Harmful Temperatures and Consumption Expenditure: Evidence from Nigerian Households

Jubril Animashaun[1,2], Lotanna Emediegwu[3], Nneka E. Osadolor[4,5], and Okiemua T. Okoror[4,6]

[1]University of Manchester, Manchester, UK

[2]University of Ilorin, Ilorin, Nigeria

[3]Manchester Metropolitan University, Manchester, UK

[4]University of Benin, Benin, Nigeria

[5]University of Ibadan, Ibadan, Nigeria

[6]University of Reading, Reading, UK

Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

Harmful Temperatures and Consumption Expenditure: Evidence from Nigerian Households

Abstract

This paper examines the effect of season-specific changes in temperature on households' consumption expenditure in Nigeria. Prior works show that small-scale farmers attenuate the effect of extreme heat on agricultural productivity by intensifying the use of non-traded inputs like land. However, attenuating weather shocks with purchased inputs such as access to irrigation water or drought-resistant varieties could endogenously lower the welfare of net-food buyers if it increases food prices and consumption expenditure. After controlling for seasonality and other time and zone-specific trends, extreme heat increases per capita consumption expenditure during dry seasons but not in wet seasons. We interpret this result as a reflection of the higher costs of production associated with extreme heat during the dry season. Relative to households in urban cities, rural households pay more for food during the dry season. Rising food expenditure as a welfare implication of extreme heat is important for quantifying predicted economic losses due to climate change. Our results support policies that offer compensated income to vulnerable households as a way to mitigate the impact of weather shocks in developing countries.

JEL Codes: I31, O13, Q51, Q54, R20

Keywords: climate change, extreme heat, food expenditure, welfare, Nigeria

1 Introduction

This paper investigates the effect of season-specific changes in temperature on consumer expenditure. It is well known that small-scale farmers attenuate the adverse effects of extreme temperatures through short-run adjustments in the use of non-traded productive inputs (Aragón et al. 2021, Jessoe et al. 2018). For instance, Aragón et al. (2021) find a more intensive use of non-traded productive inputs, like increasing area planted, increasing family labor, and changing crop mix to attenuate the effect of extreme heat on productivity loss. These findings are typical of agricultural household models under incomplete markets (Taylor & Adelman 2003, De Janvry et al. 1991). This view is particularly relevant for farmers in developing countries where market imperfections, imperfect learning, coordination failures, and weak institutions limit investment and access to climate-shock mitigating technologies.

However, a broader view sees tradable inputs such as drought-resistant technologies as important constituents of the agricultural production function during adverse weather shocks (Hertel et al. 2010). Across the agricultural value-addition chain in the Sub-Saharan Africa (SSA) region, access to irrigation water and drought-resistant technologies during heat stress involves making some costly expenditure on the part of farmers. Omitting the costs and expenditure made regarding these technologies in the production function will endogenously overstate the response of non-tradable inputs like land to weather shocks. When seen from this perspective, adapting farming and agricultural infrastructure to climate change implies greater challenges for the rural poor farmers and a plausible cause of higher food prices.[1] This means that as weather shocks intensify, constraints from access to purchased inputs could increase prices of agricultural goods.

This paper examines the welfare effect of season-specific extreme temperatures on the cost of living vis-à-vis their exacerbated impacts on household consumption. On a global scale, it is already noted that the financial cost of adaptation to climate change could likely result in an additional price increase of food staples —a total of 32 to 37 percent for rice, 52 to 55 percent for maize, 94 to 111 percent for wheat, and 11 to 14 percent for soybeans (Nelson et al. 2009). Moreover, for most households, the share of food (commodities) constitutes a higher budget share; therefore, increasing food prices could increase the cost of living and lower the relative income of net food consumers who are relatively poor (Sam et al. 2021, Hertel et al. 2010, Brown et al. 2009).

Our main contribution is to the literature exploring the margins of adjustment and the scope for mitigation to the impact of climate change on agriculture and the food system (Aragón et al. 2021, Jessoe et al. 2018, Colmer 2018, Gerber et al. 2013). An important contribution from this extant literature sees the scope mitigation from short-term productive and behavioral adjustments as important cornerstones for lowering the effects of climate change. In contrast, our contribution supports a broader view that associates the cost implication of abatement strategies to additional welfare loss on households who are net buyers of food (Hertel et al. 2010). To the best of our knowledge, our approach of using food expenditure as a channel for understanding the welfare effect of extreme heat gives better implications for quantifying economic losses due to climate change. Policymakers are beginning to recognize that understanding the impact of extreme heat on vulnerable populations presents an opportunity to serve low-income communities. Therefore, the expected outputs from our study will proffer important policy recommendations that can help design policies that strengthen the local response and foster resilience to

[1]Potential reasons for the higher costs include lack of (or imperfect) access to input markets, poor coordination efforts of extensions agents' services and information asymmetry regarding best practices.

weather shocks. It is also important for supporting policy in response to calls for improved funding of climate change adaption strategies and the use of compensating income for households facing higher food prices due to weather shocks.

To motivate our study, we incorporate weather-induced production inputs into the farm household and agricultural models (Tack & Yu 2021, Pope et al. 2011). The model incorporates life-cycle household consumption, agricultural production, and off-farm financial decisions in one coherent dynamic and intertemporal framework. Farm production depends on purchased inputs, non-tradable inputs like land, stochastic production, and weather-induced shock. Returns to agricultural investment are functions of productive use of non-tradable inputs and investment in purchased inputs that mitigate production risks from weather-induced shocks (Hertel et al. 2010). However, rural agricultural households are characterized by market imperfections that generate inefficiencies and retard asset accumulation, coordination failures, and weak socio-political and economic institutions (Barrett 2008). The implication is that under incomplete markets, the use of tradable productive inputs due to weather-induced shocks will increase production costs and plausibly lower agricultural supply. Households can draw on non-agricultural assets to fund higher expenditure as rising production costs lower staple agricultural production. However, this implies a welfare loss arising from a decline in consumer surplus as increased food prices lower net income and purchasing power (Friedman & Levinsohn 2002, Deaton & Muellbauer 1980).

On the other hand, higher food prices might only be a threat if many farm households are net food buyers as net-sellers may find higher food prices beneficial. Similarly, because consumer demand for most food items among the poor suggests "Giffen" behavior, a rise in price on essential food items will likely force them to reduce the consumption of luxurious and other expensive foods without changing the consumption of staple foods (Jensen & Miller 2008). Therefore, while weather shocks affect aggregate consumption expenditure, households may consume more and not less of food items considered as essential without significant loss to utility.

To support our theoretical prediction, we combine Nigerian household survey data with satellite imagery for our empirical analysis to construct a comprehensive dataset containing socioeconomic and meteorological variables. We utilize a methodologically data-intensive but straightforward approach that has been used in previous climate-related studies to estimate the impact of local weather conditions on several economic outcomes. Specifically, we investigate the impact of extreme temperatures on consumption outcomes like per capita, cereal, tuber, and animal and fruit consumption separately during the wet and dry seasons. The intuition is that extreme weather shocks will stimulate greater use of purchased intermediate inputs for abating the impact of climate shock than during the wet season. Similarly, we categorize households into two based on whether they live in rural or urban areas. Intuitively, compared to rural dwellers, urban dwellers are less dependent on agriculture for livelihood strategy and may less likely experience price shocks that arise from output changes. We identify these impacts from weakly exogenous and random local weather fluctuations, thereby reducing the problem of omitted variable bias.

After controlling for seasonality in agricultural supply and other time and zone-specific trends, we find that a one percent standard deviation increase in our measure of extreme heat days is associated with a 46.8% fall in consumption expenditure during the wet season. Contrastingly, a one percent standard deviation in the measure of extreme heat days during dry seasons is associated with a 24.9% increase in food expenditure per household. These findings are consistent with the variation in the cost of mitigation practices due to weather shocks exhibiting a distinct seasonal pattern; therefore, food prices are more expensive during harsh weather conditions (Brown et al. 2009). Compared to rural-based households, we find that climate variability does not significantly affect expenditure in urban areas. This result is consistent with the studies showing that climate shock will make rural households in developing countries more vulnerable than urban-based households. Given that consumption responses to weather shocks are likely to reflect substitution that prioritizes the consumption of important staples, we find that cereals and fruits are more affected by extreme temperatures. Similar studies find that extreme heat increases the quantity harvested (in absolute and relative terms) of tubers (Aragón et al. 2021), which reflects why expenditure on this food category is not responsive to weather shocks.

Furthermore, we find the pattern of consumption differs across the location. For example, while consumption is expected to increase due to rising hot days in rural areas, it is likely to fall in urban areas. Although the number of extreme weather events, such as droughts, heat, and increased precipitation, has doubled in the past 40 years (IPCC 2018), there is less confidence in the adverse implication on traditional human livelihoods. Nonetheless, unpredictable weather conditions could carry substantial economic and social costs for the rural poor, whose livelihood is mainly tied to agriculture.

To the best of our knowledge, the adjustment in Nigerian households' consumption in response to extreme temperatures has not been documented before. Similar studies have investigated how temperature and rainfall shocks influence household consumption. For instance, Aggarwal (2021) examines the impacts of temperature and precipitation variability on the monthly per capita consumption expenditure of Indian households. The study reports that an increase in consumption of 1.2 percent on average is associated with a one standard deviation rise in temperature, with heterogeneous impacts across economic sectors. In another study, Sam et al. (2021) use the IFPRI-projected climate scenarios to show that Swazi households living in rural areas could experience a significant deterioration in living standards. They report that the fall in household welfare is due to increased cereal prices following climate change. We improve upon existing literature by exploring the effect of harmful temperatures and estimating the differential impact of weather shocks based on households' vulnerabilities.

We divide the paper as follows. Section 2 provides a formal, conceptual framework for the study. Background information of our study area is supplied in Section 3. We describe the data and empirical strategy in Section 4, while the various results are discussed in Section 5. Section 6 deals with climatic projections and predicted impacts. We conclude the paper with some policy implications in Section 7.

2 Conceptual Framework

This section provides a conceptual overview of the welfare impact of adapting climate change technology in agriculture on household consumption. The model incorporates life-cycle household consumption, agricultural production, and off-farm financial decisions in one coherent framework. In the first part, we allow for tradable abatement technologies such as hired labor, drought-resistant technologies, and irrigation as important variables of the agricultural production model. In the second part, we subject households' utility from the consumption of agricultural staples, a market purchased good, and leisure to income and production constraints arising from weather-induced shocks.

2.1 Household agricultural production under exogenous weather shocks

The basic model is an abridged version of Pope et al.'s (2011) life-cycle household consumption, agricultural production, and financial decisions, as discussed in Tack & Yu (2021).

More formally, following Tack & Yu (2021), the farm's production technology is represented by:

$$y = F[(x, a)(1 + e)] \tag{2.1}$$

where x is a vector of tradable variable inputs (such as fertilizers, irrigation water, and drought and pest-resistant varieties), a is non-tradable input such as land and family labor, y is the output and can be considered an agricultural staple, and e is a stochastic production shock such as those arising from extreme-weather induced biotic and abiotic stress. Underlying many agricultural production models is the concept of risks. Our first contribution is to introduce (x) tradable inputs and climate risks abatement technologies into the agricultural production function. Since agricultural production partially depends on tradable inputs, increasing their use due to abiotic and biotic risks can affect investment, yield, and returns from agricultural production (Hertel et al. 2010). For example, under extreme heat, mitigating the effect of drought through access to irrigation water could be the best response for abating water supply to relieve soil moisture deficits and improve agricultural productivity.

Assuming that tradable input is omitted (i.e., $x = 0$), and $e > 0$, intuitively, $\frac{da}{de} > 0$ implies an increase in agricultural output as farmers increase the intensity of land and family labor use in response to abiotic stress. This is the basic rationale in Aragón et al. (2021), which finds that a one standard deviation increase in the measure of extreme heat is associated with a 6 percent increase in land used. Increasing inputs used as a short-run mitigation response to extreme weather shock could help increase the quantity of harvests and attenuate productivity loss. Much of the intuition from Aragón et al. (2021) is valid under a more general setting where mitigating the effect of heat stress does not require additional use of other inputs. On the other hand, any tradable input that alters productivity could dramatically impact agricultural output. Accounting for improvement in technological innovations, e.g., drought-resistant varieties and access to irrigation water could reduce the economic importance of the land input on agricultural production (Hertel et al. 2010).

Subsequently, we extend equation (2.1) and show that agricultural production is jointly affected by the intertemporal interactions and allocation of tradable and non-tradable resources, mainly driven by the expenditure on climate change abatement inputs. Therefore, generalizing the production function in equation (2.1) to include another function that captures the expenditure on weather adaptation measures $\boldsymbol{P}_x(x; e)$:

$$y = F(x, a, \boldsymbol{P}_x(x; e)(1 + e)) \tag{2.2}$$

And in spirit to Hansen and Singleton's (1983), but generalized to allow for diversification into non-agricultural assets, we can subject the agricultural production function to an initial wealth in period t ($\boldsymbol{I}_t$) to allow for investment less market-purchased commodities ($\boldsymbol{m}_t$).

$$y_t = \boldsymbol{I}_t — \boldsymbol{m}_t \tag{2.3}$$

And wealth, $\boldsymbol{I}_t$, is a function of:

$$I_t = \boldsymbol{K}_t + \boldsymbol{\alpha}_t + \boldsymbol{P}y_t(y_t)(1 + e_t) \tag{2.4}$$

where $\boldsymbol{K}_t$ is the value of the non-agricultural asset, $\boldsymbol{\alpha}_t$ is the value of the land asset, and $\boldsymbol{P}y_t(y_t)(e_t)$ is the profit or value of agricultural outputs after accounting for weather mitigating technology inputs ($\boldsymbol{X}_t$) and autonomous consumption of agricultural products. Similarly, agricultural production investments in period $t + 1$ is a function of end-of-period wealth in $\boldsymbol{I}_{t+1}$:

$$I_{t+1} = \boldsymbol{K}_{t+1}\boldsymbol{\beta}_t + \boldsymbol{\alpha}_{t+1}\boldsymbol{\eta}_t + \boldsymbol{P}y_{t+1}(y_t)(1 + e_{t+1}) - \boldsymbol{m}_{t+1} \tag{2.5}$$

where $\boldsymbol{\beta}_t$ captures the relative change in the value of the non-agricultural asset and $\boldsymbol{\eta}_t$ captures the change in the value of the farmland. $\boldsymbol{P}y_{t+1}(y_t)(e_{t+1})$ is the ex-post realized output (i.e., profit) that sells at output price and after accounting for $\boldsymbol{P}_{t+1}\boldsymbol{X}(\boldsymbol{x}_t; e_{t+1})$, which is the expenditure to reduce the effect of extreme heat (cost of abatement for reducing the production shock) and after accounting for home consumption of agricultural staples (i.e., autonomous consumption) less expenditure on market-purchased commodity (m_t).

We interpret these findings as evidence that agricultural production costs will increase in response to extreme temperatures. Examples of intermediate inputs include fertilizers, pesticides, drought-resistant, and early maturing varieties, hired labor, and irrigation water. Unfortunately, agricultural production and access to inputs that could abate in many developing countries are characterized by market imperfections. The implication is that short-term adjustment of supply to productive input use is endogenously determined; however, pinning down the impact could be observed as expenditure varies with season-specific changes in temperature.

2.2 Household consumption expenditure under endogenous production shocks

Following a typical household model[2], in any production cycle, the household is assumed to maximize utility from the consumption of an agricultural staple ($\boldsymbol{Xa}$), a market purchased good ($\boldsymbol{Xm}$), and leisure ($\boldsymbol{Xl}$).

$$\boldsymbol{U}_t = U(\boldsymbol{Xa}_t, \boldsymbol{Xm}_t, \boldsymbol{Xl}_t) \tag{2.6}$$

Merging the production constraint into the income constraint, utility is maximized subject to:

$$P_a\boldsymbol{Xa}_{t+1} + P_m\boldsymbol{Xm}_{t+1} = \boldsymbol{I}_{t+1} = \boldsymbol{K}_{t+1}\boldsymbol{\beta}_t + \boldsymbol{\alpha}_{t+1}\boldsymbol{\eta}_t + \boldsymbol{P}y_{t+1}(y_t)(e_{t+1}) \tag{2.7}$$

where the left-hand side function represents expenditures made on agricultural staples and a market-purchased good, respectively. The right-hand side variables are the production and income constraints. In this presentation, it is assumed that production under weather shocks is risky. However, households have access to non-farm income sources. Therefore, despite the market imperfection, they can still pay for the rising expenditures made on agricultural staples and a market-purchased good. On the one hand, tradable productive

[2]See Singh, Janakiram et al. (1986), Singh, Squire & Strauss (1986) for a more elaborate discussion.

inputs due to weather-induced shocks will increase production costs and plausibly lower agricultural supply and farm profits. On the other hand, households will draw on non-agricultural assets to fund higher expenditure as increasing production costs lower staple food production.

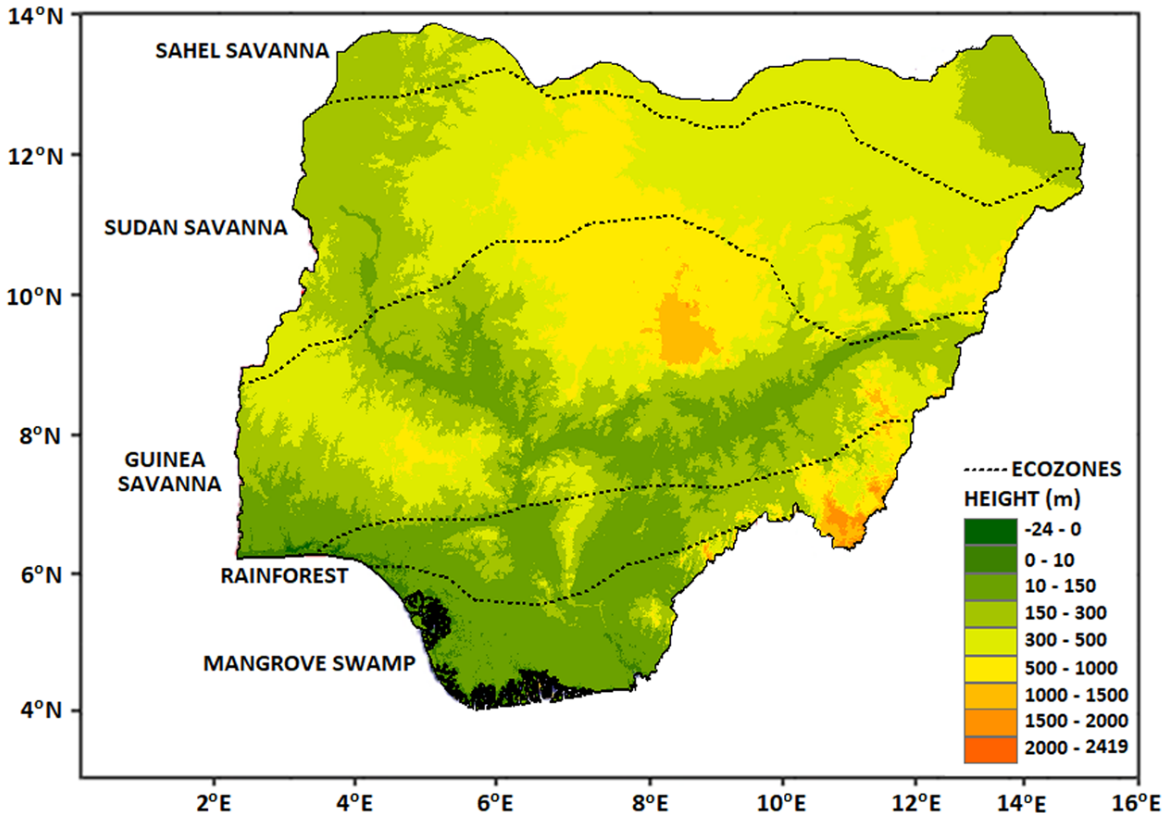
However, higher food prices might only be a threat if many farm households are net food buyers as net-sellers may find higher food prices beneficial. Similarly, because consumer demand for most food items among the poor suggests "Giffen" behavior, a rise in price on essential food items will likely force them to reduce the consumption of luxurious and other expensive foods without changing the consumption of staple foods (Jensen & Miller 2008). Therefore, while weather shocks affect aggregate consumption expenditure, households may consume more and not less of food items considered as essential without significant loss to utility.

Pinning down these mechanisms empirically remains a challenge. Still, it is essential for designing appropriate interventions for mitigating the effect of extreme weather in areas where livelihoods depend heavily on agricultural production. There are, however, at least two ways of investigating this. First, the cost of climate abatement should be higher during the dry season. Therefore, consumer expenditure on agricultural food products will be correlated with season-specific changes in temperature. After controlling for seasonality in agricultural production, higher expenditure is likely observed during the dry season than during the wet season. Second, if rising expenditure due to weather shocks is tied to higher prices and the dwindling supply of agricultural products, weather shocks would significantly aggravate expenditure in communities with high dependence on consumption from agricultural staples. For instance, in contrast to urban communities, households in rural communities could experience higher expenditure due to higher prices to the extent that they can fund rising expenditure due to climate change with non-agricultural assets. The literature explains that covariate shocks force households to adopt strategies such as selling assets or extracting natural resources to fund rising expenditure due to weather shocks (Nguyen et al. 2020). The following sections investigate these mechanisms with data and discuss the empirical strategy employed in greater detail.

3 Background

Before providing a background of the study area, we highlight the reasons for the choice of our study area. First, Nigeria provides a unique choice because of the availability of data on household consumption expenditure from the Nigerian General Household. Second, the geographical importance and the contribution of agriculture to the economy, as well as variation in weather patterns make Nigeria a suitable choice of area for investigating the impacts of weather chocks on household consumption expenditure.

Nigeria is a tropical country that lies between latitudes 4° and 14°N, and longitudes



Source: Shiru et al. (2020)

Figure 3.1: **Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios**

2° and 15°E with distinct agro-ecological zones (AEZs) (see, Figure 3.1). The sharp disparity in ecological and climatic conditions is reflected in the sharp variation in annual temperature and precipitation as one moves from the North to the South. In the South, average annual temperature ranges from 17–37°C and in the North from 12–45°C (Haider 2019). Similarly, aggregate annual rainfall amounts decrease Northwards, with the South receiving an average of 3,000 mm of rainfall per year versus 500 mm in the northeast. Future projections of extreme weather events indicate that by 2060, a rise in temperatures by 1.1–2.5°C would increase the number of extreme heat days to 260 days by 2100 (versus only ten days in 1990) (Haider 2019).

The Nigerian climate varies greatly depending on the region. Therefore, there are two seasons - rainy and dry seasons. In general, the length of the rainy season decreases from South to North. In the South the rainy season lasts from March to November, whereas in the far North it lasts only from mid-May to September.

Given the key role of agriculture to the Nigerian economy as a primary source of income for 80 percent of rural poor and contributing more than 20 percent to national gross domestic product (GDP), adverse weather events in Nigeria are generally associated with increases in the prices of agricultural produce. Besides, agricultural production in Nigeria is mainly rain-fed (less than 1 percent is irrigated) and done by smallholder farmers.

Climate variability affects relative output and input prices and hence the supply of food products. Suppose climate change exacerbates the frequency and severity of extreme weather events, such as heat waves, in Nigeria, the result will be an increase in average food prices, which could be observed in the interannual variation in consumption expenditure. In this case, climate variability will affect food expenditure as households facing higher food prices will adjust production and consumption decisions to mitigate the effect of rising food expenditure.

4 Data and Model Specification

4.1 Data Description and Sources

We combine household survey data with satellite imagery to construct a comprehensive dataset containing socio-economic and meteorological variables. Our unit of observation is the enumeration area (EA)-by year. Our final dataset is panel data consisting of more than 2000 observations spanning from 2010 to 2016. Nigeria is a prime example to study the effect of extreme heat on micro-level socioeconomic livelihoods in a tropical region. Nigeria houses more poor people than any country globally, ranks 103rd out of 119 qualifying countries on the hunger scale (UNDP 2016), and positions 152nd out of 188 countries on the 2015 UNDP Human Development Index (von Grebmer et al.

2018). Pressures from weather-related shocks are some of the identified concerns driving vegetation loss and poverty in the country (Bertoni et al. 2016, Barbier & Hochard 2016).

Socio-economic Dataset

We source our main data from the three waves of the Nigeria General Household Survey (NGHS), a multi-topic panel survey carried out annually over 12 months on a nationally representative survey of approximately 5,000 households from more than 500 EAs representing all the states in Nigeria as shown in Figure **??**.[3] The three waves used in this study are chronicled as follows: wave 1 (2010-2011), wave 2 (2012-2013), and wave 3 (2015-2016).[4] The National Bureau of Statistics (NBS) implemented the surveys with the support of the World Bank Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) project. The survey asks household members to report the amount spent on different food and non-food items in the last seven days and other health and education expenditures. We use this information to construct measures of household consumption. One major limitation of the dataset is that we do not observe expenditure over the spending period: rather, only the aggregate amount spent in the last 12 months is recorded. However, we believe these measurement errors are exogenous to our explanatory variables; consequently, such imprecision might only lead to imprecise rather than biased estimates. The survey also provides information on other socio-demographic features such as access to the market, gender of household heads, amount spent on electricity, *etc.* Given that our unit of measurement is at the EA, we average observations at household level to the EA level.

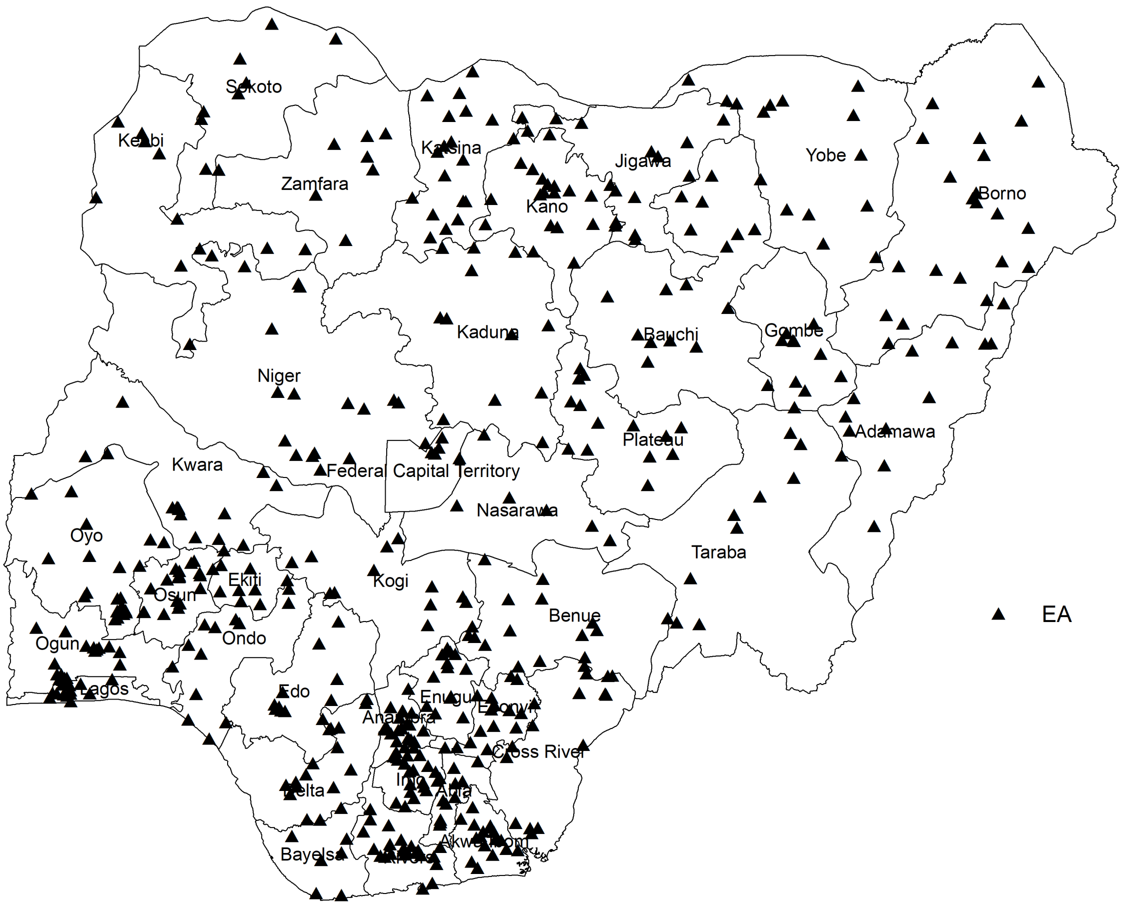
Weather Data

Our weather data comes from the National Centers for Environmental Prediction (NCEP)/Climate Prediction Center (CPC).[5] This gridded dataset contains daily maximum and minimum temperature, as well as total daily precipitation at 0.5×0.5 degree resolution (approximately 56km $\times$ 56km at the equator) from 1979 till date. Mean daily temperature is derived by averaging each day's maximum and minimum temperature for each grid cell. To link the weather and household data, we overlay a polygon of Nigerian EA on the average temperature and total precipitation for each grid cell and take the simple average across all grid cells per EA using geospatial software. While, we leave average temperature at daily level to allow us construct our measure of extreme heat, we aggregate the daily precipitation observations to obtain monthly aggregate rainfall at a location.

[3] There are 36 states in Nigeria, including the Federal Capital Territory.

[4] Year 2014 is missing in the survey.

[5] CPC data is provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their website at `https://psl.noaa.gov/`



Notes: Each black shape represents an enumeration area (EA).

As our baseline specification, we divide a typical year into dry and wet seasons to understand how seasonality drives consumption spending among Nigerian households. A typical dry season in Nigeria spans November to March, while the rest of the year is classed as wet season period. Figure A.1 in the appendix shows the temperature distribution in these two seasons.

Climate Change Projection Data

We rely on the Australian Community Climate and Earth System Simulator (ACCESS-ESM1.5) of the Commonwealth Scientific and Industrial Research Organisation (CSIRO) for our climate change projection data.[6] This general circulation model (GCM), which belongs to the sixth phase of the Coupled Model Intercomparison Project (CMIP6), comprises of atmospheric and land components compiled as a single executable, coupled to ocean and sea-ice executables.[7] We use the *middle-of-the-road* scenario (SSP3-7.0) of the model to construct an EA-day panel for average temperature and total precipitation from 1970 to 2100.[8] We use these projected data to examine the medium-term (average over 2041 - 2060) and long-term (average over 2081 - 2100) impacts of hot days on food consumption in Nigeria.

4.2 Model Specification

We use a reduced-form log-linear model specification to estimate the relation between heat exposure and consumption expenditure in Nigeria.[9] Our dependent variable is y_{iet}, where $i \in \{c/n, ce, tu, an, fr\}$, with c/n for consumption per capita, ce for cereal expenditure, tu for tubers and roots expenditure, an animal products expenditure, and *fr* for fruits and vegetables expenditure in enumeration area (EA) e and in year t. All outcomes aside from consumption per capita are derived as shown in Table 4.1. The model is specified as

$$y_{iet} = \alpha_e + \gamma_r t + \beta_1 DD_{et} + \beta_2 HDD_{et} + \lambda_1 P_{et} + \lambda_2 P_{et}^2 + \lambda H_{et} + \epsilon_{et} \tag{4.1}$$

where α_e are EA fixed effects to control for EA-specific time-invariant factors of food consumption such as average distance to the nearest market, γ_r are zone-specific trends which accounts for time-changing determinants of food consumption that are common

[6] This data is hereafter referred to as ACCESS.

[7] In lieu of presenting detailed description of the simulation processes of these global climate models (GCMs), readers are referred to Eyring et al. (2016), whereas the dataset can be retrieved from the CMIP6 website `https://pcmdi.llnl.gov/?cmip6`.

[8] SSP3-7.0 is a new shared socioeconomic pathway added to CMIP6 that lies between the worst case (SSP5-8.5) and more optimistic (SSP4-6.0) scenarios.

[9] This is a popular approach in measuring the impact of weather shocks on economic outcomes as evidenced in Emediegwu (2021), Hsiang & Meng (2015), Deschenes & Greenstone (2007)

Table 4.1: Derivatives of Consumption Purchases

Outcome Variable	Combination
Cereals	Sorghum + Maize + Millet + Rice + Other cereals
Tubers & Roots	Yam + Cassava + Banana & Other tubers
Animal Products	Poultry + Meat + Fish + Diary
Fruits & Vegetables	Fruits + Vegetables + Beans

within a geo-political zone (such as the agreement to ban open grazing in the South-West Zone of Nigeria).[10] H_{et} contains EA-specific time-varying characteristics that may influence spending on food products. These characteristics include average house rent, average education spending, average spending on mobile phone recharge and average amount on petrol. ϵ_{et} are idiosyncratic errors clustered at EA-level to account for possible correlation of the standard error terms within EA groups.

Following earlier studies like Aragón et al. (2021), Roberts et al. (2012), we model the impact of weather exposure as cumulative heat exposure and rainfall. Specifically, we construct two indices to reflect cumulative heat exposure - degree days (DD) and harmful degree days (HDD). Formally, DD is defined as

$$DD = \frac{1}{n} \sum_{d} DD(t_d)$$

$$where\ DD(t_d) = \begin{cases} 0 & if\ t \leq \kappa_{low} \\ t - \kappa_{low} & if\ \kappa_{low} < t \leq \kappa_{high} \\ \kappa_{high} - \kappa_{low} & if\ \kappa_{high} < t \end{cases}$$

where t_d is average daily temperature in day d (in °C), κ_{low}, baseline temperature, but κ_{high} is the temperature ceiling beyond which crops are hurt. In the same vein,

$$HDD = \frac{1}{n} \sum_{d} DD(t_d)$$

$$where\ DD(t_d) = \begin{cases} 0 & if\ t \leq \kappa_{high} \\ t - \kappa_{high} & if\ \kappa_{high} < t \end{cases}$$

Including HDD accounts for non-linear impact of extreme heat. It is significant to state

[10] The states are grouped into six geopolitical zones: the North Central (NC), North East (NE), North West (NW), South West (SW), South East (SE) and South (SS)

that for ease of interpretation, we calculate *average* degree days as done in Aragón et al. (2021), rather than *aggregate* degree days. Our interest parameter is β_2, which estimates the impact of extreme heat on food expenditure in Nigeria.

Concerning the choice of κ_{low} and κ_{high}, there is no unanimity in the literature on the most appropriate or a "one-fits-all" thresholds since the choice is dependent on the outcome measured. Consequently, we follow Aragón et al. (2021), Deschenes & Greenstone (2007) in selecting $\kappa_{low} = 8^oC$ and $\kappa_{high} = 32^0C$. Since we do not know the true thresholds, we further our analysis using a couple of other thresholds.[11] Rainfall is proxied by total precipitation (in mm) represented by PP and its quadratic term in equation (4.1). Moreover, the climatic variables consist of weather observations during wet and dry seasons.

With a full set of EA and zone-by-year fixed effects, we ensure that the derived estimates are truly from fluctuations in weather. This is a fair assumption because weather fluctuations are fairly exogenous to other unobserved food consumption factors. Also, to account for heteroskedasticity associated with EA sizes, a weighted version of equation (4.1) is estimated where weight is the EA population derived as the sum of household population within an EA. In addition to controlling for heteroskedasticity, population-weighted models allow us to estimate impacts on an average person rather than average EA.

5 Results and Discussion

5.1 Main Results

Table 5.1 presents the results of the effect of extreme temperature on food consumption. The result shows that HDD has a negative and statistically significant effect on consumption per capita during wet seasons (column 1). In particular, an extra day of average HDD during wet seasons is associated with a 47% decrease in consumption per capita. Conversely, we find that the same marginal increase in average HDD in dry seasons has a positive and statistically significant effect on consumption per capita. This mixed result reveals that the effect of changes in HDD on consumption per capita varies depending on the season, which explains the role of seasonality. A plausible explanation for this result is that since most plantings are done in the wet season, food prices are usually higher. This finding is similar to the findings in Aragón et al. (2021), where they conclude that extreme heat shocks can reduce aggregate supply and increase agricultural prices. Therefore, households tend to reduce their consumption expenditure as a coping

[11] Figure A.2 in the Appendix assesses the sensitivity of our results to different κ_{high}, ranging from 25°C to 35°C. The results show that higher thresholds yield similar results while lower thresholds increase the magnitude of the estimates.

strategy (Hisali et al. 2011). In the same vein, food prices are generally lower during the harvesting season (dry season), and as a consequence, households tend to consume more food. As a way out for farmers faced with climatic shocks, the farmers increase their input use to attenuate the impact of extreme weather shock, thereby increasing output in the dry season which leads to reduced prices thereby increasing household food consumption.

Table 5.1: **Effect of Temperature on Food Consumption**

		Purchases			
	ln(C/Y)	ln(cereal)	ln(tuber)	ln(animal)	ln(fruits)
	(1)	(2)	(3)	(4)	(5)
Average DD (wet season)	0.037	0.202**	0.305**	0.091	0.090
	(0.036)	(0.084)	(0.146)	(0.068)	(0.060)
Average HDD (wet season)	-0.468***	-1.119**	0.516	-0.148	-1.277***
	(0.179)	(0.561)	(0.696)	(0.433)	(0.452)
Average DD (dry season)	-0.011	-0.086	-0.200	-0.061	0.149
	(0.033)	(0.100)	(0.142)	(0.072)	(0.091)
Average HDD (dry season)	0.249*	0.356	0.872*	0.260	0.775***
	(0.145)	(0.381)	(0.515)	(0.299)	(0.244)
PRECIPITATION Controls	YES	YES	YES	YES	YES
EA controls	YES	YES	YES	YES	YES
Observations	2279	2249	2204	2279	2279
Adjusted R^2	0.61	0.68	0.66	0.64	0.55

Standard errors (in parentheses) are clustered at EA level. Temperature is measured in ^{O}C and precipitation in mm.
***p<0.01, **p<0.05, *p<0.1.

The effects of extreme heat on the purchases of cereal, tuber, animal products, and fruits are presented in columns 2, 3, 4, and 5, respectively of Table 5.1. From the results, average HDD has a negative and significant effect on cereal and fruits expenditure during wet seasons. An extra day of average HDD is associated with 112% and 128% decreases in cereal and fruits purchases, respectively. On the other hand, we find that the effect of a change in average HDD on tuber purchases in wet seasons is positive, although not significant. The results further show a positive effect of extreme heat on cereal, tuber, animal products, and fruits expenditure in dry seasons. However, while the effects on tuber and fruits purchases are statistically significant, those of cereal and animal products are not. Specifically, we find that an extra day of average HDD leads to 87% and 78% increases in tuber and fruits purchases, respectively.

These results are in line with empirical evidence in the extant literature, which suggests that while the quantity of tubers harvested decreases with extreme heat (Aragón et al. 2021), households tend to persist in their consumption of staple food items like tubers while cutting down drastically or even giving up on the consumption of other food items (Brown et al. 2009, Jensen & Miller 2008). Besides, the results suggest that households adjust their purchases in relation to the availability and, consequently, the market prices of food items. For instance, since the dry season is generally the harvesting period in Nigeria, food items tend to be a lot cheaper, stimulating household purchases. To sum up this subsection, the positive and statistically insignificant effect of extreme heat on animal product purchases indicate that the purchase and consumption of these products are not effectively determined by the weather or season. This, in part, is because the rearing of livestock necessary for the production of the products is not seasonal and less affected by weather shocks, unlike other farm products (Gerber et al. 2013).

5.2 Robustness Results

Table 5.2 presents the results of the robustness checks of the main results to alternative specifications. Each row of the table represents a different specification of the model. However, only estimates of the measure of extreme heat (HDD) are reported.

No Controls: Row 1 in Table 5.2 re-estimates equation (4.1) with *DD* and *HDD* as the only independent variables. The results show that extreme heat has a negative and significant effect on the purchase of cereals and fruits in wet seasons. Whereas, in dry seasons, a change in average HDD has a positive and significant impact on the purchase of fruits. Generally, we find that the estimates are qualitatively similar to the baseline estimates, although some effects disappear.

No Controls (Except Precipitation): In Row 2, we replicate Row 1 specification with the inclusion of the precipitation control to check if the addition of further weather controls would affect the stability of our results. The results from this specification are similar to those in Row 1 of Table 5.2. Ergo, our results are not sensitive to the inclusion or exclusion of certain controls.

Aggregate Heat Units: Further, we show that our results are robust to changes in the measure of extreme heat used. We re-analyzed the baseline model using aggregate DD/HDD in place of average DD/HDD as the measure of extreme heat. The result in Row 3 of Table 5.2 shows estimates with similar significant signs as our baseline, however, with larger estimates. The large coefficients are not surprising given the use of aggregate measure rather than an average in this scenario.

Cluster by State: We re-estimated equation (4.1) with errors clustered at state level rather than at EA level. The results presented in Row 4 of Table 5.2 show that our estimates are broadly consistent with the main specification, though slightly higher in a few cases.

Outliers Influence: Finally, we checked if our results are driven by outlier households. These are households with an average of 200,000 Nigerian naira (NGN) worth of annual food consumption. Purging our data of these households does not undermine the stability of our estimates, as shown in Row 5. The effects across the different seasons are broadly similar to those of the original specification, howbeit with slightly higher magnitudes.

Table 5.2: **Robustness Results**

	ln(C/Y)		ln(cereals)		ln(tubers)		ln(animals)		ln(fruits)	
	Average HDD (wet season)	Average HDD (dry season)	Average HDD (wet season)	Average HDD (dry season)	Average HDD (wet season)	Average HDD (dry season)	Average HDD (wet season)	Average HDD (dry season)	Average HDD (wet season)	Average HDD (dry season)
1. Excluding all controls	-0.274*	0.362***	-0.934**	0.365	-0.044	0.393	-0.174	0.150	-0.916**	0.638***
	(0.166)	(0.113)	(0.471)	(0.319)	(0.626)	(0.455)	(0.359)	(0.261)	(0.056)	(0.213)
2. Excluding all controls (except prep)	-0.278*	0.381***	-0.912**	0.421	-0.051	0.432	-0.155	0.191	-0.939***	0.664***
	(0.167)	(0.112)	(0.473)	(0.320)	(0.628)	(0.457)	(0.359)	(0.263)	(0.371)	(0.21)
3. Aggregate HDD	-0.0023***	0.0021**	-0.005**	0.002	0.002	0.006*	-0.001	0.002	-0.006***	0.005***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
4. Cluster by state	-0.494**	0.330***	-1.118	0.335	0.516	0.871**	-0.148	0.259	-1.276*	0.774***
	(0.234)	(0.119)	(1.004)	(0.464)	(0.728)	(0.357)	(0.277)	(0.266)	(0.667)	(0.252)
5. Remove outliers	-0.514***	0.357***	-1.153**	0.377	0.492	0.980*	-0.109	0.257	-1.284***	0.808***
	(0.180)	(0.135)	(0.5666)	(0.391)	(0.707)	(0.511)	(0.433)	(0.314)	(0.454)	(0.252)

Except otherwise stated, standard errors (in parentheses) are clustered at EA level. Temperature is measured in ^{O}C and precipitation in mm. We count households with an average of NGN200,000 worth of annual food consumption as outliers.
***p<0.01, **p<0.05, *p<0.1.

Overall, the results from several sensitivity checks show that our baseline estimates that measures the impact of extreme heat on Nigerian household food consumption are largely robust. Therefore, we do not expect large deviations from the baseline estimates.

5.3 Investigating Sources

A disaggregated analysis (by location) of the effect of temperature on consumption is presented in table 5.3. During the wet season, average HDD is found to have a negative and significant effect on consumption per capita of households in rural areas. Specifically, an extra day of average HDD leads to a 54.5% decrease in consumption per capita. In addition, the result shows that average HDD has a negative and significant effect on the purchases of cereal and fruits during wet seasons in rural areas. We find no significant effect for tuber and animal products. In like manner, our results show that extreme heat during wet seasons has no significant impact on both consumption per capita and food purchases in urban areas.

During the dry season, we find that extreme heat positively affects consumption per capita and food purchases in rural areas. For example, a marginal increase in average HDD is associated with a 52.3%, 138% and 106% increase in consumption per capita, tuber expenditure and fruits expenditure, respectively, in rural areas during dry seasons. These results mirror those of Table 5.1. However, for urban areas, the results show that extreme heat has no statistically significant effect on consumption per capita as well as the purchases of cereal, tuber, fruits and animal products.

The results above indicate that the effects of extreme heat are almost entirely borne by those by rural dwellers. In Nigeria, the main occupation for households in rural areas is agriculture, which serves both as a source of income and consumption. Hence, changes in climatic conditions such as extreme heat, which tends to affect their agricultural productivity, will also significantly impact the consumption of food products, many of which are locally grown. On the contrary, urban households have alternative items for consumption aside the locally cultivated agricultural products, hence may not be significantly impacted by the severe changes in temperature, which directly affects agricultural production.

6 Predicted effects of climate change

This section considers the quantitative effect of projected climate change on Nigerian household food consumption in the mid-future (2041-2060) and by the end of the century (2081-2100). Then, we calculate the predicted change in consumption expenditure by extrapolating the effect of these temperatures on household consumption.

To carry out this task, we adopt a conventional approach widely used in the climate

Table 5.3: **Effect of Temperature on Food Consumption (by Location)**

	RURAL					URBAN				
		Purchases					Purchases			
	ln(C/Y)	ln(cereal)	ln(tuber)	ln(animal)	ln(fruits)	ln(C/Y)	ln(cereal)	ln(tuber)	ln(animal)	ln(fruits)
Average DD (wet season)	0.037	0.226**	0.444***	0.080	0.076	0.023	0.080	-0.177	0.085	0.041
	(0.039)	(0.106)	(0.171)	(0.084)	(0.076)	(0.057)	(0.118)	(0.234)	(0.107)	(0.095)
Average HDD (wet season)	-0.545**	-1.276*	0.672	-0.341	-1.509***	-0.292	-0.278	0.379	-0.063	-0.369
	(0.212)	(0.676)	(0.811)	(0.522)	(0.551)	(0.315)	(0.671)	(1.384)	(0.611)	(0.538)
Average DD (dry season)	-0.010	-0.059	-0.211	0.003	0.186*	-0.066	-0.186	-0.324*	-0.199**	-0.008
	(0.035)	(0.126)	(0.177)	(0.088)	(0.111)	(0.053)	(0.121)	(0.175)	(0.092)	(0.091)
Average HDD (dry season)	0.523***	0.759	1.379*	0.647	1.055***	0.119	-0.136	-0.389	-0.483	0.377
	(0.171)	(0.538)	(0.756)	(0.435)	(0.332)	(0.206)	(0.469)	(0.579)	(0.316)	(0.329)
PRECIPITATION Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
EA controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1526	1510	1461	1526	1526	753	739	743	753	753
Adjusted R^2	0.63	0.66	0.62	0.65	0.55	0.58	0.74	0.66	0.60	0.56

Standard errors (in parentheses) are clustered at EA level. Temperature is measured in ^{O}C and precipitation in mm.
***p<0.01, **p<0.05, *p<0.1.

econometrics literature. We extrapolate the impact of the regression estimates from the baseline model on forecasted climatic changes derived from ACCESS.[12] Further, we downscale the projected average temperatures using the technique described in Aragón et al. (2021), Deschenes & Greenstone (2007). To estimate the downscaled temperature change, we add the implied temperature change for each day-location to the associated daily average temperature in our observed dataset.[13] Downscaling climate forecasts is important to eliminate bias emanating from the GCM's current climate in some locations, since observed data and GCM's historical data for the same period/place may have different observations.[14] Finally, we generate the relevant (harmful) degree days for each period and place from the projected temperature distribution.[15]

The projected change in DD and HDD for the entire sample and each division under both periods is presented in Panel A of Table 6.1. Generally, the increase in average DD is approximately double in the long run than in the mid-term, while it is triple for average HDD in both seasons. The increase in average HDD is more pronounced in rural areas than in urban locations. This discrepancy is more evidenced during wet seasons than during dry seasons, signifying that some parts of wet seasons would become drier and hotter as we go further into the century.

Panel B in Table 6.1 presents the predicted effects of projected climate change on food consumption by Nigerian households. Overall, we find a rise in household food consumption by the mid-century, although this increase appears minimal (0.6%) for consumption per capita. In terms of magnitude, we find that as extreme temperatures increase, households would consume more of tuber and fruits and less of cereals, as shown in column 4. In line with the findings of Aragon et al., 2019 that reported extreme heat increases the quantity (in absolute and relative terms) of tubers harvested. This could drop the price in the market and therefore increase the consumption of tubers. We also find heterogeneous responses to future heating across locations. For example, while consumption is expected to increase due to changes in HDD in rural areas, it is falling in the urban areas (except for fruits consumption). These heterogeneous changes widen as we move further into the century, as shown in columns 5-6.

It is significant to state some caveats at this point. One key assumption in the use of climate models for future predictions is the *ceteris paribus* assumption. Put differently, we assume that only climate (ΔDD, ΔHDD), and nothing else, changes. Hence, we have masked the possibility of future adaptation or mitigation, which could modify the overall effects. Consequently, our results should be interpreted as the upper boundary of

[12] This GCM has been described in subsection 4.1.

[13] Implied temperature change by the middle of the century is calculated as the difference between average over 2041 - 2061 and a historical period (1981 - 2010) average. For the end of the century, similar calculation holds for 2081 - 2100

[14] See Burke et al. (2015), Auffhammer et al. (2013) for more on this issue.

[15] We assume similar thresholds here as in the baseline model.

Table 6.1: Effects of Predicted Climate Change

	Mid-term			Long-run		
	All	Rural	Urban	All	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
A. Climate Change Projection						
ΔDD (wet season)	1.78	1.76	1.80	3.21	3.17	3.27
ΔDD (dry season)	1.77	1.78	1.74	3.09	3.12	3.00
ΔHDD (wet season)	0.20	0.24	0.15	0.60	0.68	0.46
ΔHDD (dry season)	0.21	0.22	0.19	0.72	0.72	0.73
B. Predicted Effect on Food Consumption						
$\Delta ln(C/Y)$	0.006	0.032	-0.094	-0.016	-1.213	-0.170
$\Delta ln(cereal)$	0.058	0.153	-0.247	-0.032	0.211	-0.524
$\Delta ln(tuber)$	0.475	0.871	-1.013	1.298	2.199	-1.799
$\Delta ln(animal)$	0.079	0.207	-0.294	0.202	0.469	-0.701
$\Delta ln(fruits)$	0.331	0.334	0.076	0.541	0.555	0.216

Notes: The entries in the table are log changes from ACCESS-ESM1.5 for mid-term climate change (Panel A) and long-run climate change (Panel B) under SSP3-7.0 scenario. Changes are relative to a 1981 - 2010 baseline.

what the effect of extreme heat on consumption expenditure among Nigeria households might look like in the future.

7 Conclusion

Our study sheds light on an important linkage between variation in extreme temperature and welfare through the effect on consumption expenditure. Existing studies show that small-scale farmers respond to extreme weather shocks through productive adjustments in non-tradable inputs to attenuate the impact of extreme weather shocks. This interpretation is consistent with predictions of producer-consumer models in the presence of incomplete markets (Aragón et al. 2021, Taylor & Adelman 2003, De Janvry et al. 1991).

Although important, non-tradable inputs such as land and family labor account for a less share of productive inputs used by small-scale farmers for abating the effect of weather shocks. Accounting for purchased intermediates such as fertilizers, irrigation water, and drought and heat-resistant varieties would give a broader effect of weather shocks on production and the plausible effect on welfare. One way is to raise the cost of production, which is transmitted through higher food prices and observed by rising expenditure during the dry seasons. Already, local food production in many parts of Sub-Saharan Africa is vulnerable to interannual weather variation, creating a sharp seasonal variation in food prices. The additional cost due to mitigating practices of extreme weather events could limit the ability of poor farmers to grow enough food, aggravate price variability, and worsen the purchasing power of net food buyers. On the other hand, since production responds sharply to food demand, the price rise could provide an opportunity for increased food production and improve the welfare of net food suppliers.

We examine how consumption expenditure responds to interannual variation on hot days using the Nigerian General Household Survey data. After conditional on the seasonality in agricultural production and other zone-time specific trends, we find that an additional average harmful degree day (HDD) is associated with a fall in consumption expenditure during the wet season but increased during dry seasons. These findings are consistent with the fact that the mitigating practices during the dry season for extreme temperatures could aggravate the prices of food staples. However, extreme heat does not significantly affect expenditure in urban areas compared to rural households. This finding is in tandem with the studies showing that climate shock will make rural households in developing countries more vulnerable and more affected than urban-based households.

Similarly, we find evidence of consumption substitution that prioritizes the consumption of important staples. These results have important policy implications. The most obvious is that the pattern of impact carries different weights depending on seasonality, location of households, and types of food commodity. More poor people generally appear to be net food consumers and live in rural areas. Without food subsidy or compensated income, this category of people may be harder hit by extreme weather events due to a fall in their purchasing power. The afore statement contrasts studies that show that many rural households gain from higher food prices, suggesting that the overall impact on poverty remains negative (Ivanic & Martin 2008). For instance, Aragón et al. (2021) show that Peruvian farmers use productive adjustments, such as changes in input use, as strategies to attenuate drops in output and consumption. However, because farming in Sub-Saharan Africa is majorly rain-fed, weather variability will continue to impact the ability of local producers to meet up with demand, particularly during the inventory-scarce dry months (Brown et al. 2009). Due to data limitations, we cannot exhaust other key aspects to understanding questions raised in this study. First, we cannot observe the prices of food commodities; only the total amount spent on food and non-food expenditure is used. Second, common to other recent studies of the climate economics literature (e.g., Deschenes & Greenstone (2007)), we can only observe the impact of short-term weather shocks, not climatic changes.

References

Aggarwal, R. (2021), 'Impacts of climate shocks on household consumption and inequality in India', *Environment and Development Economics* **26**(5-6), 488–511.

Aragón, F. M., Oteiza, F. & Rud, J. P. (2021), 'Climate change and agriculture: Subsistence farmers' response to extreme heat', *American Economic Journal: Economic Policy* **13**(1), 1–35.

Auffhammer, M., Hsiang, S. M., Schlenker, W. & Sobel, A. (2013), 'Using weather data and climate model output in economic analyses of climate change', *Review of Environmental Economics and Policy* **7**(2), 181–198.

Barbier, E. B. & Hochard, J. P. (2016), 'Does land degradation increase poverty in developing countries?', *PloS One* **11**(5), e0152973.

Barrett, C. B. (2008), 'Poverty traps and resource dynamics in smallholder agrarian systems'.

Bertoni, E., Clementi, F., Molini, V., Schettino, F. & Teraoka, H. (2016), Poverty work program: poverty reduction in Nigeria in the last decade, Technical report, The World Bank.

Brown, M. E., Hintermann, B. & Higgins, N. (2009), 'Markets, climate change, and food security in West Africa'.

Burke, M., Dykema, J., Lobell, D. B., Miguel, E. & Satyanath, S. (2015), 'Incorporating climate uncertainty into estimates of climate change impacts', *Review of Economics and Statistics* **97**(2), 461–471.

Colmer, J. (2018), 'Weather, labor reallocation and industrial production: evidence from India', *Centre for Economic Performance, London School of Economics and Political* .

De Janvry, A., Fafchamps, M. & Sadoulet, E. (1991), 'Peasant household behaviour with missing markets: some paradoxes explained', *The Economic Journal* **101**(409), 1400–1417.

Deaton, A. & Muellbauer, J. (1980), *Economics and consumer behavior*, Cambridge University Press.

Deschenes, O. & Greenstone, M. (2007), 'The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather', *American Economic Review* **97**(1), 354–385.

Emediegwu, L. E. (2021), 'Health impacts of daily weather fluctuations: Empirical evidence from COVID-19 in US counties', *Journal of Environmental Management* **291**, 112662.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J. & Taylor, K. E. (2016), 'Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization', *Geoscientific Model Development* **9**(5), 1937–1958.

Friedman, J. & Levinsohn, J. (2002), 'The distributional impacts of Indonesia's financial crisis on household welfare: A "rapid response" methodology', *The World Bank Economic Review* **16**(3), 397–423.

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G. et al. (2013), *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities.*, Food and Agriculture Organization of the United Nations (FAO).

Haider, H. (2019), 'Climate change in Nigeria: impacts and responses', *Institute of Development Studies* .

Hansen, L. P. & Singleton, K. J. (1983), 'Stochastic consumption, risk aversion, and the temporal behavior of asset returns', *Journal of political economy* **91**(2), 249–265.

Hertel, T. W., Burke, M. B. & Lobell, D. B. (2010), 'The poverty implications of climate-induced crop yield changes by 2030', *Global Environmental Change* **20**(4), 577–585.

Hisali, E., Birungi, P. & Buyinza, F. (2011), 'Adaptation to climate change in uganda: evidence from micro level data', *Global environmental change* **21**(4), 1245–1261.

Hsiang, S. M. & Meng, K. C. (2015), 'Tropical Economics', *American Economic Review* **105**(5), 257–61.

IPCC (2018), 'GLOBAL WARMING OF 1.5 ºC an IPCC special report on the impacts of global warming of 1.5 ºC above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty'.

Ivanic, M. & Martin, W. (2008), 'Implications of higher global food prices for poverty in low-income countries', *Agricultural Economics* **39**, 405–416.

Jensen, R. T. & Miller, N. H. (2008), 'Giffen behavior and subsistence consumption', *American Economic Review* **98**(4), 1553–77.

Jessoe, K., Manning, D. T. & Taylor, J. E. (2018), 'Climate change and labour allocation in rural mexico: Evidence from annual fluctuations in weather', *The Economic Journal* **128**(608), 230–261.

Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M. et al. (2009), *Climate change: Impact on agriculture and costs of adaptation*, Vol. 21, Intl Food Policy Res Inst.

Pope, R. D., LaFrance, J. T. & Just, R. E. (2011), 'Agricultural arbitrage and risk preferences', *Journal of econometrics* **162**(1), 35–43.

Roberts, M. J., Schlenker, W. & Eyer, J. (2012), 'Agronomic weather measures in econometric models of crop yield with implications for climate change', *American Journal of Agricultural Economics* **95**(2), 236–243.

Sam, A. G., Abidoye, B. O. & Mashaba, S. (2021), 'Climate change and household welfare in sub-Saharan Africa: empirical evidence from Swaziland', *Food Security* **13**(2), 439–455.

Shiru, M. S., Shahid, S., Dewan, A., Chung, E.-S., Alias, N., Ahmed, K. & Hassan, Q. K. (2020), 'Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios', *Scientific Reports* **10**(1), 1–18.

Singh, I., Janakiram, S. et al. (1986), 'Agricultural household modeling in a multicrop environment: case studies in korea and nigeria', *Agricultural Household Models: Extensions, Applications and Policy. SINGH, I, L. SQUIRE and JOHN STRAUSS (Eds.). The John Hopkins University Press, Baltimore* pp. 95–114.

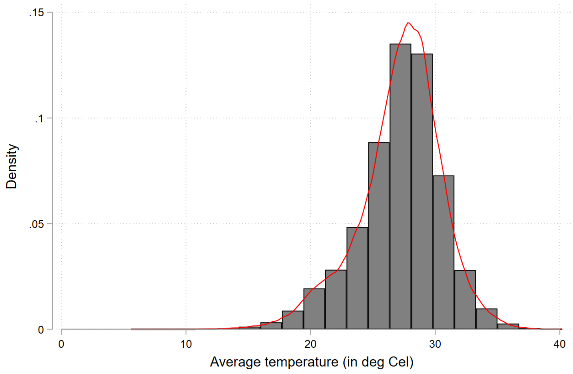
Singh, I., Squire, L. & Strauss, J. (1986), 'The basic model: theory, empirical results, and policy conclusions', *Agricultural household models: Extensions, applications, and policy* pp. 17–47.

Tack, J. & Yu, J. (2021), Risk management in agricultural production, *in* 'Handbook of Agricultural Economics', Vol. 5, Elsevier, pp. 4135–4231.

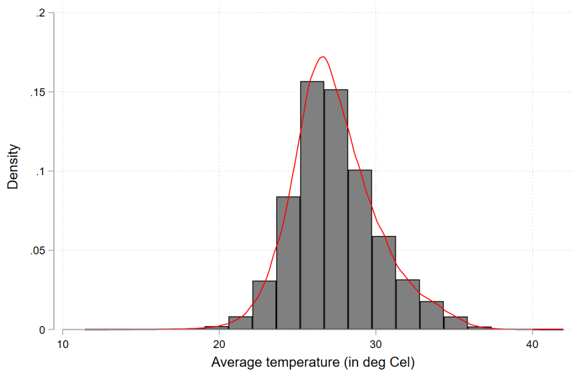
Taylor, J. E. & Adelman, I. (2003), 'Agricultural household models: genesis, evolution, and extensions', *Review of Economics of the Household* **1**(1), 33–58.

UNDP (2016), *Human Development Report 2016: Human Development for Everyone*, UNDP, New York.

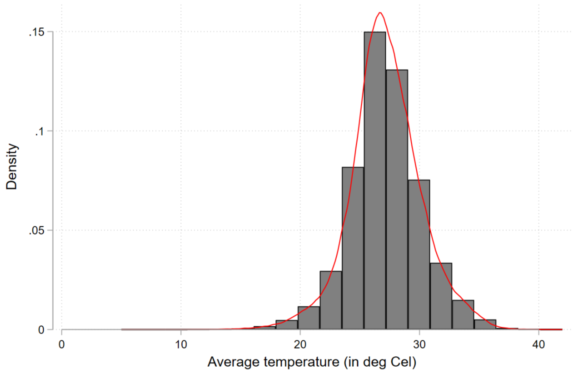
von Grebmer, K., Bernstein, J., Hammond, L., Patterson, F., Sonntag, A., Klaus, L., Fahlbusch, J., Towey, O., Foley, C., Gitter, S., Ekstrom, K. & Fritschel, H. (2018), *2018 Global Hunger Index: Forced Migration and Hunger*, Bonn and Dublin:Welthungerhilfe and Concern Worldwide.



(a) Dry Season



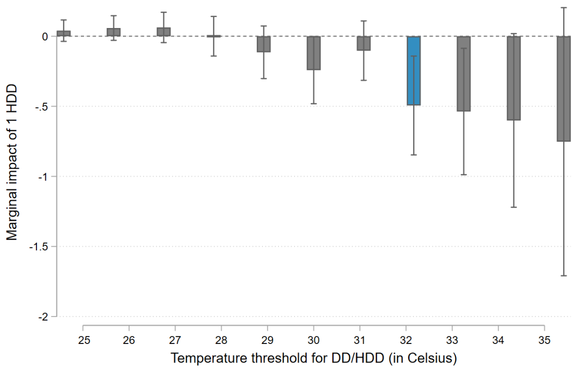
(b) Wet Season



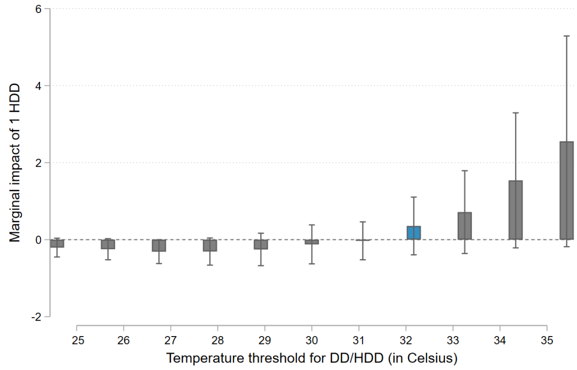
(c) Annual

Figure A.1: **Average Temperature Distribution**

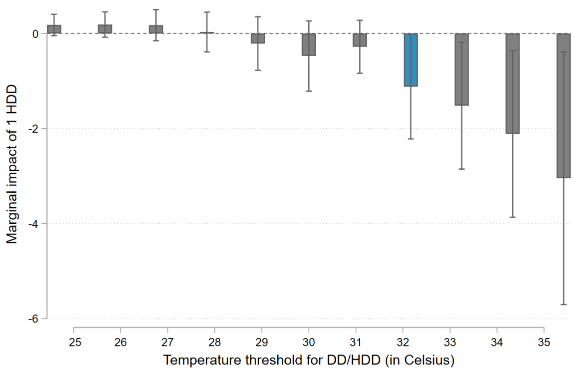
A Figures



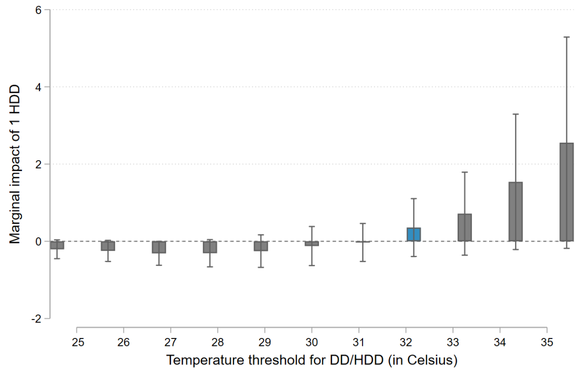
Consumption per capita (Wet Season)



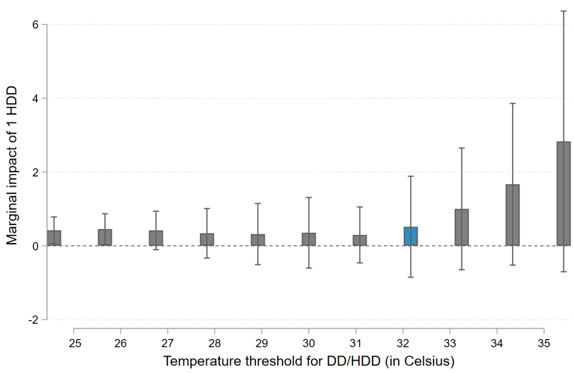
Consumption per capita (Dry Season)



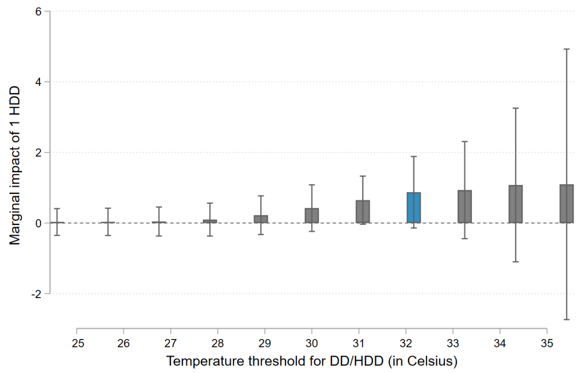
Cereals (Wet Season)



Cereals (Dry Season)

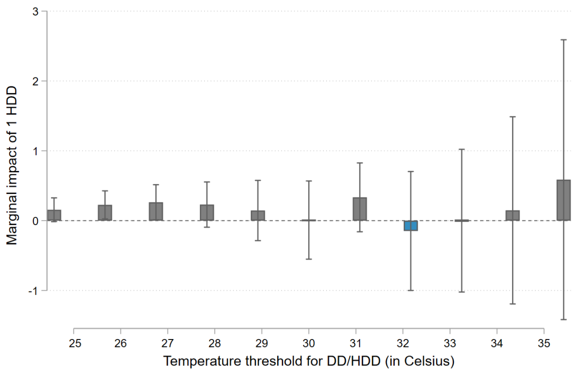


Tubers and Roots (Wet Season)

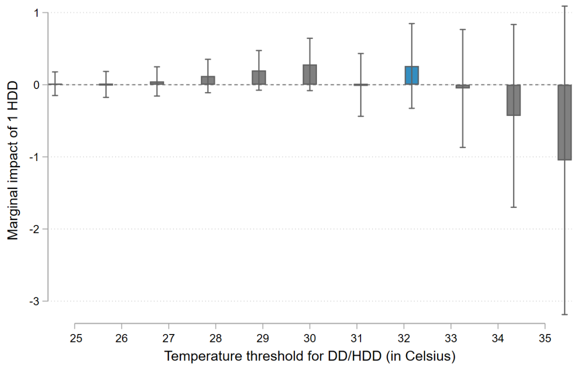


Tubers and Roots (Dry Season)

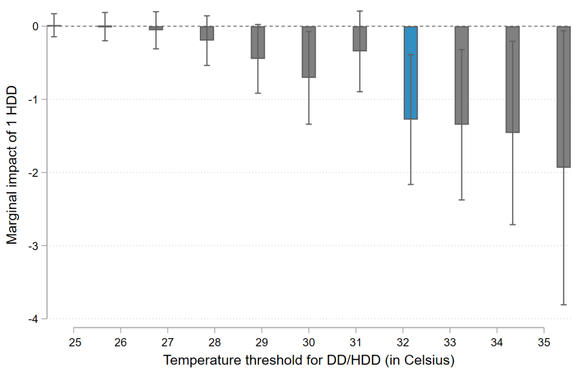
Figure A.2: Impact of HDD on Outcomes (in logs) using Different Thresholds



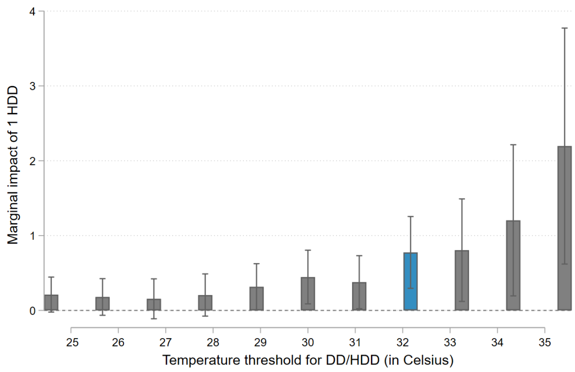
Animal Products (Wet Season)



Animal Products (Dry Season)



Fruits and Vegetables (Wet Season)



Fruits and Vegetables (Dry Season)

Figure A.2 Continued