Shock-Responsive Social Protection in Climate Disasters: Evidence from Malawi

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Abstract

Climate-related shocks disproportionately affect low-income households in developing countries, yet evidence remains limited on whether social protection systems can be effectively scaled up to support households in the aftermath of climate disasters. This paper evaluates Malawi's Scalable Program, a government-led shock-responsive social protection mechanism that uses existing cash transfer infrastructure to deliver emergency support after climate-related shocks. We study the impact of the program's transfers disbursed in response to the severe 2023/24 El Niño drought, drawing on three rounds of panel data from 1,100 households. Using a difference-in-differences estimator combined with entropy balancing, we estimate the effects of the program on food security, coping behavior, savings, agricultural adaptation, and perceptions of government support. The results show that the program reduced negative food-related coping strategies in the short term, two weeks after disbursement. Three months after payment, the immediate food security effects had faded, but beneficiary households were more likely to rely on savings and to adopt drought-resilient agricultural practices. Beneficiaries also reported significantly higher perceptions of government support during the drought, an effect that persisted three months after receiving the transfer. These findings highlight the potential of government-led shock-responsive social protection to provide immediate relief while also supporting some resilience-related channels in response to slow-onset climate disasters.

Keywords: social protection, climate change, droughts

JEL: D12 - Consumer Economics: Empirical Analysis, O12 - Microeconomic Analyses of Economic Development, Q54 - Climate; Natural Disasters; Global Warming

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Introduction

In the context of accelerating climate change, more than half the global population — approximately 4.5 billion people — faces a high risk of experiencing extreme weather events, such as a flood, drought, cyclone, or heatwave (Doan et al., 2023). Climate-related shocks disproportionately affect low-income households, whose livelihoods are more exposed to climatic hazards and whose limited resources constrain their ability to cope with associated losses (IPCC, 2023; Rodell & Li, 2023; Rohde, 2023). Compounding this vulnerability, aggregate shocks undermine informal risk-sharing systems by affecting large numbers of households simultaneously, further eroding the protective mechanisms available to the poorest (Banerjee et al., 2024). As a result, there is a growing global policy debate on how to design effective mechanisms to mitigate the immediate consequences of such shocks for low-income populations (Banerjee et al., 2024). This study contributes to this debate by expanding the limited empirical evidence on the effects of social protection programs deployed in response to a climate shock in a context of acute poverty, drawing on the case of Malawi.

Governments and humanitarian organizations often provide time-bound support to households affected by shocks (Pople et al., 2026). This support can take different forms such as food aid or basic services, but increasingly, support is provided in the form of cash transfers (Matata et al., 2023; Pople et al., 2026). In addition, governments are progressively leveraging household registries and payment systems used for regular social protection programs to channel additional time-bound cash support to low-income households affected by disasters. This is often referred to as shock-responsive social protection, which is understood as the adaptation of routine social protection programs and systems to cope with changes in context and demand following aggregate shocks (Strupat et al., 2025). In 2020 for example, governments in around 212 countries used 1,179 social protection measures in response to the Covid-19 pandemic, with half taking the form of cash transfers (Gentilini et al., 2020).

Despite their widespread use, evidence on the effectiveness of cash transfers delivered specifically in response to crisis or extreme weather events to improve household resilience remains scarce (Asfaw et al., 2017; Pople et al., 2026). Research has focused on studying the impact of regular cash transfer programs on household ability to withstand and recover from shocks. Considerable evidence has accumulated to show that regular cash transfer programs are an effective tool for protecting household consumption during adverse events (Abay et al., 2023; Adhvaryu et al., 2023; Asfaw et al., 2017; De Janvry et al., 2006; Jensen et al., 2017; Knippenberg & Hoddinott, 2019; Macours et al., 2022; Matata et al., 2023). To our knowledge, there are only three papers that explore the household resilience impact of cash transfers delivered specifically in response to disasters. Two investigate humanitarian cash transfers provided to households affected by floods in Bangladesh (Gros et al., 2019; Pople et al., 2026). The third one examines the effects of a nationwide shock-responsive social cash transfer scheme during the COVID-19 pandemic in Kenya (Strupat et al., 2025). They find that households that received a transfer reported significantly higher food consumption and wellbeing measured by different indicators.

The objective of this study is to assess whether shock-responsive social protection can help protect low-income households against climate shocks and provide evidence on the channels through which it may strengthen household resilience. To do this, we evaluate Malawi's Scalable Program, a government-led mechanism that uses existing social protection systems to deliver additional cash support after climate-related disasters. We focus on the 2023/24 El Niño drought, a slow-onset climate disaster that severely affected food production and household food security in Malawi. Malawi is one of the poorest countries in the world, with agriculture, mostly rain-fed, being the main source of income for around 50% of households (World Bank Group, 2022). The El Niño drought in 2023/24 led to a 50 percent loss in staple food

production (against the five-year average) and left about 25 percent of the population facing acute hunger by March 2024 (FEWS NET, 2024).

Our study uses a household fixed effects difference-in-differences approach combined with entropy balancing to examine the impact of the Scalable Program on households' food security and resilience after the drought. In particular, the study considers the impact that the program had on food insecurity, coping strategies, financial behavior, agricultural practices, and perceptions of government support. We use three rounds of household panel data collected by the World Bank in 2024. Data was collected in six districts from 1,100 respondents, 36% of whom received payments through the Scalable Program. The first round of data was collected before the program payments were delivered to beneficiaries and two rounds were collected afterwards.

We find that the program affected households through different short- and medium-term channels. In the short term, two weeks after payment, beneficiaries reduced their reliance on negative food-related coping strategies, including reducing meal size or frequency, limiting adult food consumption to prioritize children, and borrowing money to buy food. Three months after payment, the immediate food security effects had faded, but beneficiary households were more likely to rely on savings and to adopt drought-resilient agricultural practices. We also find that beneficiaries reported higher perceptions of government support during the drought, an effect that persisted three months after receiving the transfer.

This paper contributes to the emerging literature on shock-responsive and adaptive social protection in three main ways. First, it provides evidence on a government-led social protection program implemented in response to a climate-related disaster. This differs from previous studies that mainly focus on humanitarian cash transfers or on social protection responses to non-climate shocks. Second, it studies the response to a slow-onset disaster, the 2023/24 El Niño drought in Malawi, adding evidence from an African country with high poverty and high climate vulnerability. Third, it examines several channels through which shock-responsive social protection may support household resilience, including food-related coping strategies, savings, agricultural practices, and perceptions of government support.

This contribution is particularly relevant because governments are increasingly interested in integrating climate risk considerations into social protection systems. The evidence from Malawi suggests that pre-planned shock-responsive mechanisms can help provide timely support to poor and vulnerable households when climate disasters occur.

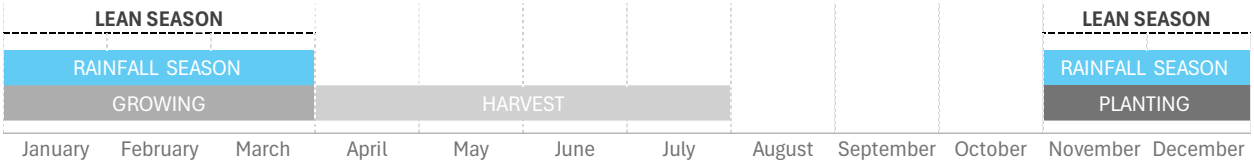
The remainder of the paper is organized as follows. Section 2 presents the context of the program. Section 3 introduces the data and the empirical strategy. Section 4 reports the estimation results and discusses the main findings. Section 5 concludes and presents policy implications.

Context

Malawi remains one of the poorest countries in the world, with poverty levels largely stagnant over recent decades. As of 2019, 50.7 percent of Malawians lived below the national poverty line, and at the international poverty line of $2.15 per day, the poverty rate was even higher at 70.1 percent (World Bank Group, 2023). This situation is particularly dire in rural areas, where 94 percent of poor households are located (World Bank Group, 2022). The economy is heavily dependent on agriculture, which accounts for 30 percent of Malawi's GDP, contributes 80 percent of export earnings, and employs over 80 percent of the population. However, the sector continues to rely primarily on rain-fed production, which contributes to chronic food insecurity.

Food security in Malawi is closely tied to the seasonal rainfall, which typically occurs from October to March and supports the country's rainfed agriculture. During this period, farmers plant and cultivate crops, with harvests taking place in April and May. After the harvest, households often earn income from selling produce or engaging in informal agricultural labor. However, as food reserves and income decrease later in the year, food insecurity intensifies. The lean season, which spans the months leading up to the next harvest (October to March), marks the peak of food insecurity. During this time, an estimated 2 million people (about 10% of the population) have faced Crisis-level food insecurity (IPC Phase 3) annually between 2021 and 2024, according to FEWS NET.

Figure 1: Seasonal Calendar in Malawi



Climate-related shocks, such as droughts and cyclones, disrupt agricultural production, exacerbate poverty, and increase vulnerability, especially among the rural population in Malawi. The country ranks 163rd out of 182 countries on the 2020 Notre Dame Global Adaptation Initiative Index, highlighting its vulnerability to climate-related disasters. Recent events, such as the Tropical Cyclone Freddy in March 2023 caused significant damage, affecting over 2 million people and leading to estimated economic losses of $506.7 million (Government of Malawi, 2023). The 2023/24 El Niño drought, a slow-onset climate disaster, reduced crop production by 50 percent compared to historical averages and left a large share of the population facing food insecurity (FEWS NET, 2024). The government of Malawi implements two regular programs that support poor households in meeting their basic needs: 1) The Social Cash Transfer Program (SCTP), an unconditional cash transfer program that targets households that are ultra-poor and labor constrained; and 2) The Climate Smart Enhanced Public Works Program (PWP) pays people to help with community projects related to climate adaptation (e.g. afforestation, soil and land conservation). To date, the government has supported approximately 126,000 households through SCTP and enrolled over 435,000 households in the PWP.

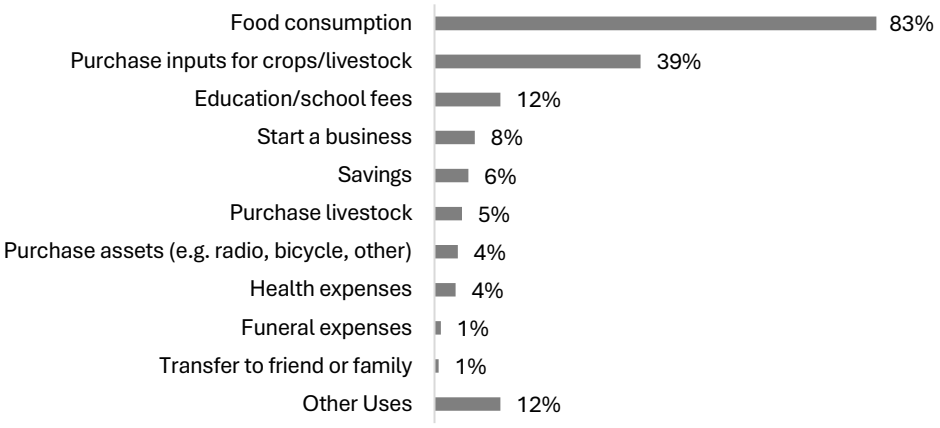
In addition to the two regular programs, the government has also put in place the Scalable Program, a pre-planned shock-responsive mechanism that enables SCTP and PWP beneficiaries to receive additional cash assistance when climate-related shocks occur. The aim of the Scalable Program is to provide timely assistance after a shock, allowing program beneficiaries to cover additional needs without engaging in negative coping strategies, such as selling livestock or pulling children out of school. During the 2023/24 rainfall season, the Scalable Program was being implemented in six districts in Malawi: Chiradzulu, Blantyre, Karonga, Nhkotakota, Ntcheu, and Thyolo. The program covered the 158,505 poor households that were SCTP or PWP beneficiaries in these districts. The Scalable Program was implemented only in these districts mainly due to budgetary constraints and to draw lessons before expanding it nationally. The districts where the program was tested were selected ex ante and not based on the impact of the El Niño drought in 2023/24.

During the 2023/24 rainfall season, the government tracked drought conditions using remote sensing and on-the-ground data sources. By April 2024, the government knew that the pre-agreed trigger levels for the Scalable Program had been reached, activating a vertical expansion of the SCTP and the PWP in the six districts covered by the program. Beneficiaries received a cash transfer of 150,000 Malawi Kwacha, around

US$86, in July and August 2024. This represents a significant amount when compared to the regular SCTP payout, which provides households on average 15,000 Malawi Kwacha, around US$8.6 per month. Figures reported by the government showed that the Scalable Program reached about 90% of all the households targeted after the El Niño drought. Payments were made through three payment service providers (PSPs) - TMN, Airtel and FDH Bank - each covering a specific district. Airtel provided scalable payments to SCTP and PWP beneficiaries in Chiradzulu, FDH Bank provided payments in Ntcheu, and TNM provided payments in the other four districts.

Most households (83%) reported using payment from the Scalable Program primarily for food consumption. A significant portion of recipients also invested in agricultural production, with 38.8% allocating funds to purchase inputs for crops or livestock. Other notable expenditures included education-related expenses (12.4%), likely helping beneficiaries cover school fees due at the start of the academic year in September. Additionally, some recipients used the funds to start a business (7.6%) or for savings (6.4%). These spending patterns suggest that the cash transfers may contribute to improved food security and greater financial resilience among beneficiaries.

Figure 2: Allocation of Scalable Program Payments (as % of beneficiaries surveyed)



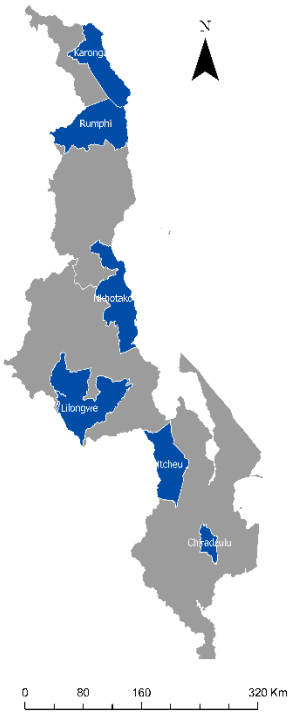
Note: Multiple answers were allowed; thus, the percentages in the figure do not add up to 100.

Data

The data used in our study is World Bank data created to monitor and measure households' well-being, vulnerability, and poverty to inform improvements on government and donors social protection programming. Our data includes three rounds of data collected in May, August, and November 2024. To ensure a comprehensive evaluation of these programs, a stratified random sampling approach was adopted. This method ensured representation across the geographical regions (north, central, and south) and beneficiary and non-beneficiary characteristics. Data was collected by community-based enumerators using smartphones.

Data was collected in six different districts. In the baseline survey in May, a total of 10 enumeration areas or clusters were sampled from each district. In the districts of Nkhotakota, Ntcheu, Rumphi and Lilongwe, a total of 15 households were randomly selected from each cluster. In the other two districts, Karonga and Chiradzulu, 25 households were randomly selected from each cluster.[4] Our sample therefore includes 1,100 households observed over three rounds (see Table 1).

Figure 3: Survey Districts



The questionnaire used to collect data captured multidimensional aspects of household well-being, including demographics, economic activities, health, education, and access to services, alongside questions that were specific to the implementation of various social protection programs. The questionnaire was drafted in English and translated into two local languages, Tumbuka and Chichewa. Administration was through face-to-face interviews on digital devices by trained enumerators.

The baseline questionnaire collected in May captured information on the household head and members (age, education, health status, livelihood activities), assets (including livestock), shock history and concerns, and food security outcomes. Food security modules included in the baseline in May and endline in November supported construction of various food security scores that are commonly used in related literature. These are the Household Dietary Diversity Score (HDDS), Food Consumption Score (FCS), Household Hunger Scale (HHS), and the Reduced Coping Strategies Index (rCSI) (Maxwell et al., 2014). In addition, the endline survey in November also included questions related to agricultural practices, as the timing of this round coincided with the start of the agricultural season. To limit financial costs and burden on participating households, the questionnaire administered at midline in July, was an abridged version of the longer questionnaire administered at baseline and endline. For example, this questionnaire only included questions related to the rCSI but not to other food security indices.

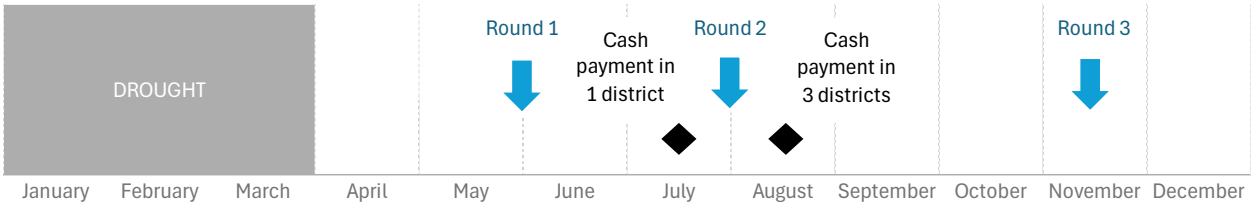
[4] The larger sample size in Chiradzulu and Karonga was driven by the fact that these two districts had been part of a previous data collection exercise that included more households and had a larger presence of local enumerators.

Table 1: Number of households surveyed during baseline, by beneficiary status and district

District	Non-beneficiaries HHs		Scalable Program HHs		Total HHs
	N	*%*	*N*	*%*	*N*
Chiradzulu	111	44.4	139	55.6	250
Karonga	135	54.0	115	46.0	250
Nkhotakota	86	57.0	64	43.0	150
Ntcheu	68	45.0	82	55.0	150
Lilongwe	150	100	0	0	150
Rumphi	150	100	0	0	150
Total	**700**	**63.6**	**400**	**36.3**	**1100**

Data was collected at key intervals to draw lessons on the Scalable Program's implementation and impact. The first round took place in late May, prior to the disbursement of any Scalable Program payments. The second round, collected in late July, happened two weeks after payments had been distributed in one district, Chiradzulu. The final round occurred in mid-November, three months after the disbursement of all Scalable Program payments and at the onset of the agricultural season. This phased approach to data collection enables the assessment of both the short-term and medium-term impact of the program. Specifically, the data collected in May is used as a baseline, the data collected in July serves to evaluate the immediate effect of the Scalable Program in Chiradzulu, and data collected in November is used to measure the mid-term effect on outcomes across the four districts in our sample where the Scalable Program was implemented (Chiradzulu, Nhkotakota, Ntcheu, and Karonga). The figure below illustrates the timeline of the data collection and program rollout.

Figure 4: Implementation timeline – Year 2024



Methodology

The objective is to evaluate the impact of the Scalable Program on household well-being and resilience to drought. The ideal estimation of a program's impact involves comparing the outcomes of the same households with and without the program, a concept known as counterfactual analysis. This approach seeks to determine what the outcomes would have been for the treated households had they not received the intervention, thereby isolating the causal effect of the program (Rubin, 1974). This is expressed as follows:

$$ATT = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1] \quad (1)$$

Where ATT is the average treatment effect on treated households, in our case, those that received the Scalable Program. $Y(.)$ is an outcome variable related to household resilience. D indicates whether a

household is a beneficiary of the Scalable Program ($D = 1$) or not ($D = 0$). $E[Y(1) \mid D = 1]$ is the resilience outcome of a household that has benefited from the program, $E[Y(0) \mid D = 1]$ is the counterfactual result for households that benefited from the program if they had not done so. This counterfactual can be constructed when an intervention or program is randomly assigned. However, in our case it is not observable due to the non-random nature of the Scalable Program. Constructing a valid counterfactual is challenging, as it requires the identification of a control group that closely resembles the treatment group in all relevant aspects except for the exposure to the program (Imbens & Rubin, 2015).

To overcome this challenge, we estimate the causal impact of the Scalable Program on households' resilience to drought using a Difference-in-Difference (DiD) approach**.** The DiD method is used to estimate the effect of the program by comparing the changes in resilience outcomes over time between the households that received payments from the Scalable Program (the treatment group) and the households that did not (the control group). By doing so, DiD uses data from treatment and control groups to obtain an appropriate counterfactual to estimate the causal effect of the program (Angrist & Pischke, 2009; Heckman et al., 1997). Using DiD we can rewrite the equation (1) as follows:

$$\text{ATT} = E[\, Y_2(1) - Y_1(1) \mid D = 1] \; - \; E[\, Y_2(0) - Y_1(0) \mid D = 0] \tag{2}$$

Where Y_1 is the resilience outcome of a household before the program has been implemented and Y_2 is the resilience outcome of a household after the program has been rolled out. $D=1$ indicates that a household is a beneficiary of the Scalable Program and therefore part of the treatment group. $D = 0$ indicates that a household is part of the control group and did not benefit from the program. $E[\, Y_2(1) - Y_1(1) \mid D = 1]$ is the expected change in outcome of program beneficiaries before and after the program was implemented, and $E[\, Y_2(0) - Y_1(0) \mid D = 0]$ is the expected change in outcome of the control.

However, the validity of DiD relies on the assumption that, in absence of the program, the resilience outcomes of the households in the treatment and control groups would follow a similar trend over time. Given that the Scalable Program targets poor households there are concerns about selection bias into treatment that could violate the tends assumption of DiD. We therefore combine DiD with entropy balance to generate a control group that has statistically similar household characteristics or covariates to the group that received the Scalable Program before the program payments were disbursed (Hainmueller, 2012).[5] Based on these details, we can rewrite equation (2) as follows:

$$\text{ATT} = E[\, Y_2(1) - Y_1(1) \mid D = 1, X = x] \; - \; E[\, Y_2(0) - Y_1(0) \mid D = 0, X = x] \tag{3}$$

where $X = x$ is a vector of observable covariates that may affect both being a beneficiary of the Scalable Program and the resilience of the household. Therefore, $E[Y_2 - Y_1 \mid D = 1, X = x]$ is the expected change in outcome of program beneficiaries, and $E[Y_2 - Y_1 \mid D = 0, X = x]$ is the expected change in outcome of the comparable control units, in this case generated using entropy balance.

We use DiD with entropy balancing through a two-step estimation method. In the first step, we generate a control group that is comparable to the treatment group using entropy balance. Entropy balance generates weights assigned to control units by solving a maximization problem under the constraint of matching the distribution of covariates (i.e., exactly balance the covariate moments) across the control and treatment groups (Zhao & Percival, 2017). In our study, the weights assigned to control units are calculated using entropy balance in the period prior to the implementation of the Scalable Program. We apply entropy

[5] We assume that the covariates were measured prior to the introduction of the intervention and are, therefore, unaffected by it.

balance using observable household characteristics available in our dataset that are correlated to both the eligibility criteria of the Scalable Program and resilience outcomes. These are: household size, household dependency ratio (number of adults vs. number of children/elderly), household head characteristics (gender, age, education level, chronic illness or disability), floor and roof materials, and whether the household is a beneficiary of other regular social protection programs. To generate this control group, we consider all the households in our sample that did not benefit from the Scalable Program at any point in time (never-treated units).

Due to its easy interpretation and quick computation, entropy balance has been widely used in the economic literature (Coulibaly, 2024; Zhao & Percival, 2017). In addition to these advantages, we use entropy balance as it outperformed other techniques, such as Propensity Score Matching and Inverse Probability Weighting (IPW), in generating a control group with characteristics comparable to those of the treatment group. However, we test the robustness of our results using DiD combined with IPW and the Doubly Robust (DR) estimator proposed by Sant'Anna & Zhao (2020). More information on the advantages of entropy balance over IPW and DR are presented in the robustness section of the paper.[6]

In the second step, we use the weights calculated in the first step using entropy balance in DiD estimations to quantify the impact of the Scalable Program on a range of outcome variables related to household wellbeing and post disaster resilience. Following similar studies (Gros et al., 2019; Pople et al., 2026), we categorize the outcome variables available in our dataset as follows:

- *Food insecurity* - Food Consumption Score, Household Dietary Diversity Score, Household Hunger Scale (HHS), and reduced Coping Strategies Index (rCSI).
- *Financial behavior* – dummies on whether households relied on savings to cope with a shock or participates in a savings group, as well as whether a household accessed credit or received transfers from relatives to cope with a shock.
- *Coping strategies* – dummies on whether households increased work, sold assets, or reduced spending on education to cope with a shock, and variables related to agricultural practices, particularly a series of dummy variables on the crops that households planted that season.[7]

In addition, we add two outcome variables related to the households' perceptions. The first one refers to whether a household perceives that they received assistance from the government when they were affected by a shock. The second one refers to their future well-being, whether they believe they will be better, same, or worse, in one month from now.

[6] Note that we do not use Callaway & Sant'Anna (2021) staggered DiD since the staggered framework does not fit the structure of program rollout in this setting. Payments across districts were staggered by only two weeks, a gap driven by administrative and logistical constraints in disbursement rather than by a phased program design. Treating Chiradzulu, the first district to receive payments, as a separate treatment cohort from the remaining districts would therefore not be appropriate and would lead to comparing effects that are not conceptually equivalent. For Chiradzulu (if treated as a first cohort) we would capture an immediate (two-week) effect of the program, while for the other districts (if treated as a second cohort) we would be capturing medium-term (three-month) effect. In addition, following a staggered approach would drop Chiradzulu from the medium-term estimation sample. We therefore treat all districts as a single treatment cohort and rely on a standard difference-in-differences estimator combined with entropy balancing.

[7] Crops considered were maize, cassava, beans, sorghum, millet, sweet potato, peas, soya, groundnuts, and rice.

Results

This section presents the estimated impacts of the Scalable Program on household welfare across two horizons: the short term, measured two weeks after payment disbursement in Chiradzulu district, and the medium term, measured three months after implementation across all eligible districts. We use DiD combined with entropy balance to assess the program's average impact on changes in food security, coping strategies, financial behaviors, and perceptions among beneficiaries of the program. We end the section by testing the robustness of our results to different estimation techniques. In addition to using entropy balance to generate comparable control group, we employ Inverse Probability Weighting (IPW) and the Doubly Robust (DR) estimator.

Short-term impact

We first examine the short-term impact of the Scalable Program among beneficiaries in Chiradzulu. Payments in this district were disbursed earlier than in other districts, occurring two weeks before the second round of data collection at the end of July. Consequently, we use this round of data to assess the immediate effects of the program following the receipt of payments by beneficiaries. The treatment group in this estimation includes information from the households that where eligible to receive the Scalable Program in Chiradzulu in Round 2. As described in the previous section, we use entropy balance to generate a comparable control group using data from the first round of data collected in May (pre-intervention period) using all other households in our sample (not yet treated households).[8] On average, the control group generated using entropy balancing has similar characteristics to the treatment group for this estimation (see the Table 2 below).

Table 2: Covariate balance for short-term analysis

		Sample		*Entropy Balance*	
	Treatment mean (1)	*Control mean* (2)	*Difference* (2) - (1)	*Control mean* (3)	*Difference* (3) - (1)
Regular program beneficiary (non=0, STCP=1, PWP=2)	1.476	0.855	-0.621***	1.474	-0.002
Household size	4.598	5.073	0.475	4.598	0.000
Dependency ratio	171.8	142.0	-29.8	171.7	-0.100
Gender of head (male=1, female=2)	1.561	1.354	-0.207***	1.561	0.000
Age of head (years)	51.57	47.60	-3.970**	51.57	0.000
Education of head (years)	6.866	7.402	5.360	6.867	0.001
Chronically ill head (no=0, yes=1)	0.219	0.231	0.012	0.219	0.000
Disability of head (no=0, yes=1)	0.024	0.026	0.002	0.024	0.000
Floor type (mud=1, other=0)	0.158	0.211	0.053	0.158	0.000
Roof type (grass=1, other=0)	0.743	0.510	-0.233***	0.743	0.000

Using DiD we find that the Scalable Program had a significant impact in the short-term in mitigating the adverse effects of drought on food insecurity. Households that reported receiving payments from the program were significantly less likely to adopt negative coping strategies, such as reducing meal size and frequency, or borrowing to purchase food. For example, Scalable Program beneficiaries on average skipped

[8] Results are similar when using never-treated households in our estimation.

52% less meals than the comparable control group in the week prior to the survey. The program also helped beneficiaries through reducing food borrowing and accessing credit.

Beyond food security, program beneficiaries were 5 times more likely than non-beneficiaries to report that government supported them in coping with shocks. Additionally, it led to improved expectations regarding future welfare. In terms of financial behaviors, there was no significant difference between program beneficiaries and a comparable control group in reliance on savings, or receipt of transfers from relatives. These findings suggest that, in the short term, the Scalable Program contributed to meaningful improvements in household well-being, particularly by reducing coping strategies related to food consumption, reducing borrowing of food and cash, and strengthening perceptions of government support.

Table 3: Short-term program impact in Chiradzulu

	Treatment effect (Δ)	*Control mean*	*% Δ*	*Std. error*	*N*
Food insecurity					
Household Hunger Scale (HHS)	-0.0583	1.446	-4%	(0.245)	1,870
Reduced Coping Strategies Index (rCSI)	-6.665***	14.32	-47%	(1.757)	1,870
Eat less preferred food	-0.404	2.895	-14%	(0.343)	1,870
Reduce size meals	-1.996***	2.968	-67%	(0.438)	1,870
Reduce number of meals	-1.593***	3.058	-52%	(0.440)	1,870
Restricted adult consumption for kids	-0.514	1.122	-46%	(0.317)	1,870
Borrow food	-0.565**	1.014	-56%	(0.250)	1,870
Finance					
Relied on savings	-0.0240	0.0495	-48%	(0.0434)	1,556
Accessed credit	-0.0942*	0.106	-89%	(0.0515)	1,556
Received transfers from a relative	0.0168	0.0819	21%	(0.0465)	1,706
Coping strategies					
Increased work	0.0691	0.600	12%	(0.0864)	1,870
Sold assets	0.0108	0.0646	17%	(0.0408)	1,556
Reduced spending in education	0.00268	0	0%	(0.00228)	1,556
Perceptions					
Assistance from GoM	0.153**	0.0278	550%	(0.0631)	1,556
Expected welfare next month (better=1, same=0, worse=-1)	0.550***	-0.445	124%	(0.135)	1,870

Note: The first column shows the DiD treatment effect for each outcome and subindex (italics). The second column shows the control mean in the post-program period, followed by the percentage change relative to the control mean (% Δ). Robust standard errors are reported on all outcomes and sub-indices. Significance levels are unchanged when clustering standard errors by enumeration area. Control group generated through entropy balancing including the following covariates: age, gender, education level, and disability or chronic illness of the household head, as well as household size, dependency ratio, roof and floor material, and SCTP and PWP recipient status. *N* is the sum of observations in the treatment and control groups before and after the program.
* p<0.10, ** p<0.05, *** p<0.01

Medium-term impact

We also examine the medium-term impact of the Scalable Program on all households that were eligible to participate in the program. According to Government of Malawi (GoM) reports, approximately 90% of all eligible beneficiaries were successfully reached. Consequently, we estimate the medium-term impact by considering all households that were eligible for the program.

In this estimation, the treatment group comprises data from the 400 households that received payments through either the Social Cash Transfer Program (SCTP) or the Public Works Program (PWP) in the four districts where the Scalable Program was implemented: Chiradzulu, Karonga, Ntcheu, and Nkhotakota. To assess the program's medium-term effects on eligible households, we use the third round of data collected in November as the post-intervention period.

To construct a comparable control group, we apply entropy balancing using data from the first round, collected in May (pre-intervention period). As in the previous estimation, the control group consists of households in our sample that were not eligible for the program, specifically all households in Lilongwe and Rumphi, as well as non-beneficiary households in the four districts where the Scalable Program was implemented.[9] The control group generated through entropy balancing exhibits characteristics similar to those of the treatment group in the pre-intervention period, ensuring a robust estimation of the program's impact (see the Table 4 below).

Table 4: Covariate balance for medium-term analysis among all eligible households

		Sample		*Entropy Balance*	
	Treatment mean	*Control mean*	*Difference*	*Control mean*	*Difference*
	(1)	(2)	(2) - (1)	(3)	(3) - (1)
Regular program beneficiary (non=0, STCP=1, PWP=2)	1.333	0.675	-0.658***	1.333	0.000
Household size	5.220	4.928	-0.292	5.220	0.000
Dependency ratio	163.6	134.1	-29.5*	163.6	0.000
Gender of head (male=1, female=2)	1.449	1.330	-0.119***	1.449	0.000
Age of head (years)	50.88	46.32	-4.560***	50.88	0.000
Education of head (years)	6.940	7.584	0.644**	6.941	0.001
Chronically ill head (no=0, yes=1)	0.229	0.231	0.002	0.229	0.000
Disability of head (no=0, yes=1)	0.017	0.0311	0.014	0.017	0.000
Floor type (mud=1, other=0)	0.193	0.214	0.021	0.193	0.000
Roof type (grass=1, other=0)	0.613	0.485	-0.128**	0.613	0.000

When considering all eligible households, three months after Scalable Program payments were disbursed, we find that the impact on food security disappears and we see that program beneficiaries are more likely to eat less-preferred foods than non-beneficiaries.

We find that in the medium-term the Scalable Program had a large and statistically significant impact on savings. Eligible households were 84% more likely than the control group to report relying on savings as a coping mechanism in response to shocks. Additionally, they were 13% more likely to participate in savings groups. This aligns with self-reported expenditure patterns, as 6% of households indicated that they allocated part of the program's payment to savings. By increasing household savings, the program provided beneficiaries with an additional mechanism to cope with shocks and enhance their overall resilience.

Furthermore, the program had a statistically significant impact on agricultural practices, particularly increasing the likelihood of planting sweet potatoes. Sweet potato is a drought-resistant crop, and it

[9] As a robustness check, we generate a control group only considering the households in the districts t=where the program was not implemented, Lilongwe and Rumphi, and obtain similar results.

generally has a higher yield output per unit of land and a higher market price per kilogram compared to other drought-resistant crops used in Malawi such as sorghum or cowpeas (Sapakhova et al., 2023). Hence, this change in agricultural practices could improve household resilience to droughts and increase their income in the future.

These results provide valuable information on the channels through which the Scalable Program builds household resilience. The fading of the food security effect by November is not a failure of the program, but rather an indication that by the time of the third survey round the transfer had already been spent. This, together with the results on savings and agricultural practices suggest that upon receiving the program payments, households immediately allocate resources in a combination of food consumption, savings, and agricultural inputs. Sustaining the food security effect would therefore require spreading payments over time or pairing the transfer with complementary interventions.

Finally, it is worth noting that the program's positive effect on beneficiaries' perceptions of government support remained statistically significant even three months after the program payments were delivered.

Table 5: Medium-term program effect among all eligible households

	Treatment effect (Δ)	Control mean	% Δ	Std. error	N
Food insecurity					
Food Consumption Score	-0.351	37.44	-1%	(1.488)	1,854
Household Dietary Diversity Score	0.362	5.086	7%	(0.235)	1,854
Household Hunger Scale (HHS)	0.035	1.575	2%	(0.168)	1,854
Reduced Coping Strategies Index (rCSI)	0.013	12.14	0%	(1.157)	1,854
Eat less preferred food	0.516**	2.835	18%	(0.225)	1,854
Reduce size meals	-0.145	2.338	-6%	(0.271)	1,854
Reduce number of meals	0.184	2.480	7%	(0.290)	1,854
Restricted adult consumption for kids	-0.228	0.928	-25%	(0.179)	1,854
Borrow food	0.071	0.851	8%	(0.162)	1,854
Finance					
Relied on savings	0.089**	0.107	84%	(0.042)	1,547
Participated in savings group	0.101*	0.773	13%	(0.060)	742
Accessed credit	-0.045	0.101	-45%	(0.036)	1,547
Received transfers from a relative	0.010	0.075	14%	(0.032)	1,854
Coping strategies					
Increased work	-0.029	0.661	-5%	(0.053)	1,854
Sold assets	0.016	0.049	34%	(0.030)	1,547
Reduced spending in education	0.012	0	0%	(0.010)	1,547
Changed agri practices: Sweet potato	0.078**	0.049	160%	(0.031)	1,853
Perceptions					
Assistance from GoM	0.085***	0.040	211%	(0.032)	1,547
Expected welfare next month (better=1, same=0, worse=-1)	-0.070	-0.261	73%	(0.088)	1,854

Note: The first column shows the DiD treatment effect for each outcome and subindex (italics). The second column shows the control mean in the post-program period, followed by the percentage change relative to the control mean (% Δ). Robust standard errors are reported on all outcomes and sub-indices. Significance levels are unchanged when clustering standard errors by enumeration area. Control group generated through entropy balancing including the following covariates: age, gender, education level, and disability or chronic illness of the household head, as well as household size, dependency ratio, roof and floor material, and SCTP and PWP recipient status. *N* is the sum of observations in the treatment and control groups before and after the program.
* p<0.10, ** p<0.05, *** p<0.01

Robustness

DiD estimator

To assess the robustness of our estimates, we complement the difference-in-differences (DiD) with entropy-balancing (EB) approach with two other popular DiD estimators used to assess the causal effects of policy interventions using panel data: Abadie (2005) Inverse Probability Weighting (IPW) DiD estimator and Sant'Anna & Zhao (2020) Doubly Robust (DR) estimator.

Compared to entropy balancing, IPW reweighs the observations in the control group of non-beneficiary households based on observable covariates. However, they employ different models to generate weights for control units. EB solves an optimization problem that directly enforces exact balance on the distribution of covariates, while IPW estimates a propensity score—the probability of treatment given covariates—and weights observations by the inverse of this estimated probability (Zhao & Percival, 2017). EB presents various advantages over IPW. For example, when using IPW exact balance of covariates between treatment and control groups is not guaranteed and often requires model refinement. By solving a constraint optimization model, EB avoids iterative propensity-score model tweaking to achieve balance. IPW is also prone to extreme weights when propensity scores are near 0 or 1, inflating variances. In contrast, EB keeps weights close to base weights, typically avoiding extreme weights and improving stability and efficiency (Zhao & Percival, 2017).

The Sant'Anna & Zhao (2020) doubly robust DiD estimator combines stabilized inverse probability weighting with ordinary least squares to model the evolution of outcomes and provide a consistent and efficient estimate of the average treatment effect (ATT) of a program or intervention. By combining outcome modeling with propensity weighting, DR yields consistent estimates if either the treatment or outcome model is correctly specified.

We report the IPW and DR results alongside the main estimates for both short-term and medium-term outcomes to evaluate the stability of magnitudes, signs, and statistical significance.

Table 6: Robustness checks

	Short-term			Medium-term		
	EB	IPW	DR	EB	IPW	DR
Food insecurity						
Food Consumption Score				-0.351	-0.151	-0.151
Household Dietary Diversity Score				0.362	0.332*	0.330*
Household Hunger Scale (HHS)	-0.0583	-0.0239	-0.0179	0.035	0.00736	0.00154
Reduced Coping Strategies Index (rCSI)	-6.665***	-6.711***	-6.641***	0.013	-0.181	-0.217
Eat less preferred food	-0.404	-0.517**	-0.507**	0.516**	0.358*	0.352*
Reduce size meals	-1.996***	-2.134***	-2.117***	-0.145	-0.352	-0.353
Reduce number of meals	-1.593***	-1.614***	-1.596***	0.184	0.106	0.0974
Restricted adult consumption for kids	-0.514	-0.449***	-0.444***	-0.228	-0.170	-0.177
Borrow food	-0.565**	-0.550***	-0.544***	0.071	0.108	0.109
Finance						
Relied on savings	-0.0240	-0.0261	-0.0272	0.089**	0.046	0.044
Participated in savings group				0.101*	0.110*	0.110*
Accessed credit	-0.0942*	-0.0973***	-0.0984***	-0.045	-0.0205	-0.0183
Received transfers from a relative	0.0168	0.0162	0.0153	0.010	-0.004	-0.005
Coping strategies						
Increased work	0.0691	0.0681*	0.0672*	-0.029	-0.0360	-0.0371
Sold assets	0.0108	0.0165	0.0168	0.016	0.0161	0.0125
Reduced spending in education	0.00268	0.00222	0.00228	0.012	0.0123	0.0118
Changed agri practices: Sweet potato				0.078**	0.0554**	0.0550**
Perceptions						
Assistance from GoM	0.153**	0.162***	0.162***	0.085***	0.0769**	0.0784**
Expected welfare next month (better=1, same=0, worse=-1)	0.550***	0.499***	0.497***	-0.070	-0.0985	-0.0976

The IPW and DR estimates closely mirror the main results. In the short term, key food-security outcomes measured by the rCSI remain large and statistically significant across all estimators. This reinforces the conclusion that the program mitigated households' reliance on reducing food consumption as a coping strategy shortly after a they received the transfer from the program. Minor differences emerge for a few outcomes: eating less preferred foods, restricting adult consumption for children, and increasing work to cope with shocks show stronger significance under IPW/DR than in the EB specification.

Medium-term results are also stable for core outcomes linked to resilience. Reliance on savings losses is positive and similar in magnitude across estimations, though it is not statistically significant using IPW and DR. However, participation in savings groups remains statistical significance under IPW/DR, suggesting that the Scalable Program supports resilience of beneficiary households in the medium term through savings.

Overall, the consistency in signs and significance indicates that short-term and medium-term effects are not sensitive to estimation choice.

Discussion

The findings of this study provide evidence on the role of shock-responsive social protection in supporting household resilience during climate disasters in contexts of acute poverty. The results show that the Malawi

Scalable Program reduced negative food-related coping strategies in the short term, while in the medium term it supported savings and drought-resilient agricultural practices. These findings are broadly consistent with the literature on cash-based interventions in shock contexts, but they also show that the channels through which cash transfers operate may change over time.

Food-related coping strategies

The Malawi Scalable Program produced significant short-term improvements in food security. In the two weeks following the transfer, beneficiaries skipped 52% fewer meals and experienced a 47% reduction in the Reduced Coping Strategies Index (rCSI) relative to comparable non-beneficiaries. These findings are consistent with evidence from other settings where cash-based interventions were used in response to shocks. Pople et al. (2026), studying cash transfers delivered in response to floods in Bangladesh, find that treated households were 36% less likely to go a full day without eating during the flood period. Similarly, Strupat et al. (2025) evaluate shock-responsive social cash transfers during the COVID-19 pandemic in Kenya and find that recipient households were 10.4 percentage points less likely to report food shortages. The consistency across these different contexts suggests that shock-response cash transfers can be an effective instrument for protecting household food security in the immediate aftermath of a shock. In addition, Strupat et al. (2025) find that the protective effects were driven specifically by the program component that added a lumpsum transfer as a top-up to the regular cash transfer amount. This is consistent with our evidence and suggests that the design of the shock response matters beyond the mere existence of a regular cash transfer program.

When looking at the persistence of the effect on food security, we find that the statistically significant effect dissipates three months after the program payments were disbursed. Beneficiary households were even more likely to eat less-preferred food, which we interpret as a first-line or mild food security-related coping strategy. This finding contrasts with Pople et al. (2026), who find that the effects on food security persisted three months after the flood, with treated children more likely to consume three or more meals per day and treated adults consuming protein on more days per week. Our finding suggest that one-time shock-responsive transfers can be effective at preventing the most severe immediate deprivations, but sustained food security improvements may require either repeated payments or complementary interventions in contexts of deep and persistent poverty such as rural Malawi. This highlights the importance of designing shock-responsive mechanisms that consider the possibility of multiple payments or linkages to longer-term social protection programs. In summary, our results suggest that scaling social protection programs to provide a one-time transfer in response to disasters can relieve immediate food deprivation. However, durably shifting the food security trajectory would require additional interventions that address the structural conditions that make households food-insecure, such as reliance on subsistence agricultural practices, limited access to credit markets, climate exposure, and a low asset base.

Medium-term resilience: savings and agricultural practices

A distinctive finding of this study is the significant impact on savings and agricultural practices three months after the transfer. This provides evidence that the program may support some resilience-related channels beyond immediate food relief. Beneficiaries were 84% more likely to report relying on savings as a coping mechanism, 13% more likely to participate in savings groups, and 160% more likely to have planted sweet potatoes, a drought-resistant crop Sapakhova et al. (2023), as a form of agricultural adaptation.

Related literature also finds effects on resilience-related outcomes. Pople et al. (2026) find that beneficiaries of the humanitarian cash transfer delivered in response to floods in Bangladesh were 8% less likely to have lost livestock and 2.4 percentage points less likely to have borrowed money. Gros et al. (2019), also studying

flood-related humanitarian cash transfers in Bangladesh, find that beneficiaries were less likely to take on high-interest debt and less likely to sell productive assets, two costly coping strategies that can have long-lasting effects on future income.

Our medium-term results are also in line with literature that studies the impact of regular social protection programs on household resilience. Matata et al. (2023), studying Kenya's regular social cash transfer program, the Hunger Safety Net Programme, find that regular cash transfers significantly improve household resilience to climate shocks based on the FAO Resilience Index Measurement and Analysis (RIMA). These findings support the idea that cash transfers can help households accumulate resources, access credit, and diversify productive strategies, which is consistent with the savings and agricultural adaptation effects observed in Malawi.

Perceptions of government support

A less commonly reported but important finding of this study concerns beneficiaries' perceptions of government support. Scalable Program beneficiaries were five times more likely to report that the government had supported them in coping with the drought two weeks after program payments were disbursed. This effect remained large and statistically significant three months later. This result points to an important dimension of shock-responsive social protection beyond its direct effects on household food security and resilience. Timely support during climate crises may also improve how beneficiaries perceive government action in response to shocks. This is in line with literature in various African countries that finds that social protection programs enhance government-citizen relations and have a positive impact on citizen's perceptions and trust in government institutions (Brinkerhoff et al., 2018; Evans et al., 2019; Ibrahim, 2023).

Conclusion

This study examines whether shock-responsive social protection can help protect low-income households during climate disasters and the channels through which it may strengthen household resilience. We evaluate Malawi's Scalable Program in the context of the severe 2023/24 El Niño drought. The program was designed before the shock to provide additional cash support through existing social protection systems. This offers an opportunity to study a government-led response to a slow-onset climate disaster that used pre-existing payment infrastructure and household registries to support low-income households.

We draw on three rounds of panel data from 1,100 households across six districts, collected before and after payments were disbursed. We apply a difference-in-differences estimator combined with entropy balancing to estimate the causal effect of the program. By examining outcomes two weeks and three months after disbursement, we distinguish between immediate protective effects of the transfer and its medium-term contribution to household resilience.

Our results show that the program had a significant short-term effect on food-related coping strategies. In the two weeks following disbursement, beneficiary households were less likely to reduce meal size or frequency, restrict adult consumption to prioritize children, or borrow money to buy food. This is consistent with previous evidence showing that cash transfers delivered in response to shocks can help protect household food security in the immediate aftermath of a crisis (Pople et al., 2026; Strupat et al., 2025). However, these food security effects were not statistically significant three months after payment. This suggests that one-time shock-responsive transfers can help reduce immediate food deprivation, but sustained improvements in food security may require repeated payments or complementary interventions in contexts of deep and persistent poverty.

In the medium term, the program affected household resilience through savings and agricultural practices. Three months after payment, beneficiary households were more likely to rely on savings and to adopt drought-resilient agricultural practices, including planting sweet potatoes. These results are in line with evidence suggesting that cash transfers can help households accumulate resources, diversify productive strategies, and reduce costly coping behaviors (Gros et al., 2019; Matata et al., 2023; Pople et al., 2026). They suggest that cash transfers delivered in response to climate shocks may support households not only by covering immediate needs, but also by enabling some decisions that can strengthen their capacity to cope with future shocks.

We also find that beneficiaries reported higher perceptions of government support during the drought. This effect was observed shortly after receiving the transfer and persisted three months later. This suggests that, beyond its direct effects on household welfare and resilience, timely support through shock-responsive social protection may also generate positive perceptions of government action during climate crises. Taken together, these findings provide evidence that integrating social protection systems with disaster response can help protect low-income households from climate-related shocks. The case of Malawi shows the relevance of pre-planned shock-responsive mechanisms that can be activated when climate disasters occur. Our results also emphasize the importance of timely support after climate shocks to reduce reliance on negative coping strategies in the short term. To enable rapid responses, governments need to establish in advance the rules, systems, and resources required to scale social protection when disasters occur.

This research has some limitations. First, due to data constraints, the analysis relies on a relatively small sample and a limited number of beneficiary households. This restricts our ability to examine heterogeneous effects across payment mechanisms) or household characteristics. Related to this limitation, future research could provide additional evidence on optimal transfer size, timing, frequency of payments, and delivery modalities. Second, although our estimation controls for observed household characteristics, unobserved factors may still influence both household welfare and program participation. Addressing this concern would ideally require experimental or randomized variation embedded in the design of shock-responsive programs, which can be ethically and operationally challenging in crisis contexts. These limitations highlight the importance of embedding monitoring, evaluation, and learning components in the design of shock-responsive programs. Despite these constraints, this study provides policy-relevant evidence on the role of government-led shock-responsive social protection in climate-disaster response.

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