Weather Shocks, Coping Strategies and Consumption Dynamics in Rural Ethiopia

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Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

Abstract

Rural households adopt a broad range of strategies to cope with adverse weather shocks. Previous studies have examined the effectiveness of individual coping strategies in mitigating the impact of adverse weather shocks, but no study to date has presented a comprehensive evaluation of alternative coping strategies. We employ household panel data spanning 15 years to estimate the impact of weather shocks on consumption and poverty dynamics in rural Ethiopia, along with the effectiveness of household coping strategies in ameliorating the impact of shocks. We find that rainfall increases are positively associated with per adult equivalent consumption, while high temperatures are negatively associated with consumption. In terms of household coping strategies, formal social safety net transfers mitigate the impact of adverse rainfall shocks on consumption and off-farm employment mitigates the impact of high-temperature shocks. Simulations suggest that rainfall shocks and formal social safety net transfers significantly influence household poverty dynamics. By contrast, high-temperature shocks and off-farm employment have less impact on poverty dynamics. The results highlight the need for social protection programs that support existing household coping strategies and that can rapidly respond to weather shocks.

Keywords: resilience, weather shocks, consumption, poverty, social protection, Ethiopia

JEL Codes: Q54, Q12, D13, I32

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1 Introduction

Adverse (poor and variable) weather conditions have been shown to reduce the mean yields of agricultural producers and increase their output variance in developing countries (Cabas, Weersink, & Olale, 2010; Felkner, Tazhibayeva, & Townsend, 2009; Fisher, Hanemann, Roberts, & Schlenker, 2012; Kaylen, Wade, & Frank, 1992; Schlenker et al., 2009; Schlenker & Roberts, 2006; Thornton, Jones, Alagarswamy, & Andresen, 2009). When households rely heavily on *rain-fed* agriculture, rainfall induced production shocks often translate into income shocks and, in turn, into negative consumption shocks. Rural households adopt a broad range of strategies to mitigate the negative impacts of adverse weather shocks. Common ex-ante resiliency strategies include precautionary savings to smooth consumption (Paxson, 1992) and diversification into income generating activities that are less vulnerable to weather shocks, including migration (Barrios, Bertinelli, & Strobl, 2006; Marchiori, Maystadt, & Schumacher, 2012), off-farm employment (Bezabih, Gebreegziabher, GebreMedhin, & Köhlin, 2010; Ito & Kurosaki, 2009), and adoption of heat and drought-tolerant crop varieties (Phiri & Saka, 2008). Ex-post, households may sell livestock or productive assets during hard times (Dercon, 2002; Kazianga & Udry, 2006; Zimmerman & Carter, 2003). Asset sales often lower future earnings potential and, thus, are seen as a negative coping strategy (Del Ninno, Coll-Black, & Fallavier, 2016). Households also make

* We are very grateful to Catherine Porter and John Hoddinott for their willingness to share data. We also thank Yisehac Yohannes, Federica Alfani and Xavier Vollenweider for assistance with data, and Kevin Boyle, Mary Marchant, Klaus Moeltner, George Norton, and Xiaojin Sun for helpful comments and suggestions on earlier versions of this paper. This work was supported by Michigan State University Global Center for Food Systems Innovation [through USAID Cooperative Agreement No: AID-OAA-13-00006], and the National Institute of Food and Agriculture, U.S. Department of Agriculture.

use of formal or informal social safety nets (FSSNs or ISSNs) to mitigate the consumption impacts of adverse weather shocks (Fafchamps, 1992, 2011; Pan, 2009).

Previous studies have examined the effectiveness of individual coping strategies such as precautionary savings (Paxson, 1992), migration (de Brauw & Harigaya, 2007; Taylor, Rozelle, & de Brauw, 2003), off-farm employment (Kochar, 1999), asset sales (Fafchamps, Udry, & Czukas, 1998; Kazianga & Udry, 2006), and FSSNs as well as ISSNs (Berhane, Gilligan, Hoddinott, Kumar, & Taffesse, 2014; Pan, 2009; Quisumbing & McNiven, 2010). But to the best of our knowledge, no study to date has presented a comprehensive evaluation of different coping strategies in terms of effectiveness in mitigating the negative impact of weather shocks. Further, the literature shows that individual coping strategies employed by households often do not fully buffer the adverse impacts of weather shocks on household welfare. For example, Dercon (2004) finds persistent negative impacts of rainfall shocks on per capita consumption in rural Ethiopia. This leaves the crucial question of which coping strategies, or combination of coping strategies, successfully buffer against adverse weather shocks and which strategies do not. A systematic evaluation of coping strategies can identify successful existing strategies, and assist policy makers and development agencies to devise social protection programs and interventions that help rural households become more resilient to adverse weather shocks.

The objectives of this paper are to assess the impact of weather shocks on household consumption and on household poverty dynamics in rural Ethiopia, and to evaluate the effectiveness of widely used coping strategies in mitigating weather shock impacts. The study differs from previous efforts in several important aspects. First, it systematically evaluates the effectiveness of a basket of rural household coping strategies in buffering against weather shocks. Household use of coping strategies may be correlated, thus examining coping strategies together provides more accurate estimates of their effectiveness by avoiding potential omitted-variable bias. We show that several coping strategies employed by rural Ethiopian households are effective, but in combination they only partially mitigate the impact of adverse weather shocks on consumption.

Second, we construct a new dataset and employ novel empirical strategies to generate more reliable estimates of the weather impacts on household consumption. Third, our results are used to simulate weather shock and coping strategy impacts on household poverty dynamics and to suggest modifications in social protection programs and policies in order to assist rural households in sub-Saharan Africa (SSA) to increase their resilience to weather shocks.

Increasing household resilience to weather shocks is a particularly important issue in Ethiopia. The country's economy is dominated by its agriculture sector, which accounts for 43% of the GDP and 90% of exports.[1] Further, agriculture is primarily *rainfed* and thus highly dependent on rainfall, which according to USAID (2015) is increasingly erratic, with marked seasonal deficits and more frequent drought and heavy rainfall events. In the past four decades alone, devastating droughts occurred in 1973-74, 1983-84, 1987-88, 1990-91, 1993-94 and 2015-16.[2] On the other hand, rural households in Ethiopia employ a variety of strategies to cope with weather shocks, including participating in the Productive Safety Net Program (PSNP) - one of the strongest formal social safety net programs in SSA. Variable weather conditions and existing extensive use of coping strategies assist us to identify the impacts of weather shocks on household consumption and evaluate the effectiveness of household coping strategies in mitigating adverse weather shocks.

The remainder of this paper is structured as follows: section 2 describes the data and the Ethiopian context; section 3 outlines the conceptual and empirical framework; section 4 presents the main results and associated robustness tests; and section 5 concludes the paper.

[1] Source: https://www.usaid.gov/ethiopia/agriculture-and-food-security.

[2] Source: http://www.fao.org/nr/water/aquastat/countries_regions/eth/index.stm.

2 Data and Context

Household-level data from the Ethiopian Rural Household Surveys (ERHS)[3] are joined with village-level climatic data from the African Flood and Drought Monitor (AFDM)[4] to form a unique panel dataset. The data contains detailed information on consumption, household characteristics and composition, household use of coping strategies, and weather shocks for households in 15 rural villages (kebeles, wards, or peasant associations) in 1994, 1999, 2004, and 2009.

2.1 Household data

The households were surveyed twice in 1994, and subsequently in 1995, 1997, 1999, 2004 and 2009, with a sample of approximately 1500 households in 15 villages across the country (locations are shown in Figure 1[5]). Within each village, households were sampled through a stratified random sample. We use household-level panel data from the 1994, 1999, 2004, and 2009 rounds to form an equally spaced, unbalanced panel dataset, with 1,121, 1,262, 1,322 and 1,333 household observations in each year, respectively, and a total sample size of 5,038 observations.

<Figure 1 here>

The 15 villages covered in the ERHS are characterized by seasonal and fluctuating rainfall (Gray & Mueller, 2012). Average annual precipitation in the study villages ranges from 470 to 1300 mm (18 to 51 inches). Historically, widespread severe droughts occurred in 1999, 2002–2003,

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[3] These data have been made available by the Economics Department, Addis Ababa University, the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15646.

[4] The AFDM, developed by Princeton University, uses available satellite remote sensing and in-situ information, a hydrologic modeling platform and a web-based user interface for operational and research use in Africa. Based on macro-scale hydrologic modeling, the system employs available data to provide real-time assessment of the water cycle and drought conditions, and puts this in the context of the long-term record dating back to 1950. http://hydrology.princeton.edu/monitor.

[5] Figure 1 also includes three additional villages that were visited in 1999 and 2009 only.

2005, and 2008. Rainfall occurs mainly during the main (Kiremt) season, but some villages also have a second minor (Belg) season.[6] For uniformity, we focus on main season rainfall.

The structured questionnaire administered to each household collected information on household demographics, assets, income, credit, food and nonfood consumption, and agricultural activities. A community questionnaire was also distributed in 1997, 2004 and 2009 to obtain village-level data on infrastructure, services, education, non-governmental organization (NGO) activity, migration, wages, and production and marketing.

The survey is notable for its low attrition rate and representativeness of Ethiopian households in non-pastoralist farming systems (Dercon & Hoddinott, 2011), but the survey design also generates some limitations for our study. First, while about 1500 households were surveyed, they are concentrated in only 15 villages, leading to moderate cross-sectional variation in village-level weather variables. Second, although the core modules of the questionnaire are consistent, some questions change over survey rounds, making it problematic to analyze changes in several important variables including exposure to idiosyncratic shocks.

2.2 Weather data

Climatic data were drawn from the African Flood and Drought Monitor (AFDM), which contains countrywide precipitation (mm), maximum temperature (K), and minimum temperature (K) on a daily basis with a grid resolution of 0.25 decimal degrees. Village level estimates are generated by inverse distance weighting interpolation using weather data from the four nearest grids around the village centroid. Thus, rainfall and temperature are treated as covariate village-level shocks.

Daily rainfall is first averaged for the main rainy season (June 16th to September 15th) in each year. These yearly rainfall data are then used to calculate the "standard deviation" of average daily

[6] The main rainy season in Ethiopia typically occurs between June 16th and September 15th, and the minor rainy season between February 1st and May 31st.

rainfall in the main rainy seasons over the past five years for each panel period. The standard deviations provide a relatively short-term inter-annual measure of rainfall variability, which can be perceived by the households and, thus, potentially influence coping strategy adoption and consumption behavior. Daily maximum and minimum temperatures are employed to derive the total growing degree days (GDDs) and total extreme heat degree days (EHDDs) in the long growing season (April 1st to September 30th) for each panel period. GDDs measure the accumulated time temperatures within the optimal temperature range for crop growth over the growing season, and thus is expected to be positively correlated with crop production. By contrast, EHDDs measure the accumulated time temperatures that are above the upper threshold of the optimal temperature range. This is a measure of the magnitude of adverse temperature shocks and is expected to be negatively correlated with crop production (see Schlenker and Roberts 2006; Roberts, Schlenker, and Eyer 2013; Schlenker et al. 2009 for more discussion). A full description of GDD and EHDD measures is presented in Appendix A.

The climatic data is used to generate six weather measures in the study: (1) the logarithm of average daily rainfall in the main rainy season in the year prior to the survey; (2) an indicator for the village receiving rainfall less than the historical average in the main rainy season in the year prior to the survey; (3) the logarithm of standard deviation of daily rainfall in the main rainy season in the five years ending in the year before the survey; (4) an indicator variable defined as 1 if the standard deviation of rainfall in the growing seasons in the past five years is higher than the historical average and 0 otherwise; (5) the logarithm of total GDDs for the long growing season in the year prior to the survey; and (6) the logarithm of total EHDDs in the long growing season in the year prior to the survey.

2.3 Variables and summary statistics

The study dependent variable is the logarithm of real monthly consumption per adult equivalent for each household.[7] Following Porter (2012) and Dercon, Hoddinott, and Woldehanna (2012), the monthly consumption measure consists of food consumption (including food expenditure and value of food received as gifts) and non-investment non-food consumption (excluding investment type consumption such as durables, health, and education expenditure). Food consumption data are projected from consumption over a one-week recall period to make aggregate household consumption comparable across survey rounds. The monthly nominal consumption measure is then deflated by a food price index (FPI) constructed from village level data collected at the same time as the household survey (Dercon and Krishnan, 1998). Adult equivalence scales are based on nutrition (calorie) needs for different age and gender groups as guided by the World Health Organization (WHO).[8] Seasonal consumption changes are accounted for with a post-harvest season indicator, defined as 1 if the household was surveyed within four months of the start of the harvest season and 0 otherwise. Harvest seasons vary across villages, as documented in Dercon & Hoddinott (2011), so the post-harvest period is village specific.

Table 1 presents the summary statistics for consumption, season of survey, household characteristics and composition, household use of coping strategies, and weather shocks from 1994 to 2009. Mean real consumption in 1994 is 82.22 Ethiopian birr (about 17.99 U.S. dollars[9]) per adult equivalent per month and steadily rises to 107.14 birr in 1999 and 117.35 birr in 2004. In 2009, mean real consumption sharply dropped to 71.32 birr per adult equivalent per month, due to

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[7] We focus on consumption rather than income data because the latter is generally underreported in the ERHS, and we are primary interested in how coping strategies are used to smooth shocks. As Bezu, Barrett, and Holden (2012) note, average household consumption expenditure per adult equivalent is $125 while household income per adult equivalent is $68 (both in 2000 constant prices). Moreover, income data was derived from a four-month recall period, causing possible measurement error (Josephson & Michler, 2015).

[8] A detailed scale table can be found in Dercon and Krishnan (1998).

[9] In 1994 the exchange rate of the Ethiopian birr with the U.S. dollar, corrected for purchasing power parity (PPP), was 0.21875. See Dercon and Porter (2011) for details.

severe droughts that occurred in several villages in Tigray region and Southern Nations, Nationalities, and Peoples' (SNNP) Region, and dramatic world food price increases in 2008 (Dercon et al., 2012). Substantial consumption variability is also found within households and within-household standard deviation (over time) is larger than between-household standard deviation. Turning to household characteristics, on average, a household owns three tropical livestock units one year prior to the survey.[10] A large share, 71%, of the households have a male head.

<Table 1 here>

We focus on five common coping strategies used by rural households in Ethiopia: (1) migration - migrants moving to urban areas in the past five years for labor market reasons such as looking for work, taking a job, and running an enterprise; (2) FSSN transfers - applying for and receiving transfers from central or local government, or an NGO in the past four months, including participating in government-sponsored programs such as the PSNP and the food-for-work program; (3) ISSN transfers - requesting and receiving transfers from an ISSN (such as relatives, friends, neighbors, and local risk sharing organizations[11]) in the past four months; (4) remittances - receiving remittances from out-migrant household members in the past four months; and (5) off-farm employment - resident household members engaging in employment activities off their own land in the past four months. Each coping strategy is characterized by a dichotomous variable indicating whether the coping strategy is employed by the household.

[10] A table of conversion factors for calculating tropical livestock units can be found in Van Campenhout & Dercon (2012).

[11] Two notable local risk sharing organizations are Equb, a local term for rotating savings and credit associations, and Iddir, an indigenous voluntary mutual help association whose main function is to help members during bereavement.

Among these coping strategies, engaging in off-farm activities is the most prevalent (34.0% of the households), followed by receiving FSSN transfers (19.7%), migration for labor market reasons (16.2%), and receiving transfers from ISSNs (7.6%). Receiving remittances is the least common coping strategy (2.4%). Overall, coping strategy use increased between 1994 and 2009, with the share of households receiving transfers from ISSNs and family remittances increasing gradually over the years. There is also a steady increase in the percentage of households receiving FSSN transfers. This reflects institutional changes in rural Ethiopia. Most notably, the Food-For-Work Project 2488, the biggest in Africa,[12] expanded in 1995, and the PSNP was launched in early 2005. Similarly, regulations restricting land rights of those who leave rural areas and the imposition of migrant registration requirements limited the interregional movement of labor in 1994 and 1999 compared to 2004 and 2009 (Dorosh, 2013). In line with changing environment, policies, and social safety net programs, the within-household standard deviation of coping strategy indicators is larger than the between-household standard deviation in all cases.

Weather shocks are village-level variables. The survey years 1994 and 2004 are worse on average than 1999 and 2009 in terms of rainfall in the main growing season and number of villages with below-historical-mean rainfall in the main growing season. Further, 2004 had the highest average number of EHDDs in the past long growing season. Substantial variation is found within villages over time for all measures, and we further explore village-specific changes in Appendix B. Figure B.1 presents the means (Panel A) and standard deviations (Panel B) for rainfall between 1980 and 2009 for survey villages. As shown, there is considerable rainfall variation across years in most villages. Average rainfall levels in the main rainy season in northern villages (such as Haresaw and Geblen) are substantially lower than in other villages. There is also greater rainfall variability in northern villages than in other villages (Associated rainfall coefficients of variation are presented in Figure B.2.) Daily minimum and maximum temperatures fluctuate little over time

[12] See Humphrey (1998) for a review of food-for-work projects in Ethiopia.

but show considerable heterogeneity across space (Figure B.3). Total GDDs and total EHDDs show greater variation over time than temperatures, with total extreme heat degree days appearing to increase in most villages and become more variable in the early 2000s, but there is also significant spatial heterogeneity in this pattern (Figure B.4).

Overall, the substantial within-household variation over time in both control variables and the dependent variable relative to across household variation supports the use of a fixed-effects model specification.

3 Conceptual and Empirical Frameworks

The benchmark conceptual models of household consumption dynamics with variable income flows are the permanent income model and the full insurance model (Morduch, 1995). Both models imply that income shocks will show a low correlation with changes in household consumption if households have access to insurance, credit, or liquid assets and if income shocks are predominantly transitory in nature (Bardhan & Udry, 1999). When these conditions are not met, the household will employ other coping strategies like asset sales, use of ISSNs and FSSNs, and ex-ante activity diversification to mitigate the impact of shocks. In the case of weather shocks, agricultural production is directly affected, causing an income shock. Observing or anticipating this shock, the household adopts coping strategies to minimize adverse impacts. If coping strategies are completely effective, then income will be stabilized, and consumption will be largely unaffected. Otherwise, the weather shock will generate fluctuations in household consumption. Figure 2 outlines the links between pre-shock economic wellbeing (consumption), shock exposure, coping strategies, and post-shock economic wellbeing.

<Figure 2 here>

3.1 Benchmark empirical models

Rainfall and temperature impacts on household consumption are identified with a fixed-effect panel data model. The mitigating impacts of coping strategies on weather shock estimates are then examined.

Fixed-effects models are the preferred estimation strategy with our dataset of four panel observations for each household. Under this specification, we are able to remove all time-invariant heterogeneity, much of which stems from household and village factors that are unobserved. In this type of multi-period panel, random-effects models are preferred to fixed-effects models when there is relatively little variation in the dependent and independent variables over time compared to cross-sectional variation at a point in time. However, decomposition of the variance of the variables reveals this not to be the case in our dataset, as shown in Table 1. Random-effects models also require that time-invariant effects are uncorrelated with the regressors, which is unlikely to be the case. Mixed-effects models can add random effects at the village, district (woreda) and region levels, but are not able to control for unobserved time-invariant heterogeneity at the household level. Spatial correlation models can improve estimation efficiency when the spatial nature of the error structure is known, but this is not the case with the non-contiguous villages in the sample.

3.1.1 Weather shock impacts

The impact of weather shocks on consumption is first assessed in the following empirical model:

$$\ln(c_{ivt}) = \alpha + \beta_1 PI_{ivt} + \boldsymbol{\beta}_2 \mathbf{H}_{ivt} + \boldsymbol{\beta}_3 \mathbf{W}_{vt} + \beta_4 D_t + \mu_i + \varepsilon_{ivt}, \tag{1}$$

where

c_{ivt} = per adult equivalent consumption of household i in village v at time t;

PI_{ivt} = permanent income of household i in village v at time t;

$\mathbf{H}_{ivt}$ = a vector of time variant characteristic variables for household i in village v at time t;

$\mathbf{W}_{vt}$ = a vector of weather variables in village v at time t;

D_t = time indicator;

μ_i = household fixed effects;

ε_{ivt} = idiosyncratic error term.

The weather variables considered in alternative specifications include: the logarithm of average daily rainfall in the main rainy season in the year prior to the survey; an indicator variable for below-historical-mean average daily main rainy season rainfall in the year prior to the survey; an interaction term of the previous two variables; the logarithm of the standard deviation of rainfall in the main growing season in the five years prior to the survey; an indicator variable for above-historical-mean standard deviation of rainfall in the main growing season in the past five years; an interaction term of the previous two variables; the logarithm of total GDDs in the long growing season in the year prior to the survey; and the logarithm of total EHDDs in the long growing season in the year prior to the survey. For other control variables, tropical livestock units one year prior to the survey, $lsuL1_{ivt}$, are used as a proxy for permanent income PI_{ivt} (Dercon et al., 2012; Porter, 2012). As an important asset of rural households, livestock holdings not only influence the productive capacity of the households, but also signal household wealth, and thus provides a good indicator of permanent income potential. Time-varying household characteristics include household composition and demographic indicators of the household head. In the estimation, we also allow for intra-household correlation of the idiosyncratic error terms, and thus generate standard error estimates that are robust to cross-sectional heteroskedasticity and within-panel (serial) correlation.

Household's coping strategies are not included in equation (1), and the coefficients of interest, $\boldsymbol{\beta}_3$, measure the *net* impacts of weather shocks on the real consumption of the household after the household has made decisions on the implementation of coping strategies that may mitigate the impact of shocks. Formally, if

$$\ln(c_{ivt}) = \alpha + f(\mathbf{W}_{vt}) + g(\mathbf{S}(\mathbf{W}_{vt}, \mathbf{W}_{v,t-1}, ..., \mathbf{H}_{ivt})) + \mathrm{h}(\mathbf{H}_{ivt}),$$

where $\mathbf{S}$ is a set of coping strategies which depend on past realizations of weather shocks, then $\boldsymbol{\beta}_3$ measures

$$\boldsymbol{\beta}_3 = \frac{\partial \ln(c_{ivt})}{\partial \mathbf{W}_{vt}} = \frac{\partial f}{\partial \mathbf{W}_{vt}} + \frac{\partial g}{\partial \mathbf{S}} \frac{\partial \mathbf{S}}{\partial \mathbf{W}_{vt}}.$$

3.1.2 Mitigating impacts of adverse weather shocks through coping strategies

A second model is estimated with weather shock-coping strategy interaction terms to evaluate the relative effectiveness of coping strategies in mitigating the impacts of weather shocks on per adult equivalent consumption:

$$\ln(c_{ivt}) = \alpha + \beta_1 PI_{ivt} + \boldsymbol{\beta}_2 \mathbf{H}_{ivt} + \boldsymbol{\beta}_3 \mathbf{W}_{vt} + \boldsymbol{\beta}_4 (\mathbf{W}_{vt} * \mathbf{S}_{ivt}) + \beta_5 D_t + \mu_i + \varepsilon_{ivt}. \qquad (2)$$

where $\mathbf{S}_{ivt}$ is a set of indicator variables for the adoption of specific coping strategies. The variables contained in $\mathbf{S}_{ivt}$ are:

$dlabmigo_{ivt}$ = an indicator if household i in village v has an out-migrant for labor market reasons between year $t-4$ and year t;

$dtrsffssn_{ivt}$ = an indicator if household i in village v has received FSSN transfers between year $t-1$ and year t;

$dtrsfissn_{ivt}$ = an indicator if household i in village v has received ISSN transfers (excluding remittances from migrant household members) between year $t-1$ and year t;

$drem_{ivt}$ = an indicator if household i in village v has received remittances from migrant household members between year $t-1$ and year t;

$doffrm_{ivt}$ = an indicator if household i in village v has members working off-farm for cash or in kind between year $t-1$ and year t.

The vector of coefficients of interest, $\boldsymbol{\beta}_4$, measures the relative effectiveness of each coping strategy in mitigating the impact of weather shocks, $\boldsymbol{\beta}_3$, on consumption after controlling for weather, idiosyncratic shocks, and other factors. Specifically, a positive sign for a coefficient indicates that the coping strategy mitigates the negative impact of a shock on consumption.

Time invariant heterogeneity is controlled for by using household fixed-effects in equations (1) and (2). There is concern about potential reverse causality between coping strategies and consumption in equation (2): as a household may adopt a coping strategy because their consumption level drops, and potential endogeneity in the coping strategy variables needs to be controlled for in the estimation. This concern is addressed through the timing of the dependent variable and the coping strategy variables. Coping strategy adoption occurs either five years or four months prior to the survey, whereas food consumption occurs in the week before the survey. In this case, it is reasonable to assume that strategy adoption affects consumption, rather than that prior consumption changes drives later coping strategy adoption.

3.2 Robustness checks

Another concern is that consumption in the current period may depend on consumption in previous periods and, therefore, that lagged consumption is endogenous. In this case, a dynamic panel data model is more appropriate for the estimation of equations (1) and (2) than a static fixed-effects panel data model.

As robustness checks, we consider alternative specifications of equations (1) and (2) as follows:

$$\ln(c_{ivt}) = \alpha + \beta_1 \ln(c_{iv,t-1}) + \beta_2 PI_{ivt} + \boldsymbol{\beta}_3 \mathbf{H}_{ivt} + \boldsymbol{\beta}_4 \mathbf{W}_{vt} + \mu_i + \varepsilon_{ivt}, \tag{3}$$

$$\ln(c_{ivt}) = \alpha + \beta_1 \ln(c_{iv,t-1}) + \beta_2 PI_{ivt} + \boldsymbol{\beta}_3 \mathbf{H}_{ivt} + \boldsymbol{\beta}_4 \mathbf{W}_{vt} + \boldsymbol{\beta}_5 (\mathbf{W}_{vt} * \mathbf{S}_{ivt}) + \beta_6 D_t + \mu_i + \varepsilon_{ivt}, \tag{4}$$

where $c_{iv,t-1}$ is per adult equivalent consumption of household i in village v at time $t-1$.

Difference and system Generalized Methods of Moments (GMM) are used to estimate equations (3) and (4), with lags of dependent and independent variables as instruments to control the endogeneity of the lagged dependent variable (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Holtz-Eakin, Newey, & Rosen, 1988).

If the set of instruments are valid and the lagged dependent variable is not significantly different from zero, our benchmark models are valid. Alternatively, if the lagged dependent variable ($c_{iv,t-1}$) is significant, then the GMM estimators consistently capture the causal effects of weather shocks and/or coping strategies. Since the system GMM estimator requires more assumptions, especially with respect to initial conditions, it is not preferable to the difference GMM estimator when the two provide conflicting results.

4 Results and Discussion

4.1 The impact of weather shocks on consumption

Several specifications of equation (1) are estimated to investigate potential asymmetric effects of rainfall on consumption. Rainfall variables are defined as continuous for the results in columns (1) of Table 2, and dichotomous in columns (2). In the first specification, average daily rainfall is included and is also interacted with an indicator for poor rainfall. Similarly, the standard deviation rainfall measure is included and is also interacted with an indicator for above average variability of rainfall. If rainfall impacts are asymmetric, the coefficients on the interaction terms will be significant. In the second specification, two dichotomous variables are used to simply indicate whether average daily rainfall is below the historical mean and whether the standard deviation of rainfall in the previous five years is above the historical mean.

<Table 2 here>

The results show that rainfall has a positive and significant impact on real consumption per adult equivalent and the impact is asymmetric: if average daily rainfall is above the historical mean and increases by 10%, real consumption increases by 3.3%; if average daily rainfall is below the historical mean and decreases by 10%, real consumption drops by 2.8%. An asymmetric effect of rainfall on consumption is also reported by Porter (2012). The standard deviation of rainfall in the previous five years and whether the standard deviation is above the historical mean, by contrast, have no impact on consumption. Focusing just on the impact of low rainfall, findings in column (2) suggest that below average rainfall decreases per adult equivalent consumption by 18.2% compared to above-historical-mean rainfall. Extreme temperature also influences per-adult equivalent consumption. If total extreme heat degree days in the previous year increases by 100% (roughly the average increase seen from 1994 to 2009),[13] real consumption drops by 3.4% in column (1) and 2.4% in column (2). Total GDDs and the standard deviation of rainfall in the past five years are not significant in this parsimonious specification. Note again that both columns (1) and (2) results are net effects of weather shocks after households have adjusted their coping strategies. Therefore the results show that households are unable to fully buffer consumption against rainfall and high-temperature shocks with current coping strategies.

[13] The mean total EHDDs in the previous year for 1994, 1999, 2004, and 2009 are 9.03, 26.67, 33.72, and 14.48, respectively, so a 100% hypothetical increase in total EHDD is reasonable.

Livestock holdings have a positive impact on consumption, as expected. Evidence of pronounced seasonality in consumption is also found. Households surveyed during post-harvest season consume 26.6% (column (1)) or 29.7% (column (2)) more than those surveyed at other times.

As noted, equation (1) is also estimated using the Arellano-Bond (difference) and Blundell-Bond (system) GMM estimators (Roodman, 2009) as a robustness check (Table C.1). The lagged dependent variable is not significant in the two difference GMM specification results, and only significant at the 10% level in the two system GMM specification results. Further, Sargan and Hansen tests of over-identifying restrictions do not support the validity of the set of instruments in the four specifications. Thus, the fixed-effects panel models results reported in Table 3 are supported as the preferred specification.

4.2 The effectiveness of coping strategies

Estimation results for equation (2) that include coping strategies interacted with below average rainfall and with extreme heat variables are reported in Table 3. After controlling for the effects of coping strategies, below average rainfall still has a negative and significant impact on consumption. In column (1), if average daily rainfall is below the historical mean and decreases by 10%, real consumption drops by 2.8%. In column (2), below-historical-mean rainfall on average decreases per adult equivalent consumption by 20.2%. This reduction is slightly larger in magnitude than the net effect of below-historical-mean rainfall that embodies the ameliorative effect of coping strategy adoption (18.2% in Table 2). The effect of an adverse temperature shock (more extreme heat degree days) on consumption is also negative and significant: an increase in EHDDs by 100% reduces consumption by 3.1% in column (1) and 2.6% in column (2). This reduction is also slightly larger in magnitude than the net effect of an increase in EHDDs that embodies the associated adoption of coping strategies (2.4% in column (2) of Table 2).

<Table 3 here>

Among the five coping strategies examined, receiving FSSN transfers is effective in smoothing consumption against adverse rainfall shocks, and participation in off-farm employment is effective in smoothing consumption against adverse temperature shocks. Results in column (2) suggest that per adult equivalent consumption is reduced by 9.5% when households receive FSSN transfers with rainfall below its historical mean, as compared to 20.2% without FSSN transfers. With total EHDD increasing by 100%, consumption decreases by 0.5% when households participate in off-farm employment, compared to 2.6% in households without off-farm employment.

Sending migrants to urban areas for labor market reasons is not effective in buffering consumption against adverse rainfall or temperature shocks. The major motive for migration might be to improve the well-being of those that migrated out as shown in de Brauw, Mueller, and Woldehanna (2013), rather than the welfare of those who stay. Receiving ISSN transfers or remittances also has no significant effects on consumption, confirming the findings of Ligon, Thomas, and Worrall (2002) that ISSN use may be negatively correlated with covariate shocks, and, thus, provide a poor safety net against covariate shocks. In fact, Gao and Mills (2016) find that weather shocks have no significant impacts on the receipt of ISSN or on former household member transfers.

In the robustness check presented in Table C.2, the lagged dependent variables are not significant for both the difference and system GMM specifications although Sargan and Hansen tests support the validity of instruments. Thus, results again support the fixed-effects model as the preferred specification when weather shocks–strategies interaction terms are included in the specification.

4.3 Poverty simulations

The panel dataset also allows us to examine poverty dynamics of rural households in Ethiopia in terms of the frequency of households that are always poor, that are never poor, and that move in and out of poverty between survey rounds. The poverty line used to classify households in each round as poor or nonpoor is set at 50 birr per capita per month in 1994 prices, based on the cost of a calorie intake of 2,300 kcal per adult per day (Dercon et al., 2012). A household is defined as "never poor" if its per capita consumption is greater than 50 birr per month in all four periods, as "chronically poor" if its per capita consumption is less than or equal to 50 birr per month in all four periods, and as "transiently poor" in all other cases. Results in column (1) of Table 4 indicate that most households (72.8%) are transiently poor, while 10.7% are chronically poor.

<Table 3 here>

The estimation results for equation (2) are then used to simulate changes in poverty dynamics from universal household exposure to adverse weather shocks and from universal household use of coping strategies. Specifically, we use parameter estimates for consumption responses to below average rainfall levels (panel A) and to EHDD increases (panel B) to simulate weather shocks. Column (2) of Table 4 provides separate simulated poverty levels for scenarios of all households with rainfall below historical means and all households with 100% EHDD increases. Rainfall plays an important role in shaping poverty dynamics. If all households have below-average rainfall, transient and chronic poverty levels increase to 73.4% and 14.3%, respectively, and the share of never poor decreases to 12.3% (column (2)). By contrast, a 100% increase in EHDDs slightly increases chronic poverty level to 10.9% and decreases the share of never poor households to 15.8%. Next, we examine the impact of universal application of coping strategies on household poverty dynamics with two simulations. The first examines the impact of formal social assistance when all households are exposed to below-average rainfall. For contrast, column (3) simulates poverty dynamics with no households receiving FSSN transfers and column (4) simulates poverty dynamics when all households receive FSSN transfers. FSSN transfers have a major impact on household poverty dynamics in the face of rainfall shocks, reducing chronic poverty level from 15.7% to 10.6% and increasing the share of never poor from 11.5% to 15.8%. The second simulation examines the impacts of off-farm employment when all households experience a 100% increase in EHDDs. The influence of off-farm employment on household poverty dynamics is relatively limited. With the universal use of off-farm employment as a coping mechanism in the face of heat shocks, chronic poverty level declines from 11.6% to 9.6% and the share of never poor increases from 14.6% to 16.9%.

5 Concluding Remarks and Policy Implications

Our results show that Ethiopian households actively employ coping strategies in the face of weather shocks, but are still not able to fully buffer consumption. Off-farm employment and FSSN transfers are shown to be effective in partially mitigating adverse weather shock impacts on household consumption, while migration, remittances, and transfers from ISSNs are not effective.

Policies to increase household resiliency to weather shocks can focus on either supporting existing household efforts or on generating a broader array of effective options. Rural economic diversification tends to follow from general economic growth (Davis et al., 2000). Policies can support the process of household diversification into off-farm activities through efforts to stimulate off-farm sectors of the rural economy, including micro-enterprise credit and entrepreneurship training. As a cautionary note, for equitable growth in the rural economy, off-farm diversification policies need to ensure that opportunities are not generated disproportionately for better-off households (de Janvry & Sadoulet, 2001). Further, agriculture will remain an important component of the rural Ethiopian economy and continued investments in agricultural technologies and infrastructure to improve drought resilience can have broadly distributed positive economic impacts on households by lowering exposure to production variability due to weather shocks.

Ethiopia's formal social safety net program, PSNP, also appears to be effective in ameliorating negative rainfall shocks. However, PSNP, like most formal social protection programs in SSA, does not appear to rapidly respond to negative rainfall shocks. Further work is needed to make PSNP and similar formal social safety programs in SSA more adaptive and more responsive to weather shocks (Del Ninno & Mills, 2014). Consistent with previous findings, ISSNs are not effective mechanisms for smoothing covariate weather shocks, as others in the network are likely to be similarly impacted. Migration is also not found to be an effective coping mechanism, due in part to low remittance flows back to rural areas. Remittance flows from out-migrants and the spatial scope of the ISSNs can, however, be increased through efforts to lower the transaction costs associated with money transfers and successes across SSA with money transfers through mobile phones are already being documented (Jack & Suri, 2014).

Finally, the use of formal rainfall insurance to mitigate weather shocks is not reported as a coping strategy by households, but pilot programs in Ethiopia (Bogale, 2015; Dercon, Hill, Clarke, Outes-Leon, & Taffesse, 2014) or other countries (Akter, 2012; Chantarat, Barrett, Mude, & Turvey, 2007; Giné, Menand, Townsend, & Vickery, 2012; Tadesse, Shiferaw, & Erenstein, 2015) have shown promising results. More research is needed to identify the role that sustainable index-based rainfall insurance policies and other emerging mechanisms can play as part of integrated household coping strategies to reduce the significant burden of adverse weather shocks.

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Tables

Table 1 Summary statistics

	1994		1999		2004		2009		1994-2009			
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Overall Mean**	**Overall SD**	**Between SD**	**Within SD**
Consumption and Seasonality												
Per adult equivalent consumption in 1994 prices (birr/month)	82.224	82.672	107.140	93.243	117.352	126.802	71.322	53.255	94.799	94.952	63.908	72.965
Log of per adult equivalent consumption	4.059	0.846	4.378	0.774	4.428	0.809	4.029	0.709	4.228	0.804	0.554	0.594
Dummy for post-harvest season (0/1)	0.161	0.367	0.046	0.209	0.000	0.000	0.000	0.000	0.047	0.212	0.101	0.187
Household Characteristics and Composition												
Tropical livestock units, lagged one year	2.091	2.481	3.204	3.147	2.977	3.289	3.332	3.468	2.931	3.176	2.882	1.579
Sex of household head (mal=1, fem=0)	0.797	0.403	0.726	0.446	0.714	0.452	0.611	0.488	0.708	0.455	0.391	0.243
No. female adults aged 15-60	1.698	1.169	1.562	1.002	1.399	0.965	1.534	0.941	1.542	1.022	0.738	0.716
No. girls aged 5-15	0.880	1.014	0.887	0.960	0.868	0.987	0.875	1.004	0.877	0.991	0.730	0.683
No. girls aged <5	0.459	0.679	0.390	0.639	0.278	0.522	0.288	0.536	0.349	0.598	0.360	0.483
No. females aged >60	0.210	0.466	0.130	0.346	0.162	0.394	0.183	0.402	0.170	0.403	0.292	0.282
No. male adults aged 15-60	1.579	1.168	1.455	1.122	1.320	1.053	1.420	1.089	1.438	1.110	0.825	0.753
No. boys aged 5-15	0.900	1.045	0.945	0.994	0.888	1.005	0.897	0.982	0.907	1.005	0.740	0.695
No. boys aged <5	0.464	0.674	0.391	0.626	0.295	0.547	0.310	0.577	0.361	0.608	0.368	0.496
No. males aged >60	0.119	0.324	0.147	0.361	0.194	0.474	0.218	0.420	0.172	0.404	0.298	0.280
Household Use of Coping Strategies												
Dummy for sending migrants to urban areas for labor market reasons in the past five years (0/1)	0.043	0.203	0.145	0.352	0.239	0.427	0.202	0.401	0.162	0.368	0.224	0.297
Dummy for receiving FSSN transfers in the past four months (0/1)	0.063	0.244	0.130	0.336	0.228	0.419	0.343	0.475	0.197	0.398	0.224	0.338
Dummy for receiving ISSN transfers in the past four months (0/1)	0.059	0.235	0.058	0.234	0.067	0.251	0.117	0.322	0.076	0.265	0.154	0.219
Dummy for receiving remittances in the past four months (0/1)	0.012	0.111	0.011	0.105	0.033	0.179	0.037	0.188	0.024	0.153	0.090	0.124
Dummy for participation in off-farm employment in the past four months (0/1)	0.384	0.487	0.194	0.396	0.337	0.473	0.444	0.497	0.340	0.474	0.273	0.397

Weather Shocks												
Log of average daily rainfall in the main rainy season, lagged one year	1.442	0.357	1.821	0.267	1.496	0.345	1.786	0.559	1.642	0.434	0.357	0.263
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year (0/1)	0.879	0.327	0.113	0.316	0.726	0.446	0.200	0.400	0.467	0.499	0.198	0.466
Log of the standard deviation of average daily rainfall in the main rainy season in the past five years, lagged one year	-0.012	0.223	-0.028	0.352	0.244	0.829	0.549	0.425	0.199	0.571	0.389	0.438
Dummy for above-historical-mean standard deviation of rainfall in the main rainy season in the past five years, lagged one year (0/1)	0.316	0.465	0.000	0.000	0.509	0.500	0.701	0.458	0.389	0.488	0.216	0.450
Log of total GDDs in the long growing season, lagged one year	6.762	0.305	6.795	0.332	6.804	0.321	6.747	0.332	6.777	0.324	0.328	0.056
Log of total EHDDs in the long growing season, lagged one year	0.556	2.246	2.253	2.007	2.845	1.397	1.055	2.301	1.714	2.205	1.882	1.271
Number of observations	1121		1262		1322		1333		5038			

Note: Calculated from the ERHS for observations with complete information on main variables. Standard deviation in parentheses. Sample size varies across survey years due to missing values.

Table 2: Weather shocks and consumption

	(1) FE1	(2) FE2
Dummy for post-harvest season	0.2355****	0.2599****
	(0.050)	(0.051)
Tropical livestock units, lagged one year	0.0354****	0.0360****
	(0.006)	(0.006)
Sex of household head (male=1, female=0)	0.1424****	0.1417****
	(0.041)	(0.042)
Log of average daily rainfall in the main rainy season, lagged one year	0.3305****	
	(0.051)	
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.0500**	
	(0.021)	
Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	-0.0258	
	(0.035)	
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year # Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	0.0129 (0.048)	
Log of total GDDs in the long growing season, lagged one year	0.1368	0.1867
	(0.387)	(0.373)
Log of total EHDDs in the long growing season, lagged one year	-0.0338**	-0.0240*
	(0.014)	(0.014)
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		-0.2010****
		(0.026)
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year		-0.0042
		(0.025)
Constant	3.1529	3.4177
	(2.574)	(2.495)
Number of observations	5038	5038
Rho	0.35	0.38

Note: Standard errors in parentheses. Household composition variables and survey round indicators are included in the estimation but omitted from the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

Table 3: Effectiveness of coping strategies in mitigating the impact of weather shocks

	(1) FE1	(2) FE2
Dummy for post-harvest season	0.2666****	0.2792****
	(0.051)	(0.052)
Tropical livestock units per household, lagged one year	0.0356****	0.0362****
	(0.006)	(0.006)
Sex of household head (male=1, female=0)	0.1340***	0.1365***
	(0.041)	(0.042)
Log of average daily rainfall in the main rainy season, lagged one year	0.3495****	
	(0.052)	
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.0651**	
	(0.025)	
Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	0.0003	
	(0.037)	
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year # Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	-0.0085 (0.049)	
Log of total GDDs in the long growing season, lagged one year	0.1087	0.2756
	(0.414)	(0.401)
Log of total EHDDs in the long growing season, lagged one year	-0.0314**	-0.0256*
	(0.015)	(0.015)
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.0074 (0.038)	
Dummy for receiving FSSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.1408**** (0.038)	
Dummy for receiving ISSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.0330 (0.056)	
Dummy for receiving remittances in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.0640 (0.067)	
Dummy for participation in off-farm employment in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.0149 (0.027)	
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Log of total EHDDs in the long growing season, lagged one year	0.0010	-0.0015
	(0.013)	(0.014)
Dummy for receiving FSSN transfers in the past four months # Log of total EHDDs in the long growing season, lagged one year	-0.0164	-0.0122
	(0.010)	(0.010)
Dummy for receiving ISSN transfers in the past four months # Log of total EHDDs in the long growing season, lagged one year	0.0241	0.0210
	(0.018)	(0.018)
Dummy for receiving remittances in the past four months # Log of total EHDDs in the long growing season, lagged one year	-0.0348	-0.0434
	(0.033)	(0.033)

Dummy for participation in off-farm employment in the past four months # Log of total EHDDs in the long growing season, lagged one year	0.0224**	0.0207**
	(0.009)	(0.009)
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		-0.2252****
		(0.035)
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year		-0.0037
		(0.025)
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		0.0134
		(0.057)
Dummy for receiving FSSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		0.1255**
		(0.054)
Dummy for receiving ISSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		-0.0452
		(0.083)
Dummy for receiving remittances in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		-0.0615
		(0.105)
Dummy for participation in off-farm employment in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year		0.0071
		(0.039)
Constant	3.3082	2.8334
	(2.756)	(2.681)
Number of observations	5038	5038
Rho	0.36	0.39

Note: Standard errors in parentheses. Household composition variables and survey round indicators are included in the estimation but omitted from the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

Table 4 Weather shock and coping strategy impacts on poverty dynamics

	(1)	(2)	(3)	(4)
Panel A: Rainfall shock: below historical mean				
	Status quo	All households with below average rainfall	All households with below average rainfall and no FSSN transfers	All households with below average rainfall and FSSN transfers
Never poor	16.6	12.3	11.5	15.8
Transiently poor	72.8	73.4	72.8	73.7
Chronically poor	10.7	14.3	15.7	10.6
Panel B: Temperature shock: EHDDs increase by 100%				
	Status quo	All households with 100% EHDD increase	All households with 100% EHDD increase and no off-farm employment	All households with 100% EHDD increase and off-farm employment
Never poor	16.6	15.8	14.6	16.9
Transiently poor	72.8	73.3	73.8	73.5
Chronically poor	10.7	10.9	11.6	9.6

Note: Simulations are based on 1,033 households with complete information for all four rounds. The number indicates the share of households (in percent) in each poverty category.

Figures

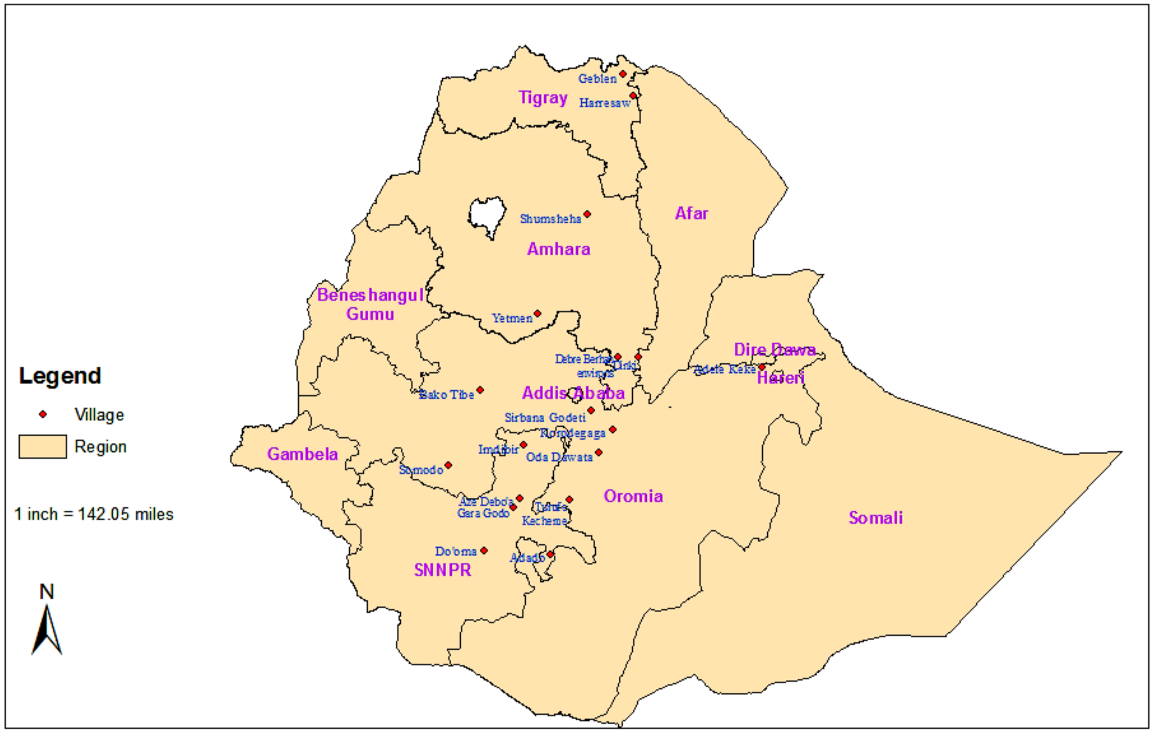


Figure 1 Locations of surveys villages

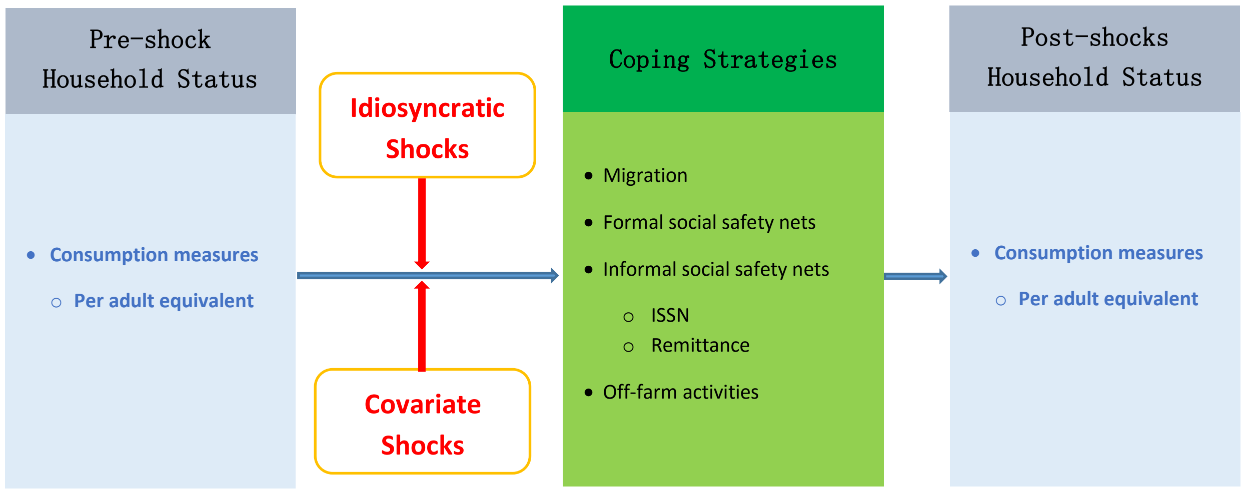


Figure 2 Conceptual framework for identifying effective coping mechanism

Appendices

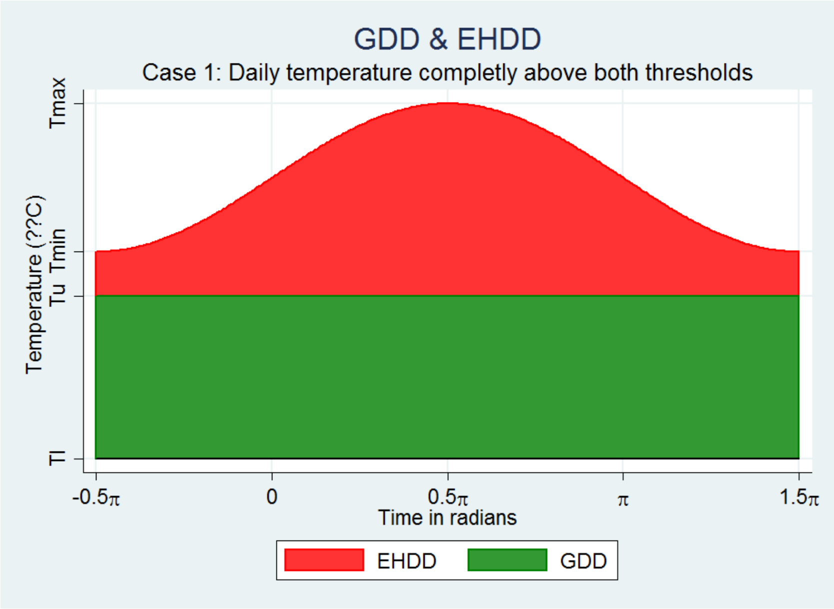
Appendix A Calculation of GDD & EHDD

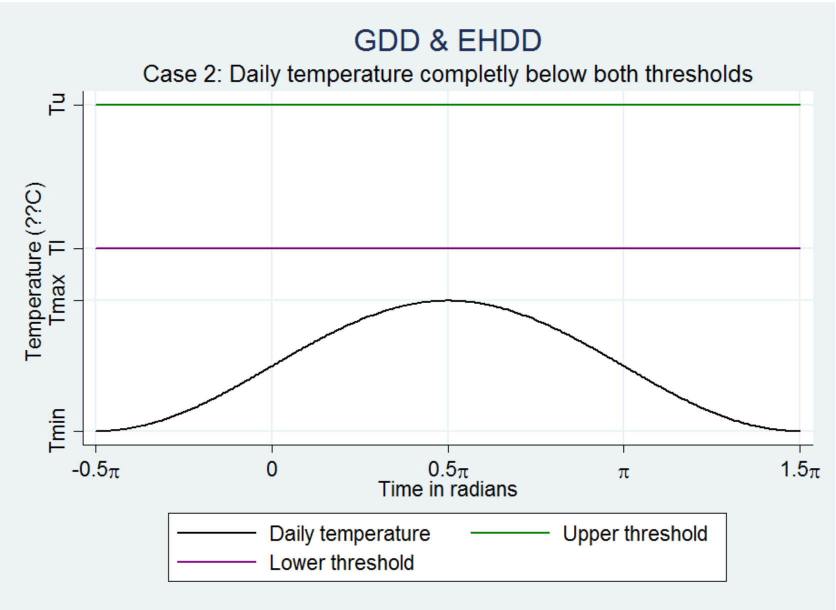
Diurnal temperature is approximated using a sine curve parameterized with the maximum and minimum daily temperatures:

$$T = \frac{T_{\max} + T_{\min}}{2} + \frac{T_{\max} - T_{\min}}{2}\sin(t),$$

where t is time in radians from $-\pi/2$ to $3\pi/2$, $T_{\max}$ is daily maximum temperature, and $T_{\min}$ is daily minimum temperature (Arnold, 1960; Baskerville & Emin, 1969; Snyder, 1985). T_u and T_l are defined as the upper and lower temperature thresholds suitable for crop growth, respectively.[14] Daily growing degree day accumulations are then calculated by integrating the area under the sine curve, under T_u, and above T_l, and daily extreme heat degree day accumulations are calculated by integrating the area under the sine curve above T_u. Depending on the relationship between daily maximum and minimum temperatures and the upper and lower thresholds, there exist six possible cases for the calculations of GDD and EHDD, as shown in figures A.1-A.6 below.

[14] The optimal temperature ranges (in degree Celsius) for major staple crops in Ethiopia are: maize (18-33), teff (22-28), wheat (15-23), barley (15-20), and sorghum (27-35) (Source: FAO Ecopcrop database, http://ecocrop.fao.org). Therefore, we set $T_l = 15, T_u = 28$ in our data.





Case 1: $T_l < T_u < T_{\min} < T_{\max}$

$$GDD \quad = T_u - T_l$$

$$EHDD = \frac{T_{\max} + T_{\min}}{2} - T_u$$

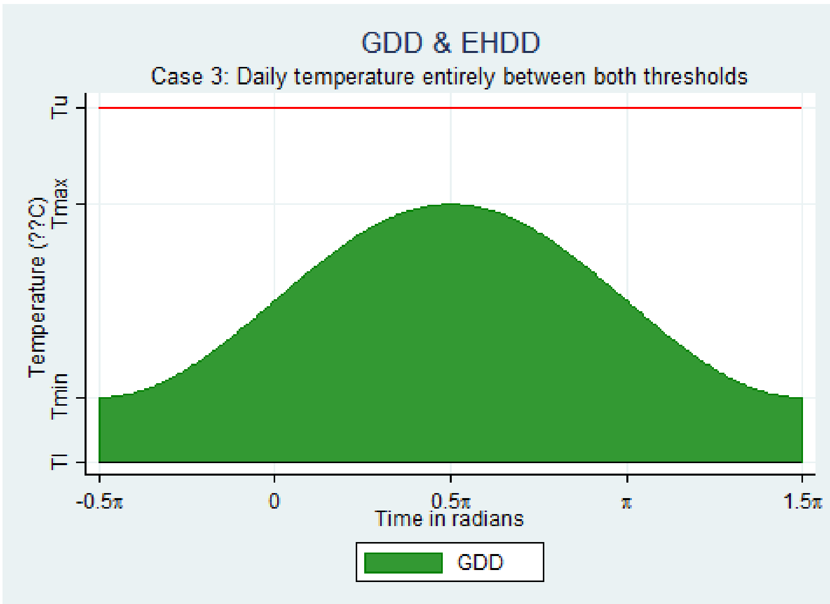
Figure A.1 Calculating GDD and EHDD – case 1

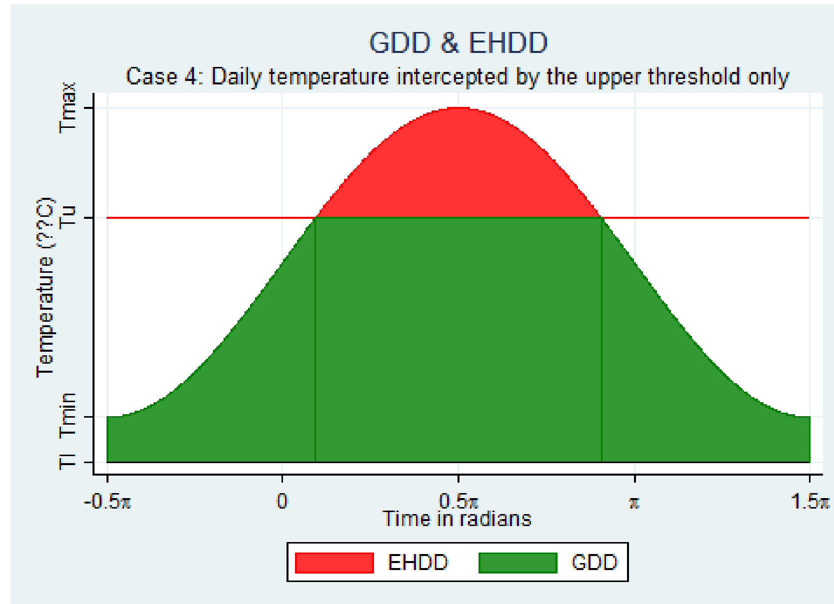
Case 2: $T_{\min} < T_{\max} \leq T_l < T_u$

$$GDD \quad = 0$$

$$EHDD = 0$$

Figure A.2 Calculating GDD and EHDD – case 2





Case 3: $T_l < T_{\min} < T_{\max} \le T_u$

$$GDD = \frac{T_{\max} + T_{\min}}{2} - T_l$$

$$EHDD = 0$$

Figure A.3 Calculating GDD and EHDD – case 3

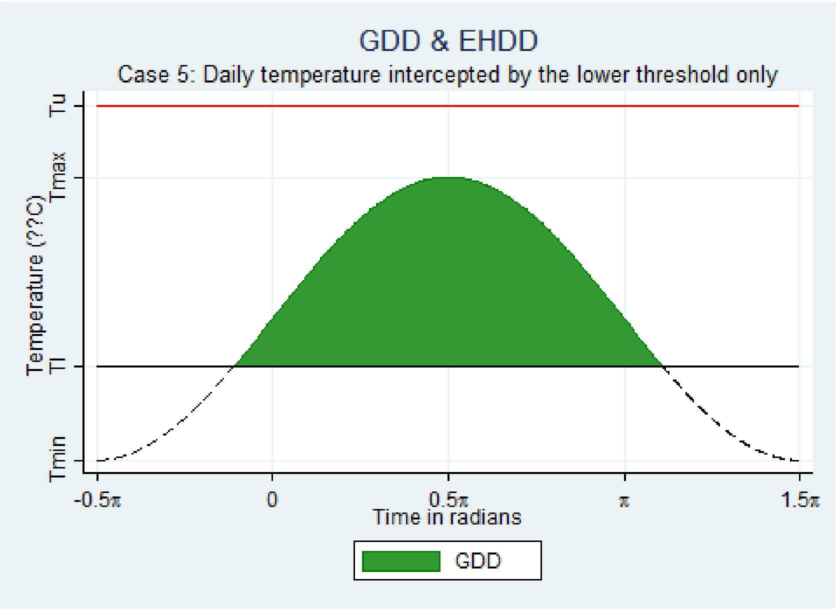
Case 4: $T_l < T_{\min} \le T_u < T_{\max}$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max} + T_{\min}}{2} - T_l\right)\left(\frac{\pi}{2} + \theta_u\right) + (T_u - T_l)\left(\frac{\pi}{2} - \theta_u\right) - \frac{T_{\max} - T_{\min}}{2}\cos\theta_u \right]$$

$$EHDD = \frac{1}{\pi}\left[\left(\frac{T_{\max} + T_{\min}}{2} - T_u\right)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max} - T_{\min}}{2}\cos\theta_u \right]$$

$$\theta_u = \arcsin\left[\frac{2T_u - (T_{\max} + T_{\min})}{T_{\max} - T_{\min}} \right]$$

Figure A.4 Calculating GDD and EHDD – case 4



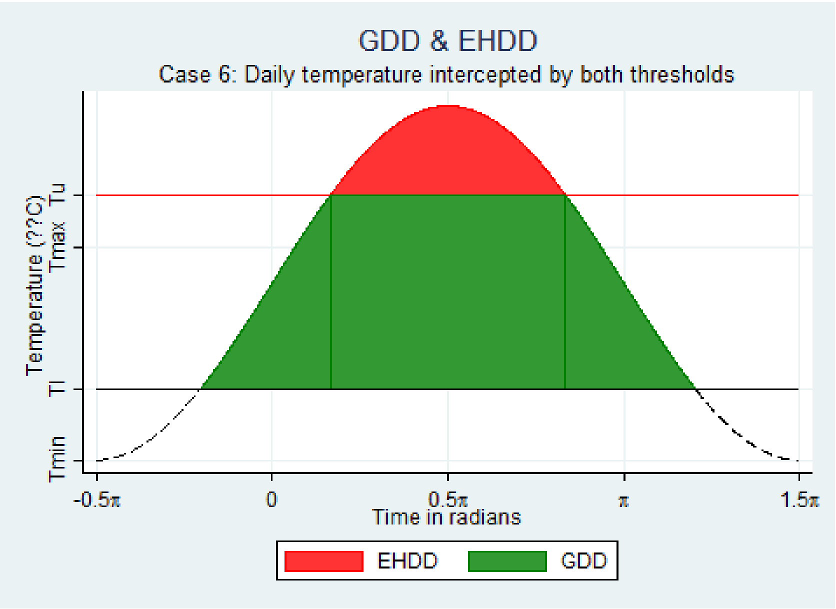
Case 5: $T_{\min} \le T_l < T_{\max} \le T_u$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_l\right)\left(\frac{\pi}{2} - \theta_l\right) + \frac{T_{\max}-T_{\min}}{2}\cos\theta_l \right]$$

$$EHDD = 0$$

$$\theta_l = \arcsin\left[\frac{2T_l - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

Figure A.5 Calculating GDD and EHDD – case 5



Case 6: $T_{\min} \le T_l < T_u < T_{\max}$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_l\right)(\theta_u - \theta_l) + (T_u - T_l)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max}-T_{\min}}{2}(\cos\theta_l - \cos\theta_u) \right]$$

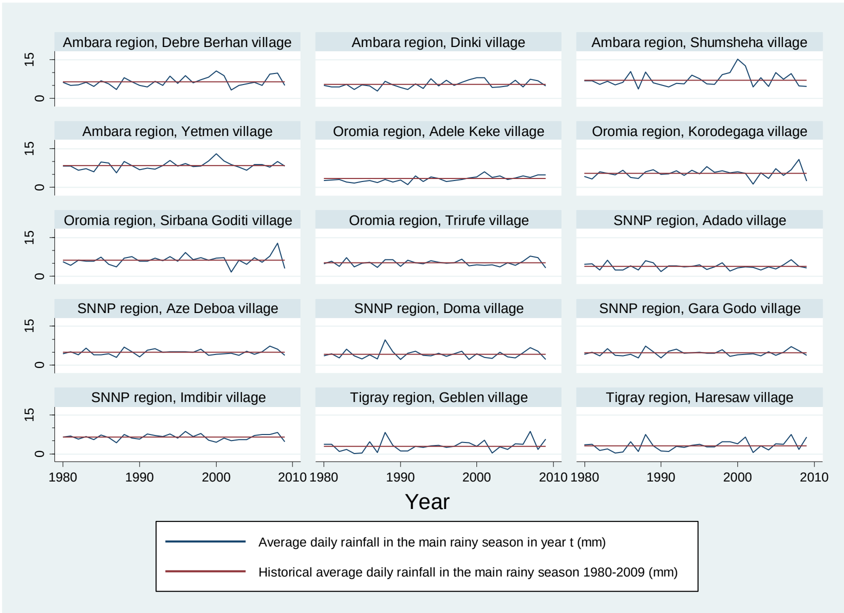
$$EHDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_u\right)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max}-T_{\min}}{2}\cos\theta_u \right]$$

$$\theta_u = \arcsin\left[\frac{2T_u - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

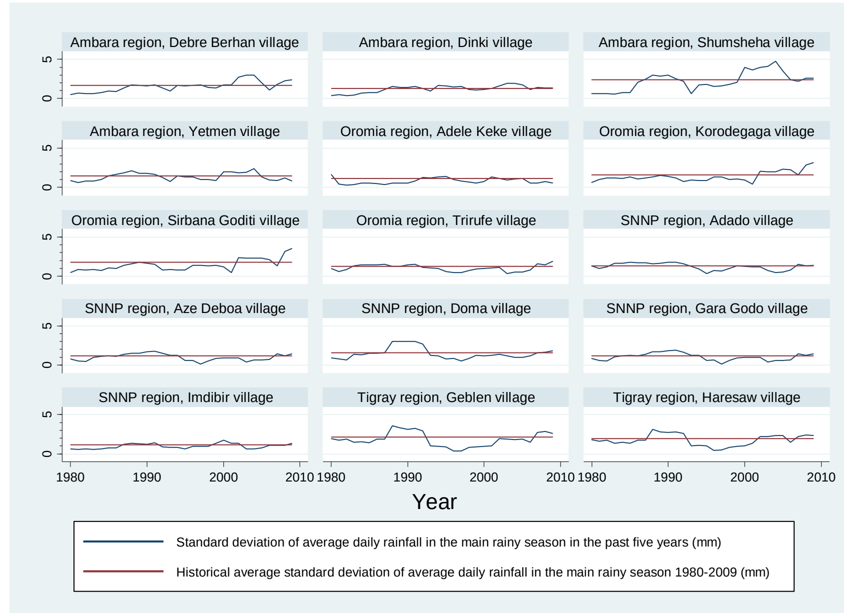
$$\theta_l = \arcsin\left[\frac{2T_l - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

Figure A.6 Calculating GDD and EHDD – case 6

Appendix B Figures about weather trends across villages



Panel A



Panel B

Figure B.1 Rainfall mean and standard deviation over years across villages

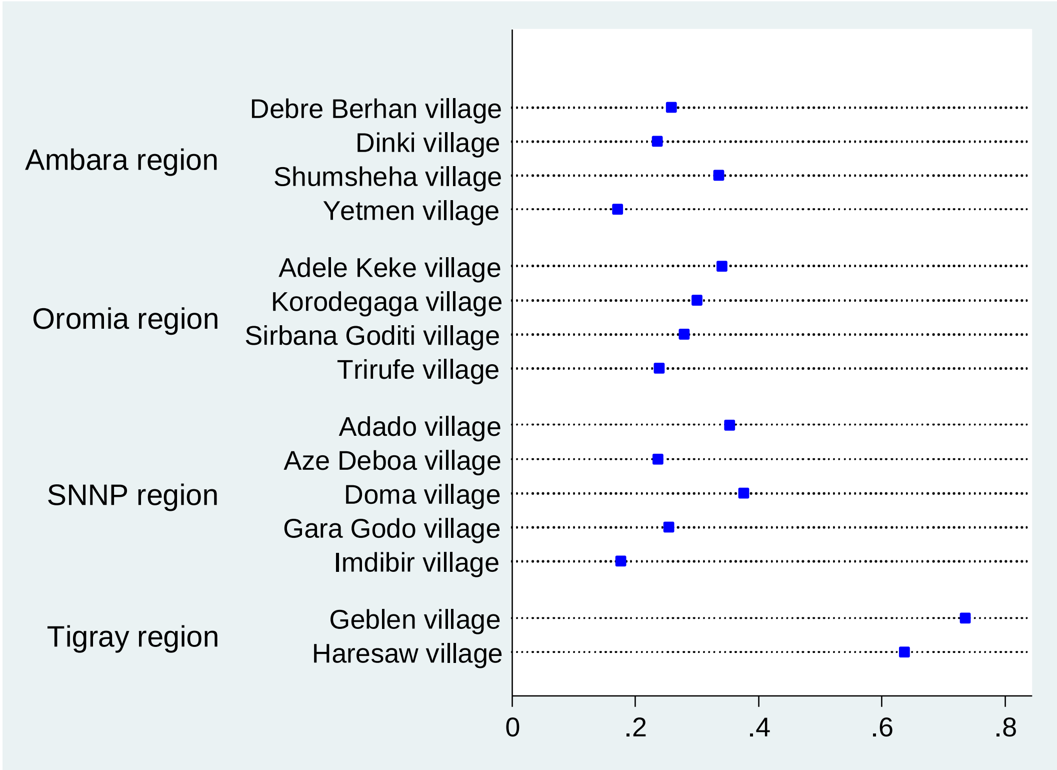
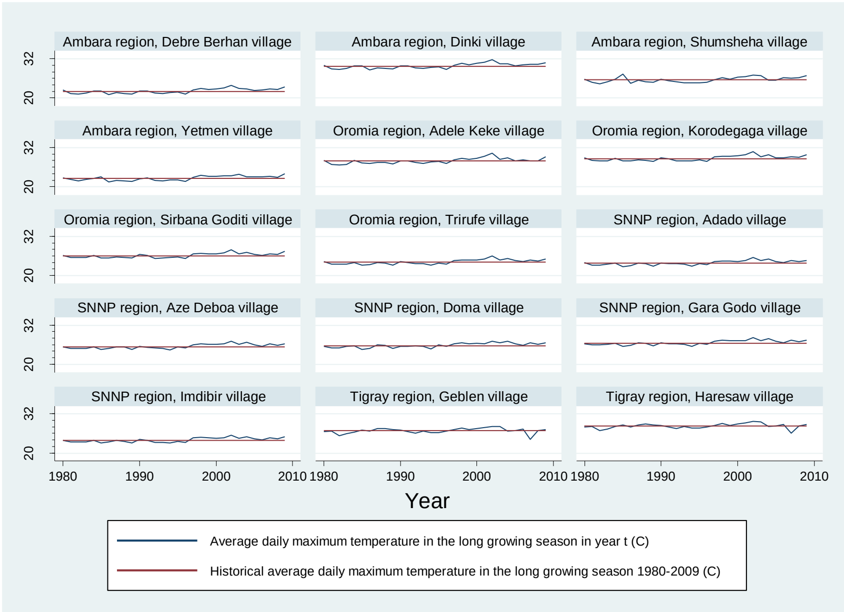


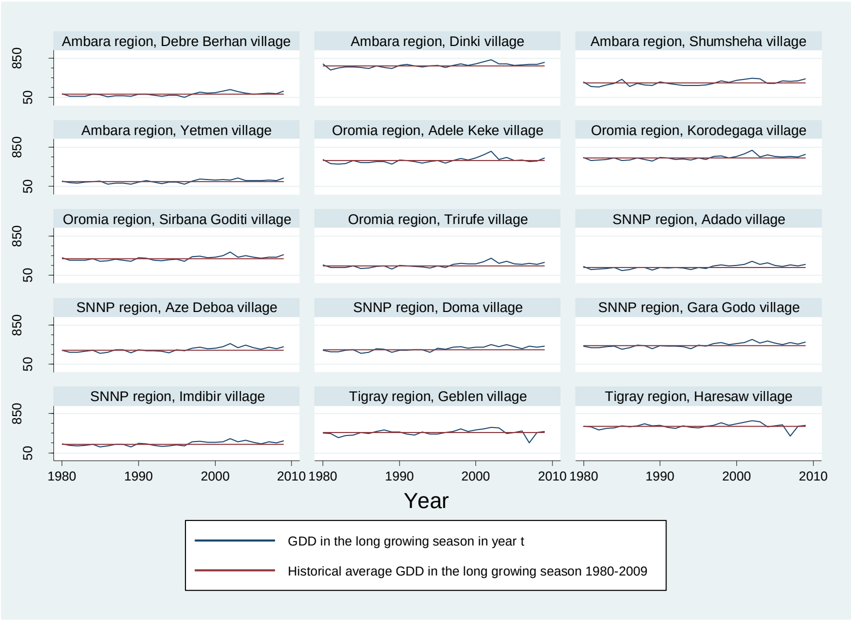
Figure B.2 Coefficient of variation for rainfall across villages



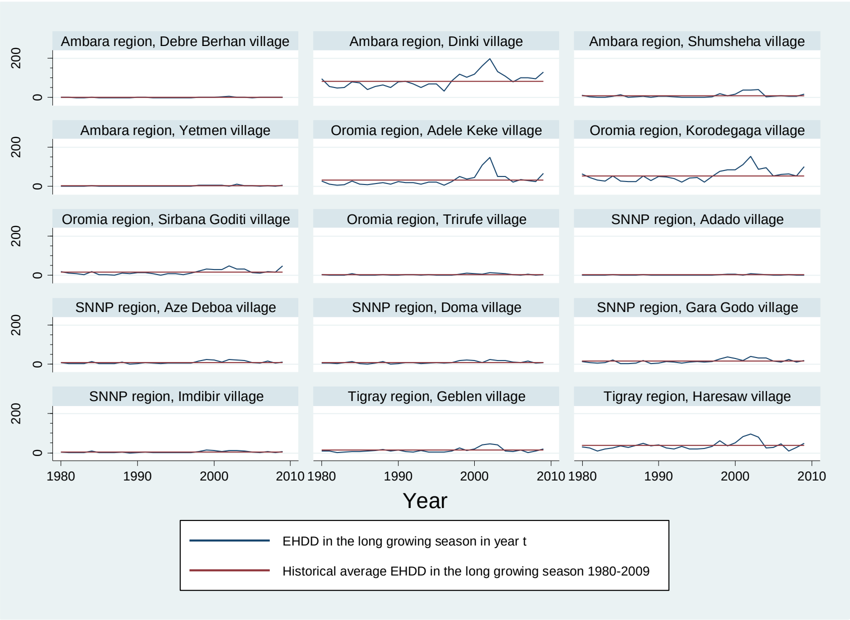
Panel A

Panel B

Figure B.3 Maximum and minimum temperatures over years across villages



Panel A



Panel B

Figure B.4 GDDs and EHDDs over years across villages

Appendix C Robustness checks

Table C.1 Weather shocks and consumption

	(1) **Diff1**	(2) **Sys1**	(3) **Diff2**	(4) **Sys2**
Log of real consumption per adult equivalent, lagged one round (five years)	0.0040	-0.0423*	0.0155	-0.0474*
	(0.031)	(0.025)	(0.031)	(0.025)
Dummy for post-harvest season	0.2521**	0.1312	0.3176***	0.0405
	(0.109)	(0.098)	(0.109)	(0.098)
Tropical livestock units, lagged one year	0.0223***	0.0490****	0.0266****	0.0612****
	(0.008)	(0.005)	(0.008)	(0.005)
Sex of household head (male=1, female=0)	0.0671	0.0445	0.0702	0.0626*
	(0.050)	(0.031)	(0.050)	(0.032)
Log of average daily rainfall in the main rainy season, lagged one year	0.4573****	0.4971****		
	(0.063)	(0.033)		
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.0477	0.0891****		
	(0.029)	(0.022)		
Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	-0.1150**	0.0333		
	(0.053)	(0.036)		
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year # Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	-0.0423	-0.0209		
	(0.053)	(0.044)		
Log of total GDDs in the long growing season, lagged one year	2.1335****	0.1351	3.8018****	-0.5085****
	(0.618)	(0.098)	(0.542)	(0.092)
Log of total EHDDs in the long growing season, lagged one year	-0.0099	-0.0311**	-0.0223	0.0529****
	(0.019)	(0.016)	(0.020)	(0.016)
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			-0.1359****	-0.1602****
			(0.030)	(0.028)
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year			-0.1736****	-0.0576**
			(0.033)	(0.029)
Constant		3.2320****		8.4099****
		(0.701)		(0.630)
Number of observations	2270	3595	2270	3595
Number of instruments	22	25	20	23
AR(1)	0.00	0.00	0.00	0.00
Sargan	0.00	0.00	0.00	0.00
Hansen	0.00	0.00	0.00	0.00

Note: Standard errors in parentheses. Household composition variables and survey round indicators are included in the estimation but omitted from the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

Table C.2 Effectiveness of coping strategies in mitigating the impact of weather shocks

	(1) Diff1	(2) Sys1	(3) Diff2	(4) Sys2
Log of real consumption per adult equivalent, lagged one round (five years)	-0.0058	-0.0310	-0.0005	-0.0040
	(0.073)	(0.046)	(0.064)	(0.052)
Dummy for post-harvest season	0.7485^{**}	0.4050^{***}	0.6167^{**}	0.3553^{**}
	(0.316)	(0.141)	(0.265)	(0.162)
Tropical livestock units per household, lagged one year	0.0466^{**}	0.0635^{****}	0.0414^{***}	0.0769^{****}
	(0.020)	(0.009)	(0.016)	(0.010)
Sex of household head (male=1, female=0)	0.1038	0.0382	0.1317	0.0658
	(0.112)	(0.046)	(0.081)	(0.053)
Log of average daily rainfall in the main rainy season, lagged one year	-0.0274	0.3830^{****}		
	(0.258)	(0.067)		
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.3824	0.1083		
	(0.256)	(0.136)		
Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	0.0734	0.1113		
	(0.154)	(0.073)		
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year # Log of the standard deviation of average daily rainfall in the main rainy seasons in the past five years, lagged one year	-0.3072^{*}	-0.1701^{*}		
	(0.178)	(0.091)		
Log of total GDDs in the long growing season, lagged one year	4.2550	-0.2116	0.0306	-0.7711^{***}
	(3.078)	(0.209)	(3.090)	(0.234)
Log of total EHDDs in the long growing season, lagged one year	0.1942^{*}	0.1040	0.0894	0.1812^{**}
	(0.111)	(0.067)	(0.116)	(0.073)
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.1878	0.0213		
	(0.769)	(0.428)		
Dummy for receiving FSSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	0.8847	0.2995		
	(0.691)	(0.355)		
Dummy for receiving ISSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	3.4797	1.2333		
	(2.286)	(1.158)		
Dummy for receiving remittances in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.2376	-0.2915		
	(2.314)	(0.960)		
Dummy for participation in off-farm employment in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year # Log of average daily rainfall in the main rainy season, lagged one year	-0.6145	-0.7532^{*}		
	(0.596)	(0.413)		
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Log of total EHDDs in the long growing season, lagged one year	-0.1631	-0.1019	-0.2564	-0.2440
	(0.275)	(0.169)	(0.267)	(0.201)
Dummy for receiving FSSN transfers in the past four months # Log of total EHDDs in the long growing season, lagged one year	-0.2949^{**}	-0.2441^{****}	-0.2527^{*}	-0.2848^{****}
	(0.132)	(0.061)	(0.132)	(0.073)
Dummy for receiving ISSN transfers in the past four months # Log of total EHDDs in the long growing season, lagged one year	-0.9921	-0.2582	-0.4105	-0.2513
	(0.641)	(0.326)	(0.665)	(0.293)

Dummy for receiving remittances in the past four months # Log of total EHDDs in the long growing season, lagged one year	0.4699	0.1728	0.6007	0.2076
	(1.258)	(0.660)	(1.186)	(0.795)
Dummy for participation in off-farm employment in the past four months # Log of total EHDDs in the long growing season, lagged one year	0.2458*	0.1658***	0.2629**	0.2795****
	(0.145)	(0.064)	(0.106)	(0.078)
Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			-0.0805	0.1982
			(0.370)	(0.193)
Dummy for above-historical-mean standard deviation of rainfall in the main rainy seasons in the past five years, lagged one year			-0.1716**	-0.0091
			(0.084)	(0.063)
Dummy for sending migrants to urban areas for labor market reasons in the past five years # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			0.5583	0.5273
			(1.074)	(0.779)
Dummy for receiving FSSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			1.3837**	1.2171**
			(0.679)	(0.547)
Dummy for receiving ISSN transfers in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			1.9176	1.6531
			(3.752)	(1.992)
Dummy for receiving remittances in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			0.3647	0.7400
			(3.038)	(1.807)
Dummy for participation in off-farm employment in the past four months # Dummy for below-historical-mean rainfall in the main rainy season, lagged one year			-1.9058**	-2.5976****
			(0.753)	(0.645)
Constant		5.6579****		9.7089****
		(1.435)		(1.543)
Number of observations	2270	3595	2270	3595
Number of instruments	41	53	39	51
AR(1)	0.00	0.00	0.00	0.00
Sargan	0.82	0.25	0.21	0.41
Hansen	0.81	0.33	0.30	0.46

Note: Standard errors in parentheses. Household composition variables and survey round indicators are included in the estimation but omitted from the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.