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Weather Extremes and Household Welfare in Rural Kenya

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By

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Abstract

Households in rural Kenya are sensitive to weather shocks through their reliance on rain-fed agriculture and livestock. Yet the extent of vulnerability is poorly understood, particularly in reference to extreme weather. This paper uses temporally and spatially disaggregated weather data and three waves of household panel survey data to understand the impact of weather extremes – including periods of high and low rainfall, heat, and wind– on household welfare. Particular attention is paid to heterogeneous effects across agro-ecological regions. We find that all types of extreme weather affect household well-being, although effects sometimes differ for income and calorie estimates. Periods of drought are the most consistently negative weather shock across various regions. An examination of the channels through which weather affects welfare reveals that drought conditions reduce income from both on- and off-farm sources, though households compensate for diminished on-farm production with food purchases. The paper further explores the household and community characteristics that mitigate the adverse effects of drought. In particular, access to credit and a more diverse income base seem to render a household more resilient.

Keywords: food security, household welfare, Kenya, resilience, weather shocks

JEL classifications: D60, I32, O13, Q12

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Acronyms

AE	-	Adult Equivalents
FE	-	Fixed Effects
TAPRA	-	Tegemeo Agricultural Policy Research and Analysis
CDD	-	Cumulative Degree Days
CHIRPS	-	Climate Hazards Group InfraRed Precipitation with Stations
CMM	-	Cumulative Millimeter-Pentads
CWS	-	Cumulative Wind Speed Days
GDP	-	Gross Domestic Product
HH	-	Household
Ksh	-	Kenyan Shillings
MERRA	-	Modern-Era Retrospective Analysis for Research and Applications
NASA	-	National Aeronautics and Space Administration
TLU	-	Tropical Livestock Units
USD	-	United States Dollar

1. Introduction

Households in rural Kenya derive their livelihoods primarily from agriculture (Kabubo-Mariara and Karanja 2007), leaving them sensitive to the vagaries of weather. Yet the extent of vulnerability is poorly understood, particularly in reference to extreme weather.[2] Instead, most studies focus on seasonal means or aggregate rainfall, even as intra-seasonal variability can have significant consequences for agricultural production (Rowhani et al. 2011; Thornton et al. 2014). A better understanding of the impacts of weather shocks is necessary both to establish the causes of poverty and food insecurity, and to identify potential interventions to reduce vulnerability (Skoufias 2003). This challenge is increasingly relevant as climate projections point to an increasing frequency and intensity of weather extremes over this century (Cooper et al. 2008; IPCC 2014).

This paper uses longitudinal household survey data, in combination with temporally and spatially disaggregated weather data, to estimate the effects of exposure to extreme weather conditions on household welfare in rural Kenya. Specifically, we focus on periods of drought, high rainfall, heat stress, and high wind speed. Indicators of household welfare include monetary (income and poverty incidence) and non-monetary measures (calorie availability and energy deficiency). As weather shocks are not expected to affect all households equally, this paper also examines the heterogeneous effects across agro-ecological regions. We further probe the channels through which weather shocks affect household welfare, with consideration of the sources of income and calories. Results show that periods of drought are the most consistently negative weather shock across agro-ecological regions and various indicators of welfare. Given the significance of rainfall variability, we next explore which household and community characteristics mitigate the adverse effects of drought, including crop and income diversification, access to financial services, and asset stocks. Because these characteristics may improve household resilience to weather shocks, the results bear clear policy implications regarding poverty alleviation and adaptation to climate variability.

[2] In this paper, we use the terms 'weather shock', 'weather extreme' and 'climate variability' interchangeably.

The paper contributes to the literature on climate variability and welfare in several ways. First, it capitalizes on the recent availability of gridded climate data sets[3] that combine information from ground stations, satellites, and climate models to explore the effects of short-term weather shocks at highly disaggregated geographical levels. Second, we seek to ensure that all relevant aspects of weather are captured by accounting for the effects of rainfall, temperature, and wind. Many similar studies consider a single climate variable, such as rainfall. However, because weather variables are often correlated, the inclusion of just one may result in omitted variable bias (Auffhammer et al. 2013). In addition, while other studies often focus on a single indicator of welfare, this paper considers a range of outcome variables that span both monetary and non-monetary measures of household welfare. This comprehensive approach reveals the extent to which results are influenced by the choice of welfare metric. Third, while several papers explore the effects of climate variability in Kenya on crop yield or farm income, to our knowledge, this is the first to empirically assess the effects of local weather shocks on household income (on- and off-farm) and calorie availability using panel methods. Fourth, the paper extends beyond the estimation of welfare effects to consider the role of household and community characteristics in reducing sensitivity to negative weather shocks. This aims to inform the design of public policy and risk management strategies.

The remainder of the paper is organized as follows. Section 2 includes an overview of the literature on the welfare effects of climate variability and an introduction to rural Kenya. Section 3 presents our conceptual framework and research questions, while section 4 introduces the data sources and empirical methods. Descriptive statistics are outlined in section 5, and section 6 includes the results of our econometric analysis. Section 7 concludes with a summary of key findings and a discussion of policy implications.

[3] 'Gridded' data sets capture the spatial distribution of parameters by converting individual data points into a regular grid of estimated values across a surface.

2. Background

A growing body of literature explores the effects of weather shocks on household welfare and risk management capacity in developing countries. Rural households that rely on subsistence agriculture, or otherwise draw their livelihoods from the food system, are particularly sensitive to climate variability (Davies et al. 2013). Temperature, precipitation, and extreme weather events are often (though not always) found to affect economically relevant outcomes, including income and consumption levels, asset stocks, and investments in health and education (Baez et al. 2010; Dell et al. 2014). The literature thus rejects the hypothesis that households are able to fully protect themselves against such shocks. Furthermore, climate change is widely expected to bring both rising temperatures and increasing climate variability, with more significant deviations from historical patterns and more frequent and intense extreme weather events, such as heat stress, drought, and floods (IPCC 2014). These are expected to produce adverse effects "above and beyond" those due to changes in mean variables alone (Thornton et al. 2014), with agricultural productivity growing increasingly volatile (Ahmed et al. 2013).

A number of studies document the effects of climate variability or extreme weather events on household welfare. In Mexico, Skoufias and Vinha (2013) found that deviations from expected temperature and rainfall negatively affect household consumption, though the effect varies by type of shock and by agro-ecological region. Similarly in Tanzania, drought shocks (Christiaensen et al. 2007) and positive deviations in temperature (Hirvonen 2014) are found to reduce household welfare, measured as per capita expenditure or consumption. Severe rainfall failures or drought have also been found to affect income, consumption, and health outcomes in Ethiopia (Dercon et al. 2005; Porter 2012) and Zimbabwe (Hoddinott 2006). In Vietnam, the experience of a recent flood, storm, or drought all negatively affect household welfare (Arouri et al. 2015), with substantial effects seen from hurricanes (Thomas et al. 2010). Notably, households are better prepared to deal with such shocks in communities that are frequently exposed to disasters.

Several papers that focus on economic outcomes at the country or regional level also merit mention. Dell et al. (2012) investigate the effects of annual temperature deviations on country growth rates and find that a 1°C increase in temperature reduces the GDP growth rate in poor countries by an average of 1.3 percentage points. The same effect is not seen in wealthier countries.

Hsiang and Narita (2012) instead focus on exposure to windstorms and find that higher wind speeds produce greater economic losses at the country level. Within Tanzania, region-level crop yield data are studied to understand the effects of seasonal climatic means and intra-seasonal variability of temperature and rainfall (Rowhani et al. 2011). Rainfall variability, in particular, is seen to reduce yields for several key crops.

The impact of weather shocks or natural disasters does depend on a household's level of resilience, or its capacity to absorb and/or mitigate damage. Skoufias (2003) provides an overview of the relationship between *ex ante* (mitigating) and *ex post* (coping) household strategies and the impact of natural disasters on welfare. In Ethiopia, Porter (2012) finds that while households suffer following severe rainfall failures, less extreme rainfall variation does not affect consumption. Rather, households are able to compensate for losses in farm income by increasing their non-farm earnings; the non-farm sector evidently serves as a safety net. Other resilience-enhancing factors may include asset stocks that can be liquidated, income diversification, public transfers, and credit (Davies et al. 2013). Inter-household transfers may compensate for income shortfalls, although covariate shocks make local transfers less feasible (Arouri et al. 2015).

Several approaches are commonly used to identify the effects of weather shocks. Seasonal observations, such as total rainfall or average temperature, can be used to capture inter-seasonal climate variability. Some authors account for the underlying climate distribution in a given site by calculating the number of standard deviations of seasonal rainfall or temperature from the long-term mean (e.g. Thiede 2014), or by constructing a binary term to indicate outcomes that are distant from the long-term mean (e.g. Baez et al. 2015; Skoufias and Vihna 2013). However, the nonlinear and asymmetric effects of weather are not captured when daily observations are aggregated or averaged into seasonal values. For example, Schlenker and Roberts (2009) use daily temperature data and find a nonlinear relationship between temperature and crop yields in the U.S. Yields increase with rising temperatures (captured as degree-days) up to a certain crop-specific threshold, ranging from 29-32ºC, beyond which they decrease *more* rapidly than they had risen below this threshold. This asymmetric relationship is similarly documented for various crops in sub-Saharan Africa (Lobell et al. 2011; Schlenker and Lobell 2010).

Finally, many studies focus on the effect of one weather variable in isolation, usually rainfall. Measures based on temperature have not received the same attention (Skoufias and Vinha 2013). However, to the extent that two weather variables are correlated, the inclusion of just one variable will result in the classic omitted variable bias, as the coefficient captures the combined effect of both variables (Auffhamer et al. 2013). In this paper, we seek to more exhaustively capture weather shocks by including measures of heat stress, rainfall excess and deficiency, and high winds.

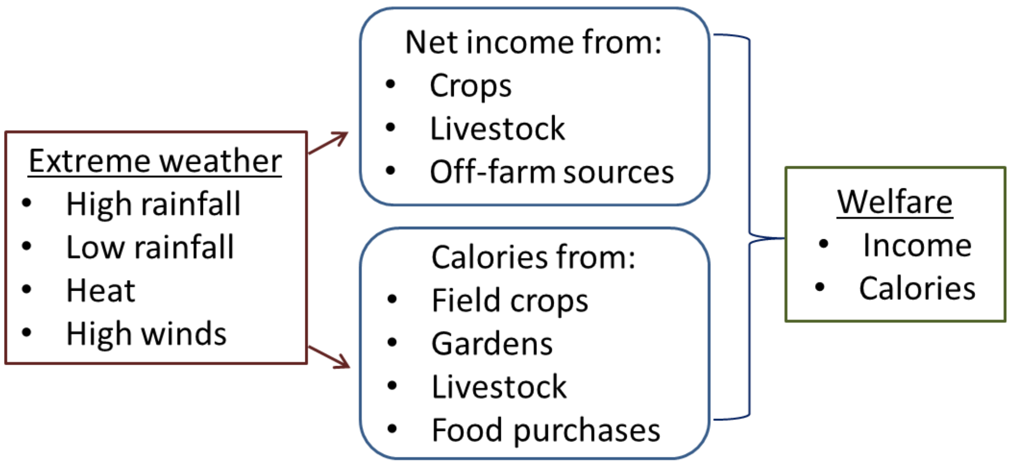
Households in our study site, rural Kenya, are sensitive to weather shocks through their widespread dependence on agriculture for both income and food security. Agriculture accounts for approximately 26% of Kenya's GDP and 75% of employment (Herrero et al. 2010). However, gaps remain in the existing knowledge regarding weather variability and welfare in Kenya. Several papers explore the relationship between seasonal weather and net crop revenue (Kabubo-Mariara and Karanja 2007; Ochieng et al. 2016), but do not consider the effect on household welfare. Other papers explore the determinants of household welfare in rural Kenya, but do not focus specifically on the effects of weather shocks. For example, Barrett et al. (2006) explore the long-term dynamics of asset-based poverty traps in Kenya without explicitly considering such shocks. Muyanga et al. (2013) study the determinants of wealth trajectories, pooling monetary losses from non-health shocks. And Christiaensen and Subbarao (2005) rely on cross-sectional data to identify the determinants of vulnerability, finding that rainfall shocks affect households only in the drier regions.

Kenya is characterized by a diverse topography and highly localized climatic patterns, with conditions varying from a tropical climate along the coast to an arid environment in the north. Mean temperatures and precipitation vary markedly with elevation, and most of the population resides in the non-arid areas of higher agricultural potential. Kenya experiences major droughts (affecting all or nearly all regions) approximately every ten years, and more localized droughts at a higher frequency. Although parts of the country are regularly afflicted by floods, droughts affect a significantly larger number of people. Future climate projections for East Africa consistently indicate that temperatures will rise, though there is less agreement regarding changes in rainfall (Herrero et al. 2010).

3. Conceptual Framework and Research Questions

We begin with a simple conceptual framework that illustrates how exposure to extreme weather can affect household welfare in a rural setting (Figure 1). Specifically, welfare can be measured in monetary or caloric terms. Income is comprised of net returns from on- and off-farm activities, and calorie availability is similarly comprised of calories sourced from on-farm production, as well as the market. In this framework, exposure to extreme weather can affect household welfare through any of these channels. As well, the strength of weather's effect on welfare can vary in different regions, and can further be influenced by household or community characteristics.

Figure 1. Conceptual framework for the effect of extreme weather on household welfare



As discussed in the introduction, four related research questions are investigated in this paper:

(1) What are the impacts of various weather shocks on household welfare in rural Kenya?
(2) Do the impacts differ for households in different agro-ecological regions?
(3) Through which channels do weather shocks affect household welfare?
(4) Which community or household characteristics mitigate the adverse effects of low rainfall (the weather shock with the most consistently negative effects on welfare)?

4. Methods

4.1 Data

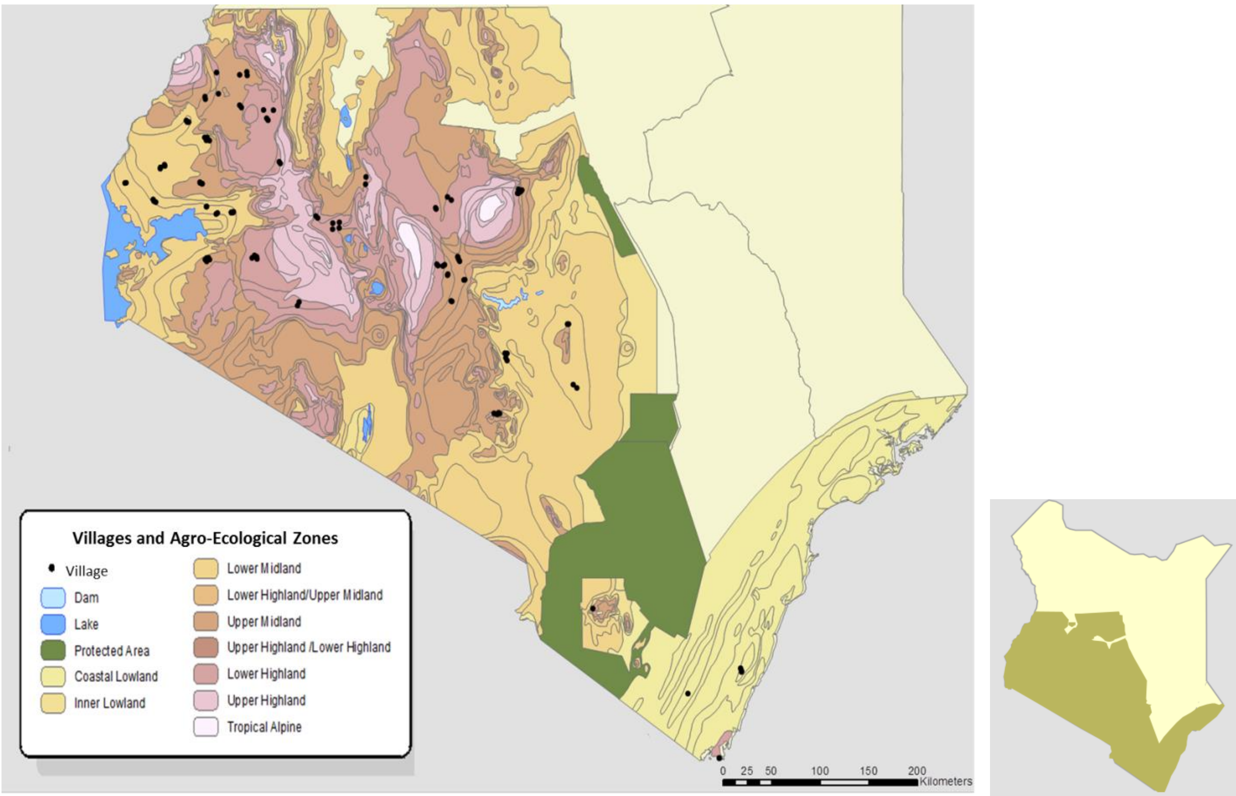
To address our research questions, this study draws from three data sources: (1) Panel survey data from households in rural Kenya (called the Tegemeo Agricultural Policy Research and Analysis (TAPRA) Rural Household survey) collected by the Tegemeo Institute of Agricultural Policy and Development of Egerton University, Kenya, in collaboration with Michigan State University; (2) historical precipitation data from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) data set, version 1.8 (Funk et al. 2014); and (3) historical temperature and wind speed data from the National Aeronautics and Space Administration (NASA) Modern-Era Retrospective Analysis for Research and Applications (MERRA) data set (Rienecker et al. 2011).[4]

The complete TAPRA survey spans 13 years, with households visited in 1997, 2000, 2004, 2007, and 2010, and the sample covers 107 villages across 8 agro-ecological zones in Kenya (Figure 2). Note that this sample excludes pastoral households. Due to data limitations in the first panel wave and the use of an alternate meteorology source in the final wave,[5] this paper is based only on the three waves from 2000 to 2007, which refer to the 1999/2000, 2003/04, and 2006/07 agricultural years. We also omit households with unusually high income levels (> 10 standard deviations above the sample mean). Of the 1,500 sedentary households interviewed in 1997, 1,264 remained in the sample through 2007 and are not dropped as outliers. All analyses are based on this balanced panel. While the re-interview rate is high at 84%, attrition bias is still a potential problem. However, regression-based tests for attrition bias (Wooldridge 2010) fail to reject the null hypothesis of no bias for three of the four dependent variables ($p>0.10$), indicating that attrition is not a major concern in these data (see Table A1 in the appendix). The TAPRA survey includes information on household composition, land and other asset holdings, crop and livestock production and sales over the previous year, non-farm sources of income, and distances to key services.[6] From these data, we are able to compute net household income. All monetary values are inflated to 2007 Kenyan shillings (Ksh).

[4] The NASA-MERRA data set is generated with version 5.2.0 of the Goddard Earth Observing System.
[5] As the NASA-MERRA temperature data is derived from different meteorology sources before and after 2008, and trend analysis is not recommended over this break (Rieneker et al. 2011), we omit year 2010 from this analysis.
[6] Because land owned was not captured in 2000, this variable is imputed with a household regression.

The historical rainfall data from CHIRPS are at the pentad level and a spatial resolution of 0.05° (approximately 5 km^2 at the equator). As rainfall exhibits far greater spatial variation than temperature, particularly in rugged areas (Dell et al. 2014), this paper includes the finest-resolution data available. The daily historical temperature and wind speed data from the NASA-MERRA data set are at a spatial resolution of 0.5° (approximately 50 km^2 at the equator). All climate variables are estimated for each village in the sample. While both data sets are quite new, the NASA-MERRA data have been used by several other authors (Hirvonen 2014; Thiede 2014).

Figure 2. TAPRA survey villages and agro-ecological zones



Sources: International Livestock Research Institute (map of agro-ecological zones) and authors' summary.

4.2 Identification Strategy and Econometric Models

To understand the effect of weather shocks on household welfare, we rely on the year-to-year fluctuations in observed weather at the village level. These random draws from the current climate distribution are exogenous, and we therefore use the standard panel method summarized in Dell et al. (2014):

$$Y_{it} = \alpha + \boldsymbol{W_{it}}\boldsymbol{\beta} + \boldsymbol{Z_{it}}\boldsymbol{\delta} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

where Y_{it} = outcome variable for household *i* at time *t*, $\boldsymbol{W_{it}}$ = a vector of weather shocks, $\boldsymbol{Z_{it}}$ = a vector of exogenous household characteristics, μ_i = time-invariant household-level unobserved effects, θ_t = time fixed effects, and ε_{it} = the idiosyncratic error term. The effects of weather shocks on household welfare are captured by $\boldsymbol{\beta}$. The time fixed effects, θ_t, capture shocks common to all households in a given year, and are controlled for with a vector of year dummies. Equation (1) is estimated using the fixed effects (FE) estimator. Under the assumption of strict exogeneity of the observed regressors (i.e., the weather shocks, $\boldsymbol{W_{it}}$, exogenous household characteristics, $\boldsymbol{Z_{it}}$, and year dummies) conditional on μ_i, this estimation strategy ensures that unobserved, time-constant household-level factors (μ_i) will not bias the estimated coefficients, even if these unobservables are correlated with the observed regressors (Wooldridge 2010). This fixed effects approach to identify the effect of weather shocks has been used by a number of authors (e.g. Dell et al. 2012; Hirvonen 2014; Porter et al. 2012).

In this paper, equation (1) is used to estimate the impacts of various weather shocks on household welfare in rural Kenya (our first research question). Y_{it} takes the form of a welfare metric (monetary or caloric measures of household welfare), and $\boldsymbol{W_{it}}$ is a vector of weather shocks (including measures of rainfall, temperature, and wind) that will be defined in section 4.3. Standard errors are clustered at the village level to correct for possible serial correlation and heteroskedasticity, and because our key variables of interest, the weather shocks, are at the village level.

To explore whether these impacts differ for households in different agro-ecological regions (our second research question), the weather shocks of $\boldsymbol{W_{it}}$ are interacted with indicators of the households residing in different regions (to be defined in the next section).

$$Y_{it} = \alpha + \boldsymbol{W_{it}\beta} + [\boldsymbol{W_{it}} * \boldsymbol{Region_i}]\boldsymbol{\gamma} + \boldsymbol{Z_{it}\delta} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

The region-specific effects of weather shocks are captured by $\boldsymbol{\gamma}$. To address our third research question regarding the channels through which weather shocks affect household welfare, equations (1) and (2) are again used, with Y_{it} now taking the form of income or calories derived from the specific sources depicted in the middle boxes of Figure 1. Finally, to identify the community or household characteristics that mitigate the adverse effects of low rainfall, the following equation is used:

$$Poor_{it} = \alpha + \boldsymbol{W_{it}\beta} + \varphi[Low\_rain_{it} * M_{it}] + \omega M_{it} + \boldsymbol{Z_{it}\delta} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

where $Poor_{it}$ is a binary variable indicating a household's poverty status, and M_{it} takes the form of any characteristic that may reduce a household's sensitivity to low rainfall. Here, φ captures the potentially moderating influence of a given variable.

4.3 Variables

Table 1 provides detailed definitions of the key variables included in this paper. The welfare indicators used as dependent variables ($\boldsymbol{Y_{it}}$) are constructed as follows. Net household income is measured by summing the net crop income (gross value of crop production minus fertilizer and land preparation costs), net livestock income (gross livestock income minus feed, salaried labor, and veterinary costs),[7] and off-farm income (income from salaried/wage employment, pensions, and remittances, and net income from any business activities) for the year preceding the interview. This value is adjusted to reflect income per day and scaled to the number of adult equivalents (AE) in the household. Household poverty status refers to the rural poverty line of Kenya as derived from the Kenya Integrated Household Budget Survey of 2005/06 (Republic of Kenya 2007). In 2007 shillings, this correlates to approximately 60 Ksh per AE per day, though the value is adjusted for the cost of living in each province.

In the absence of information on household expenditures or reported consumption, we construct food security indicators based on the estimated amount of calories produced/retained or acquired by each household over the previous year (Lukmanji et al. 2008, USDA 2011). Calorie availability is therefore measured as the number of calories a household has retained (i.e. has produced and

[7] Other costs associated with crop and livestock production were not captured in the TAPRA surveys and cannot be netted out.

has not sold) from the production of crops and several key livestock products, or has acquired through staple food purchases. This is also scaled to calories per AE per day. Note that this rough measure may be an underestimate of calorie availability as it omits meat, poultry, and fish due to lack of data. At the same time, it may be an overestimate if households provide food items as gifts or payment for hired labor. A household is considered 'energy deficient' when its calorie estimate falls below 2,250 calories per AE per day (Republic of Kenya 2007).

As noted in section 4.2 and Figure 1, we will also explore the channels through which welfare outcomes are affected by weather shocks. Income per AE per day is thus divided into three exhaustive categories, including the net incomes derived from crop production, livestock production, and off-farm sources. Calories per AE per day are similarly divided into four categories, including calories retained or acquired from field crop production, vegetable/ fruit production, livestock products, and the market (i.e. food purchases).

The weather shock variables ($\boldsymbol{W_{it}}$) are intended to capture household exposure to extreme weather conditions in the previous main growing season. Kenya is characterized by multiple rainfall regimes, including some regions that experience unimodal rainfall (one growing season per year) and others with bimodal rainfall. However, even in areas with two seasons, a majority of crop production takes place in the 'main' season, and our analysis is therefore restricted to weather outcomes during the main season.[8] The timing of the main growing season in each agro-ecological zone is determined in reference to the maize production calendars provided by FAO (2015), as maize is Kenya's main staple crop.

$\boldsymbol{W_{it}}$ contains four measures of weather shocks that capture the extent to which households are exposed to extreme weather (high and low rainfall, heat, and wind). These are defined in Table 1, and an example of their calculation is also provided in the appendix (Table A2). Specifically, cumulative millimeter-pentads over 75 mm (CMM_{75+}) gauges the extent of high-rainfall periods during the season, while cumulative millimeter-pentads under 15 mm (CMM_{15-}) gauges the extent of low-rainfall periods. These thresholds loosely mirror those used in a similar paper for Mexico

[8] Robustness tests using weather outcomes over the entire year, rather than the main growing season, produce results generally consistent with those reported here.

(Guerrero Compeán 2013), and are intended to capture the cutoffs beyond which precipitation may be considered too much or too little for optimal crop growth. Cumulative degree days over 32°C (CDD_{32+}) is intended to capture exposure to extreme heat during the daytime, as crop growth often suffers above the threshold of 29-33°C (Schlenker and Roberts 2009), and warming is more harmful during the day (Lobell et al. 2011). A cutoff of 32°C is also used by Burgess et al. (2011). Cumulative wind speed days over 5 m/s (CWS_{5+}) are similarly intended to capture exposure to windy, storm-like conditions.[9] In all cases, a higher value indicates greater (longer or more intense) exposure to a given weather shock.

In addition to weather shocks, all of our models control for a number of household characteristics ($\boldsymbol{Z_{it}}$), including demographics and distances to key services, such as roads and piped water. Several variables are intended to capture a household's wealth status prior to the weather shock, including land holdings, a Tropical Livestock Units (TLU) index, and an index of physical asset holdings. The TLU index includes cattle, sheep, goats, pigs, poultry, and rabbits (Harvest Choice 2015), with units based on typical livestock weight and feeding needs. As there are no commonly used weights to construct an asset index, we build our index with principal component analysis (Filmer and Pritchett 2001). This method generates weights that estimate the association between a given asset and a household's unobserved, latent wealth level. The asset index is centered at zero, with higher values indicating greater wealth.

To explore our fourth research question regarding the factors that mitigate a household's sensitivity to low rainfall, several additional characteristics will be assessed (M_{it} in equation (3)). These include a measure of the diversity of income sources that together form the household's income portfolio, a measure of field crop diversity, a measure of credit availability in the village, and an indicator that the household holds membership in a savings group. These are also defined at the bottom of Table 1. Three of these variables are excluded from the main analysis, either because

[9] In the U.S., the term 'windy' officially refers to winds of ≥ 20 miles per hour (8.9 m/s) (NOAA 2015). However, the NASA-MERRA data set provides daily average wind speeds, and we could find no reference for what counts as a 'windy day' in rural Kenya. Because the threshold used in this analysis is not derived from prior research, a sensitivity analysis was conducted with alternate definitions of 'windy day'. To conserve space, results are not reported here, though they are robust to different wind speed cut-offs.

the information is missing for one panel wave, or due to concerns of potential endogeneity with current welfare.

Table 1. Definitions of key variables

VARIABLE	DEFINITION
Welfare	
Income/ AE/ day	Net income in year/ adult equivalents (AE)/ 365 days
Household (HH) is poor	1= Household has an income per AE per day below 67 Ksh, the rural poverty line in 2007 shillings, 0= Otherwise
Calories/ AE/ day	(Sum of calories retained from crop and garden production, consumed as milk, retained from egg and honey production, and acquired through staple food purchases)/ AE/ 365 days Note that this estimate omits meat and fish consumption, as these data were not collected. Estimates of crops lost to spoilage are netted out of the numerator.
HH is energy deficient	1= Less than 2,250 calories/ AE/ day, 0= Otherwise
Weather shocks	
Cumulative millimeter-pentads over 75 mm (CMM_{75+}) (100s)	$\left[\sum_{i}^{n} Max\ (0, Rain_i - 75)\right]/100$ where *i* indexes pentads, *n* is the number of pentads in the main growing season, and $Rain_i$ is rainfall (mm) in pentad *i*.
Cumulative millimeter-pentads under 15 mm (CMM_{15-}) (100s)	$\left[\sum_{i}^{n} Max\ (0, 15 - Rain_i)\right]/100$ where *i* indexes pentads, *n* is the number of pentads in the main growing season, and $Rain_i$ is rainfall (mm) in pentad *i*
Cumulative degree days over 32°C (CDD_{32+}) (10s)	$\left[\sum_{j}^{k} Max\ \left(0,\ Max\ temp_j - 32\right)\right]/10$ where *i* indexes days, *k* is the number of days in the main growing season, and $Max\ temp_j$ is the maximum daytime temperature (°C) on day *j*. Temperatures are estimated at 2 meters.
Cumulative wind speed days over 5 m/s (CWS_{5+}) (10s)	$\left[\sum_{j}^{k} Max\ (0,\ Wind\ speed_j - 5)]\right]/10$ where *i* indexes days, *k* is the number of days in the main growing season, and $Wind\ speed_j$ is average wind speed (meters per second) on day *j*. Wind speed is estimated at 10 meters and refers to the daily average.
Key household characteristics	
Credit availability	Proportion of households surveyed in village that received credit; calculated at district level for villages with fewer than 10 respondents
HH is member of savings group	1= Any household member belongs to a savings group, 0= Otherwise
No. income sources	Number of sources of HH income out of 6 categories (crop, livestock, agricultural wage, business, salary, and remittance income)
No. field crops	Number of different field crops planted in past year

Source: Authors' summary.

5. Descriptive Statistics

Table 2 presents summary statistics for the outcome variables (top panels) and key weather variables (bottom panel), disaggregated by three major agro-ecological categories: lowlands (coastal and inner lowlands), midlands (lower and upper midlands), and highlands (lower and upper highlands). As the exchange rate in 2007 was approximately 67 Ksh = USD $1, the average household subsists on $2.54 per adult equivalent per day. With reference to the national rural poverty line, 36.1% of households are identified as poor.[10] With regard to calories available, the average household has produced (and retained) or acquired approximately 3,868 calories per AE per day. Across the three agro-ecological categories, it is evident that households in the lowlands experience diminished welfare, as compared with the midlands, while those in the highlands experience the highest levels of welfare. It should be noted that households can conceivably alter their composition in response to observed weather, as by sending away members when they cannot be fed. By scaling the outcome variables to household size, we may be underestimating the effect of a weather shock. However, the outcomes of interest are difficult to interpret when they are not scaled to the household's level of need.

The middle panel of Table 2 sheds light on the sources of income and calories. Among all households, an average of 39% of income is derived from off-farm sources, while just 44% is generated from crop production. The emphasis on crop production is highest in the highlands (at 47%), while the emphasis on off-farm income is highest in the lowlands (at 65%). As for calories, 65% come from field crop production, while just 14% are purchased. However, in the lowlands, the emphasis on purchased calories is considerably higher at 28%. It is evident that households in each region possess markedly different livelihood portfolios, and that sensitivity to weather shocks may correspondingly vary across regions. The bottom panel of Table 2 provides summary statistics of household exposure to extreme weather conditions in the main growing season over the panel years. Households in the lowlands experience, on average, the greatest exposure to rainfall deficits and high winds, while those in the highlands rarely experience periods of high temperature or high winds.

[10] Note that this national poverty line is measured in per-adult-equivalent terms (Republic of Kenya 2007). When measured in per capita terms relative to the international extreme poverty line of USD $1.25 per day, the sample poverty rate is considerably higher at 44.2%.

Household characteristics, to be included as controls in all models, are summarized in the top panel of Table 3. Across the three agro-ecological categories, households differ in terms of wealth indicators, with the largest average farm size and greatest measures of wealth all found in the highlands. Households in the more sparsely populated lowlands reside at the greatest distance, on average, from a tarmac or motorable road. The bottom panel includes additional characteristics that will be assessed as factors that potentially mitigate the negative effects of a weather shock. (Two variables from the top panel will also be regarded as potential mitigating factors, including credit availability and the asset index). On average, households fashion their livelihood portfolio from 3.5 sources (e.g. farm production, salary work, etc.) and cultivate 4.6 different field crops.

Table 2. Household welfare indicators and exposure to weather shocks (summary statistics)

	(1)		(2)		(3)		(4)			
	All HHs		Lowlands		Midlands		Highlands		Tests	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	(2) = (3)	(3) = (4)
Welfare indicators										
Income/ AE/ day (2007 Ksh)	139.81	(165.24)	113.44	(162.77)	128.73	(154.77)	187.87	(188.84)	*	***
1=HH is poor	0.36	(0.48)	0.48	(0.50)	0.39	(0.49)	0.21	(0.41)	***	***
Calories/ AE/ day	3,868.11	(3,303.73)	3,503.64	(3,050.00)	3,844.71	(3,338.46)	4,109.07	(3,285.51)	**	**
1=HH is energy deficient	0.34	(0.47)	0.41	(0.49)	0.34	(0.47)	0.29	(0.45)	***	***
Sources of income and calories										
Crop income/ AE/ day	60.94	(94.85)	29.16	(72.68)	57.06	(89.71)	87.96	(112.07)	***	***
Livestock income/ AE/ day	24.19	(53.47)	10.65	(41.37)	19.23	(38.14)	46.47	(85.50)	***	***
Off-farm income/ AE/ day	54.68	(97.83)	73.63	(129.09)	52.44	(94.01)	53.44	(92.79)	***	
Field crop calories/ AE/ day	2,490.22	(2,590.81)	1,771.89	(2,244.44)	2,441.37	(2,543.24)	2,974.03	(2,794.04)	***	***
Vegetable or fruit calories/ AE/ day	551.42	(1,360.98)	562.50	(1,376.42)	636.58	(1,488.43)	268.39	(739.65)		***
Livestock product calories/ AE/ day	243.84	(376.73)	148.18	(254.98)	205.59	(288.70)	411.91	(575.48)	***	***
Purchased calories/ AE/ day	532.01	(769.54)	971.67	(1,191.40)	513.61	(724.90)	393.55	(575.36)	***	***
Exposure to weather shocks										
CMM_{75+} (100s mm)	0.40	(0.64)	0.24	(0.41)	0.50	(0.73)	0.17	(0.25)	***	***
CMM_{15-} (100s mm)	1.80	(0.84)	2.40	(0.70)	1.77	(0.88)	1.61	(0.62)	***	***
CDD_{32+} (10s °C)	0.61	(1.46)	0.72	(1.15)	0.78	(1.66)	0.00	(0.01)		***
CWS_{5+} (10s m/s)	0.83	(2.73)	7.18	(6.00)	0.19	(0.49)	0.04	(0.05)	***	***
Observations	3,792		363		2,625		804			

Note: Asterisks denote the level of significance for a t-test of difference in means, *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculations.

Table 3. Basic household characteristics (summary statistics)

	(1) All HHs		(2) Lowlands		(3) Midlands		(4) Highlands		Tests	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	(2) = (3)	(3) = (4)
Adult equivalents	5.25	(2.55)	6.20	(3.38)	5.08	(2.45)	5.39	(2.35)	***	***
Proportion HH members < 15 or > 59 years	0.46	(0.24)	0.46	(0.22)	0.47	(0.24)	0.43	(0.23)		***
1= Female headed	0.19	(0.39)	0.15	(0.36)	0.21	(0.41)	0.13	(0.34)	***	***
Head's age	56.20	(13.53)	55.28	(13.62)	56.57	(13.43)	55.43	(13.76)	***	**
Years education of head	6.43	(4.90)	5.01	(4.81)	6.58	(4.92)	6.60	(4.78)	***	
TLU index[a]	3.28	(7.14)	4.54	(17.05)	2.34	(2.74)	5.77	(8.68)	**	***
Asset index[b]	0.02	(1.36)	(0.40)	(0.71)	(0.13)	(1.12)	0.68	(1.97)	***	***
Land owned (acres)	5.53	(7.48)	5.34	(5.34)	4.35	(5.55)	9.47	(11.42)	***	***
Distance to motorable road (km)	0.96	(1.61)	1.58	(2.94)	0.86	(1.26)	0.98	(1.73)	***	*
Distance to tarmac road (km)	7.68	(7.75)	11.91	(13.35)	7.45	(7.14)	6.50	(5.23)	***	***
Distance to fertilizer seller (km)	4.44	(7.07)	13.72	(15.68)	3.53	(4.62)	3.25	(3.57)	***	*
Distance to piped water (km)	5.44	(8.50)	8.83	(13.15)	5.05	(6.99)	5.19	(9.87)	***	
Distance to health center (km)	3.09	(3.32)	2.54	(4.68)	2.89	(2.62)	4.01	(4.31)		***
Credit availability in village (proportion HHs)[b]	0.44	(0.31)	0.31	(0.23)	0.45	(0.29)	0.48	(0.38)	***	**
Elevation (m)[c]	1,599.69	(491.01)	743.50	(789.14)	1,559.74	(264.03)	2,116.66	(159.57)	***	***
1= HH is member of savings group[d]	0.13	(0.34)	0.05	(0.21)	0.14	(0.34)	0.15	(0.36)	***	
No. income sources (out of 6 categories)[e]	3.45	(1.08)	3.40	(1.02)	3.49	(1.07)	3.36	(1.13)		***
No. field crops planted	4.56	(1.56)	3.75	(1.53)	4.67	(1.58)	4.57	(1.43)	***	*
Observations	3,792		363		2,625		804			

Note: Asterisks denote the level of significance for a t-test of difference in means, *** p<0.01, ** p<0.05, * p<0.1.
[a] In regression analysis, this value refers to TLU as of one year before interview.
[b] In regression analysis, these refer to the previous panel wave. The average value of the asset index is not precisely zero because some observations were dropped from analysis after the index was constructed.
[c] Elevation not included in the fixed-effects regressions.
[d] This variable is only available for years 2004 and 2007, such that no lagged value is available. However, because membership in a savings group is a long-term financial commitment, we believe that households may not readily exit or enter a savings group in response to a short-term shock.
[e] In regression analysis, this refers to the previous panel wave, and values are only available for years 2004 and 2007.
Source: Authors' calculations.

6. Results and Discussion

While the descriptive statistics of section 5 shed light on the extent to which households are exposed to extreme weather, econometric analysis is needed to discern the consequences of these shocks. We now turn to our first and second research questions focused on the (sometimes region-specific) impacts on household welfare. Table 4 reports the parameter estimates for the key variables of interest in equations (1) and (2), the weather shocks and the interactions of these shocks with agro-ecological regions.[11] Results indicate that an increase in exposure to periods of high rainfall (CMM_{75+}) does not significantly affect income levels or affect the likelihood of falling below the poverty line (columns 1 and 3), on average and holding other factors constant.[12] At the same time, this shock significantly increases the number of calories that households are estimated to have available (column 5). The second variable (CMM_{15-}) captures exposure to periods of low rainfall. This weather shock significantly lowers income (column 1), with exposure to 100 cumulative rainfall-pentads below 15 mm (the unit of CMM_{15-}) reducing income by 25.6 Ksh, or 18.3% of mean income. Low rainfall also exacerbates poverty (column 3), though surprisingly, it does not affect our indicator of caloric availability (column 5). Below, we explore potential reasons for this lack of impact. Overall, the results suggest that rainfall shocks, particularly periods of low rainfall, are most relevant for household welfare in rural Kenya.

For each indicator of welfare, the even-numbered columns consider heterogeneous effects across the three agro-ecological regions. Because the highlands are exposed so infrequently to temperatures above 32°C or wind speeds above 5 m/s, these interactions are omitted. Compared with those in the midlands, households in the highlands experience significantly reduced income when exposed to high rainfall (column 2). Specifically, exposure to 100 cumulative rainfall-pentads over 75 mm (the unit of CMM_{75+}) reduces income by 98.2 Ksh, or 49.4% of mean income in the highlands. However, note that these households are exposed to an average of just 17.4 rainfall-pentads over 75 mm (Table 2). To the extent that climate change is expected to bring even more precipitation to this region (Herrero et al. 2010), sensitivity to 'excess' rainfall poses a

[11] See Table A3 in the appendix for a sample of full regression results. Complete results for all regressions are available from the authors upon request.
[12] Although not reported here, the use of alternative monetary measures of welfare, including a log-transformation of income and measures of poverty gap (the distance below the poverty line) and poverty severity (the squared poverty gap), produces results that are generally consistent with the two monetary indicators included in this paper.

concern. An increase in exposure to high temperatures (CDD_{32+}) has the unexpected effect of reducing the likelihood of poverty and improving calorie availability in the midlands (columns 4 and 6). While wind (CWS_{5+}) has a minimal effect on welfare in the general population, it seems that households in the lowlands experience significantly diminished food security when exposed to periods of high winds (columns 6 and 8). Wind shocks are most relevant, and most damaging, in the southeast of the country.

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Table 4. Effects of weather shocks on household welfare (FE regression results)

	Income per AE per day		HH is poor		Calories per AE per day		HH is energy deficient	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CMM_{75+}	-6.45	-4.32	0.02	0.04**	260.80**	259.02**	-0.02	-0.01
	(0.26)	(0.46)	(0.14)	(0.05)	(0.03)	(0.04)	(0.36)	(0.66)
CMM_{15-}	-25.60**	-29.09***	0.08**	0.12***	-208.07	-323.17	0.02	0.05
	(0.02)	(0.01)	(0.02)	(0.00)	(0.39)	(0.19)	(0.62)	(0.24)
CDD_{32+}	1.73	2.11	-0.03***	-0.03***	100.03	157.90**	-0.01	-0.02
	(0.50)	(0.47)	(0.00)	(0.00)	(0.18)	(0.04)	(0.30)	(0.13)
CWS_{5+}	9.71	0.08	-0.02	0.00	-6.00	617.57***	0.01	-0.04
	(0.10)	(0.99)	(0.21)	(0.91)	(0.97)	(0.00)	(0.57)	(0.16)
Highlands * CMM_{75+}		-88.46***		-0.02		152.99		-0.11*
		(0.00)		(0.77)		(0.79)		(0.09)
Highlands * CMM_{15-}		46.70		-0.13		558.67		-0.11
		(0.15)		(0.19)		(0.53)		(0.28)
Lowlands * CMM_{75+}		60.12**		-0.29*		1,167.80		0.24**
		(0.03)		(0.05)		(0.53)		(0.03)
Lowlands * CMM_{15-}		59.30		-0.38**		2,609.92		-0.51**
		(0.37)		(0.04)		(0.19)		(0.05)
Lowlands * CDD_{32+}		0.12		-0.02		-245.99		0.16**
		(1.00)		(0.69)		(0.78)		(0.02)
Lowlands * CWS_{5+}		-9.37		0.11*		-1,868.20***		0.14*
		(0.52)		(0.08)		0.00		(0.07)
HH fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,792	3,792	3,792	3,792	3,792	3,792	3,792	3,792

*** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses, based on standard errors clustered at village level.
Source: Authors' calculations.

Thus far, we have focused only on the effects of weather shocks on aggregate measures of household welfare, with sometimes unexpectedly weak results. Turning to our third research question regarding the channels through which weather shocks affect welfare, Table 5 now disaggregates our key outcome variables (income and calories) by their individual components. Because the results of equation (1) closely resemble the patterns for households in the midlands, we report only the results for models that include interaction terms for the agro-ecological regions (equation 2). With respect to income (columns 1-3), low rainfall reduces net income from both crop production and off-farm sources for households in the midlands. It seems that the rural economy is so tightly connected to agriculture that even off-farm income-generating opportunities suffer in years of poor weather. At the same time, it is clear that high rainfall affects household income in the highlands through a negative impact on crop income (column 1), without any compensating effect from livestock or off-farm income (columns 2-3). As tea is commonly grown in the highlands, this may be attributed to the sensitivity of tea yields to high rainfall (Ochieng et al. 2016). Recall that low rainfall in the lowlands had no particular effect on income (Table 4, column 2). For households in the lowlands, there is a compensating effect whereby heat shocks enhance off-farm income while the coefficient on crop income is negative and close to significant ($p=0.12$). In general, off-farm income in the lowlands appears quite responsive to weather shocks.

A more interesting story emerges with regard to the sources of calories (columns 4-7). While periods of rainfall deficit strongly reduce the calories produced from field crops in the midlands, it seems that households compensate for much of this shortfall with calories purchased. This coping behavior explains the lack of impact seen in Table 4. With regard to calories in the lowlands, heat shocks seem to reduce calories sourced from vegetable production and livestock products, which produces the increase in energy deficiency seen in Table 4. As well, it seems the negative effect of high winds in this region comes entirely through an effect on field crop production.

Table 5. Mechanisms of weather shock impact (FE regression results)

	Income per AE per day			Calories per AE per day			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Crop production	Livestock	Off-farm	Field crops[a]	Vegetables/ fruits	Livestock products[b]	Purchased
CMM_{75+}	-4.74	1.40	-0.99	165.03*	91.21*	5.94	-17.90
	(0.39)	(0.62)	(0.71)	(0.09)	(0.09)	(0.72)	(0.63)
CMM_{15-}	-17.38***	1.32	-13.02**	-548.89***	-63.14	-75.14***	355.30***
	(0.01)	(0.71)	(0.04)	(0.01)	(0.60)	(0.01)	0.00
CDD_{32+}	2.03	0.90	-0.82	41.21	119.88***	13.468**	-14.87
	(0.30)	(0.43)	(0.64)	(0.44)	(0.01)	(0.04)	(0.60)
CWS_{5+}	8.79	5.24*	-13.95***	752.04***	-29.68	10.75	-119.00**
	(0.17)	(0.07)	(0.00)	0.00	(0.60)	(0.54)	(0.03)
Highlands * CMM_{75+}	-63.69***	-9.69	-15.08	77.90	-178.52	124.27	101.25
	0.00	(0.29)	(0.34)	(0.87)	(0.19)	(0.13)	(0.51)
Highlands * CMM_{15-}	20.60	6.50	19.60	217.29	408.90*	79.96	-61.15
	(0.27)	(0.63)	(0.21)	(0.73)	(0.08)	(0.48)	(0.69)
Lowlands * CMM_{75+}	-2.05	9.65	52.52***	1,695.61	-554.89	26.67	-116.41
	(0.93)	(0.53)	(0.00)	(0.45)	(0.16)	(0.58)	(0.82)
Lowlands * CMM_{15-}	95.70*	6.57	-42.97**	1,142.97	646.34	147.50*	620.94
	(0.08)	(0.80)	(0.04)	(0.52)	(0.25)	(0.07)	(0.28)
Lowlands * CDD_{32+}	-27.90	5.31	22.71***	209.95	-411.63**	-63.11***	14.52
	(0.12)	(0.54)	(0.01)	(0.82)	(0.01)	(0.00)	(0.93)
Lowlands * CWS_{5+}	-17.81*	-11.25	19.69**	-1,451.13***	-71.78	-37.97	-230.68
	(0.08)	(0.11)	(0.01)	(0.01)	(0.65)	(0.26)	(0.36)
HH fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
HH controls	Y	Y	Y	Y	Y	Y	Y
Observations	3,792	3,792	3,792	3,792	3,792	3,792	3,792

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; p-values in parentheses, based on standard errors clustered at village level.
[a] Refers to all crops that are not vegetables or fruits
[b] Refers to milk, eggs, and honey retained
Source: Authors' calculations.

The preceding results generally indicate that exposure to rainfall deficits is the most consistently negative weather shock for households in rural Kenya, particularly for income. Using equation (3), Table 6 now explores the mitigating factors that mediate a household's sensitivity to low rainfall, thus addressing our fourth research question. The dependent variable in this exercise is a household's poverty status, although similar results are seen with a continuous measure of income. Results indicate that the availability of credit significantly improves a household's ability to withstand the shock of low rainfall (column 1). Membership in a savings group similarly seems to help households avoid falling below the poverty line, though this is not statistically significant (p=0.16).[13] The coefficients on the interactions of CMM_{15-} with the size of a household's asset stock and its income base diversity are negative and significant, indicating that they may also be effective safeguards against the effects of drought. For crop diversity, the negative but insignificant coefficient (p=0.24) provides weak, if any, evidence that this attenuates a household's sensitivity to low rainfall.

[13] Although not reported here, this coefficient is statistically significant when income is maintained as a continuous variable.

Table 6. Mitigating factors for effect of rainfall deficit on poverty status (FE regression results)

	Dependent variable: HH is poor				
	(1)	(2)	(3)	(4)	(5)
CMM_{75+}	0.03*	0.01	0.02	0.01	0.03*
	(0.08)	(0.60)	(0.15)	(0.79)	(0.05)
CMM_{15-}	0.13***	0.00	0.07**	0.12*	0.11**
	(0.00)	(0.92)	(0.03)	(0.06)	(0.01)
CDD_{32+}	-0.03***	-0.06***	-0.03***	-0.06***	-0.03***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
CWS_{5+}	-0.03	0.05	-0.02	0.07	-0.03
	(0.11)	(0.58)	(0.17)	(0.45)	(0.15)
Credit availability (lagged)	0.15				
	(0.24)				
Credit * CMM_{15-}	-0.13**				
	(0.04)				
1= Member of savings group		0.13			
		(0.13)			
Savings group * CMM_{15-}		-0.07			
		(0.16)			
Asset index (lagged)			0.05***		
			(0.00)		
Asset index * CMM_{15-}			-0.03***		
			(0.01)		
No. income sources (lagged)				0.08***	
				(0.01)	
Income sources * CMM_{15-}				-0.04**	
				(0.01)	
No. field crops					-0.01
					(0.38)
Field crops * CMM_{15-}					-0.01
					(0.24)
HH fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Other HH controls[a]	Y	Y	Y	Y	Y
Observations	3,792	2,528	3,792	2,528	3,792

*** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses, based on standard errors clustered at village level.
[a] Lagged credit availability and asset index are included as controls in all columns, though the coefficients are only reported for the models where these are evaluated as mitigating factors.
Source: Authors' calculations.

7. Conclusions and Policy Implications

This paper has delved into the consequences of exposure to extreme weather in rural Kenya, with consideration of both income- and calorie-based measures of welfare. Several noteworthy findings emerge from our analysis: Periods of rainfall deficit have a strong and negative influence on income, although this effect is not immediately evident for calorie availability. This highlights the usefulness of considering multiple proxies of welfare when evaluating weather shocks. We also find several instances of heterogeneous effects, whereby the effect of each type of weather shock clearly differs by agro-ecological region. While exposure to high rainfall seems to have a minimal effect on household income in the full sample, it evidently does reduce household income in the rainier highlands. Exposure to high wind speed also has a negligible effect in the full sample, yet is detrimental to calorie availability in the lowlands. Overall, it seems difficult to generalize about the welfare effects of weather shocks, as defined in this manner.

An investigation of the channels through which weather affects our aggregate estimates of income and calories reveals that exposure to low rainfall reduces income from both on-farm and off-farm sources, particularly in the midlands. The non-farm economy evidently does not serve as a 'perfect' safety net for households in rural Kenya in their attempt to maintain their income level. However, as households seek to maintain their consumption level, they do compensate for the negative crop production effects of low rainfall by increasing food purchases. Even as income is volatile, it seems that households are (to some extent) able to smooth consumption with a 'pivot' to the food market. Note that an analysis of only the yield effects of weather shocks would overlook the manner in which households do cope with bad weather.

In the highlands (lowlands), the negative effects of high rainfall (wind) are seen mostly in regard to crop production, which highlights the sensitivity of smallholder farming to erratic weather. At the same time, if rural Kenyan households did not draw an average of 39% of their income from off-farm sources, they would surely be more sensitive to weather shocks. Finally, our examination of factors that potentially mitigate the adverse effects of low rainfall on income reveals that access to financial services is an important coping mechanism. While asset stocks and income diversity also seem relevant, access to credit and membership in a savings group seem to play a sizable role in offsetting the negative effect of low rainfall.

Our results point to a number of pathways for policies to improve households' capacity to withstand a negative shock. First, as access to food markets seems to be an important safety net for rural households to adjust their calorie sources in response to bad weather, policies should aim to ensure a well-functioning food market and ease of market access. This includes the maintenance of physical and communication infrastructure used by consumers, retailers, and food traders; support for a competitive market that responds fluidly to signals of supply and demand; and, where appropriate, the easing of trade restrictions for food products across borders. Second, as our results suggest that extreme weather mostly affects household welfare through crop production, policies should prioritize the development of crop varieties with enhanced tolerance for extreme weather (see Thornton et al. 2014). These include varieties that are alternately better able to withstand periods of drought and/ or water-logged soils.

Third, our results point to several geographically defined stresses that may be alleviated with targeted policies or programs. In the lowlands, where wind seems to reduce calorie production from field crops, farmers may benefit from setting up windbreaks to mute the effects of sandstorms and/or wind-sourced erosion. And in the highlands, where excess rainfall seems to reduce income from crop production, it seems that more effective drainage systems ought to be promoted. Fourth, our results suggest that access to financial services (particularly credit) has great potential to improve household resilience to weather shocks. Programs and policies to improve access to credit and savings could therefore assist households to prepare for, and recover from, exposure to bad weather. Such policies may include support for credit providers and efforts to extend banking services in rural Kenya (e.g., smaller bank outposts in more remote regions, and training provided to savings groups). Finally, where households lack the capacity to withstand a negative shock, our results suggest that policy makers should remain vigilant of such shocks and be prepared to offer *ex post* support.

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Appendix

Table A1. Tests for attrition bias

Dependent variable	Coef. on $R_{i,t+1}$	p-value
Income per AE per day	-27.62	(0.55)
HH is poor	-0.09	(0.18)
Calories per AE per day	-1,247.85**	(0.04)
HH is energy deficient	-0.03	(0.73)

Source: Authors' calculations.

Note: We test for attrition bias using a dummy variable method (Wooldridge 2010) with the following regression:

$$Y_{it} = \alpha + \tau R_{i,t+1} + \boldsymbol{W_{it}\beta} + \boldsymbol{Z_{it}\delta} + \mu_i + \theta_t + \varepsilon_{it} \tag{A.1}$$

This is based on equation (1), which is introduced in section 4.2. Y_{it} = outcome variable for household *i* at time *t*, $\boldsymbol{W_{it}}$ = a vector of weather shocks, $\boldsymbol{Z_{it}}$ = a vector of household characteristics, μ_i = household fixed effects, θ_t = time fixed effects, and ε_{it} = a stochastic error term. Added to equation (1) is $R_{i,t+1}$, a binary indicator for whether household i remains in the panel at time $t+1$. Thus, only years 2000 and 2004 are included in the regressions, which otherwise mirror those of Table 4 (odd columns). If the key coefficient (τ) is significant, it indicates attrition bias.

Table A2. Calculation of cumulative degree days over 32°C (CDD$_{32+}$) (example)

Day:	1	2	3	4	5	6	7	8	9	10	Total
Maximum temperature (°C)	28	26	27	29	33	35	34	32	29	26	
Degrees over 32°C	0	0	0	0	1	3	2	0	0	0	6

Note: Suppose the main growing season lasted for 10 days. The above table provides the maximum daytime temperature on each day. Following the definition of CDD$_{32+}$ provided in Table 1, we next specify the number of degrees above 32°C for each day. Where the maximum temperature is below 32°C, the day receives a value of zero. Cumulative degree days over 32°C is the sum of the bottom row (far right column), and as this is reported in 10s, the final value for CDD$_{32+}$ in this example would be 0.6.

Table A3. Effects of weather shocks on household welfare (FE full regression results)

	(1) Income per AE per day	(2) HH is poor	(3) Calories per AE per day	(4) HH is energy deficient
CMM_{75+}	-6.45	0.02	260.80**	-0.02
	(0.26)	(0.14)	(0.03)	(0.36)
CMM_{15-}	-25.60**	0.08**	-208.07	0.02
	(0.02)	(0.02)	(0.39)	(0.62)
CDD_{32+}	1.73	-0.03***	100.03	-0.01
	(0.50)	(0.00)	(0.18)	(0.30)
CWS_{5+}	9.71	-0.02	-6.00	0.01
	(0.10)	(0.21)	(0.97)	(0.57)
Adult equivalents	-18.64***	0.05***	-521.84***	0.08***
	0.00	0.00	0.00	0.00
Proportion HH members < 15 or > 59 years	-29.64*	0.04	657.33*	0.00
	(0.06)	(0.36)	(0.07)	(0.96)
1= Female-headed	-16.71	0.07	116.41	0.05
	(0.16)	(0.15)	(0.64)	(0.21)
Age of the HH head	2.22	0.01	94.00**	-0.01**
	(0.25)	(0.33)	(0.01)	(0.04)
Age^2	-0.01	0.00	-0.75**	0.00**
	(0.54)	(0.25)	(0.02)	(0.04)
Years education of head	2.28**	0.00	9.51	0.00
	(0.04)	(0.39)	(0.70)	(0.28)
TLU (as of one year ago)	1.70**	-0.00***	2.71	-0.00*
	(0.04)	(0.01)	(0.93)	(0.09)
Asset index (previous wave)	-6.91	0.016**	-78.30	0.01
	(0.25)	(0.03)	(0.25)	(0.66)
Land owned (acres)	-0.41	-0.00***	17.54	-0.00**
	(0.66)	(0.01)	(0.31)	(0.03)
Distance to motorable road (km)	3.24**	-0.01**	71.25	0.00
	(0.05)	(0.01)	(0.16)	(0.63)
Distance to tarmac road (km)	-0.29	-0.01**	11.05	0.00
	(0.78)	(0.03)	(0.55)	(0.73)
Distance to fertilizer seller (km)	-0.05	0.00	13.18	0.00
	(0.94)	(0.86)	(0.26)	(0.57)
Distance to piped water (km)	-0.33	0.002*	-3.24	0.00
	(0.44)	(0.08)	(0.77)	(0.75)
Distance to health center (km)	0.80	0.00	8.52	0.00
	(0.30)	(0.29)	(0.72)	(0.22)
Credit availability (previous wave)	30.03*	-0.10*	1,165.26**	-0.05
	(0.09)	(0.09)	(0.01)	(0.47)
1= Year is 2007	-27.73***	0.04	-716.57***	0.13***
	(0.00)	(0.13)	0.00	0.00
1= Year is 2004	-14.47*	0.04	-17.12	-0.02
	(0.06)	(0.11)	(0.92)	(0.51)
Constant	186.17***	-0.06	3,110.04**	0.28
	(0.00)	(0.78)	(0.02)	(0.20)
Observations	3,792	3,792	3,792	3,792
Within R-squared	0.07	0.05	0.12	0.11

*** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses and based on standard errors clustered at village level.
Source: Authors' calculations.