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The gendered effects of climate shocks on labour and welfare in Zambia

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Abstract: This paper exploits several waves of two major nationwide representative surveys to document the impacts of climate shocks on individuals and households in Zambia. We merge these datasets with historical precipitation and temperature data at the district level. First, we show the gendered effects of the shocks, which have a higher negative impact on women. Women have a lower probability of being in the labour force and fewer hours of work when experiencing shocks. Second, we show that households affected by climate shocks have 16% lower consumption, which is mainly explained by female-headed households. We show that social protection policies mitigate income reduction but not consumption, which may suggest that climate shocks affect households directly by reducing their income, but also indirectly by raising food prices.

Key words: Zambia, climate shocks, labour, gender, consumption

JEL classification: N36, O12, O15

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1 Introduction

Climate change intensifies economic and social vulnerabilities worldwide, with its impacts often magnified along gender lines (UN Secretariat 2022). As extreme weather events such as droughts, floods, and hurricanes become more frequent and severe, households face increased pressures—spending more time on domestic responsibilities while also striving to offset income losses. Gender disparities make these challenges especially acute for women. In many developing countries, women's lower labour force participation, restricted access to resources, high representation in informal and agricultural sectors, and primary caregiving roles increase their vulnerability. However, we still lack empirical evidence to further understand how climate impacts manifest on women, especially in low-income countries. For instance, Fruttero et al. (2024) reviewed the most recent literature and found only five research papers focusing on the gendered impacts of climate shocks on women's labour, income, and consumption in low-income countries, with only one paper studying Tanzania showing higher impacts on women.[1]

In this paper, we study the impacts of climate shocks on labour outcomes, time use, income, and consumption in Zambia. We use two main data sources: the Labour Force Surveys (LFS) for 2017, 2018, 2019, 2020, and 2021 from the International Labour Organization (ILO); and the Living Condition Measurement Survey (LCMS) 2015 and 2022 from the Zambia Statistical Agency (ZAMSTAT).[2] Both datasets have information on individuals' socioeconomic characteristics, district of residence, and the quarters in which they were interviewed. We merge these data with granular rainfall and temperature data that allow us to create clear measures of climate shocks per district. We use the LFS and LCMS datasets to organize important evidence about the Zambian labour market over the specified years. While information is primarily disseminated through annual reports corresponding to the survey years, public access to the underlying raw data is often restricted. For instance, in 2021, 23% of the population had a job, 4% was unemployed, and 72% was outside the labour force—meaning unemployed and not looking for a job. Women represented 37% of the labour force. Services was the sector with the most individuals in the labour force (47%), followed by agriculture (22%) and manufacturing (12%). The monthly food consumption per capita in 2022 was about US$18, around half of households fell below the basic food basket value per capita, and 26% of households had a woman as the household head.

Climate shocks may affect labour outcomes by impacts on businesses (Feriga et al. 2024; Kala et al. 2023), but also through direct reduction of families' well-being. Several channels may explain the reduction of well-being, such as reductions in income and consumption, destruction of family assets, withdrawal of children from school, and higher incidence of health problems. We focus on the reduction of well-being measured by consumption and income losses. The LCMS has detailed information about the goods consumed by families. Although the LFS also includes wages and self-employment income, researchers usually rely on consumption as a better measure of well-being in low-income countries as it is a more stable measure of well-being. In a country with a high level of poverty and informality, income tends to fluctuate more than consumption (Meyer and Sullivan 2003). Many families may report no income level in household surveys, but they still manage to maintain a minimum level of consumption for subsistence. Unfortunately, the information about income (LFS) and consumption (LCMS) is available at the household level but not at the individual level.

We study an important and representative context. Zambia is a predominantly agricultural country with a large presence of mining companies. Its status is often between low- and lower-middle-income countries. The country has a profile similar to many African countries. In 2024, Zambia faced the worst drought in

[1] See: Gray and Mueller (2012), Anglewicz and Myroniuk (2018), Dillon et al. (2011), Marchetta et al. (2019), and Lee et al. (2021).

[2] We also use the In-Depth Vulnerability Survey for 2023 from the Disaster Mitigation and Management Unit (DMMU) in the descriptive statistics.

the last 60 years (Sinyangwe and Savage 2024). Even though the country is not ranked as one of the most vulnerable countries in terms of climate index, it has been facing many extreme weather episodes such as floods, flash floods, and droughts. The most recent household survey, from 2024, suggests that about 60% of the population is below the poverty line and that a large portion of Zambia's infrastructure is inadequate. These climate shocks pose a serious threat to economic stability and growth, food security, and overall public health.

The main results suggest extreme precipitation shocks reduce the probability of being in the labour force. In addition, there is a significant differential effect between men and women. When affected by a climate shock, men are more likely to be in the labour force when the precipitation is very low, but only in the informal sector. Women are less likely to be in the labour force than men in all extreme climate events and have a higher probability of being self-employed in episodes of extreme rainfall and extreme temperature, which is compensated by a lower probability of being in the formal and informal labour markets. Our main results also suggest that when experiencing a climate shock in the past quarter, women are more likely to work in the services sector, while men are more likely to work in the manufacturing sector.

We then turn to the impacts on income and consumption. Unfortunately, data on income and consumption are available only at the household level, making gender analysis challenging. We show that extreme rainfall reduces income by 10%. The main results in our preferred specification suggest that a growing season with very low precipitation reduces the food consumption per capita by about 19.8%. In our second specification, a past month with an episode of extreme rainfall reduces consumption by 16.4%, a past month with a drought spell reduces consumption by 14.1%, and a past month with extremely high temperatures reduces consumption by 20%. The results by consumption decile also suggest that poorer households are more affected by the climate shocks.

Finally, by interacting the climate shock measures with an indicator of whether the household receives a social protection programme, we can provide evidence of its potential mitigation effects on well-being. This analysis is important because Zambia is a low-income country with one of the oldest unconditional cash transfers, started in 2003, and with many different social protection programmes such as the Food Security Pack (Ministry of Community Development and Social Services 2021), and the Women's Livelihoods programme (Girls' Education and Women's Empowerment and Livelihoods Project n.d). In our analysis we found that social protection programmes, especially social cash transfers, may cushion income losses but not consumption losses during climate shocks. A potential explanation is that climate shocks may also increase food prices (Birgani et al. 2022; Hill and Porter 2017). Unfortunately, the lack of panel data in Zambia does not allow us to explore the effects of migration, an essential mechanism through which individuals could adapt to climate change. For instance, Afridi et al. (2022) show that women affected by climate shocks in India are less likely to work outside their village and migrate to cope with adverse agricultural productivity shocks.

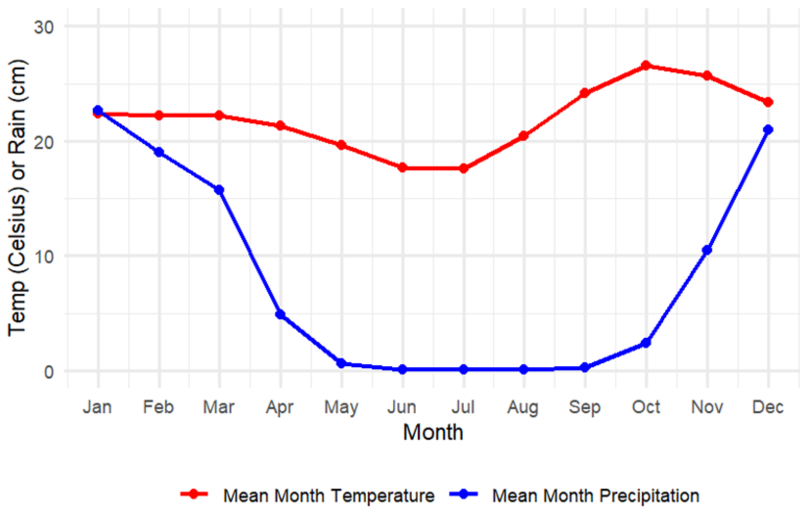
This paper has at least two main contributions to the literature. First, we expand the literature on climate shocks and labour relocation to a low-income country. The existing evidence for low-income countries focuses on other outcomes and mostly relies on small sample data from experiments. We extensively explore the two most important surveys in the country to provide new evidence that can be useful for guiding future research and policy in low-income countries. Because of the lack of data availability, the existing evidence is highly concentrated on developed and upper-middle-income countries, such as India (Afridi et al. 2022; Colmer 2021; Liu et al. 2023), Brazil (Branco and Féres 2021; Xie 2024), Mexico (Jessoe et al. 2018), and China (Garg et al. 2020; Huang et al. 2020; Zhang et al. 2018). For instance, some of these papers have panel data covering more than a decade, with information on the district of residence and the timing of the interview, which is not the reality of Zambia's data landscape. Our paper is closely related to Afridi et al. (2022), which shows the gendered effects of climate change in India. However, we found much stronger effects of climate shocks on female labour force participation. The little evidence for African countries focuses on differential migration responses by gender (Anglewicz and Myroniuk 2018; Dillon et al. 2011; Gray and Mueller 2012).

Second, we contribute by measuring the impacts of climate shocks on income and 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 climate shocks on economic activity, but mixed evidence on income inequality (Dang et al. 2024; Tol 2018, 2022). 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 (Meyer and Sullivan 2003). 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 GDP per capita, income, productivity,[3] and mortality (Deschênes and Greenstone 2011; Heutel et al. 2021; Kahn 2005).

2 Zambia profile and climate vulnerability

Zambia is a large, landlocked country located in south-central Africa. It is bordered by Angola, Botswana, the Democratic Republic of Congo, Malawi, Mozambique, Namibia, Tanzania, and Zimbabwe. Zambia has a tropical climate with three marked seasons: cool and dry (May to August), hot and dry (September to November), and warm and wet (December to April). Figure 1 shows these patterns of temperature and precipitation. In the last decade, the country has experienced substantial economic growth as Africa's second-largest copper producer. Other main exports include cobalt, cotton, coffee, flowers, tobacco, and maize. Despite the economic growth and partially due to the vulnerability of falling commodity prices, the country still has almost two-thirds of the population living in poverty conditions (see ZAMSTAT 2022). Due to the low income level, low human capital development, and high economic vulnerability, Zambia has been classified as one of the world's 45 least developed countries (United Nations n.d.). Moreover, Zambia encounters many environmental challenges, including loss of biodiversity, deforestation, air pollution, droughts, floods, and extreme temperatures.

Figure 1: Average rainfall and temperature per month



Note: the figure displays the average rainfall (cm) and temperature (Celsius) for each month in Zambia between 1980 and 2022. Averages were calculated considering equally weighted districts.

Source: authors' compilation.

[3] See Garg et al. (2020), Tol (2018), Burke and Emerick (2016), Adhvaryu et al. (2020), and Somanathan et al. (2021).

Using data from Zambia's 2023 In-Depth Vulnerability Survey—with interviews in June and July 2023—we present contextual information on climate vulnerability in Table 1. This survey is conducted by the DMMU in Zambia. The survey targets low-income families living in areas affected and at risk of being affected by climate shocks. Estimates from the survey[4] indicate that, in 2023, around 33% of individuals were in households impacted by drought since October 2022, and 30% were in households impacted by flood. We look at how being impacted by one of these shocks is related to indicators of hunger and coping strategies asked in the survey. Comparisons are made with simple OLS regressions of indicators on drought and flood dummies using household sample weights.

Table 1: Weather shocks on 2023 In-Depth Vulnerability Survey

	Constant	Drought	Floods
Panel A: Hunger (30 days)			
No food in the house due to lack of resources	0.4549***	0.0650**	0.0594*
	(0.0287)	(0.0287)	(0.0327)
Household member slept hungry	0.4218***	0.0775**	0.0595*
	(0.0277)	(0.0305)	(0.0335)
Household member had a full day without eating	0.2695***	0.1162***	0.0537*
	(0.0240)	(0.0307)	(0.0289)
Panel B: Reduced coping strategies (7 days)			
Less expensive food	0.6434***	0.0915***	0.0504*
	(0.0283)	(0.0250)	(0.0277)
Borrowed food	0.4267***	0.0363	0.0916***
	(0.0200)	(0.0238)	(0.0253)
Limited portions at mealtime	0.5113***	0.0990***	0.1033***
	(0.0337)	(0.0312)	(0.0324)
Restricted adult consumption to favour children	0.3937***	0.0592**	0.0773**
	(0.0258)	(0.0256)	(0.0329)
Panel C: Livelihood coping strategies (30 days)			
Reduced expenditures on essential non-food items	0.4484***	0.0378	0.0129
	(0.0249)	(0.0260)	(0.0286)
Borrowed money for food or health needs	0.3659***	0.0230	0.0606***
	(0.0244)	(0.0242)	(0.0228)
Used savings for food or health needs	0.2046***	0.0245	0.0096
	(0.0200)	(0.0242)	(0.0197)
Sold oxen or mature female livestock	0.0549***	0.0163	0.0154*
	(0.0067)	(0.0118)	(0.0090)
Withdrew children from school	0.0662***	-0.0009	0.0222*
	(0.0085)	(0.0139)	(0.0113)
Begged	0.2104***	0.0740***	0.0411*
	(0.0203)	(0.0242)	(0.0236)
Engaged in child labour	0.0765***	-0.0176	0.0248
	(0.0108)	(0.0159)	(0.0151)
Share of individuals impacted	–	0.3266***	0.2999***
		(0.0346)	(0.0284)

Note: this table displays estimates intended to capture correlations between being affected by a climate shock and vulnerability indices. We estimate a linear regression such as $Y_i = \beta_0 + \beta_1 Shock + \varepsilon$. Each Y_i is displayed in the table rows, while the shocks are a self-reported indication of being affected by a drought or flood. Standard errors are clustered at the district level. All regressions have a sample size of 11,247 households and are weighted according to household sample weights. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' own calculations based on data from the In-Depth Vulnerability Survey conducted by the DMMU.

From Table 1, Panel A shows that 45% of people were in households that lacked food in the past 30 days. Additionally, drought or floods increased the lack of food by 6.5 and 5.9 percentage points (p.p.), respectively. Individuals who were impacted by these disasters were also more likely to be in house-

[4] The estimates are intended to capture correlations only. We estimate a linear regression such as $Y_i = \beta_0 + \beta_1 Shock + \varepsilon$. Each Y_i is displayed in the table rows, while the shocks are a self-reported indication of being affected by a drought or flood.

holds where a member slept hungry or went a full day without eating compared to those who were not impacted. These differences are especially pronounced for households that experienced drought, with an 11 p.p. higher rate than the baseline of having a household member go a full day without eating.

Panel B from Table 1 shows the relationship between natural disasters and households' reduced coping strategies, illustrating how households adjust. Droughts and floods are both associated with higher rates of adjustment, such as consuming less expensive food, having limited portions at mealtime, and restricting adult consumption to favour children. Interestingly, individuals who faced drought did not present a higher rate of resorting to borrowing food than the baseline, while households that faced floods had a 9 p.p. higher rate.

Panel C of Table 1 shows that individuals in households impacted by floods had higher rates than baseline for borrowing money for food and health needs, selling oxen or mature female livestock, and withdrawing children from school. Both drought and flood are associated with higher rates of begging.

3 Data

3.1 Labour Force Survey

The primary dataset in our analysis is the Zambia LFS. The LFS is a nationally representative household-level sample survey designed to collect information on labour market activities.[5] From the survey, we also observed the district where the household is located and the quarter of the year the survey interview took place. The quarters in our sample are divided according to the order of the month in a year: January to March (Q1), April to June (Q2), July to September (Q3), and October to December (Q4). The LFS comprises a series of cross-sectional studies over time; for this analysis we use the 2017, 2018, 2019, 2020, and 2021 surveys.[6]

For each survey year, the final sample size was calculated in such a way as to have appropriate power to produce estimates for the country, area of residence (urban and rural), and each province.[7] In order to draw sampling units, a two-stage cluster sampling technique was involved. The primary sampling units are standard enumeration areas (SEAs), identified from an original sampling frame compiled from the 2010 Census of Population and Census.

Table 2 summarizes the main variables used in this study. The outcomes of interest for our analysis are related to the individuals' labour characteristics. This concept includes variables such as labour force participation (employed or actively seeking a job), employment type (formal sector, informal sector, or self-employed), industry type, and hours worked in the main activity. Table A3 in Appendix A shows the sample size for the analytical sample by survey years, and Table A4 shows the distribution by household location at the province level.

[5] The LFS is conducted by the Zambia Statistics Agency in partnership with the Ministry of Labour and Social Security.

[6] The 2018 survey year information only comprises data on one-quarter of interviews for 16.9% of the individuals.

[7] Zambia has a total of nine provinces: Central, Copperbelt, Eastern, Luapula, Lusaka, Northern, North-Western, Southern, and Western.

Table 2: Labour Force Survey: descriptive statistics

	Total	Male	Female
Panel A: Individual characteristics			
Age	22.33	22.51	22.16
	(18.26)	(18.27)	(18.25)
Lives in urban (=1)	0.35	0.35	0.36
	(0.48)	(0.48)	(0.48)
Education (in years)	6.52	6.84	6.19
	(3.84)	(3.93)	(3.71)
Household size	6.43	6.56	6.47
	(3.56)	(3.57)	(3.47)
Panel B: Employment characteristics			
In labour force (=1)	0.35	0.44	0.26
	(0.48)	(0.50)	(0.44)
Employed at the formal sector (=1)	0.24	0.31	0.16
	(0.43)	(0.46)	(0.37)
Employed at the informal sector (=1)	0.30	0.34	0.25
	(0.46)	(0.47)	(0.43)
Self-employed/ HH consumption (=1)	0.46	0.35	0.59
	(0.50)	(0.48)	(0.49)
Industry: Elementary services (=1)	0.40	0.33	0.53
	(0.49)	(0.47)	(0.50)
Industry: Agriculture (=1)	0.29	0.30	0.26
	(0.45)	(0.46)	(0.44)
Industry: Manufacture (=1)	0.13	0.16	0.06
	(0.33)	(0.37)	(0.24)
Hours worked in the last week in main activity	11.51	15.84	7.92
	(20.93)	(23.60)	(17.54)
Hours worked in the last week in secondary activity	0.27	0.40	0.16
	(3.14)	(3.81)	(2.42)

Note: this table displays the descriptive statistics of the main variables used in this study using the LFS 2017, 2019, 2020, and 2021.

Source: authors' calculations.

3.2 Living Conditions Measurement Survey

Zambia's LCMS is a nationwide survey conducted by the country's Central Statistical Office with the main purpose of measuring the well-being of the population. Among other information, the survey measures the household consumption of a variety of food and non-food items. We use two waves of the survey in our analysis: (1) the 2015 LCMS, which conducted interviews between April and May 2015, and (2) the 2022 LCMS, which had interviews from June 2022 to July 2022. We are able to observe each household's district and the date of the interview.

The main variable of interest in our analysis is the household's value of food consumption per capita over a one-month period. The consumption measure includes expenditure on products bought and estimates for self-produced goods and gifts. The original data considered different time spans of household consumption for different goods (7 days, 14 days, and 30 days). We adjusted all consumption to the monthly equivalent and divided by the number of people in the household to obtain the monthly consumption value per capita. All values are adjusted to 2022 prices. Table 3 summarizes the main variables used in this study.

Table 3: Living Conditions Measurement Survey: descriptive statistics

Panel A: Household head characteristics	
Household head age	43.71
	(0.2981)
Female household head	0.2643
	(0.0068)
Household head never attended school	0.1022
	(0.0112)
Household head highest education grade	7.788
	(0.2915)
Panel B: Household characteristics	
Total household wages per capita (2022, ZMW)	479.1
	(105.7)
Food consumption per capita (2022, ZMW)	358.3
	(24.92)
Number of people in household	5.115
	(0.0441)
Number of children under six years	0.5633
	(0.0264)
Panel C: Participation in social programmes (only 2022)	
Keeping Girls in School	0.0126
	(0.0022)
School Feeding Program	0.0346
	(0.0100)
Social Cash Transfer	0.0715
	(0.0109)

Note: this table displays the descriptive statistics of the main variables used in this study using the LCMS 2015 and 2022.

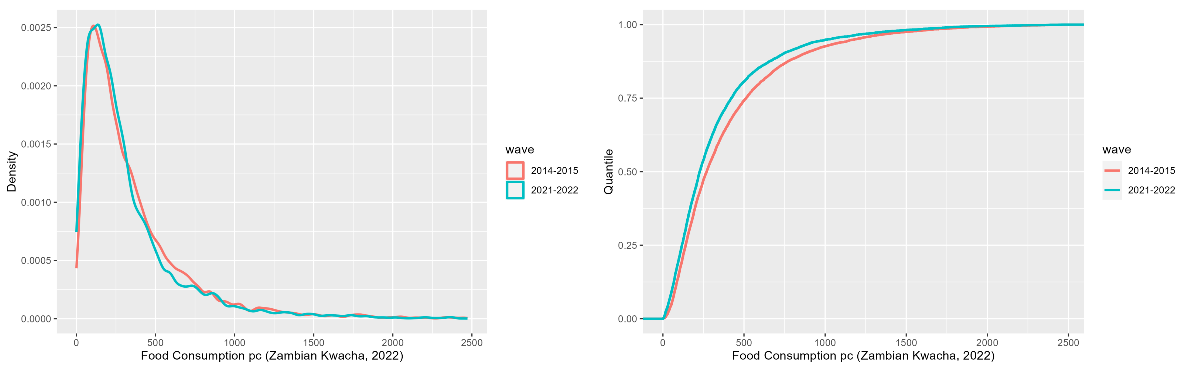
Source: authors' calculations.

Figure 2 shows the density and cumulative distribution functions of monthly household food consumption value per capita in our sample for 2015 and 2022. Considering information from Zambia's 2022 Poverty Assessment, the total food basket for a family of six costs ZMW1,522, translating to ZMW254 per capita (ZAMSTAT 2023). Based on the empirical distribution of food consumption per capita, around half the households fall below the basic food basket value per capita.

Figure 2: Distribution of food consumption value per capita

(a) Density

(b) CDF



Note: this figure presents the distribution (a) of food consumption per capita by LCMS survey year, and the cumulative distribution of consumption per capita (b) by LCMS survey year.

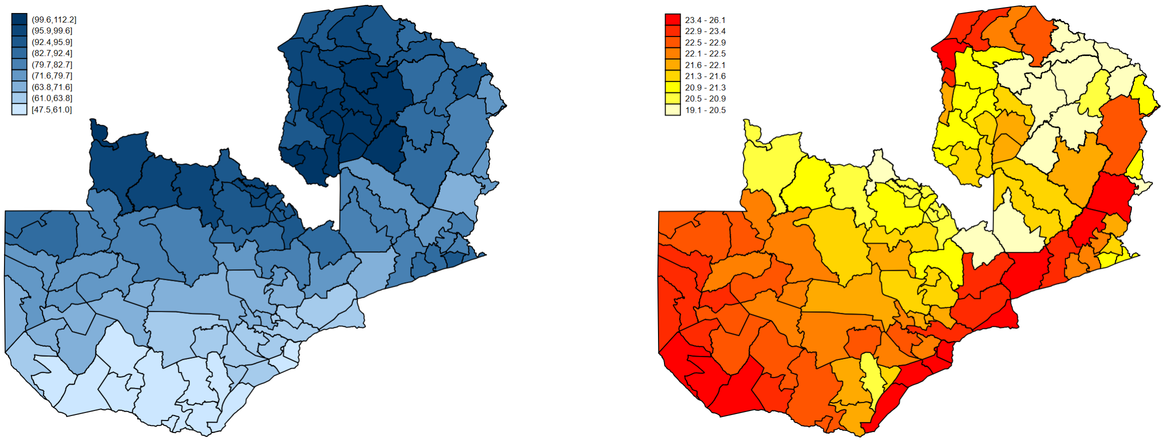
Source: authors' compilation.

3.3 Climate data

This study uses historical data on temperature (degrees Celsius) and precipitation (centimetres) for the climate-related variables from 1980 to 2022. The temperature data comes from the Modern-Era Retrospective Analysis from Research and Applications (MERRA-2) provided by NASA, offering daily mean temperatures measured at a 2-metre height.[8] The precipitation data comes from the Global Precipitation Climatology Centre (GPCC) of the National Oceanic and Atmospheric Administration (NOAA), offering monthly cumulative data based on global station data.[9] In both cases, the data was aggregated at the district level and later integrated into the individual-level data.

Figure 3: Rainfall and temperature in Zambia by district

(a) Rainfall (all districts) (b) Temperature (all districts)



Note: the figure displays the average rainfall (mm) and temperature (Celsius) in Zambia between 2014 and 2020, by district.

Source: authors' compilation.

4 Methodology

First, this paper aims to understand how climate shocks can affect different individual labour market outcomes in Zambia. To do so, we define climate shocks as the occurrence of extreme events in our precipitation and temperature distributions. First, we define the period, corresponding to the years 2017–21, equivalent to the LFS years available, and 2015 and 2022 for the LCMS. The only time information available in the survey is the quarter in which the interview took place. Next, we define an extreme event of temperature and precipitation if the temperature lies in the first or the last decile of the country distribution for this period (below the 10th percentile and above the 90th percentile).[10] Then, for each quarter of the year, we determine the number of months that the precipitation and temperature fall into these distribution bins for each survey year. Finally, we create an independent dummy variable if, in at least one month in the previous quarter of the year, the temperature or precipitation was extreme (among the distribution's tails).

The baseline empirical strategy to understand the contemporary impacts of precipitation and temperature shocks can be formalized in the fixed-effects model:

$$Y_{idt} = \beta_T Temperature_{d,t-1} + \beta_P Precipitation_{d,t-1} + X'_{idt}\beta X + \delta_d + \theta_t + \varepsilon_{idt} \tag{1}$$

The dependent variable Y_{idt} is a labour market measure of individual i, in district d, interviewed at year-quarter t. The outcomes can be: labour force participation, employment type, hours worked, and sector of work. The identification strategy takes advantage of variations in time and geographical distribution

[8] The data was represented in grids with a spatial resolution of 0.5×0.625 degrees.

[9] Data was represented in grids of 1×1degree resolution.

[10] Appendix A shows all the main results using another measure of extreme weather using precipitation and temperature below the 25th percentile and above the 75th percentile. The signs of the estimates are the same, and the magnitudes have only minor changes. Therefore, the results do not change.

of the climate shocks to correctly identify the parameter of interest β_T and β_P, representing extreme temperature and precipitation shocks. We also control for a set of demographic characteristics, including dummies for females, individuals living in rural areas, age bin groups, and education level. All regression includes district and year-quarter fixed effects as well as the sampling survey weights. Standard errors are clustered at the district level.

To capture the short- and medium-term effects of climate shocks on household food consumption in Zambia, we analyse the effects on consumption on average and at different points of the consumption distribution. To estimate the distributional effects of climate shocks, we follow a RIF-OLS approach, following Firpo et al. (2009). Short-term shocks are measured using the tail events in the past month's accumulated precipitation and mean temperature, while medium-term shocks use analogous measures for the past growing season (from November to April).

Our main specifications for capturing temperature and precipitation shocks follow the general form described in Equation 2:

$$Y_{idt} = \beta_T Temp_{dt} + \beta_P Prcp_{dt} + \theta_X X_{idt} + \mu_d + \varphi_y + \varphi_m + \varepsilon_{idt}, \tag{2}$$

The dependent variable Y_{idt} is a measure of food consumption per capita of household i, in district d, at the year-quarter t. When estimating the average effect of climate shocks, the dependent variable takes the form of the natural logarithm of per capita food consumption in the households. For the analysis of different deciles of consumption, the dependent variable takes the form of the re-centred influence function of log food consumption per capita at the appropriate point of the distribution. The explanatory variables of interest are represented by $Temp_{dt}$ and $Prcp_{dt}$, each containing a set of two dummies for low and high tails of the temperature and precipitation, respectively, leaving non-extreme weather as a comparison group. Short-term (past month) and medium-term (past growing season) climate shocks are estimated in separate regressions due to the fact that there might be an overlap between the two.

The identification strategy leverages variations in the time and district of the climate shocks to identify the parameters β_T and βP, representing the impacts of extreme precipitation and temperature events. X_{idt} is a vector of demographic and socioeconomic characteristics, which includes dummies for female heads of household and household heads who never attended school, a control for the head's highest education grade, and a squared polynomial for the head's age. Auxiliary analysis on social benefits as mitigating factors for shocks includes controls for households being recipients of benefits and interactions of being recipients with climate shocks. All regressions include district (μ_d), year (φ_y), and month-of-the-year (φ_m) fixed effects.

5 Results

5.1 The gendered effects on labour

Panel A of Table 4 shows that a past quarter with at least one month of extreme precipitation reduces the probability of being in the labour force by 3.3 p.p. Panel B shows that female individuals drive this result. Column (1) also shows that using the entire sample, the labour force participation increases by 3.6 p.p. when experiencing a past quarter with at least one month of extreme temperatures. However, Panel B shows a very important differential effect by gender. When experiencing an extreme temperature episode, the labour force participation of men increases by 9 p.p., while women's labour force participation decreases by 10.9 p.p. This is the same result as for episodes of drought, measured by the past quarter with at least one month of very low precipitation.

Table 4: Impact of weather shocks on employment outcomes (LFS)

	Labour force	Hours worked	Formal job	Informal job	Self-employed or HH consumption
	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline results					
Precipitation below p10 (past quarter)	0.019	0.464	–0.023	0.054**	–0.031
	(0.013)	(0.491)	(0.016)	(0.025)	(0.024)
Precipitation above p90 (past quarter)	–0.033*	–0.425	–0.015	–0.005	0.020
	(0.018)	(0.584)	(0.021)	(0.019)	(0.021)
Temperature above p90 (past quarter)	0.036*	1.199*	–0.018	0.042	–0.024
	(0.021)	(0.636)	(0.023)	(0.029)	(0.031)
Fit statistics					
Observations	64,530	81,341	30,217	30,217	30,217
R-squared	0.190	0.181	0.275	0.189	0.340
Panel B: Interaction with female					
Precipitation below p10 (past quarter)	0.064***	0.470	–0.013	0.061**	–0.048*
	(0.020)	(0.505)	(0.017)	(0.026)	(0.029)
Precipitation above p90 (past quarter)	0.017	–0.465	0.019	0.036*	–0.055***
	(0.018)	(0.590)	(0.022)	(0.021)	(0.020)
Temperature above p90 (past quarter)	0.090***	1.283**	0.026	0.031	–0.057
	(0.022)	(0.636)	(0.025)	(0.030)	(0.035)
Individual is female × precipitation below p10	–0.095***	–3.718**	–0.027	–0.017	0.044
	(0.025)	(1.677)	(0.028)	(0.016)	(0.040)
Individual is female × precipitation above p90	–0.102***	–8.676***	–0.073***	–0.092***	0.165***
	(0.013)	(1.833)	(0.019)	(0.013)	(0.018)
Individual is female × temperature above p90	–0.109***	–5.617***	–0.099***	0.034***	0.065**
	(0.017)	(1.905)	(0.023)	(0.012)	(0.031)
Fit statistics					
Observations	64,530	81,341	30,217	30,217	30,217
R-squared	0.186	0.181	0.274	0.188	0.333
Fixed effects					
Year-quarter	Yes	Yes	Yes	Yes	Yes
District	Yes	Yes	Yes	Yes	Yes

Note: this table shows the results of the impact of experiencing at least one month of an extreme weather event in the past quarter on the main employment outcomes according to Equation 1. Column (1) is an indicator of being in the labour force. Column (2) shows the number of hours in the main job. Column (3) is an indicator of whether the individual has a formal job contract. Column (4) is an indicator of whether the individual does not have a formal job contract. Column (5) is an indicator of whether the individual works for self-consumption only. Controls include age, household size, and gender. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

Columns 2–4 provide additional evidence of what might have been happening when climate shocks hit. The gender differences are striking. When experiencing a climate shock, men have a higher probability of working in the informal sector, while women have a higher probability of enrolling in self-employed activities or working in activities focusing on the household's own consumption. For instance, when experiencing a past quarter with at least one month of extreme rainfall, women have a 16.5 p.p. higher probability of working for self-consumption, are 7.3 p.p. less likely to have a formal job, and 9.2 p.p. less likely to have an informal job. Any measure of climate shock negatively impacts women's probability of having a formal job. This result highlights women's vulnerability when having a formal job acts as a mechanism for cushioning income losses during crises (Lastunen et al. 2021).

Table 5 shows that climate shocks affect sectoral allocation. While Panel A doesn't show much evidence for all individuals, Panel B shows, again, important gendered effects. A past quarter with at least one month of extreme climate shock increases the probability of men working in manufacturing and decreases their probability of working in the services sector. The effects on agriculture are null. However, women experiencing climate shocks in the past quarter have a higher probability of working in services and a lower probability of working in the manufacturing and agriculture sectors.

Unfortunately, the lack of panel datasets does not allow us to explore the mechanism that may explain these patterns. Therefore, our contribution is to present the pattern and argue about the need for future research to explain why men's and women's labour are affected in different ways in Zambia.

Table 5: Impact of weather shocks on employment structure (LFS)

	Manufacturing	Agriculture	Services
	(1)	(2)	(3)
Panel A: Baseline results			
Precipitation below p10 (past quarter)	0.010	0.014	–0.021
	(0.010)	(0.020)	(0.016)
Precipitation above p90 (past quarter)	–0.015	–0.006	0.009
	(0.014)	(0.022)	(0.020)
Temperature above p90 (past quarter)	–0.019	0.021	0.021
	(0.016)	(0.029)	(0.025)
Fit statistics			
Observations	24,972	24,972	24,972
R-squared	0.055	0.303	0.177
Panel B: Interaction with female			
Precipitation below p10 (past quarter)	0.036**	0.023	–0.054***
	(0.017)	(0.020)	(0.019)
Precipitation above p90 (past quarter)	0.021	0.004	–0.050**
	(0.015)	(0.021)	(0.019)
Temperature above p90 (past quarter)	0.010	0.038	–0.035
	(0.021)	(0.029)	(0.027)
Individual is female × precipitation below p10	–0.074**	–0.026*	0.094***
	(0.029)	(0.014)	(0.022)
Individual is female × precipitation above p90	–0.091***	–0.028**	0.151***
	(0.018)	(0.014)	(0.020)
Individual is female × temperature above p90	–0.075***	–0.047***	0.146***
	(0.023)	(0.014)	(0.018)
Fit statistics			
Observations	24,972	24,972	24,972
R-squared	0.048	0.303	0.168
Fixed effects			
Year-quarter	Yes	Yes	Yes
District	Yes	Yes	Yes

Note: this table shows the results of the impact of experiencing at least one month of an extreme weather event in the past quarter on the probability of working in manufacturing (column 1), agriculture (column 2), or services (column 3) according to Equation 1. Controls include age, household size, and gender. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

5.2 The effects on welfare

In this subsection, we turn to study the impacts of climate shocks on household welfare measured by consumption reported in the LCMS. Consumption is a better measure of welfare in low-income countries as it is less volatile than income (Meyer and Sullivan 2003). In situations of climate shocks in a country highly dependent on agricultural production and with a lack of skills, insurance markets, and machinery, food prices may be extremely volatile. Therefore, shocks may raise food prices significantly, and even if the families have mechanisms to cushion income losses, it may not be enough to stabilize the level of consumption. Therefore, we turn to the analysis of the LCMS.

Table 6 presents the average effects of medium- and short-term rainfall and temperature shocks on household food consumption per capita. Columns (1) and (2) show that an extremely dry growing season (below 10th percentile in the sample, 361 mm) reduces average food consumption per capita by around 20% at the time of the interview, compared to households that faced non-extreme weather in the growing season. Interestingly, extremely high levels of rain in the growing season (above the 90th percentile in the sample, 1,195 mm) show positive point estimates for impacts on food consumption but are statistically insignificant. However, the threshold for high precipitation in our sample might not be truly representative of an extreme since it is around the expected annual rainfall in a humid subtropical climate zone—the climate in portions of Zambia. Extremes of average temperature in the growing season did not show significant effects on food consumption and had virtually no impact on the estimates of the effects of precipitation shocks.

Table 6: Impact of weather shocks on HH food consumption value per capita of the poorest households

	Log HH food Consumption pc			
	(1)	(2)	(3)	(4)
Growing season rain above p90	0.1423	0.1339		
	(0.0986)	(0.1000)		
Growing season temp. above p90		0.0965		
		(0.2423)		
Past month rain above p90			–0.1486**	–0.1641***
			(0.0597)	(0.0572)
Past month rain below p10			–0.1243*	–0.1410*
			(0.0737)	(0.0777)
Past month temperature above p90				–0.2082**
				(0.0877)
Fixed effects				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Observations	19,682	19,682	19,682	19,682
R^2	0.29003	0.29031	0.28998	0.29199
Within R^2	0.11124	0.11159	0.11117	0.11369

Note: this table shows the results of experiencing an extreme weather event in the previous growing season according to Equation 2. The dependent variable is the logarithm of the household food consumption per capita. It includes the food consumption produced by the household. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

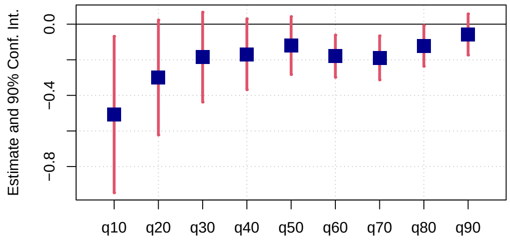
Column (4) in Table 6 suggests that both extremely low (below 10th percentile in the sample, exactly 0 mm) and high (above 90th percentile in the sample, 148 mm) past month rainfall negatively impact per capita food consumption by approximately 14% and 16%. Extremely high past month temperatures (above 90th percentile in the sample, 23°C) are related to a 20% reduction in food consumption per capita relative to the food consumption in households that faced non-extreme weather. Results in column (3), where past month temperature extremes are not included, are qualitatively the same as column (4) for rainfall.

The results from Table 6 are in line with the suggestive evidence from the 2023 In-Depth Vulnerability and Needs Assessment (IVA). The reduction in the value of food consumption per capita in response to climate shocks is consistent with the increases in rates for hunger measures and limited food expenses and consumption among households impacted by drought or floods.

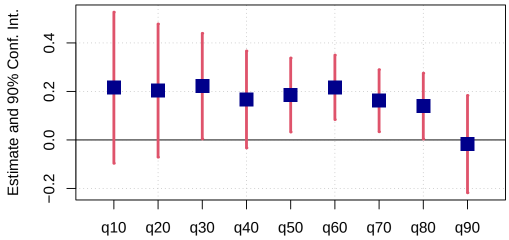
Figure 4 presents the impacts of short- and medium-term precipitation shocks at different points of the food consumption distribution. In Figure 4(a) we see that the negative effects of an extremely dry growing season are more pronounced at the very bottom of the distribution, being around 50% reduction in food consumption value per capita for the first decile. Negative effects are also significant at around the 60th and 70th percentiles, representing a 20% decrease in food consumption per capita for households at that area of the distribution.

Figure 4: Unconditional quantiles analysis: impact of weather shocks on HH food consumption value per capita

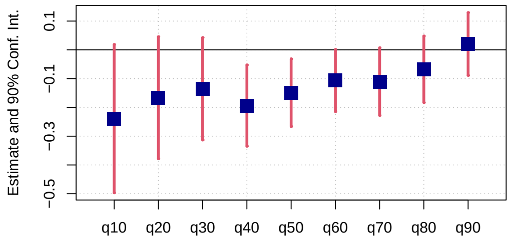
(a) Growing season rain below p10



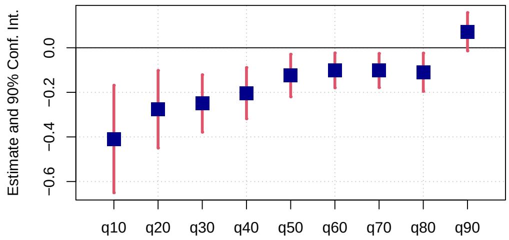
(b) Growing season rain above p90



(c) Past month rain below p10



(d) Past month rain above p90



Note: the figure displays estimated coefficients of Equation 2 for the main climate shocks measures on the food consumption value per capita per decile of the consumption distribution. The blue dots are the estimated coefficients and the red bars are the 90% confidence interval.

Source: authors' calculations.

From Figure 4(b), it's possible to observe mostly positive effects of high growing season rainfall on food consumption, in line with the average effect result. Point estimates imply an increase in consumption close to 20% for all except the top decile, which presents no change induced by high growing season rainfall. Positive effects are significant, at a 90% confidence level, at the 30th percentile, and from the median until the 80th percentile.

Figure 4(c) and (d) show the distributional impacts of short-term precipitation shocks measured by extreme low and extreme high rainfall in the past month. Extreme low precipitation in the past month has a significant negative impact of approximately 20% and 15% in the 40th percentile and at the median of the distribution of food consumption per capita. Point estimates of the impacts of very low precipitation suggest a decreasing trend (in magnitude) from the bottom deciles up to the top of the distribution, which is unaffected.

Extreme high levels of rainfall in the past month have statistically significant negative impacts on food consumption in all points of the distribution except at the very top, the 90th percentile. At the very bottom of the distribution there is a 40% reduction on food consumption per capita as a response to high rainfall shock; this shrinks to a 20% reduction at the 40th percentile, and remains at around a 10% reduction from the median until the 80th percentile. The results from Figure 4(c) and (d) suggest a case where households are continuously more protected from precipitation shocks as their welfare increases in other dimensions—namely, food consumption per capita.

Finally, Table 7 shows the gendered effects of climate shocks on consumption. We interact with an indicator equal to 1 if the household head is a woman. The table shows some evidence that households with a female head observe a higher negative impact of climate shocks on consumption when the temperature in the growing season is above p90.

Table 7: The gendered effects of climate shocks on food consumption and expenses

Dependent variables:	Log HH food consumption pc	Log HH food expenses pc
Model:	(1)	(3)
Variables		
Growing season temp. above p90	0.1500	0.1589
	(0.2505)	(0.2846)
Growing season rain above p90	0.1312	0.5553**
	(0.1009)	(0.2195)
Growing season rain below p10	–0.1905	–0.0454
	(0.1186)	(0.1482)
Female household head × growing season temp. above p90	–0.1817***	–0.2241***
	(0.0606)	(0.0708)
Female household head × growing season rain above p90	0.0191	–0.0081
	(0.0645)	(0.0711)
Female household head × growing season rain below p10	–0.0237	0.0576
	(0.0672)	(0.0588)
Fixed effects		
District	Yes	Yes
Year	Yes	Yes
Month	Yes	Yes
Fit statistics		
Observations	19,682	19,621
R^2	0.29091	0.41888
Within R^2	0.11234	0.16391

Note: this table shows the results of experiencing an extreme weather event in the previous growing season according to Equation 2. It adds to Table 6 by showing the heterogeneous impacts of female-headed households. The dependent variable in column (1) is the logarithm of the household food consumption per capita, and in column (2) is the logarithm of the household food expenses per capita. It does not include the food consumption produced by the household. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

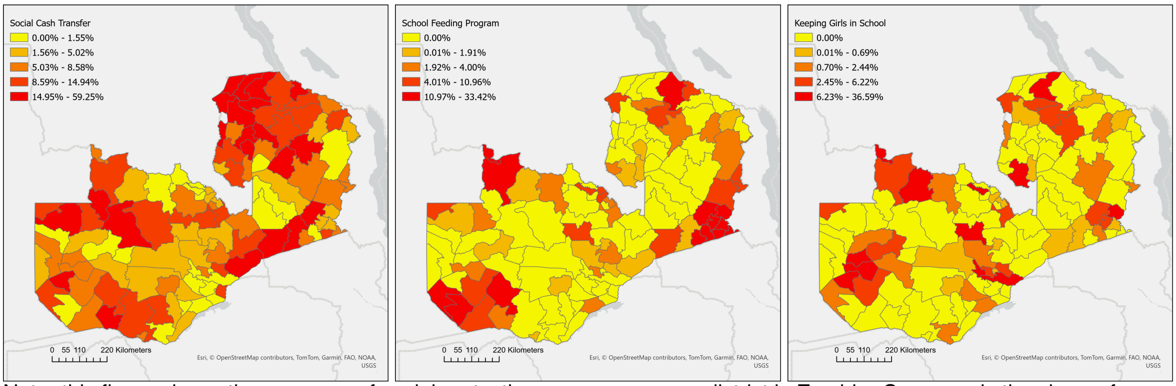
Source: authors' calculations.

5.3 Do social protection policies cushion welfare losses?

Social programmes that are not specifically focused on extreme weather events can also provide insurance against climate disasters (Deryugina 2017). As these shocks negatively impact local economies, more households might be placed under the conditions to be eligible for social programmes. Furthermore, the occurrence of natural disasters can increase the salience of socioeconomic conditions in impacted areas, and in the presence of limited state capacity, policy-makers might relocate funds to these impacted regions. However, this is a description of an ideal scenario with sufficient fiscal space to increase the covered population, which is not the case in most low-income countries, including Zambia (Banda et al. 2024; Hirvonen et al. 2024). Figure 5 shows the coverage of each social protection programme per district using the LCMS.

Appendix Tables A6 and A7 show some distributional statistics of social protection in Zambia using the LFS. Overall, 7% of the rural population and 2% of the urban population said they receive some kind of social protection programme. Of the beneficiaries, 54% receive the Fertilizer Input Support programme, 37% receive the Social Cash Transfer programme, and 19% receive the School Feeding Program. It's also possible to observe that most of the beneficiaries are in Lusaka and Copperbelt provinces.

Figure 5: Coverage of social programmes, LMCS 2022
(a) Social Cash Transfer (b) School Feeding Program (c) Keeping Girls in School



Note: this figure shows the coverage of social protection programmes per district in Zambia. Coverage is the share of households receiving the social programme divided by the total population.

Source: authors' calculations.

Using data from the 2022 LCMS, which includes household status on three separate government programmes, we analyse if extreme weather is associated with social programmes' coverage and if they mitigate the impacts of weather shocks. Due to the fact that we are limited to the 2022 survey, we are only able to analyse the past month's weather shocks due to a lack of variation in past growing season weather at the district level. Variation on past month shocks is also limited, encompassing, at most, two different months per district. For this reason, we focus only on extremely low rainfall and temperature shocks during this exercise. Considering all limitations, we find the present evidence in this analysis to be only suggestive. Figure A2 adds by showing that there is no clear evidence between the share of the population covered by social protection programmes and the district being more warm or wet.

We look at the coverage and mitigating effect of two government programmes: (1) the Social Cash Transfer programme and (2) the School Feeding Program. In 2022, only the Social Cash Transfer covered all districts of Zambia, with the School Feeding Program being present in 39 districts. For a household to receive Social Cash Transfer, it needs to satisfy three criteria: residency at the locality for six months or more, household meeting an incapacitation and destitution condition, and passing a formal welfare assessment.[11] The selection of districts to be covered by the School Feeding Program is driven by a need-based set of criteria: high dropout, low net enrolment and attendance rates, high rate of underweight, and extreme poverty.

Table 8 shows a positive relation between low rainfall in the past month and households receiving any social programme.[12] However, there was no significant relation between weather shocks and participation in the School Feeding Program or receiving Social Cash Transfer. Since participation in the programmes is not automatic, it is unlikely that weather events will impact coverage in the short term. This is consistent with the lack of significant effects for the School Feeding Program and Social Cash Transfer.

Table 9 presents our estimates for how government programs can interact with weather shocks and their effects on households' food consumption. We do not find statistically significant evidence of short-term weather shocks having effects mitigated by any of the social programmes studied. However, Appendix

[11] To meet incapacitation and destitution status, the household needs to satisfy one of the following conditions: (1) female-headed household with three children or more; (2) household headed by a child aged 18 years or below; (3) household with a person who is chronically ill, on palliative care, or with severe disability (with certification from a government health facility); (4) a household with an elderly member aged 65 years or above (with proper documentation).

[12] This also includes recipients of other programmes such as Food Security Pack, Input Fertilizers, and Keeping Girls in School. However, we don't have disaggregated information for these other programmes.

Table A2 shows the impact of climate shocks on the income level of the poorest households in Zambia (bottom tercile) using the LFS. The results suggest a 10% negative impact on income when experiencing a past quarter with at least one month with precipitation above the 90 percentile. Additionally, this table shows that receiving any social benefit—Social Cash Transfer or the Input Fertilizer programme—offsets the negative impact. The results are the same for the sample with only female-headed households.

Table 8: Likelihood of receiving social programmes, 2022

Dependent Variables:	Any social programme	Social Cash Transfer	School Feeding Program
Model:	(1)	(2)	(3)
Variables			
Past month temperature below p10	–0.0102	0.0139	–0.0223
	(0.0223)	(0.0121)	(0.0174)
Past month rain below p10	0.0544**	0.0068	0.0321
	(0.0209)	(0.0169)	(0.0305)
Fixed effects			
District	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	8,028	8,028	8,028
R^2	0.14543	0.18912	0.13694
Within R^2	0.06247	0.10998	0.00764

Note: this table shows the results of experiencing an extreme weather event in the past month according to Equation 2. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

Table 9: Food consumption and social programmes, 2022

	Log HH food consumption pc		
	(1)	(2)	(3)
Past month rain below p10	–0.0930	–0.0790	–0.0772
	(0.0927)	(0.0911)	(0.0880)
Social Cash Transfer × past month rain below p10	0.1882		
	(0.1461)		
Keeping Girls in School × past month rain below p10		0.0670	
		(0.2919)	
School Feeding Program × past month rain below p10			–0.3831
			(0.2751)
Fixed effects			
District	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	8,028	8,028	8,028
R^2	0.27946	0.28009	0.28086
Within R^2	0.08837	0.08916	0.09013

Note: this table shows the results of experiencing an extreme weather event in the previous growing season according to Equation 2. The dependent variable is the logarithm of the household food consumption per capita. It includes the food consumption produced by the household. This table shows the potential mitigation effects of social protection policies. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

6 Conclusion

This paper provides a comprehensive analysis of the gendered impacts of climate shocks on labour outcomes, income, and consumption in Zambia, a low-income country facing increasing climate variability and severe weather events. Our findings reveal that extreme precipitation and temperature shocks significantly reduce labour force participation, with pronounced differences between men and women. While men are more likely to remain in the labour force during extreme drought, albeit in informal sectors, women are disproportionately driven into self-employment, particularly in service industries, and away from formal and informal employment. These patterns highlight the compounding vulnerabilities faced by women in a labour market already characterized by low participation and high informality. In terms of well-being, our analysis shows that extreme climate events, such as droughts and floods, substantially reduce household income and food consumption, with the poorest households bearing the brunt of these shocks.

This paper underscores the urgent need for gender-sensitive policies that address the disproportionate impacts of climate shocks on women, especially in low-income countries. Strengthening social protection programmes, improving access to adaptive resources for women, and addressing food price volatility are critical steps towards building resilience against future climate risks. The findings also point to the importance of improving data availability in low-income countries to better understand and address the multifaceted impacts of climate change on labour markets and well-being. The lack of panel data in Zambia limits a deeper understanding of how individuals and households are impacted by shocks.

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Appendix A

Table A1: Variable of interest definitions (LFS)

Variable name	Type	Description
1. Labour force	Dichotomical	Equals 1 if an individual, aged 15 or older, is employed or actively seeking a job at the time of the survey.
2. Formal sector	Dichotomical	Equals 1 if an employed individual is in the formal sector (e.g. has medical insurance, a formal contract, etc.).
3. Informal sector	Dichotomical	Equals 1 if an employed individual does not meet the criteria to be considered in a formal sector job.
4. Self-employed or household consumption	Dichotomical	Equals 1 if an individual is self-employed or works on farming, rearing animals, or fishing and the production is used for family consumption.
5. Manufacture	Dichotomical	Equals 1 if an individual can be categorized as a plant and machine operator or assembler.
6. Services	Dichotomical	Equals 1 if an individual can be categorized as a services and sales worker.
7. Agriculture	Dichotomical	Equals 1 if an individual works as an agricultural, forestry, or fishery worker.
8. Hours worked (main)	Continuous	Total number of hours dedicated to the main activity in a week.
9. Hours worked (secondary)	Continuous	Total number of hours dedicated to the secondary activity in a week.
10. Receiving SP	Dichotomical	Equals 1 if at least someone in the household is receiving at least one social benefit from a list of seven programmes.

Source: authors' compilation.

Table A2: The effects of climate shocks on household income per capita

	All HH			Female-headed HH		
	Any social benefit	Social Cash Transfer	Input Fertilizer	Any social benefit	Social Cash Transfer	Input Fertilizer
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation below p10 (past quarter)	0.022	0.024	0.023	0.010	0.012	0.011
	(0.022)	(0.022)	(0.022)	(0.030)	(0.030)	(0.030)
Precipitation above p90 (past quarter)	–0.099***	–0.097***	–0.095***	0.044	0.047	0.048
	(0.029)	(0.030)	(0.029)	(0.035)	(0.035)	(0.035)
Temperature above p90 (past quarter)	–0.055	–0.055	–0.054	0.035	0.036	0.036
	(0.040)	(0.040)	(0.040)	(0.038)	(0.038)	(0.038)
HH receiving × precipitation below p10	0.028	0.017	0.034	–0.008	0.011	0.027
	(0.032)	(0.032)	(0.037)	(0.039)	(0.042)	(0.052)
HH receiving × precipitation above p90	0.114***	0.214***	0.075***	0.111***	0.175***	0.139**
	(0.022)	(0.042)	(0.026)	(0.034)	(0.042)	(0.058)
HH receiving × temperature above p90	0.047	0.122***	0.060	0.029	0.070	0.060
	(0.031)	(0.034)	(0.036)	(0.042)	(0.060)	(0.071)
Fit statistics						
Observations	93,165	93,165	93,165	24,142	24,142	24,142
R-squared	0.224	0.223	0.224	0.212	0.212	0.211

Note: this table shows the results of the impact of experiencing at least one month of an extreme weather event in the past quarter on incomes according to Equation 1. Controls include age, household size, and gender. Standard errors are clustered at the district level. All regressions include district and year-quarter fixed effects. Significance codes: *** 0.01, ** 0.05, * 0.1.

Source: authors' calculations.

Table A3: Sample distribution by survey year (LFS 2017–21)

	(1) Total	(2) 2017	(3) 2018	(4) 2019	(5) 2020	(6) 2021
Area of residence						
Rural	57.27	57.91	58.02	57.25	56.74	57.06
	(38,092,306)	(9,129,912)	(1,655,044)	(9,839,965)	(10,050,016)	(7,417,369)
Urban	42.73	42.09	41.98	42.75	43.26	42.94
	(28,425,274)	(6,635,527)	(1,197,581)	(7,348,814)	(7,661,637)	(5,581,715)
Sex						
Male	49.56	48.38	72.58	48.65	48.09	49.15
	(32,968,564)	(7,627,972)	(2,070,457)	(8,363,126)	(8,517,561)	(6,389,449)
Female	50.44	51.62	27.42	51.35	51.91	50.85
	(33,549,016)	(8,137,467)	(782,169)	(8,825,653)	(9,194,093)	(6,609,634)
Observations	160,701	43,862	8,258	33,654	44,952	29,975

Source: authors' calculations.

Table A4: Sample distribution by province (LFS 2017–21)

	(1) Total	(2) Rural	(3) Urban	(4) Male	(5) Female
Provinces					
Central	9.37	12.43	5.27	9.44	9.30
	(6,232,859)	(4,733,690)	(1,499,169)	(3,112,886)	(3,119,973)
Copperbelt	15.10	4.48	29.34	15.17	15.04
	(10,045,035)	(1,705,719)	(8,339,316)	(5,000,926)	(5,044,109)
Eastern	12.07	18.50	3.46	12.16	11.98
	(8,030,085)	(7,045,261)	(984,824)	(4,010,410)	(4,019,675)
Luapula	7.12	9.34	4.14	7.07	7.16
	(4,734,165)	(3,556,011)	(1,178,153)	(2,331,595)	(2,402,570)
Lusaka	19.12	4.55	38.66	19.06	19.19
	(12,721,194)	(1,732,659)	(10,988,536)	(6,283,431)	(6,437,763)
Muchinga	5.85	7.37	3.82	5.95	5.76
	(3,893,256)	(2,807,649)	(1,085,607)	(1,960,894)	(1,932,361)
Northern	8.09	11.71	3.24	8.19	7.99
	(5,381,227)	(4,460,566)	(920,661)	(2,699,289)	(2,681,937)
North Western	4.91	6.01	3.43	4.88	4.94
	(3,266,569)	(2,290,450)	(976,119)	(1,610,158)	(1,656,410)
Southern	12.19	16.01	7.08	12.09	12.30
	(8,111,312)	(6,097,776)	(2,013,536)	(3,984,434)	(4,126,878)
Western	6.17	9.61	1.55	5.99	6.34
	(4,101,879)	(3,662,525)	(439,354)	(1,974,539)	(2,127,340)
Observations	160,701	104,016	56,685	79,608	81,093

Source: authors' calculations.

Table A5: Sample distribution by labour force participation (LFS 2017–21)

	(1) Total	(2) Rural	(3) Urban	(4) Male	(5) Female
Working-age population (15+)	100.00	100.00	100.00	100.00	100.00
	(37,195,922)	(20,160,035)	(1,703,5887)	(18,382,208)	(18,813,714)
Labour force participation					
In labour force	32.50	22.42	44.43	41.25	23.95
	(12,087,443)	(4,519,136)	(7,568,307)	(7,581,994)	(4,505,449)
Unemployed	4.52	3.14	6.14	5.13	3.92
	(1,679,991)	(633,499)	(1,046,493)	(942,838)	(737,153)
Outside of labour force	62.99	74.44	49.43	53.62	72.13
	(23,428,488)	(15,007,401)	(8,421,087)	(9,857,376)	(13,571,112)
Observations	89,967	55,524	34,443	44,581	45,386

Source: authors' calculations.

Table A6: Households beneficiary of social protection programs (LFS 2017–21)

	All sample			Only SP recipients		
	(1) Total	(2) Rural	(3) Urban	(4) Total	(5) Rural	(6) Urban
Total number of HH member from SP db	0.10	0.16	0.04	1.26	1.27	1.22
	(1,310,604)	(1,097,533)	(213,071)	(15,776,484)	(1,097,533)	(213,071)
Someone in the HH is beneficiary of at least one social benefit programme	0.08	0.13	0.03	1.00	1.00	1.00
	(1,041,199)	(866,329)	(174,870)	(12,533,499)	(866,329)	(174,870)
Social protection type HH is beneficiary of Social Cash Transfer programme	0.03	0.05	0.01	0.37	0.36	0.38
	(381,794)	(314,574)	(67,220)	(4,595,871)	(314,574)	(67,220)
HH is beneficiary of Public Welfare assistance	0.00	0.00	0.00	0.03	0.03	0.05
	(32,804)	(23,596)	(9,208)	(394,885)	(23,596)	(9,208)
HH is beneficiary of Fertiliser Input Support programme	0.04	0.07	0.01	0.54	0.57	0.40
	(563,917)	(494,081)	(69,835)	(6,788,182)	(494,081)	(69,835)
HH is beneficiary of Food Security Pack	0.00	0.01	0.00	0.05	0.05	0.06
	(49,075)	(39,117)	(9,958)	(590,739)	(39,117)	(9,958)
HH is beneficiary of School Feeding Program	0.02	0.03	0.00	0.19	0.20	0.14
	(201,948)	(177,129)	(24,818)	(2,430,958)	(177,129)	(24,818)
HH is beneficiary of Women Empowerment programme	0.00	0.00	0.00	0.04	0.03	0.09
	(43,121)	(27,038)	(16,083)	(519,074)	(27,038)	(16,083)
HH is beneficiary of OVC bursary	0.00	0.00	0.00	0.04	0.03	0.09
	(37,946)	(21,998)	(15,947)	(456,775)	(21,998)	(15,947)
Observations	29,528	18,220	11,308	2,903	2,438	465

Source: authors' calculations.

Table A7: Social protection coverage by demographic characteristics (LFS 2017–21)

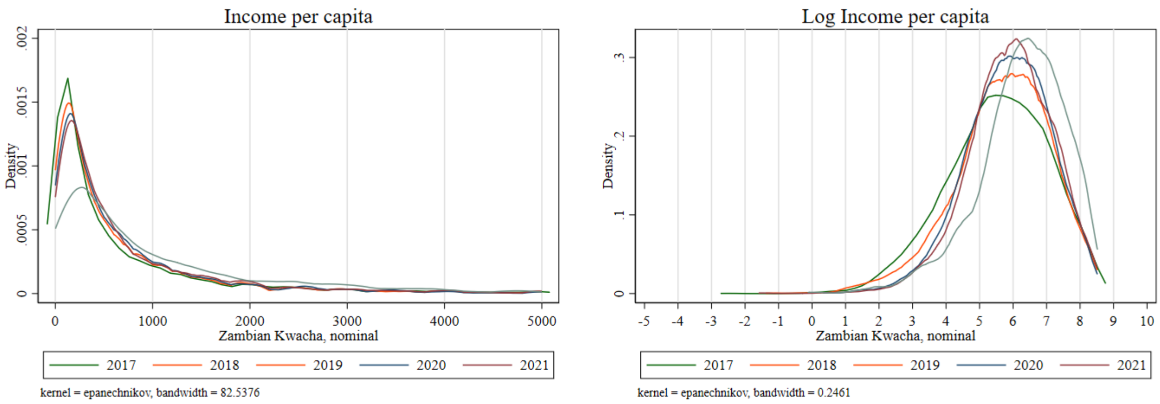
	(1) Total	(2) Non-SP recipient	(3) SP Recipient
hhsize	4.93	4.93	4.85
	(61,737,754)	(56,616,509)	(5,121,245)
Vulnerable population:			
max_above60	0.15	0.13	0.29
	(1,823,565)	(1,518,633)	(304,933)
max_below12	0.59	0.62	0.27
	(7,440,706)	(7,156,866)	(283,840)
Province			
Central	0.09	0.09	0.05
	(1,090,006)	(1,036,256)	(53,750)
Copperbelt	0.15	0.16	0.08
	(1,938,217)	(1,856,829)	(81,388)
Eastern	0.12	0.11	0.23
	(1,526,832)	(1,279,477)	(247,355)
Luapula	0.07	0.07	0.11
	(913,097)	(799,894)	(113,203)
Lusaka	0.21	0.23	0.03
	(2,646,555)	(2,609,607)	(36,947)
Muchinga	0.05	0.05	0.09
	(653,573)	(560,837)	(92,735)
Northern	0.07	0.07	0.12
	(887,858)	(764,528)	(123,330)
North Western	0.05	0.05	0.06
	(592,802)	(526,476)	(66,325)
Southern	0.13	0.12	0.16
	(1,577,046)	(1,406,741)	(170,305)
Western	0.06	0.06	0.07
	(703,004)	(632,344)	(70,660)
Observations	29,529	26,590	2,939

Source: authors' calculations.

Figure A1: Distribution of income per capita (LFS 2017–21)

(a) August-October

(b) November-January

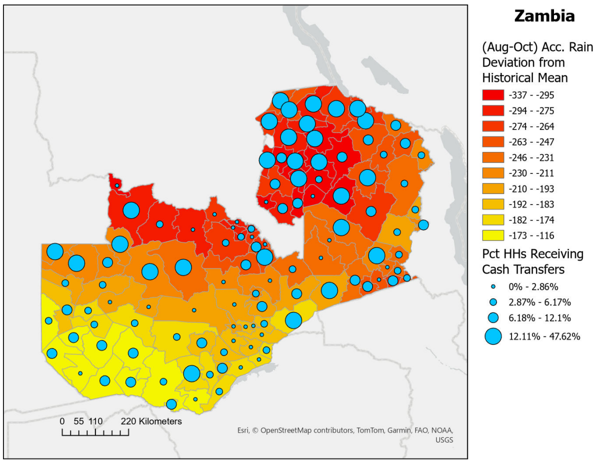


Note: this figure presents the distribution (a) of food consumption per capita by LCMS survey year, and the cumulative distribution of consumption per capita (b) by LCMS survey year.

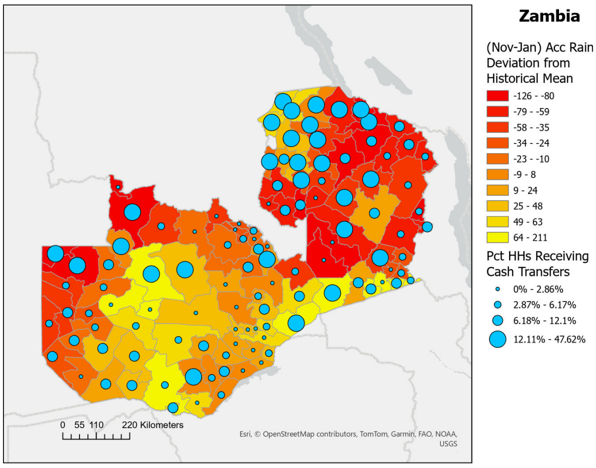
Source: authors' compilation.

Figure A2: Precipitation and share of Social Cash Transfer beneficiaries

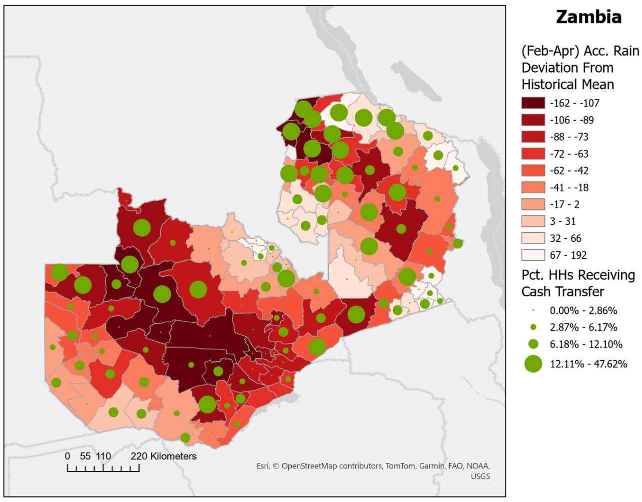
(a) August-October



(b) November-January



(c) February-August



Note: this figure presents each district's percentage of households receiving cash transfer in the LMCS 2022 over the district's precipitation deviation from the historical mean for three different quarters before the survey.

Source: authors' compilation.