



(e) High temperature – expenses



(f) High temperature – consumption

Note: blue squares represent the point estimates. Red bars represent 90% confidence intervals. Standard errors are clustered at the district level. Observations are weighted according to survey weights. All regressions include district, year-quarter, and region-year fixed effects. All regressions include a full set of controls.

Source: authors' compilation based on data.

[5] Additional analysis on the consumption of meat and fish suggests changes in the composition of bundles consumed. In Appendix Table A2, we see that a growing season with low rainfall decreases the likelihood that a household consumed meat or fish items, and high rainfall decreases both expenses and total consumption value of items in the category.

In Table 4, we conduct an alternative analysis of weather impacts on the distribution of expenses and consumption by comparing the status of households above or below fractions of the basic food basket value. We observe that extreme high temperatures in the past growing season reduce the share of households with expenses above the full, half, and quarter value of the basic food basket by 3.7 p.p., 6.2 p.p., and 7.5 p.p., respectively. However, we also find a negative impact of high temperatures on the probability that the household has consumption below a quarter value of the basic food basket (1.9 p.p.), indicating that for very low points of the distribution, this shock also impacts total consumption, which had not been captured in the previous distribution analysis. Furthermore, consistent with our RIF-OLS results, we see that high rain in the past growing season decreases the share of households with expenses above a quarter value of the basic food basket by 3 p.p.

Table 4: Weather impacts on share of households with expenses and consumption above the basic food basket value

Dependent variables:	HH expenses pc above food basket			HH consumption pc above food basket		
	Full value	1/2 value	1/4 value	Full value	1/2 value	1/4 value
Model:	(1)	(2)	(3)	(4)	(5)	(6)
High temperature (80p)	-0.037**	-0.062***	-0.075***	0.023	-0.002	-0.019*
	(0.018)	(0.019)	(0.019)	(0.028)	(0.020)	(0.011)
Low Rain (20p)	0.019	0.009	0.005	-0.016	-0.027	-0.007
	(0.018)	(0.022)	(0.020)	(0.021)	(0.018)	(0.013)
High Rain (80p)	-0.013	-0.021	-0.030**	0.010	0.007	0.006
	(0.012)	(0.014)	(0.013)	(0.019)	(0.011)	(0.007)
Fit statistics						
Observations	45,499	45,499	45,499	45,499	45,499	45,499
R^2	0.3599	0.3412	0.2803	0.1608	0.1493	0.1301
Within R^2	0.1223	0.1044	0.0672	0.0494	0.0296	0.0239

Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Contrary to findings in many low-income countries, we find no evidence of informal transfers mitigating adverse effects of climate shocks. In Appendix Table A3, we present estimates of the interaction of the family transfer indicator with climate shocks.

5.2 Self-production

The self-production of basic goods is essential to households in Mozambique. Close to 80% of individuals live in households that engage in some level of self-production, and almost half of the average share of consumption is derived from self-production, as seen in Appendix Table A4. Although self-production is ubiquitous in rural areas, present in households of around 97% of the rural population, and comprises 68% of consumption, it is still relevant in non-rural settings, where 52% live in households engaging in the activity and representing around 19%

of consumption. Thus, it is important to analyse how weather shocks impact this dimension of consumption and how they might interact.

Table 5: Past growing season extreme weather interaction with self-production

	Log HH non-durables pc			(Urban) Log HH non-durables pc		
Dependent variables:	Expenses	Self	Consumption	Expenses	Self	Consumption
Model:	(1)	(2)	(3)	(4)	(5)	(6)
High temperature (80p)	-0.169	0.134*	-0.313*	-0.093	0.221**	-0.297**
	(0.113)	(0.074)	(0.167)	(0.125)	(0.111)	(0.130)
Low rain (20p)	-0.009	-0.094	-0.331	-0.048	-0.070	-0.212
	(0.134)	(0.085)	(0.223)	(0.093)	(0.094)	(0.166)
High rain (80p)	0.228**	0.084	0.138*	0.090	0.125	0.129
	(0.104)	(0.062)	(0.082)	(0.086)	(0.117)	(0.087)
Self-production × High temperature (80p)	-0.004		0.380***	-0.050		0.418***
	(0.104)		(0.141)	(0.106)		(0.105)
Self-production × Low rain (20p)	0.032		0.368*	-0.107		0.278
	(0.126)		(0.218)	(0.112)		(0.219)
Self-production × High rain (80p)	-0.346***		-0.137*	-0.262**		-0.193**
	(0.109)		(0.080)	(0.101)		(0.087)
Fit statistics						
Observations	45,499	29,654	45,499	28,198	13,152	28,198
R^2	0.4348	0.4238	0.2339	0.4398	0.2338	0.2751
Within R^2	0.1518	0.1416	0.1047	0.1308	0.0504	0.0920

Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

In Table 5, we observe that self-production mediates high temperature and high rainfall shocks in the growing season differently. While high temperature shocks impact negatively expenses, the value of self-production increases among households engaging in the activity. The final picture is that high temperature in the growing season reduces non-durable essential goods consumption per capita by 31% among households that did not have self-production, but this effect disappears for households engaging in the activity. However, when there is a high rainfall shock in the growing season, expenses on essential goods are impacted differentially between households with and without self-production. Expenses increase for households that do not self-produce and decrease for ones that do, but the self-production value does not increase significantly. In terms of total consumption, households that do not self-produce have a higher value of consumption per capita after the shock, but self-producing ones do not change total consumption meaningfully. These effects are broadly repeated when analysing urban households separately. Nevertheless, urban households are not more likely to self-produce in the presence of shocks, while rural ones become even more likely to engage in the activity in cases of low rain or high temperature in the growing season.[6]

[6] As seen in Appendix Table A5.

We also analyse the effects of the past growing season weather extremes on household reliance on self-production on average and at different total consumption levels in Table 6. Both high temperature and high rainfall increase the average share of self-production in total household consumption of non-durable essential goods. The effect is present for households above and below the consumption level of the basic food basket. High temperature shocks in the growing season increase the share of self-production by 5 p.p., on average for the whole sample, while high rainfall increases the share of self-production by 2.3 p.p. For the bottom of the distribution, looking at households consuming below 1/4 of the value of the basic food basket per capita, high temperature shocks increase the self-production share by 4 p.p., but the effects of high rainfall are not significant.

Table 6: Share of self-produced consumption of non-durable essential goods

Dependent variable:	Self-production share of total consumption				
	All sample	Total consumption in relation to food basket			
		Above	Below	Below 1/2	Below 1/4
Model:	(1)	(2)	(3)	(4)	(5)
High temperature (80p)	0.053***	0.047***	0.041*	0.008	0.041*
	(0.013)	(0.016)	(0.021)	(0.024)	(0.023)
Low rain (20p)	-0.003	-0.001	-0.0002	0.001	-0.015
	(0.012)	(0.015)	(0.015)	(0.018)	(0.023)
High rain (80p)	0.023**	0.024**	0.033**	0.028	0.018
	(0.011)	(0.011)	(0.014)	(0.020)	(0.032)
Fit statistics					
Observations	45,499	34,614	10,885	3,885	1,530
R^2	0.6598	0.7032	0.5956	0.6495	0.7573
Within R^2	0.3591	0.3555	0.3756	0.4437	0.5840

Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

5.3 Social programmes

The social protection system in Mozambique is based on two main programmes: the contributory ones, known as PASP (*Programa de Acção Social Produtiva*) and PASD (*Programa de Apoio Social Directo*), and the non-contributory ones, called PSSB (*Programa de Subsídio Social Básico*). In this study, we focus on the PSSB, which is the most important programme targeting low-income households in the country. It started in 1997, and currently, more than 450,000 households benefit from it, with a budget of more than US$100 million per year. The PSSB, like many other social protection programmes in low-income countries, faces many problems regarding its sustainability due to the lack of government revenues to fund the programme. As extensively detailed by Almeida et al. (2024), the PSSB beneficiaries usually spend many months without receiving the benefit payments, and the total budget is not enough to attend all the eligible households.

Table 7: Linear probability model: share of households receiving social programme

Dependent variables: Model:	PSSB (1)	PASP (2)	PASD (3)	Any programme (4)
High temperature (80p)	-0.002	-0.006	-0.003	-0.011
	(0.004)	(0.006)	(0.014)	(0.016)
Low rain (20p)	0.004	-0.0003	-0.001	0.003
	(0.005)	(0.003)	(0.006)	(0.008)
High rain (80p)	0.009	-0.003	0.009	0.014
	(0.006)	(0.002)	(0.015)	(0.016)
Mean dep. variable	0.015	0.003	0.014	0.032
Observations	17,434	17,434	17,434	17,434
R^2	0.0791	0.0591	0.0724	0.0836
Within R^2	0.0416	0.0065	0.0206	0.0377

Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Table 7 shows that there is no clear correlation between being a beneficiary of a social protection policy and being affected by climate shocks. This is not surprising considering the limited capacity of these programmes. While in developed countries climate disasters might trigger more households to be enrolled in social programmes due to negative effects on local economies, helping insure victims (Deryugina 2017), we do not find evidence of this mechanism for Mozambique on the extensive margin.

Even though there is limited fiscal capacity to increase the covered population in the event of climate shocks, we find that social programmes can mitigate the impact of shocks for the groups that were already covered, as we show in Table 8. The table presents estimates for the interaction between climate shocks and the PSSB benefit indicator.[7] The results in columns (4) to (6) suggest that PSSB mitigates the climate-induced reduction in household expenses of non-durable essential goods per capita. In addition, the main positive impact of the social protection programmes is to mitigate consumption losses. The results suggest that the programmes may create the minimum necessary conditions for the families to work in their own production of goods.

[7] Results are similar when considering interactions benefiting from any of Mozambique's programmes, as seen in Appendix Table A7.

Table 8: Interaction of social programmes and household consumption

	Log HH non-durables per capita (2019/20–2022)					
Dependent variables:	Expenses	Self	Consumption	Expenses	Self	Consumption
Model:	(1)	(2)	(3)	(4)	(5)	(6)
PSSB	-0.130	0.060	-0.012	-0.327**	-0.024	-0.173
	(0.106)	(0.116)	(0.089)	(0.164)	(0.226)	(0.177)
High temperature (80p)	-0.166*	0.175**	0.057	-0.167*	0.178**	0.056
	(0.087)	(0.088)	(0.065)	(0.087)	(0.088)	(0.065)
Low rain (20p)	-0.030	-0.212**	-0.159**	-0.030	-0.221**	-0.163**
	(0.091)	(0.088)	(0.078)	(0.091)	(0.089)	(0.078)
High rain (80p)	-0.089	0.159	-0.0010	-0.106	0.155	-0.005
	(0.087)	(0.099)	(0.053)	(0.087)	(0.100)	(0.054)
PSSB $\times$ High temperature (80p)				0.207	-0.108	0.181
				(0.235)	(0.225)	(0.165)
PSSB $\times$ Low rain (20p)				0.018	0.511*	0.354*
				(0.283)	(0.270)	(0.190)
PSSB $\times$ High rain (80p)				0.640***	0.179	0.218
				(0.200)	(0.267)	(0.196)
Fit statistics						
Observations	17,434	11,646	17,434	17,434	11,646	17,434
R^2	0.4361	0.3759	0.2498	0.4365	0.3762	0.2501
Within R^2	0.1335	0.1080	0.1333	0.1341	0.1085	0.1336

Note: standard errors (in parentheses) are clustered at the district levels. Observations are weighted according to survey weights. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

6 Conclusion

This paper offers a comprehensive analysis of the distributional impacts of climate shocks on household consumption in Mozambique, a country acutely vulnerable to climate change. Our findings reveal that extreme weather events, such as unusually warm or rainy growing seasons, significantly reduce expenditures of households on essential goods. However, households adjust via self-production to mitigate the impact of these shocks on total consumption. In contrast, extreme dry growing seasons, measured by low SPEI levels, decrease both expenditures and total consumption. The effects of climate shocks are more pronounced for households below the median of the expenditures distribution.

Our study highlights the relevance of different coping mechanisms. Self-production for own consumption is heavily present in the country, especially in rural areas but also among urban households. In the presence of extremely high temperature and high rainfall in growing seasons, households change consumption patterns, increasing reliance on self-production. Contrary to findings in many low-income countries, however, we do not find evidence of informal (family) transfers mitigating adverse impacts of climate shocks. Nevertheless, social programmes are able to cushion the negative impacts of an extreme climate during the growing season for covered households.

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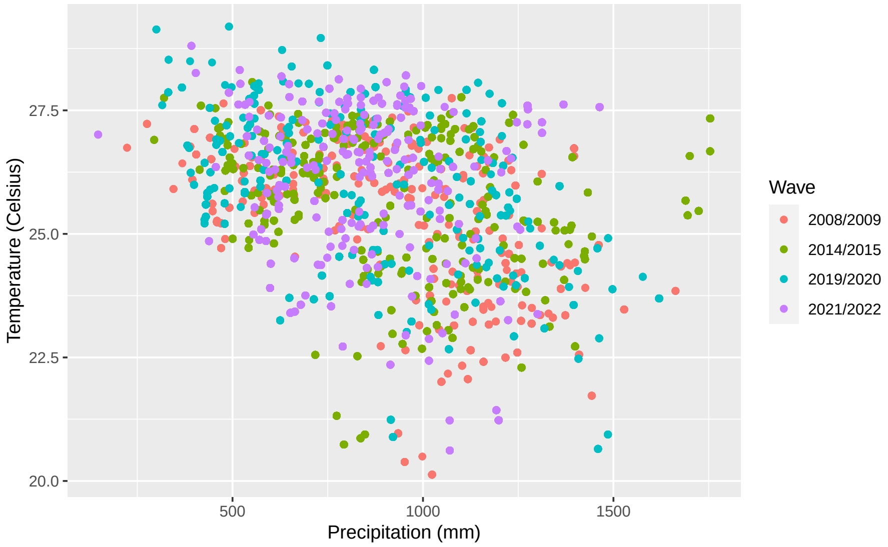
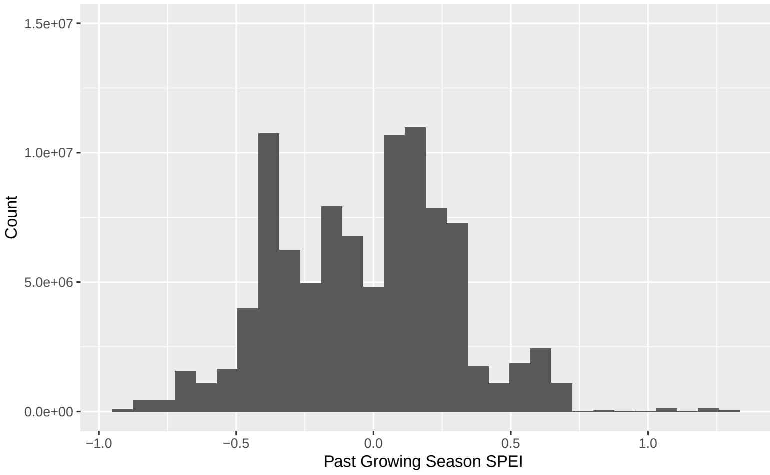
Appendix

Figure A1: Temperature and precipitation across different IOF waves



Source: authors' compilation based on data.

Figure A2: SPEI histogram



Note: Standardized Precipitation-Evapotranspiration Index (SPEI) levels on the horizontal axis. The vertical axis measures the number of persons (using survey weights) under each SPEI level.

Source: authors' compilation based on data.

Table A1: Past growing season statistics

Variables	All surveys	2019/20—2022
Average temperature (Celsius)	25.7	26.0
	(0.007)	(0.012)
Precipitation (mm)	892.5	852.7
	(1.28)	(1.81)
SPEI	-0.026	-0.025
	(0.002)	(0.003)
Low average temperature (below 20p)	0.032	0.008
	(0.0008)	(0.0007)
High average temperature (above 80p)	0.167	0.426
	(0.002)	(0.004)
Low precipitation (below 20p)	0.101	0.195
	(0.001)	(0.003)
High precipitation (above 80p)	0.185	0.127
	(0.002)	(0.003)
Low SPEI (below 20p)	0.101	0.195
	(0.001)	(0.003)
High SPEI (above 80p)	0.175	0.133
	(0.002)	(0.003)

Note: all estimates are constructed using survey weights.
Source: authors' compilation based on data.

Table A2: Low rain reduces probability of consuming meat; high temperature and high rainfall reduce amount spent on meat, effect remains in consumption in the case of high rain

		Log HH meat/fish per capita		
Dependent variables:	Consumed meat/fish	Expenses	Self	Consumption
Model:	(1)	(2)	(3)	(4)
High temperature (80p)	0.012	-0.135**	0.138	-0.056
	(0.019)	(0.064)	(0.124)	(0.068)
Low rain (20p)	-0.027*	0.066	-0.063	-0.019
	(0.014)	(0.055)	(0.101)	(0.060)
High rain (80p)	-0.002	-0.081*	-0.075	-0.085**
	(0.018)	(0.042)	(0.081)	(0.041)
Fit statistics				
Observations	45,499	32,282	5,953	34,462
R^2	0.1523	0.3110	0.2139	0.2172
Within R^2	0.0401	0.1613	0.0473	0.1134

Note: standard errors (in parentheses) are clustered at the district levels. All regressions follow the main specification including district, year-quarter, and region-year fixed effects.
Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Table A3: Family transfers are not mitigating shocks, on average

	Log household non-durables per capita					
Dependent variables:	Expenses	Self	Consumption	Expenses	Self	Consumption
Model:	(1)	(2)	(3)	(4)	(5)	(6)
High temperature (80p)	-0.177***	0.125*	-0.009	-0.186***	0.118	-0.014
	(0.063)	(0.075)	(0.064)	(0.063)	(0.075)	(0.063)
Low rain (20p)	0.041	-0.025	0.002	0.058	-0.010	0.018
	(0.059)	(0.071)	(0.057)	(0.058)	(0.069)	(0.052)
High rain (80p)	-0.086*	0.076	0.020	-0.105**	0.038	-0.023
	(0.046)	(0.066)	(0.045)	(0.047)	(0.074)	(0.045)
Low SPEI (20p)				-0.095*	-0.089	-0.091*
				(0.057)	(0.068)	(0.053)
High SPEI (80p)				0.015	0.059	0.069**
				(0.039)	(0.052)	(0.033)
Family transfer × High temperature (80p)	-0.009	0.028	0.050	-0.008	0.031	0.052
	(0.069)	(0.069)	(0.060)	(0.069)	(0.068)	(0.059)
Family transfer × Low rain (20p)	-0.109	-0.075	-0.113	-0.091	-0.049	-0.094
	(0.114)	(0.094)	(0.093)	(0.114)	(0.098)	(0.089)
Family transfer × High rain (80p)	0.063	0.028	0.024	0.069	0.042	0.045
	(0.070)	(0.077)	(0.042)	(0.070)	(0.082)	(0.044)
Family transfer × Low SPEI (20p)				-0.031	-0.053	-0.035
				(0.090)	(0.102)	(0.072)
Family transfer × High SPEI (80p)				-0.032	-0.011	-0.042
				(0.056)	(0.071)	(0.041)
Observations	45,499	29,654	45,499	45,499	29,654	45,499
R^2	0.4339	0.4245	0.2266	0.4342	0.4250	0.2278
Within R^2	0.1504	0.1428	0.0963	0.1508	0.1435	0.0976

Note: standard errors (in parentheses) are clustered at the district levels. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Table A4: Self-production statistics

Sample	Had self-production	Share of consumption self-produced	Observations
All	0.794	0.488	45,499
	(0.002)	(0.002)	
Urban	0.522	0.188	28,198
	(0.003)	(0.002)	
Rural	0.969	0.680	17,301
	(0.001)	(0.002)	
Any social benefit (2019/20–2022)	0.826	0.444	640
	(0.015)	(0.014)	
PSSB (2019/20–2022)	0.938	0.608	303
	(0.014)	(0.019)	

Note: all estimates are constructed using survey weights.
Source: authors' compilation based on data.

Table A5: Families in rural areas rely more on self-production, and probability of engaging in activity increases with weather shocks for rural families

Dependent variable:	Had self-production		
	All	Urban	Rural
Model:	(1)	(2)	(3)
Grow season district low temperature (20p)	-0.050	-0.049	-0.057
	(0.039)	(0.039)	(0.055)
Grow season district high temperature (80p)	0.037***	0.038	0.025**
	(0.013)	(0.025)	(0.011)
Grow season district low rain (20p)	-0.001	-0.016	0.014*
	(0.009)	(0.022)	(0.007)
Grow season district high rain (80p)	0.011	0.003	0.007
	(0.008)	(0.019)	(0.008)
Rural	0.313***		
	(0.033)		
Rural × Time trend	-0.012***		
	(0.002)		
Fit statistics			
Observations	45,499	28,198	17,301
R^2	0.4511	0.2812	0.1389
Within R^2	0.1084	0.0672	0.0359

Note: standard errors (in parentheses) are clustered at the district levels. All regressions follow the main specification including district, year-quarter, and region-year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Table A6: Linear probability model: probability of household receiving social programme

Dependent variables:	PSSB	PASP	PASD	Any programme
Model:	(1)	(2)	(3)	(4)
Low temperature (20p)	-0.012	-0.004	-0.013*	-0.028
	(0.012)	(0.006)	(0.007)	(0.019)
High temperature (80p)	-0.002	-0.006	-0.003	-0.011
	(0.004)	(0.006)	(0.014)	(0.016)
Low rain (20p)	0.004	-0.0003	-0.001	0.003
	(0.005)	(0.003)	(0.006)	(0.008)
High rain (80p)	0.009	-0.003	0.009	0.014
	(0.006)	(0.002)	(0.015)	(0.016)
Family transfer	0.005*	-0.002	0.008*	0.011**
	(0.003)	(0.002)	(0.004)	(0.005)
Self-production	0.005	-0.002	0.005	0.007
	(0.003)	(0.002)	(0.007)	(0.008)
Rural	0.012	-0.018	0.292***	0.282***
	(0.048)	(0.032)	(0.051)	(0.073)
Rural $\times$ Time trend	-0.0008	0.001	-0.023***	-0.022***
	(0.003)	(0.002)	(0.004)	(0.006)
Woman head	0.005	0.0004	0.005*	0.010***
	(0.003)	(0.001)	(0.003)	(0.004)
Age	0.002***	0.0002***	0.0003***	0.002***
	(0.0003)	(6.07×10^{-5})	(0.0001)	(0.0003)
Age square	$-1.8\times10^{-6***}$	$-1.6\times10^{-7***}$	$-3.23\times10^{-7***}$	$-2.19\times10^{-6***}$
	(2.61×10^{-7})	(5.91×10^{-8})	(1.06×10^{-7})	(2.77×10^{-7})
Single	0.001	0.006	0.003	0.011
	(0.004)	(0.007)	(0.009)	(0.012)
Household size	-0.003***	0.0008	0.0001	-0.002
	(0.0007)	(0.0009)	(0.0004)	(0.001)
Knows writing	-0.006	0.004	0.005**	0.003
	(0.004)	(0.003)	(0.002)	(0.005)
Primary school education	0.005	-0.003	-0.002	0.001
	(0.004)	(0.002)	(0.003)	(0.005)
Secondary school education or higher	0.005	-0.005**	-0.009**	-0.008
	(0.004)	(0.002)	(0.004)	(0.006)
Mean dep. variable	0.015	0.003	0.014	0.032
Observations	17,434	17,434	17,434	17,434
R^2	0.0791	0.0591	0.0724	0.0836
Within R^2	0.0416	0.0065	0.0206	0.0377

Note: clustered (district) standard errors are in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1
Source: authors' compilation based on data.

Table A7: Any social programmes: mitigating weather shock impacts

	Log HH non-durables per capita (2019/20–2022)					
Dependent variables:	Expenses	Self	Consumption	Expenses	Self	Consumption
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Any social programme	-0.075	0.002	-0.091	-0.231	-0.097	-0.285*
	(0.086)	(0.129)	(0.083)	(0.146)	(0.262)	(0.150)
Low temperature (20p)	0.690***	0.202	-0.066	0.692***	0.216	-0.066
	(0.176)	(0.278)	(0.164)	(0.177)	(0.277)	(0.165)
High temperature (80p)	-0.166*	0.175**	0.056	-0.170*	0.185**	0.052
	(0.087)	(0.088)	(0.065)	(0.087)	(0.090)	(0.065)
Low rain (20p)	-0.031	-0.212**	-0.159**	-0.029	-0.226**	-0.162**
	(0.091)	(0.089)	(0.078)	(0.091)	(0.089)	(0.077)
High rain (80p)	-0.089	0.160	0.0002	-0.105	0.145	-0.010
	(0.087)	(0.099)	(0.054)	(0.088)	(0.101)	(0.055)
Any social programme $\times$ High temperature (80p)				0.268	-0.066	0.316**
				(0.180)	(0.236)	(0.144)
Any social programme $\times$ Low rain (20p)				0.077	0.422	0.316**
				(0.210)	(0.288)	(0.152)
Any social programme $\times$ High rain (80p)				0.345*	0.313	0.269*
				(0.206)	(0.279)	(0.155)
District	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter	Yes	Yes	Yes	Yes	Yes	Yes
Region-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,434	11,646	17,434	17,434	11,646	17,434
R^2	0.4361	0.3759	0.2500	0.4364	0.3764	0.2509
Within R^2	0.1334	0.1080	0.1335	0.1339	0.1087	0.1346

Note: clustered (district) standard errors are in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Source: authors' compilation based on data.

Table A8: Linear probability model: heterogeneity

Dependent variables:	PSSB	PASP	PASD	Any programme
Model:	(1)	(2)	(3)	(4)
Panel A: Family transfer				
Low temperature (20p)	-0.004	-0.003	-0.010	-0.018
	(0.010)	(0.006)	(0.006)	(0.017)
High temperature (80p)	0.0003	-0.006	-0.005	-0.011
	(0.004)	(0.006)	(0.013)	(0.015)
Low rain (20p)	0.003	-0.002	0.0007	0.002
	(0.005)	(0.002)	(0.006)	(0.008)
High rain (80p)	0.004	-0.004	0.006	0.006
	(0.007)	(0.003)	(0.010)	(0.013)
Family transfer × Low temperature (20p)	-0.064**	-0.012	-0.024	-0.093*
	(0.029)	(0.019)	(0.024)	(0.049)
Family transfer × High temperature (80p)	-0.012**	0.001	0.008	-0.003
	(0.006)	(0.004)	(0.010)	(0.011)
Family transfer × Low rain (20p)	0.006	0.008*	-0.010	0.004
	(0.005)	(0.005)	(0.008)	(0.011)
Family transfer × High rain (80p)	0.019*	0.004	0.010	0.030
	(0.011)	(0.003)	(0.020)	(0.021)
Fit statistics				
Observations	17,434	17,434	17,434	17,434
R^2	0.0800	0.0597	0.0729	0.0842
Within R^2	0.0425	0.0072	0.0211	0.0384
Panel B: Has self-production				
Low temperature (20p)	0.007	-0.004	0.010	0.010
	(0.009)	(0.005)	(0.014)	(0.016)
High temperature (80p)	0.004	-0.008	0.019	0.014
	(0.006)	(0.006)	(0.019)	(0.021)
Low rain (20p)	-0.0005	0.0007	0.004	0.004
	(0.005)	(0.002)	(0.015)	(0.016)
High rain (80p)	0.009	0.003	-0.008	0.004
	(0.012)	(0.003)	(0.008)	(0.016)
Self-production × Low temperature (20p)	-0.032	-0.002	-0.032	-0.063**
	(0.020)	(0.010)	(0.019)	(0.030)
Self-production × High temperature (80p)	-0.007	0.002	-0.025*	-0.029*
	(0.005)	(0.003)	(0.013)	(0.015)
Self-production × Low rain (20p)	0.006	-0.001	-0.006	-0.001
	(0.006)	(0.002)	(0.015)	(0.018)
Self-production × High rain (80p)	0.0002	-0.006*	0.019	0.011
	(0.013)	(0.003)	(0.017)	(0.020)
Fit statistics				
Observations	17,434	17,434	17,434	17,434
R^2	0.0793	0.0592	0.0739	0.0844
Within R^2	0.0418	0.0066	0.0221	0.0386

Note: clustered (district) standard errors are in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.
Source: authors' compilation based on data.