Heterogeneous impact of extreme temperatures on household farms: evidence from Sub-Saharan Africa*

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Abstract

This paper investigates the heterogeneous impact of extreme heat on household farms in low-income countries. Our source of heterogeneity is farm size, as it has been shown to matter for productivity and agricultural practices. Using a large panel dataset from Uganda, Tanzania, Ethiopia, and Malawi, we show that extreme heat reduces agricultural output and food security, independently of farm size. We do find, however, that some responses to temperature shocks are different, e.g., small farms increase land use. These findings suggest that all household farms are vulnerable to the negative impact of climate change, even the largest ones.

JEL classification: O13, Q12, Q54.
Keywords: climate change, agriculture, subsistence farming.

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1 Introduction

Climate change, with its associated rising temperatures, is expected to have a profound impact on agricultural activities (IPCC, 2019). Of particular concern are household farms, which are characterized by their small scale, reliance on traditional methods, and significant allocation of output for household consumption. These farms play a vital role in providing employment, food, and rural income in many developing countries (Lowder et al., 2021). For that reason, their fate carries significant implications for the well-being of a large portion of the world's poor and can shape the impact of climate change on food security, population displacement, and conflict.

Numerous studies find that extreme temperatures have a negative effect on household farms' productivity. Recent research efforts have also sought to understand how these farms mitigate and adapt to weather shocks.[1] However, our understanding of how the impacts of extreme temperatures are distributed across various household farms remains limited. This is a significant gap considering that household farms are not homogeneous but differ in terms of technology and socioeconomic characteristics. Does this heterogeneity imply different vulnerability to extreme temperatures? This study examines this question focusing on farm size as a relevant dimension of heterogeneity.

Our empirical analysis utilizes a large and unique panel dataset that combines household surveys from four East African countries: Uganda, Tanzania, Ethiopia, and Malawi. We examine how agricultural productivity is impacted and how farmers respond to mitigate these effects, including changes in input use, agricultural practices, and labor allocation. To address endogeneity concerns, our identification strategy leverages within-location weather variations and incorporates a comprehensive set of time and household fixed effects.

[1] For example, see Lobell et al. (2011a); Burke et al. (2015); Carleton and Hsiang (2016); Chen et al. (2016); Zhang et al. (2017); Aragón et al. (2021). For evidence on some mitigation responses such as adjusting land use, cropping patterns, and agricultural practices see Jagnani et al. (2021); Aragón et al. (2021); Cui and Xie (2022); Cui and Tang (2023).

We investigate heterogeneous effects by farm size, considering the well-established relationship between size and productivity found in previous studies. This relation suggests that farm size is possibly linked to technological differences, unobserved input quality, market distortions, and socioeconomic factors like wealth and income.[2] In turn, these factors could influence farmers' mitigation response to weather shocks. Additionally, size might directly affect mitigation costs if some approaches, such as adopting new inputs or diversifying crops, exhibit economies of scale.

Our study reveals that extreme temperatures have a substantial detrimental effect on agricultural productivity. The magnitude of this impact is significant, with a 1℃ increase in temperature throughout the growing season resulting in a decrease in productivity ranging from 15% to 20%. Moreover, we observe substantial negative effects on agricultural output and food security. These outcomes imply that the current mitigation measures employed by households in East Africa cannot offset the detrimental effects of high temperatures.

We do not find, however, any significant heterogeneous impacts by farm size. The effects of extreme temperatures on agricultural productivity, output, and food security are similar across farms of different sizes. Importantly, this outcome is not due to farm size being an irrelevant source of heterogeneity. Our observations indicate that relatively larger farms tend to have lower yields, adopt more diverse crop portfolios, and demonstrate a greater likelihood of using modern inputs.

While we find no differences in the impact of high temperatures on productivity, we do find suggestive evidence of heterogeneous mitigation responses. All farmers respond by increasing off-farm work for household members. Additionally, large farmers tend to intensify their pesticide usage, while small farmers allocate more land and farm labor. Notably, we

[2] For a comprehensive review, see Barrett (1996), Desiere and Jolliffe (2018), and Barrett et al. (2010) and their references. Most of these studies reveal an inverse yield-size relationship. However, some macroeconomic research indicates a positive relationship between total factor productivity and farm size (Adamopoulos and Restuccia, 2014; Chen et al., 2017; Restuccia and Santaeulalia-Llopis, 2017; Adamopoulos and Restuccia, 2019). Aragon et al. (2022) provides an explanation for these seemingly contradictory findings.

do not find any evidence of changes in cropping patterns, a mitigation strategy previously documented in other studies, across farms of any size.

Our results suggest that technological and socio-economic differences associated with farm size do not seem to provide an advantage in mitigating the impact of rising temperatures. It seems that all household farms, regardless of size, are equally vulnerable to the adverse effects of extreme temperatures. These results underscore the importance of including a broader range of stakeholders in climate change adaptation and mitigation initiatives.

2 Data and methods

We compile a panel dataset at the household level by utilizing data from four countries in East Africa, specifically Malawi, Uganda, Tanzania, and Ethiopia. Our primary data source consists of panel household surveys conducted between 2008 and 2016 as part of the World Bank's Living Standards Measurement Study - Integrated Agricultural Surveys (LSMS-ISA) project. These surveys offer comprehensive information on agricultural outcomes and activities within a given cropping season.[3] We only focus on data from the long rainy season to increase comparability across countries.[4]

We define a household farm as a collection of production units, such as plots or parcels, that are managed by a household. To ensure consistency, we limit our sample to households that responded to the agricultural module and exclude the top 1% of observations based on farm size. As a result, our final dataset consists of a panel comprising 9,459 households and over 32,000 observations. Table 1 provides summary statistics for our key variables, categorized by farm size.

[3] Ethiopia collects information for one cropping season, but other surveys distinguish two cropping seasons each year: dry and rainy seasons in Malawi, long and short-rainy seasons in Tanzania, and two rainy seasons for each semester in Uganda.

[4] Table A.1 in the Appendix lists the panel surveys, rounds, and cropping seasons used in the analysis.

Table 1: Summary statistics

	All	Farm size		
		Small	Medium	Large
Average degree days (°C)	15.7	15.5	15.8	15.9
Average harmful degree days (°C)	0.804	0.737	0.838	0.838
Farm size (has)	1.39	0.42	1.07	2.69
Area planted (has)	1.11	0.46	0.96	1.92
Farm labor (person-days)	408.9	217.6	407.2	604.6
log(agricultural output)	0.000	-0.452	0.038	0.420
log(yields)	0.000	0.099	-0.011	-0.088
log(per capita agric. output)	0.000	-0.329	0.047	0.286
% did not have enough food	0.310	0.337	0.309	0.283
% uses chemical fertilizer	0.218	0.177	0.230	0.247
% use pesticides	0.110	0.077	0.107	0.145
% uses improved seeds	0.185	0.135	0.189	0.231
Concentration index (crop area)	0.432	0.479	0.419	0.398
% area planted with grains	0.388	0.365	0.397	0.404
No. HH members	5.927	5.033	5.858	6.904
No. HH members work off-farm	0.945	0.898	0.921	1.016
No. children work off-farm	0.061	0.041	0.058	0.080
No. obs.	32,628	10,968	10,853	10,807

Notes: Concentration index is the HerfindahlâHirschman concentration index based on crop shares of area planted. Farm size is the average area of land (in hectares) a household owns or has user rights. HH= household. Per capita output = output/no. household members. Yields= output/area planted. The reference period for "did not have enough food" and "off-farm work" is last 12 months. Logs of agric. output, yields, and per capita output are normalized using country-specific mean and standard deviations.

Agricultural variables Our main outcome variables are measures of agricultural output and input, practices, and productivity. To assess agricultural output, we calculate the value of harvested crops by multiplying self-reported quantities with a baseline price proxy. For each crop, we utilize the median national unit value from the first year of the survey rounds. This measure of output is similar to a Laspeyres index of production.

We focus on two key inputs: land (area planted) and labor. To determine the area planted, we aggregate the reported cultivated area across all plots for a given cropping season. To measure farm labor, we sum up the number of person-days employed on the farm, encompassing both domestic and hired labor. In addition, we construct an indicator to identify child labor, which includes paid and unpaid work performed by children between the ages of 5 and 15. Furthermore, we gather information on various indicators of agricultural practices, such as using chemical fertilizers, pesticides, and crop composition.

We employ two measures to assess agricultural productivity: yields and the time-variant component of total factor productivity (time-variant TFP). Yields are calculated by dividing the value of agricultural output (adjusted for inflation) by the corresponding area planted. This measure allows us to evaluate partial productivity, focusing on the output generated per unit of land. The time-variant TFP is determined as the residual obtained from a log-log regression of output on inputs, specifically the area planted and farm labor. This regression model accounts for household and time fixed effects. The time-variant TFP captures the unexplained variation in output that cannot be attributed to changes in the measured inputs, providing insights into overall productivity changes over time.

Temperature and precipitation We use data on daily daytime temperature from the MOD11C1 product provided by NASA and monthly data on precipitation from the CHIRPS reanalysis product. We first aggregate the raw weather data at the sub-county level to link weather to household data. Then, we construct measures of cumulative exposure to heat and water during the growing season, i.e., the period during which plants grow actively.[5]

We measure cumulative exposure to water using the average monthly precipitation during the growing season. In the case of heat, we follow the extant literature and construct two measures of cumulative exposure to heat: average degree days (DD) and harmful degree days (HDD). DD measures the cumulative exposure to temperatures between a lower bound, usually 8℃, up to an upper threshold τ, while HDD captures exposure to extreme heat (above τ).[6] This last variable is our regressor of interest.

We define τ as the 80th percentile of a country's temperature distribution during the growing season. This value ranges from 27 ℃ to 35 ℃. We choose this approach to obtain country-specific τ and account for differences in temperature distributions. The percentile is chosen to produce values of τ in a similar range as previous studies.[7] We check the robustness of our main results by using a wide range of values for τ (see Figure B.3 in the Appendix).

Farm size We construct measures of farm size based on the area of land available to a farmer. Available land includes land owned by the farmer and land over which she has user rights. Our measure of farm size is the average available land over cropping seasons.

The median farm is around 1 ha, with most farms between 0.5 to 2 ha. However, distributions vary by country, with smaller farms in Malawi and larger ones in Tanzania. To increase cross-country comparability, our baseline specification uses a categorical variable of farm size. Based on country-specific tertiles, this variable classifies farms into three categories (small, medium, and large).[8]

[5]For Malawi, the growing season corresponds from November to April. For Tanzania, it is the period April-June, while for Ethiopia is June-October. In the case of Uganda, we take into account that the southern part has two distinct growing seasons: February-July and September-January, while the north has one primary growing season April-October.

[6]Formally we define $DD = \frac{1}{n}\sum_{d=1}^{n}(\min(h_d,\tau) - 8)\mathbb{1}(h_d \geq 8)$ and $HDD = \frac{1}{n}\sum_{d=1}^{n}(h_d - \tau))\mathbb{1}(h_d > \tau)$, where h_d is the average daytime temperature in day d and n is the total number of days in a growing season with valid temperature data.

[7]For instance, Schlenker and Roberts (2006) and Deschenes and Greenstone (2007) set this value between 29-32℃ in the context of US. Aragón et al. (2021) use a value of 33℃ in Peru.

[8]Figure B.1 in the online appendix displays the farm size distribution for each country.

Baseline model We estimate the following regression model:

$$y_{it} = \alpha DD_{it} + \sum_{k=1}^{3} \beta_k HDD_{it} \times size_i^k + \gamma PP_{it}^2 + \eta_t + \rho_i + \epsilon_{it}, \quad (1)$$

where y is the outcome of farmer i in season-year t. y is an outcome such as agricultural output, food security, or input use. DD and HDD are degree and harmful degree days, while PP^2 is monthly precipitation and its square. $size^k$ are indicators of farm size (small, medium, or large). Our baseline specification includes country-season, country-year, and household fixed effects (η_t and ρ_i) and cluster standard errors at the household level. We use the relative number of observations from each country as sampling weights.

This specification is similar to previous studies on the effect of extreme heat on agriculture (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Aragón et al., 2021). We use similar measures of cumulative exposure to heat (DD and HDD) and exploit within-locality variation in weather. The main differences are that we include household fixed effects and interaction terms. They allow us to reduce the scope of omitted variables and examine the heterogeneous effects of HDD by farm size (β_k).

3 Main findings

We find evidence of a negative impact of extreme heat (HDD) on measures of agricultural productivity (see Figure 2).[9] The magnitude is economically relevant: each additional 1°C of high temperatures (i.e., above the 80th percentile) in all days of the growing season reduces productivity by 15-20%. These findings are consistent with the negative impact of extreme heat documented in other countries. Moreover, the magnitude is comparable to estimates from other studies covering similar study areas but using different methodologies.[10]

[9] All regression estimates are available in the online appendix (Tables A.2 and A.3).

[10] For instance, using historical data from agronomic controlled trials in Sub-Saharan Africa, Lobell et al. (2011b) find that an increase of 1°C degree in all days of the growing season reduces maize yields by 10-40%

We find, however, no evidence of heterogeneous impacts by farm size. This result does not seem to be driven by model specification or choice of HDD threshold. We check the robustness of our results by (1) clustering errors at the regional level, (2) adding interactions of farm size with DD, (3) using normalized farm size instead of size categories, (4) using a more parsimonious model with region instead of household fixed effects, and (5) varying the value of τ, the temperature above which we consider heat to be harmful. In all cases, we find that HDD's impact on productivity measures is the same, regardless of farm size.[11]

This result is surprising, given that size is related to observable farm differences (see Table 1). Larger farms are more likely to use modern inputs, have a more diversified crop portfolio, and lower yields. They also have relatively better off: they obtain greater per capita output and are less likely to lack enough food. We corroborate these observations using a formal regression model (see Table A.6 in the online appendix).

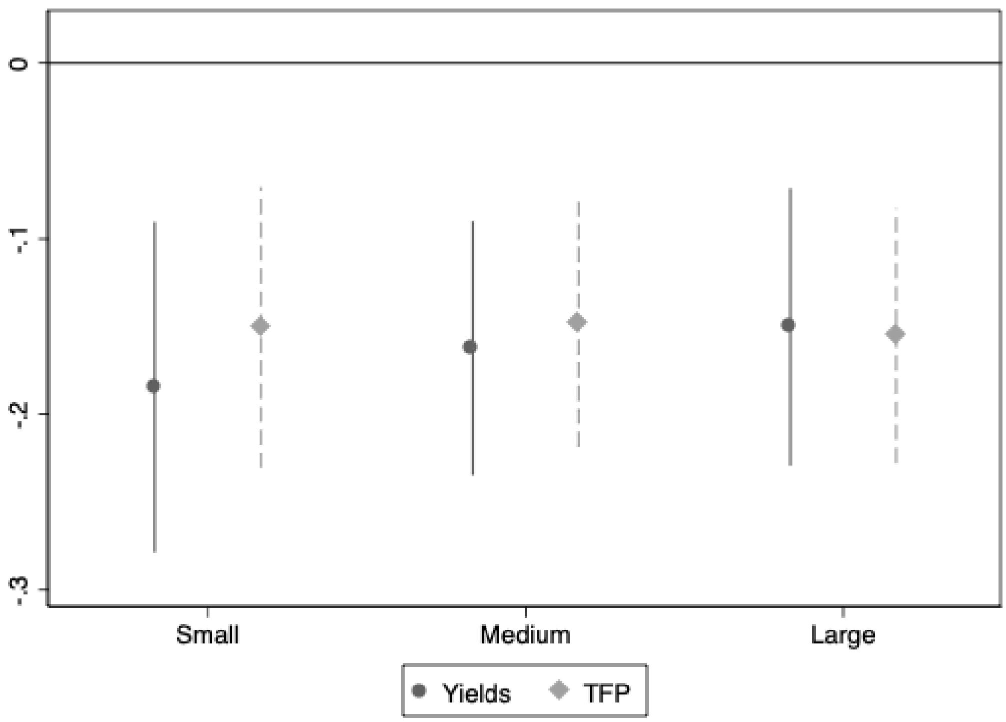
We interpret these findings as evidence that any difference associated with farm size (such as scale, productivity, or socioeconomic status) does not affect households' vulnerability to extreme temperatures. To further explore this interpretation, we examine the impact of HDD on agricultural output and an indicator of lacking enough food in the last year. These outcomes are proxies of agricultural income and food security and thus can better capture the result of farmers' mitigation actions.

Similar to our baseline results, we find evidence of a negative impact HDD on these outcomes but no significant differences by farm size. This result is interesting since it implies that any mitigation measures, whether to smooth production or food consumption, do not fully offset the harmful effects of extreme temperatures. This outcome is consistent with previous studies, which find that, in some contexts, households cannot entirely smooth consumption (Fafchamps et al., 1998; Kazianga and Udry, 2006; Carter and Lybbert, 2012).

depending on farming techniques and local climatic conditions.

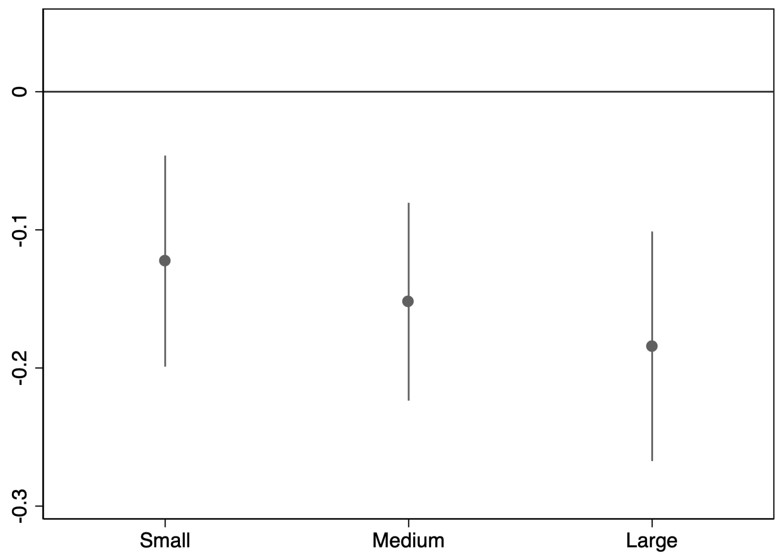
[11] See Tables A.4 and A.5, and Figure B.3 in the online appendix.

Figure 1: Effect of HDD on agricultural productivity, by farm size

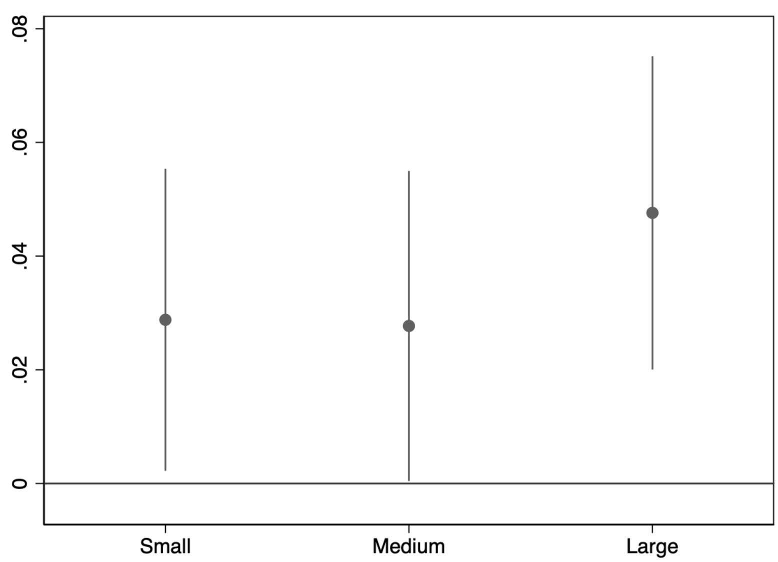


Notes: Figure displays estimates of the impact of HDD by size (β) on the log of yields (circles, solid black line) and the time-variant component of total factor productivity (diamond, dashed gray line). Vertical lines represent the 95% confidence interval.

Figure 2: Effect of HDD on agricultural output and food security, by farm size



(a) Agricultural output



(b) Food insecurity

Notes: Notes: Figure (a) displays estimates of the impact of HDD by size (β) on the log of total agricultural output (panel a) and an indicator of not having had enough food in the last 12 months (panel b). This last variable is used as a measure of food security. Vertical lines represent the 95% confidence interval.

4 Farm size and mitigation responses

In this section, we investigate the responses of farmers to extreme heat events and explore potential variations based on farm size. Drawing from prior research and data availability, we focus on three specific types of mitigation responses: adjustments in agricultural inputs (such as land and farm labor), modifications in agricultural practices, and an increase in off-farm labor.

Changes in agricultural inputs We find evidence of heterogeneous impacts by farm size. Specifically, medium and large farms show no significant adjustments in agricultural inputs in response to extreme heat events. However, small farms exhibit an increase in agricultural inputs (see Figure 3). The effect size is comparable for both inputs, with an approximate 5% increment in both area planted and farm labor for every average HDD. Although the estimates for farm labor are only marginally significant (p-value: 0.070), the overall pattern suggests that small farms are more likely to increase their inputs in the face of extreme heat compared to medium and large farms.

Consistent with our findings, similar responses to extreme temperatures have been observed in other regions, specifically in Peru and Ethiopia. Aragón et al. (2021) reported increases in both the area planted and domestic farm labor in Peru as a response to extreme temperature events. Similarly, He and Chen (2022) documented an increase in cropland among Ethiopian households in the face of extreme temperature conditions. Interestingly, their study revealed that the expansion of cropland primarily occurred among households with limited assets.

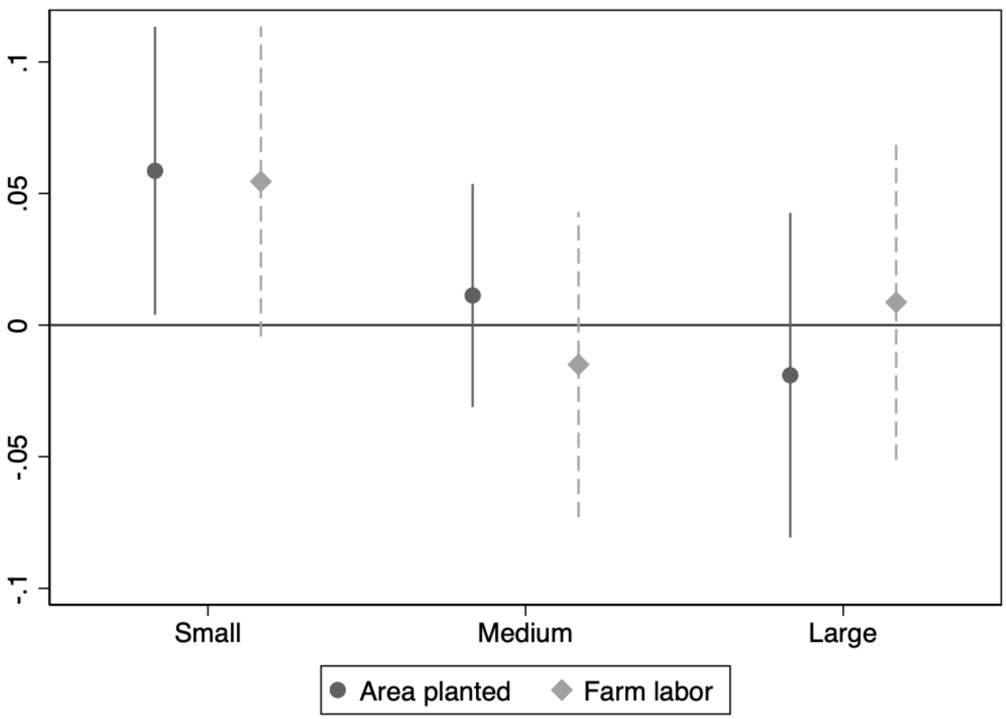
The observed increase in the area planted may appear counterintuitive, as land is traditionally considered a fixed input. However, this phenomenon can be explained by the specific characteristics of our study context. In our context, planting activities are distributed over several months (USDA, 2023). Moreover, farmers engage in the cultivation of multiple crops, each with its own distinct planting schedule. This flexible planting schedule allows for adjustments in the area planted during the growing season when weather shocks are realized. As a result, land is more akin to a variable input.

One plausible explanation for the observed increase in input use is that households engage in higher levels of agricultural activity as a coping mechanism to smooth consumption. In this view, farmers employ additional inputs to offset the decline in agricultural output and subsequent consumption. In a standard production model, this response may seem suboptimal as farmers should ideally reduce inputs (and output) to mitigate the adverse effects of extreme heat on their farm profits. However, this response can be optimal in a context characterized by incomplete markets and non-separability of consumption and production decisions (De Janvry et al., 1991; Aragón et al., 2021).

Based on this interpretation, we can identify three possible explanations for the heterogeneous responses. Firstly, the differences may stem from varying marginal benefits in smoothing consumption. If small farmers initially have lower consumption levels, they would benefit more from actions to mitigate further reductions. Secondly, the disparities could be attributed to access to different coping strategies. For example, larger farms may possess more precautionary savings, more extensive support networks, or better credit access. Lastly, the discrepancies might arise from constraints on expanding agricultural activity. Larger farms may face limitations such as poorer soil quality in marginal lands or the absence of complementary inputs like monitoring labor. Unfortunately, due to data limitations, we cannot explore these explanations empirically.

Agricultural practices Numerous studies indicate that farmers adjust their agricultural practices to mitigate the negative effects of extreme heat. These responses encompass various strategies, such as altering crop composition, employing fertilizers and pesticides, or adjusting planting schedules. Due to data limitations, our analysis focuses on two groups of outcomes.

Figure 3: Effect of HDD on land and farm labor, by farm size



Notes: Figures display estimates of the impact of HDD by size (β^k) on the log of area planted (circles, solid line) and log of farm labor (diamond, dashed line). Farm labor is the total number of person-days worked on the farm by household members and hired workers. Land and labor are normalized using country-specific means and standard deviations. Vertical lines represent the 95% confidence interval.

Firstly, we examine cropping patterns using indicators such as the Herfindahl-Hirschman concentration index, which quantifies the concentration of area planted across different crops, and the proportion of land allocated to grain crops. Secondly, we investigate the use of chemical fertilizers and pesticides.[12]

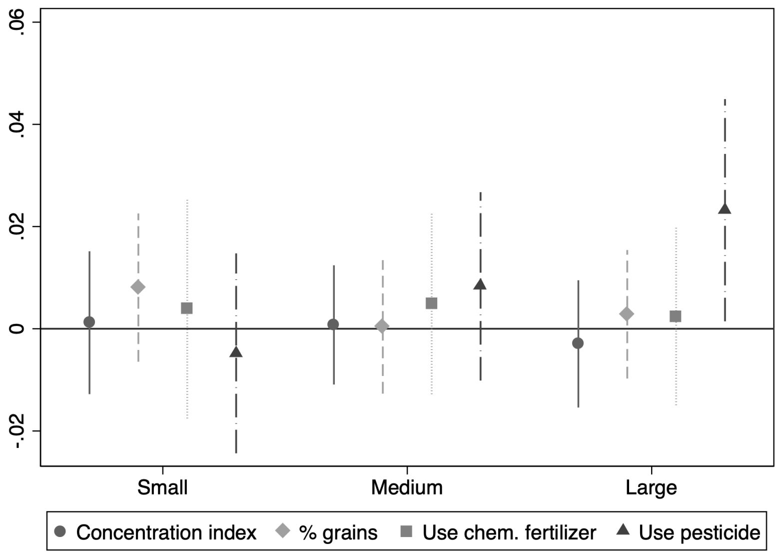
We do not observe any significant impact of HDD on any of these outcomes (see Figure 4a). However, we do find an increase in the use of pesticides among larger farms. This finding aligns with the results of Jagnani et al. (2021), who similarly document increased pesticide usage in response to extreme heat in Kenya. Nevertheless, the lack of effect on cropping patternS contrasts with previous studies. For instance, Ahmed et al. (2022) find that, in response to extreme heat, farmers in Ethiopia expand the area planted with maize, while Li (2023) observe a substitution of rice with non-rice crops among farmers in Bangladesh. Changes in crop composition have also been documented in the US context (Cui, 2020).

Off-farm work Lastly, we examine the impact of HDD on off-farm labor (see Figure 4b). As shown in previous studies, households have the potential to mitigate the impact of agricultural shocks on consumption by engaging in off-farm activities (Rosenzweig and Stark, 1989; Kochar, 1999; Call et al., 2019).

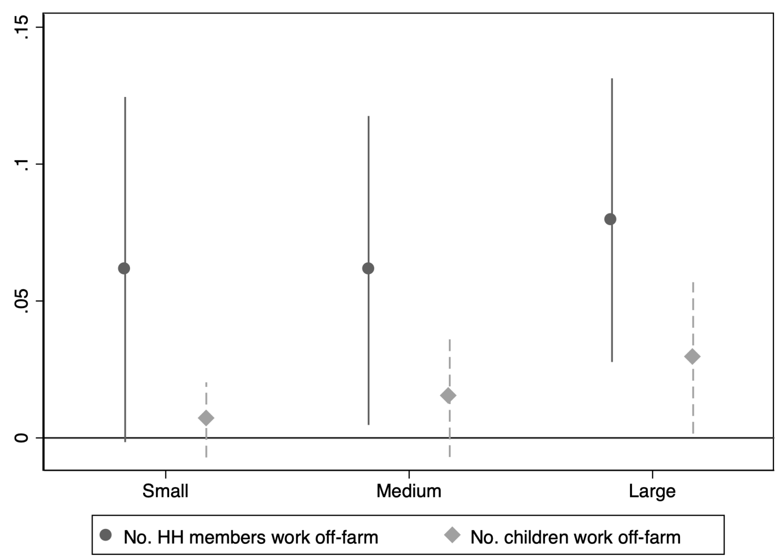
Our findings reveal an increase in the number of household members with paid off-farm employment over the past 12 months. The effect is similar for all farms, regardless of size. Additionally, we observe a rise in the number of children involved in off-farm work, although this effect is only significant for larger farms. It is important to note that the magnitude of these effects is relatively small, amounting to approximately 5-7 percent of the mean for each average HDD. However, it is worth mentioning that our analysis may underestimate the overall impact as our measure of off-farm work solely captures the extensive margin (i.e., number of workers) and not the intensive margin (i.e., number of hours worked).

[12] Grains include maize, rice, millet, sorghum, wheat, teff, enset, and oats

Figure 4: Effect of HDD on agricultural practices and off-farm work, by farm size,



(a) Agricultural practices



(b) Off-farm work

Notes: Figures display estimates of the impact of HDD on measures of agricultural practices and off-farm work by size (β^k). The outcomes in panel (a) are crop diversification index (circles, solid line), the share of area planted with grains (diamond, dashed line), the probability of using chemical fertilizer (squares, dotted line), and the probability of using pesticides (triangles, dash, and dot line). Outcomes in panel (b) are the number of household members with paid off-farm jobs in the last 12 months. We distinguish between all household members (circles, solid line) and children 5-15 years old (diamond, dashed line). This last regression restricts the sample to households with non-zero children. Vertical lines represent the 95% confidence interval.

5 Conclusion

This paper examines the heterogeneous impact of extreme temperatures on household farms, by size farmers by farm size. Our findings support previous research indicating the detrimental impact of high temperatures on agricultural productivity and output. Additionally, we identify significant disparities in productivity and agricultural practices between small and large subsistence farms.

However, we find no evidence of significant differences in the impact of extreme heat by farm size. We interpret this finding as evidence that, despite their technological and socioeconomic differences, both large and small farms face similar limitations in mitigating the negative consequences of extreme temperatures.

There are at least two unsolved issues that warrant further research. Firstly, our analysis focuses on relatively small household farms, limiting our understanding of the impact of extreme temperatures on larger, modern farms, including commercially-operated family farms. It is possible that farm size becomes more influential in these contexts. Secondly, we are unable to explore the underlying reasons for the variation in farmers' responses. Understanding these factors is crucial for assessing the distributional impacts of climate change and informing mitigation and compensation policies.

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ONLINE APPENDIX

A Additional Tables

Table A.1: List of household panel surveys

Country	Survey name	Round	Season	N
Ethiopia	Socioeconomic Survey (ERSS)	2011-12 2013-14 2015-16	Long rainy	6,886
Malawi	Integrated Household Survey (IHS)	2010-11 2013 2016-17	Rainy	2,596
Tanzania	Tanzania National Panel Survey (TZNPS)	2008-09 2010-11 2012-13	Long rainy	4,069
Uganda	National Panel Survey (UNPS)	2011-12 2013-14 2015-16	Jan-Jun and Jul-Dec	19,077

Table A.2: Effect of weather on agricultural productivity, output and food security

	ln(yields)	ln(agric. output)	ln(agric. output)	Did not have enough food
	(1)	(2)	(3)	(4)
Average DD	0.011	0.010	0.037**	-0.001
	(0.016)	(0.014)	(0.017)	(0.006)
Average HDD × small farm	-0.185***	-0.151***	-0.123***	0.029**
	(0.048)	(0.041)	(0.039)	(0.014)
Average HDD × medium farm	-0.162***	-0.149***	-0.152***	0.028***
	(0.037)	(0.037)	(0.042)	(0.014)
Average HDD × large farm	-0.150***	-0.155***	-0.184***	0.048**
	(0.040)	(0.036)	(0.037)	(0.014)
Average rainfall	0.686*	0.553*	1.134***	0.210
	(0.362)	(0.335)	(0.419)	(0.168)
Average rainfall sq.	-0.214	-0.141	-0.424	-0.072
	(0.249)	(0.241)	(0.304)	(0.142)
Input controls	No	Yes	No	No
Observations	32,034	31,928	32,575	30,658
R-squared	0.970	0.883	0.860	0.618

Notes: Standard errors (in parenthesis) are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions also include country-year and country-season fixed effects. Farm size is the area of average land endowment (land owned or with user rights). Weather variables measured over the growing season. DD= degree days. HDD= harmful degree days.

Table A.3: Effect of weather on agricultural inputs, practices, and off-farm work

	ln(area planted)	ln(farm labor)	Concentration index (crops)	% area planted with grains	Uses chem. fertilizer	Use pesticides	No. household members with off-farm jobs	
							All	Children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average DD	0.000	0.021*	0.001	0.006*	0.001	0.002	0.008	0.002
	(0.012)	(0.012)	(0.003)	(0.003)	(0.005)	(0.004)	(0.010)	(0.003)
Average HDD × small farm	0.059**	0.055*	0.001	0.008	0.004	-0.005	0.061*	0.007
	(0.028)	(0.030)	(0.007)	(0.007)	(0.011)	(0.010)	(0.032)	(0.007)
Average HDD × medium farm	0.011	-0.015	0.001	0.000	0.005	0.008	0.061***	0.015**
	(0.022)	(0.031)	(0.006)	(0.007)	(0.009)	(0.011)	(0.029)	(0.011)
Average HDD × large farm	-0.019	0.009	-0.003	0.003	0.002	0.023**	0.08**	0.029
	(0.032)	(0.03)	(0.006)	(0.006)	(0.009)	(0.009)	(0.026)	(0.014)
Average rainfall	-0.188	0.205	0.012	0.309***	0.077	0.049	-0.029	-0.846**
	(0.253)	(0.285)	(0.079)	(0.087)	(0.120)	(0.105)	(0.266)	(0.392)
Average rainfall sq.	0.274	0.142	-0.091	-0.158**	-0.128	-0.094	0.465**	2.959**
	(0.194)	(0.196)	(0.065)	(0.069)	(0.087)	(0.062)	(0.205)	(1.291)
Observations	32,034	32,458	31,950	31,950	32,564	27,435	22,912	14,554
R-squared	0.979	0.803	0.675	0.748	0.804	0.559	0.604	0.393

Notes: Standard errors (in parenthesis) are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions also include country-year and country-season fixed effects. Farm size is the area of average land endowment (land owned or with user rights). Weather variables measured over the growing season. Column 8 includes only households with children aged 5-15. DD= degree days. HDD= harmful degree days. Logs of area planted and farm labor are normalized using country-specific means and standard deviations.

Table A.4: Robustness checks: cluster at regional level, interactions with DD

	ln(yields) (1)	ln(agric. output) (2)	ln(yields) (3)	ln(agric. output) (4)
Average DD	0.008	0.009		
	(0.031)	(0.029)		
Average DD × small farm			0.025	0.020
			(0.022)	(0.019)
Average DD × medium farm			0.01	0.021
			(0.025)	(0.025)
Average DD × large farm			-0.005	-0.015
			(0.027)	(0.023)
Average HDD × small farm	-0.190***	-0.153***	-0.205***	-0.165***
	(0.066)	(0.056)	(0.046)	(0.039)
Average HDD × medium farm	-0.164**	-0.15**	-0.163***	-0.166***
	(0.074)	(0.067)	(0.039)	(0.037)
Average HDD × large farm	-0.152**	-0.158**	-0.129***	-0.121***
	(0.072)	(0.069)	(0.045)	(0.042)
Cluster S.E.	region (n=636)		household (n=9,459)	
Input controls	No	Yes	No	Yes
Observations	30,820	30,714	32,034	31,928
R-squared	0.971	0.884	0.970	0.883

Notes: Standard errors (in parenthesis) are clustered at the regional (columns 1 and 2) or household level (columns 3 and 4). * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions also include household, country-year and country-season fixed effects, monthly precipitation, and its square.

Table A.5: Robustness checks: continuous farm size and region fixed effects

	ln(yield) (1)	ln(agric. output) (2)	ln(yield) (3)	ln(agric. output) (4)
DD	0.011	0.010	0.011	0.023***
	(0.016)	(0.014)	(0.011)	(0.006)
HDD	-0.165***	-0.151***	-0.124***	-0.075***
	(0.026)	(0.023)	(0.020)	(0.012)
HDD × norm. farm size	0.007	-0.005	-0.007	-0.013**
	(0.022)	(0.020)	(0.008)	(0.007)
ln(area planted)		0.314***		0.387***
		(0.018)		(0.014)
ln(farm labor)		0.336***		0.389***
		(0.014)		(0.011)
Fixed effect	Household (n=9,459)		Region (n=611)	
Observations	32,034	31,928	31,032	32,113
R-squared	0.970	0.883	0.951	0.784

Notes: Standard errors (in parenthesis) are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions also include country-year and country-season fixed effects, monthly precipitation, and its square. Farm size is the area of average land endowment (land owned or with user rights). The variable is normalized using country-specific means and standard deviations.

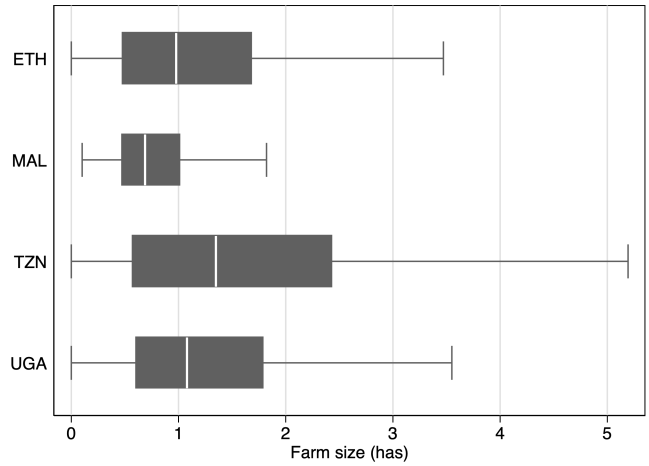
Table A.6: Farm size, productivity and agricultural practices

	ln(yields)	ln(agric. output)	Input ratio ln(labor/land)	Use chem. fertilizer	Use pesticides	Use improv. seeds	Concentration index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Normalized	-0.106***	0.095***	-0.226***	0.038***	0.018***	0.029***	-0.041***
farm size	(0.010)	(0.015)	(0.008)	(0.003)	(0.003)	(0.004)	(0.002)
Input controls	no	yes	no	no	no	no	no
Mean dep. var.	6.362	8.404	2.865	0.218	0.110	0.185	0.434
Observations	32,211	30,949	32,113	32,580	28,085	26,853	32,583
R-squared	0.945	0.740	0.905	0.483	0.130	0.075	0.278

Notes: Standard errors (in parenthesis) are clustered at the household level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include region (n=71), country-year and country-season fixed effects, DD, HDD, monthly precipitation, and its square. Column 2 includes the log of land and labor as in column 2 in Table **??**. Farm size is the area of average land endowment (land owned or with user rights). This variable is normalized using country-specific mean and standard deviation.

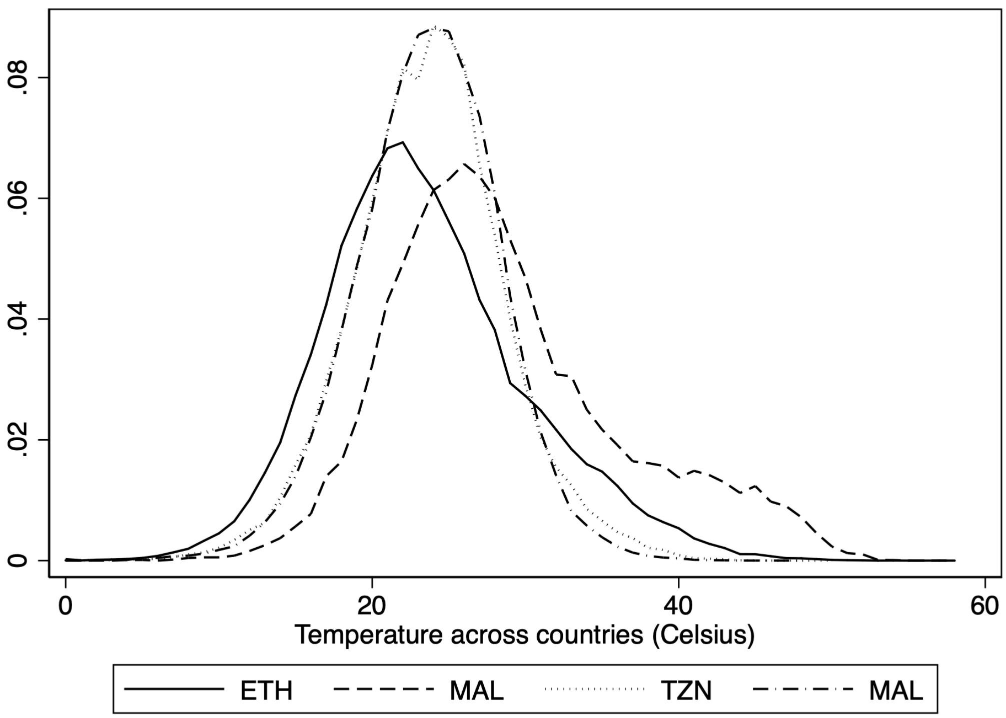
B Additional Figures

Figure B.1: Distribution of farm size



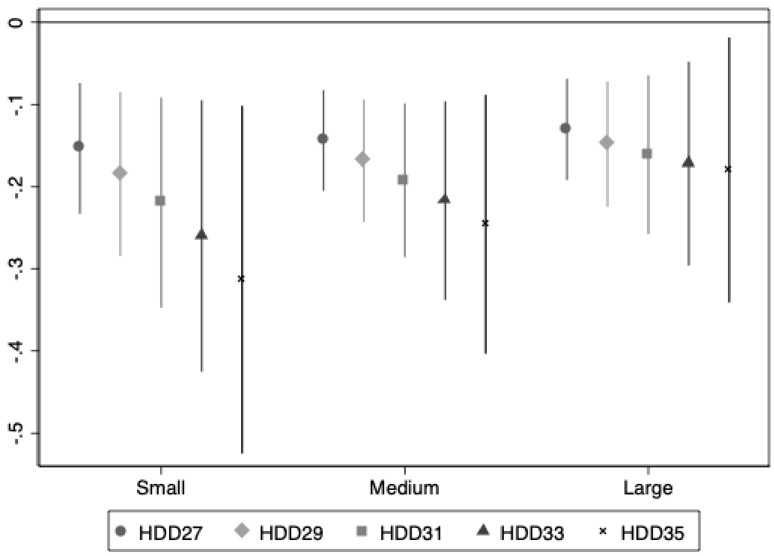
Notes: Figure displays the distribution of farm size (in has) by country. Box plot excludes outliers and shows range (min-max), percentile 25th, 50th and 75th..

Figure B.2: Distribution of daily temperature, by country

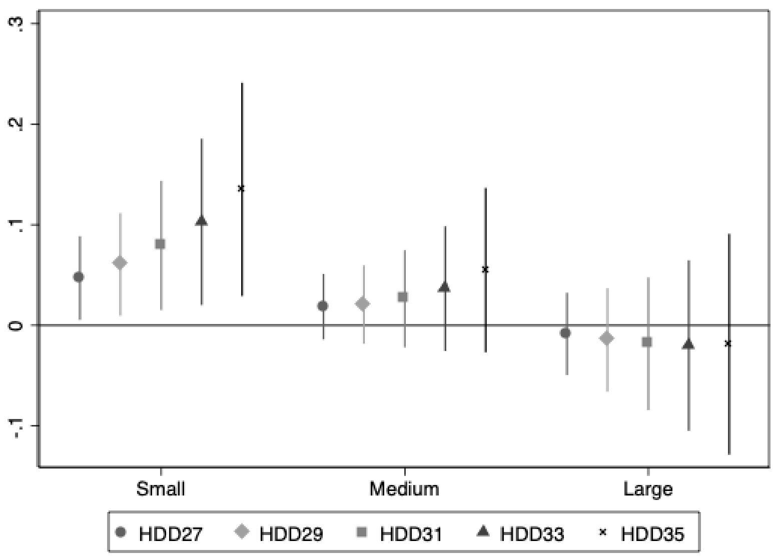


Notes: Figure displays the distribution of average daily temperature (in Celsius) during the growing season.

Figure B.3: Effect of HDD on yields and area planted (by farm size) using alternative definitions of HDD



(a) ln(yields)



(b) ln(area planted)

Notes: Figure displays estimates (point estimates and 95% confidence intervals) of the impact of HDD by size (β^k). Regressions use alternative values of τ to define harmful degree days (HDD). HDD27 refers to estimates using $\tau = 27$°C. Note that our baseline results use the 80th percentile of a country's distribution of daily temperatures.