Norwegian University of Life Sciences (NMBU)

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Sofie Waage Skjeflo and Nina Bruvik Westberg

CLTSNMBU

Centre for Land Tenure Studies Working Paper 04/14

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June 1, 2014

Abstract

We use recent panel data on Tanzanian farm households to investigate how previous exposure to weather shocks affects the impact of a current shock. Specifically, we investigate the impact of droughts on agricultural outcomes and investments in children's health, measured by their short- and long-term nutritional status. As expected, we find that droughts negatively impact yields, with the impact increasing in the severity of the shock, and that severe droughts have a negative impact on short-term nutritional outcomes of children. We also find suggestive evidence that the more shocks a household has experienced in the past, the less crop yields are affected by a current shock. This suggests that households are able to learn from their past shock experience, and could imply that households are able to adapt to climate risk. Our results also suggest that the impact of a shock depends on when the household last experienced a shock. In terms of child health, we are not able to detect any clear effect of previous shock exposure on the impact of a current shock, nor do we find any impact on long run nutritional outcomes.

JEL classification: I12, I130, Q12, Q54

Keywords: Climate risk, income shocks, adaptation, child health, Tanzania

*School of Economics and Business, Norwegian University of Life Sciences. E-mail: sofie.skjeflo@nmbu.no

†Corresponding author. School of Economics and Business, Norwegian University of Life Sciences. E-mail: nina.westberg@nmbu.no.

‡Work in progress, please do not cite without permission. We would like to thank Olvar Bergland, Stein Holden, Andreas Kotsadam, Knut Einar Rosendahl and the Kafferanse group at the Norwegian University of Life Sciences for useful input and suggestions. All remaining errors are of course our own.

1 Introduction

The most recent report from the Intergovernmental Panel on Climate Change concludes that climate change is likely to have severe impacts on agriculture in sub-Saharan Africa with large consequences for food security, creating an urgent need for adaptation (Niang et al., 2014). The report finds that although adaptation strategies are already being used to cope with current climate variability, there are considerable institutional, financial, physical, political and informational barriers to adapting to climate change for small-scale farmers in Africa.

This paper uses nationally representative panel data from Tanzania, coupled with gridded weather data, to explore the impact of climate risk on agricultural output and children's health. We aim to contribute to the literature on impacts of climate variables on economic outcomes. There is a large literature on the impact of climate shocks on economic and health outcomes using cross-sectional data.[1] The more recent literature uses panel data to control for time-invariant factors while exploiting exogenous variation in temperature, precipitation and extreme events (see Dell et al. (2013) for a recent review). A limitation of these studies is that using short-run weather variation to predict long-run impacts of climate change requires out-of sample extrapolations that may not be valid (Dell et al., 2013). For instance, Burke and Emerick (2012) show that US farmers are unable to adapt to longer term variations in climate, as opposed to findings based on short-term weather variations. Similarly, when assessing the impacts of climate risk, defined as the probability of experiencing a negative climate shock, extrapolating from the impact of one climate shock to impacts of increased climate variability due to climate change may not be valid. Our contribution is to investigate whether the impact of a climate shock, more specifically a severe drought, depends on a household's previous experience with such shocks. As far as we know, this is the first paper that does this. Understanding how longer-run exposure to negative climate shocks affects households can then be used to better understand the scope of adaption to increased climate variability due to climate change.

We focus on two outcomes in this paper: crop yields and children's health, measured by their short-run and long-run nutritional status. Farmers with previous exposure to shocks may be less severely affected by a new shock if they are able to learn from previous shocks, for instance through altered crop and input choices, new farming techniques and income diversification. On the other hand, exposure to repeated shocks could make households more

[1] We will not attempt a full review, but some examples are Miguel (2005); Feng et al. (2012) and Kudamatsu et al. (2012).

vulnerable to new shocks, for instance if the households cope by depleting assets, including human capital. In this case, we would expect the negative impact of a shock to be increasing in the number of shocks the household has experienced previously.

In view of the link between agricultural outcomes and weather, particularly in rain-fed agriculture, several studies have investigated the potential impacts of climate change on agriculture. An early application of panel data to this task is the study of U.S. agriculture by Deschênes and Greenstone (2007), the results of which were later discussed by Fisher et al. (2012). Assessing impacts on African agriculture, Schlenker and Lobell (2010) match historical country-level yield data on five crops in sub-Saharan Africa to weather data from 1961 to 2002. They use their estimated parameters to predict crop production losses due to climate change by year 2065, and find that the production of maize, groundnut, sorghum, millet and cassava is expected to decrease by respectively 22, 18, 17, 17, and 8 percent. Relevant to our context, Rowhani et al. (2011) use regional panel data on maize-, rice- and sorghum yields in Tanzania from 1992 to 2005. The data is coupled with observations from weather stations and gridded, extrapolated weather data. They find that precipitation variability during the growing season, measured in terms of the coefficient of variation, has a negative impact on all three crops. Ahmed et al. (2011) use the same data to investigate the impact of rainfall and temperature on yields, and the impact of projected future climate variability on poverty distributions.

Evidence of the impact of weather variability on agriculture at the household level is less common. Rosenzweig and Binswanger (1993) find that households alter their agricultural investment portfolio in response to changes in rainfall patterns. Using the ICRISAT village surveys from India, which include daily rainfall data, they find that a delay in monsoon onset significantly reduces crop- and total farm profits. Further, they find that farmers exposed to more weather variability choose less risky and less profitable investments, and that this effect is stronger for poorer households who are less able to cope with income variability after a shock.

The impacts of climate variability on households is perhaps better understood when broadening the focus beyond agricultural output. A few papers look at the impacts of climate variability on consumption, implicitly assuming that the mechanism of impact is through agriculture. Skoufias and Vinha (2013) use household panel data from Mexico, coupled with daily historical rainfall station data, interpolated to the municipality level. Using total precipitation and growing degree days (GDD)[2] for the agricultural year and the rainy season,

[2]GDD is a cumulative measure of temperature.

they define weather shocks as a period where precipitation or GDD is more than one standard deviation above or below their historical mean. The authors cannot conclude on a general shock impact, but find some evidence that households are unable to perfectly smooth consumption following a shock. Lazzaroni and Bedi (2014) apply two rounds of the Living Standards and Measurement Survey (LSMS) in Uganda, to investigate the impact of weather variability on food consumption. Data on precipitation, number of rainy days and temperature for the two seasons preceding each survey are drawn from 13 meteorological stations, and they define weather indicators as deviations of these measures from the long term local means.[3] Rainfall is not found to affect consumption, but the authors find relatively large, and significant effects of temperature on food consumption. A one percent increase in the maximum temperature is expected to decrease food consumption by three percent, according to their results.

Several studies have analyzed the effect of weather shocks on health, either implicitly or explicitly assuming an income effect through agriculture. The impact on children's health is seen as particularly important – if parents are unable to maintain investments in their children's human capital (for instance through schooling or health) during shocks, the effect of negative shocks may persist over generations (Dercon, 2002). With this motivation, Jensen (2000) compares children's health and educational outcomes in Cote d'Ivoire based on their exposure to a recent weather shock.[4] In the exposed areas, malnutrition (defined as weight-for-height Z-score more than two standard deviations below the reference median) increased among children aged 0-10 years, school enrollment decreased by more than one third and the use of medical services for children that were ill decreased, without significant difference between the exposed and unexposed children prior to the shock. Similarly, Hoddinott and Kinsey (2001) find that experiencing a drought[5] results in a slower growth rate in height for Zimbabwean children aged 12-24 months old. Maccini and Yang (2009) extend the perspective to adult outcomes and focus on positive rainfall shocks rather than negative ones. They find that Indonesian rural females who experienced 20 percent more rainfall than the district mean as infants attain greater height as adults (0.57 cm on average).[6]

In terms of short-term nutritional status (weight-for-age), the evidence on impacts of

[3] The historical period varies between 1960-1990 (precipitation) and 1980-2010 (temperature).

[4] Defined as rainfall more than one standard deviation below the historical mean.

[5] Identified as a season with rainfall below the average historical mean.

[6] Others again analyze the impact of weather shocks on mortality, which can be viewed as the cumulative result of negative impacts on children's health. For instance, Rose (1999) explores gender differences in child mortality following a positive rainfall shock, Kudamatsu et al. (2012) analyze the impact of droughts on infant mortality among African farming households, whereas (Burgess et al., 2013) assess the differential impact of extreme temperatures on infant and overall mortality in rural versus urban areas.

weather shocks are less clear. More rainfall can trigger increased risk of disease that in part counteracts the income effect (a "disease channel"). Tiwari et al. (2013) investigate the impact of excess monsoon rainfall on short- and long run nutritional status in Nepal. Clusters from the Demographic Health Surveys (DHS) are matched with predicted weather patterns based on rainfall and elevation. A contemporaneous shock (disease channel) results in lower weight-for-age for infants, whereas a positive shock in the previous season (income effect) increases weight-for-age for all age-groups below three years old. Height-for-age is only positively affected by more rainfall in the second year of life, and this holds only for children aged 12-35 months.[7] Lechtenfeld and Lohmann (2014) widen the focus to self-reported illness among adults and health expenditures, in addition to self-reported anthropometric measures. They assess the effect of a drought severity index[8] on these measures using four rounds of household panel data from rural Vietnam. A higher drought severity index increases the probability of illness and reduces weight among adults and children, whereas they find no significant impact of weight-for-age Z-scores of children below five. They attribute this effect to an income effect, through increases agricultural yields, and do not discuss a possible disease channel.

Although several papers have analyzed the reduced form impact of weather shocks on health, few assess this explicitly through its effect on agriculture - instead implicitly assuming that this is the main channel. A related, and equally important, question is how previous shock exposure may interact with a new shock in explaining differences in both agricultural and health outcomes. We exploit detailed plot level data on crop production and anthropometric measures of respondents in the Tanzania National Panel Survey to explore these questions. Our results show that experiencing severe droughts negatively affects crop yields, with the impact increasing in the severity of the shock. Our results also indicate that the more shocks a household has experienced previously, the less severe the impact of a current shock on yields, suggesting that households may learn from previous shocks how to mitigate impacts of current shocks. We find that households are not able to protect children from the most severe shocks – the short run nutritional outcome of young children is negatively affected by a severe drought in the previous rainy season. On the other hand, we are not able to detect a negative impact from less severe droughts, and we do not find any evidence that previous exposure to severe shocks has an impact on how a current severe shock affects

[7] This contrasts to Maccini and Yang (2009), who find a positive effect on stature from more rainfall in the first year of life. They use however a more long-term outcome, i.e. adult height.

[8] Defined as the annually aggregated deviations of monthly district level rainfall shortfall from the local historical mean.

nutritional outcomes.

In the following we present our conceptual framework in Section 2, Section 3 gives an overview of the setting, while the data and the empirical strategy to be employed are described in Sections 4 and 5. The results are presented in Section 6 and followed by a discussion of possible caveats and paths for future work in Section 7. Section 8 concludes the paper.

2 Conceptual framework

The impact on farming households of repeated shock exposure, for instance droughts or flooding, in the context of a rural developing country, is not obvious. Market imperfections in insurance and savings are often pervasive, leaving households' response to income shocks largely dependent on their own endowments, and linking poverty vulnerability to risk (Dercon, 2002). The effect of a weather shock, such as a drought, and its interaction with previous shock exposure on households' consumption and welfare is expected to manifest itself through agriculture. The majority of the farming households in our sample rely on rain-fed agriculture,[9] and we would therefore expect rainfall variability to affect their agricultural output. Previous exposure may have led the household to develop techniques to better tackle new shocks, such as shifting the timing of planting or fertilizer application, switching crop varieties and types, and implementing soil- or water conservation technologies (Burke and Lobell, 2010; Di Falco and Veronesi, 2013). Alternatively, their ability to invest in (costly) adaptive strategies may be reduced. Previous shock exposure may have triggered asset depletion, such as selling of livestock or other productive assets, or reduced investment in health and education (Dercon, 2002), reducing their investment capabilities and their ability to deal with more recent shocks. A first step to understanding potential long run impacts of climate risk is therefore to investigate the impact of shocks and repeated shock exposure on agriculture, and more specifically crop yields.

Rural households may derive income and consumption from other sources than own farm production. Income diversification (Rose, 2001), asset depletion (Rosenzweig and Wolpin, 1993), self-insurance through savings (Paxson, 1992) and altered labor supply (Kochar, 1995; Rose, 2001) are possible smoothing strategies to adapt to fluctuations in agricultural income (Morduch, 1995; Dercon, 2002). The extent to which rainfall variability affects total income and consumption is therefore not readily derived based on own production only. Moreover, the combined effect of multiple households' responses may result in increased food prices and

[9] In a given year less than 5% of the households in our sample have one or more irrigated plots.

lower wages when markets are poorly integrated (Jayachandran, 2006), which again affects households' consumption depending upon their position in the market.

Even if all income sources were identified, measuring households' total income would be problematic. The alternative measure, consumption, is believed to suffer less from measurement error in rural settings, but is also difficult to capture (Deaton, 2005). However, a desirable outcome from income and consumption smoothing is better child health outcomes. We therefore investigate the effect of a shock and previous exposure to similar shocks on child health, measured by the short- and long-run nutritional status of children.

Rainfall variability and experience with past rainfall variability may affect children's nutritional status in several ways. Firstly, is the above-mentioned income effect, whereby households' income available for consumption may fall due to lower yields. For households that are net buyers of food, a related increase in food prices will add to this. The extent to which a drought affects child nutrition thus depends on the opportunities for income- and consumption smoothing. If households are able to perfectly smooth consumption when facing agricultural income shocks, we do not expect any impact on investment in children's health. Secondly, rainfall shocks can have an additional direct effect on health, through access to clean water and the prevalence of vector- and water-borne diseases (Tiwari et al., 2013). The causal mechanisms behind the impact of shocks and previous shock exposure on child nutritional outcomes is therefore more complicated than the effect on agricultural outcomes. However, since the disease environment is affected by current rainfall, and agricultural income is affected by rainfall in the past growing season, it is possible to separate between the two channels. This is further discussed in section 5.

We posit four possible scenarios for the effect of households' previous exposure to droughts on current drought impacts on children's health. Firstly, if households are able to learn income- and consumption smoothing methods from previous shocks, then we expect the impact of a current shock on child nutrition to be decreasing in the household's previous shock experience. If learning mainly occurs through (better) income- and consumption smoothing, we would expect to find adaptation only for child health outcomes, and not for yield outcomes. Secondly, if we observe adaptation both for yield and children's health, we cannot disentangle adaptation through agricultural measures from adaptation through income- and consumption smoothing. Thirdly, we may observe adaptation in yield, but no adaptation in terms of child health, or even a negative effect (depletion). This could indicate that households adapt by producing less risky, but less nutritious crops, or that agricultural adaptation is costly, and that this is taking place at the expense of children's health for instance in terms of time use (Kim, 2009). Lastly, if we observe that previous shock exposure magnifies the negative impact of a current shock on child nutrition then this could indicate an asset depletion story.

We expect the timing of past shocks to affect the total impact of a new shock, through the depletion and adaptation responses available to the household. Rebuilding the asset stock following a shock may take time. Households' ability to cope with a new shock could therefore be greater the more time has passed since the last shock, implying a negative relationship between the impact of a new shock and years since the last shock. On the other hand, it may be easier to learn from a more recent shock than from shocks that happened a long time ago, whereby the negative impact of a new shock increases with time. Combined, this would imply a u-shaped relationship between the time since the last shock the household experienced, and the absolute impact magnitude of a shock today: *(i)* Households' with recent previous shock exposure, e.g. in the past one or two years, have acquired knowledge on how to better tackle a new shock. However, given the recent income loss due to the previous shock, their ability to invest both time or cash in these adaptive techniques is reduced. *(ii)* If more years have passed since the last shock occurred, households have more resources to draw upon while at the same time maintaining the knowledge of how to better tackle a new shock. *(iii)* Given an even longer time horizon between the current and last shock, households are likely to have more resources available. Assuming that their knowledge has dissipated, then their ability to use their resource base to tackle a new shock is diminished, resulting in a larger total impact of a new shock.

An alternative scenario is a linear relationship between the absolute impact of a new shock and the time passed since the previous shock. The more time that has passed, the larger the resource base the household has manage to rebuild, while at the same timing maintaining the knowledge of how to best respond to a new shock.

3 Climate and agriculture in Tanzania

We focus on farmers' behavioral responses to weather variability in Tanzania, where the climate is characterized by both large regional, inter-seasonal and intra-annual variations. Northern and eastern regions experience two rainy seasons (bimodal), while the rest of the country has one single rainy season (unimodal) (McSweeney et al., 2010, 2014). These rainfall patterns are largely the result of the Inter-Tropical Convergence Zone (ITCZ) and its movement across the country. Climate variability is in addition affected by the El Niño Southern

Oscillation[10] and La Niña[11] (Camberlin et al., 2001; Wolff et al., 2011).

Apart from the humid coastal areas, the country is covered by highlands that provide a temperate climate for farming. Cereals such as maize, rice and sorghum are farmed extensively, with maize being the most common crop. A large share of the maize production takes place in the southern highlands, whereas sorghum is mostly found in the drier central highlands and rice in southern regions (Rowhani et al., 2011). Given the limited use of irrigation, the timing of agricultural activities is closely linked to the seasonal rainfall patterns. The rainy season in the unimodal areas (*Msimu*) usually starts in October-November and lasts until April-May, with a dry-spell in-between, allowing for harvest from June to August. In the bimodal areas, the short rainy season (*Vuli*) typically lasts from October to December, whereas the long rainy season (*Masika*) occurs between March and June, with harvesting in July-August.

A substantial share of the Tanzanian population relies on agriculture as their main income source, with around 80 percent of the population residing in rural areas. Population density is relatively low throughout the country, with some exceptions, but birth rates are high, each woman on average gives birth to just over five children (TNBS and ICF Macro, 2011).

According to historical records, average annual rainfall has decreased over the past decades in Tanzania, whereas mean annual temperature has increased (McSweeney et al., 2010, 2014; Hulme et al., 2001). In terms of extreme rainfall weather events, the pattern is less clear (McSweeney et al., 2010, 2014). Climate model predictions suggest an increase in mean temperature, and in particularly so during the dry season, whereas predictions on rainfall are less clear - Ahmed et al. (2011) note for instance an increase.[12]

4 Data

4.1 Household panel

We use the Tanzania National Panel Survey (NPS), a panel of nationally representative household surveys from 2008/09 (NPS1) and 2010/11 (NPS2). Households were sampled from 409 populated enumeration areas that were drawn from the Tanzania Population and

[10] Warmer sea surface temperature in Pacific, that may result in more than average rainfall in the short rainy season but less in the long rainy season (Camberlin et al., 2001).

[11] Cooler sea surface temperature in Pacific, that may result in droughts in the northern parts of the country, whereas more than average rainfall is likely to occur in southern parts (Wolff et al., 2011).

[12] Hulme et al. (2001) characterize the predictions from climate models for the African continent as uncertain due to incomplete and lacking knowledge of the ENSO's effect and the failure to incorporate changing land cover/use.

Housing Census from 2002. The first round covers 3265 households (2063 in rural areas) and their 4321 farm plots, and was collected in the period October 2008-October 2009. The second round covers 3924 households, 3168 of them reinterviewed from round 1, and their 3882 farms plots, and was collected between October 2010 and November 2011. The observations are matched at the household- and plot-level across the two survey rounds. Around 7 percent of the plots were measured with GPS in the first round and 80 percent in the second round (NBS, 2011). A third round of the panel was collected in 2012/13, but this data has not yet been released. We intend to expand our analysis with this data as soon as it is made publicly available.

The NPS has the advantage of providing detailed data on both agricultural production and child anthropometrics, allowing us to investigate our hypotheses from multiple angles. Moreover, the panel nature of the data makes it possible to compare households within the same enumeration area, rather than across enumeration areas. Data on agricultural activities is gathered for the agricultural season preceding the interview. Thus, for NPS1 the agricultural season of interest when matching with climate data is 2007/08, whereas agricultural data from NPS2 is matched with the 2009/10 season. Figure A1 shows a map of the enumeration areas from 2008/09 to which the weather data is matched.

In some specifications we use the unbalanced plot panel data, which gives us 5416 observations when we include households that reside in the same location across the two survey years and cultivated crops in both seasons.[13] The balanced household panel gives us 2436 observations. For children's nutritional outcomes, we pool[14] the data and use nutritional outcome variables on 3189 children that are 60 months or younger residing in farming households.[15] We cannot include the children measured following the harvest from the rainy season 2010/11, i.e. those measured after April in the unimodal areas and after June in bimodal areas. We will expand our analysis to all children, including those measured in the period July-November 2011, upon accessing weather data for 2011.

[13] We have to drop 542 plot observations due to lack of plot id in 2010/11. Achieving a balanced plot panel would require dropping an additional 50 percent of the plots, leaving us with 1865 plots that we observe in both years. Since the results are largely unchanged, we chose to use the unbalanced panel.

[14] There are unfortunately too few observations on children below 61 months in the same households over the two rounds of the survey to use the panel structure in this case.

[15] We include children of farming households that were excluded in the yield analysis due to outliers or missing observations on agriculture.

4.2 Climate data

We use University of Delaware (UDel) gridded precipitation and temperature data, described in Willmott and Matsuura (2012a,b). Each grid cell is 0.5 x 0.5 degrees, equivalent of around 55 x 55 km at the equator. The data is interpolated from weather station observations and provides monthly data on precipitation in milimeters and monthly mean air temperature in degrees Celsius.[16] Each set of GPS coordinates at the enumeration area level is matched to a grid cell. This results in the 391 enumeration areas being matched to 149 grid cells covering mainland Tanzania and Zanzibar, whereby several enumeration areas fall within the same grid cell.[17]

4.3 Measuring climate shocks

Previous studies on the impact of climate variability on agricultural output suggests that both precipitation and temperature are important. We define a negative precipitation shock in three ways: annual precipitation in *(i)* the 10th percentile of the local historical distribution, *(ii)* the 15th percentile of the local historical distribution, or *(iii)* the 20th percentile of the local historical distribution. Basing our definition of a drought period on deviations from the *local* precipitation pattern means that we control for the average local climate, which may be correlated with other characteristics that could influence our outcome variables (Kudamatsu et al., 2012). Moreover, a relative rather than an absolute measure of drought suggests that any deviations from the local historical mean, e.g. rainfall in the bottom 10th, 15th or 20th percent of the distribution, should be orthogonal to other factors that may affect households' adaptation. In any given year households in a grid cell have 10, 15 or 20 percent probability of experiencing a shock as defined above. This is choice of a relative measure is in line with previous work.[18]

We proceed by identifying the historical distribution of rainfall in each grid cell based on the monthly precipitation data for the period 1960-2010. We restrict ourselves to the years following 1960, as it provides a more representative distribution for recent weather patterns while at the same time giving us sufficient data to construct a distribution from which we

[16] The climate data from UDel has been used extensively over the past years. We choose to use this data given its detailed historical and spatial coverage. We plan to do sensitivity analysis using different climate data in order to assess the robustness of our results.

[17] We have to drop 18 enumeration areas due to lack of precipitation data. These are located along the coast or on islands. Given our focus on agricultural production, we do not believe that omitting these enumeration areas will bias our results, as many are involved in other occupations than agriculture and the total number of observations dropped at the household level in total for both years is 134.

[18] For instance, Burke et al. (2014) define a shock as rainfall below both the 15th percentile of a gamma distribution, and confirm the findings when using the 10th and 20th percentile.

draw our historical shocks.[19] All measures are constructed for the entire agricultural season, i.e.. July-June. We also define shocks based on precipitation in the relevant rainy season in the unimodal and bimodal areas of Tanzania. We assume a fixed growing season, and define the first month of the growing season as October.[20] Unfortunately, the University of Delaware data only contains monthly mean air temperatures, which prevents us from developing a good indicator of temperature shocks[21], but we include mean temperature during the growing season as a control in our analysis of agricultural outcomes.

When investigating the impact of shocks on child health we identify the most recent agricultural season prior to the child's measurement, since this is the season relevant to the child's food consumption prior to being measured. The relevant season differs between the unimodal and bimodal areas, and we investigate the impact of shocks in the relevant season depending on when the child was measured. For children in households residing in unimodal areas, we use the rainfall shock in 2007/08 for all those measured prior to May 2008 in the first survey round, whereas for those measured in May or later are assigned a shock value based on the 2008/09 agricultural season. We set the cut-off to June for the bimodal areas. The same procedure is used for the second survey round. See Figure A2 for a timeline of child shocks.

We identify previous exposure to the above shocks in two ways. The first method is to count the number of similar shocks that have occurred over the last 10 year period, in other words 1997/98-2006/07 for the first survey round, and 1999/00-2008/09 for the second survey round. This results in a previous exposure variable that is time-variant across the rounds. A timeline describing the timing of the surveys and agricultural shocks is shown in Figure A3. The second approach that we take is to count the number of years that have passed since the household was last exposed to a similar shock. For each survey round, we count backwards from the relevant agricultural season. We thus obtain a measure of risk exposure that varies over time.[22]

Since the previous shock exposure variable is based on the local historical distribution

[19] The same approach is taken by Burke et al. (2014).

[20] We choose to define the growing season based on the main rainy season, and in accordance with recorded planting times for maize which varies from October/November to December/February in the unimodal areas (Kaliba et al., 1998b,c,a) and from January/February to March/April (Mafuru et al., 1999; Nkonya et al., 1999; Kaliba et al., 1998b) in the bimodal areas. This differs from Ahmed et al. (2011) who use a general growing period for the entire country, i.e. from January to June, for maize, rice and sorghum.

[21] Schlenker and Lobell (2010) and Lobell et al. (2011) use growing degree days (GDD) as a measure of accumulated temperature exposure for crops during the growing season, and degree days above 30 degrees celsius as a measure of exposure to extreme heat.

[22] The first method of capturing previous shock exposure is similar to the approach taken by Burke et al. (2014).

of rainfall over the past 50 years, all households across grid cells have an equal probability of experiencing a shock in a given year (withstanding temporal correlation). Consequently, areas that experience more weather shocks in the past decade should not differ systematically from areas that experience more shocks in any other decade of the 50 years period we have.

4.4 Measuring agricultural output

We vary our measure of (log) agricultural output, employing maize, cereal and total yield (output per hectare) at both the plot and household level. Total yield includes all crops, including legumes, vegetables, roots, tubers and cash crops. Around 60 percent of the plots are covered with mono- or intercropped maize, followed by around 12 percent allocated to rice paddy. Beans, groundnuts and pigeon peas are typical crops used for intercropping, whereas few farmers have cash crops, such as tobacco, cotton and cashew nuts. For each output measure we exclude the lower and upper 1 percentile of the plot observations, in addition to plots exceeding 100 hectares.[23]

Each measure has both disadvantages and advantages. We suspect that using total yield is likely to bias our results upwards. Households that experienced a shock may be more likely to harvest cassava (heavy weight) than those that did not experience a shock, thus resulting in a higher total yield. The five cereals (maize, sorghum, millet (bulrush and finger), wheat and rice) that enter into the cereal yield variable are on the other hand more homogenous in weight, and we avoid to a greater extent differences in drought-tolerant characteristics when using maize yield only. Restricting the agricultural yield data to only maize or cereal reduces on the other hand our number of observations, primarily at the plot level, but also at household level.

4.5 Descriptive statistics

In Table 1 we report descriptive statistics at the plot and household level. The household head is on average 49 years of age, and one fourth of the households are female headed. Four percent of the households experience rainfall below the first decile in one of the surveyed agricultural seasons, e.g. 2007/08 and/or 2009/10, whereas 11 percent have experienced rainfall below the second decile in these same seasons. In terms of previous exposure, the households have experienced between zero and four shocks, defined as rainfall below the first decile, over the past decade. The number of years since a similar shock occurred varies

[23] Based on this we drop 184, 99, 82 plot observations for total-, cereal and maize yields, respectively.

between one and 41 years for the rainfall below the first decile, and one and 20 years for rainfall below the second decile. Maize yields average around 800 kg per hectare, whereas cereal and total yield is somewhat higher.

4.6 Measuring children's health

We use three measures of children's nutritional status as outcome variables. Firstly, *(i)* weight-for-age, which is referred to as the "classical index" in WHO (1986), capturing underweight, and can be supplemented or replaced by the following two; *(ii)* weight-for-height, which reflects short-run nutrition, and recovers quickly after period of insufficient nutrition (wasting, index of acute malnutrition) and *(iii)* height-for-age, which captures long-run nutrition (stunting, index of chronic malnutrition). It is important to use both stunting and wasting as outcome variables separately, since they react differently to the nutritional state, and are different biological concepts. Wasting is more prevalent between 12 and 24 months of age, while stunting is more prevalent above 24 months. Growth is a slow process, and cannot be reversed (you cannot lose height), while weight may react quickly to nutrition and disease (WHO, 1986). According to WHO (1986) it is most appropriate to look at these outcome variables for children younger than 5 years. The weight-for-age, weight-for-height and height-for-age of the children in our sample are linked to the WHO reference population by creating Z-scores.[24] The standard allows us to create Z-scores for individuals aged 0-60 months.

We report the summary statistics on anthropometric measures for children belonging to farmers (e.g. having positive total yield) in Table 2. In line with Alderman et al. (2006) we drop individuals with Z-scores below -6 or above 6, resulting in the exclusion of 75 observations. Children are on average 1.8 and 0.9 standard deviations below the international reference population for height-for-age and weight-for-age, respectively. There are in other words more cases of stunting than wasting.

[24]We subtract median and divide by standard error of appropriate sex and age category of reference population.

5 Empirical specification

5.1 Agricultural yield

To investigate how previous exposure to shocks affects the impact of a shock on agricultural yield, we estimate the following regression:

$$\mathrm{Y}_{phct} = \alpha_p + \beta_1 \mathrm{Shock}_{ct} + \beta_2 \mathrm{Shock}_{ct} \times \mathrm{PrevShock}_{ct} + \beta_3 \mathrm{PrevShock}_{ct} + \beta_4 X_{hct} + u_{phct} \quad (1)$$

where Y_{phct} is the outcome of interest (log of total yield) for plot p in household h in enumeration area c at time t, and α_p is a plot-specific intercept. Shock_{ct} is a dummy equal to one if precipitation was below the 10th, 15th or 20th percentile at time t, $\mathrm{PrevShock}_{ct}$ is the number of years an enumeration area c was exposed to such a shock in the past. We look here at the number of shocks experienced over a 10-year period prior to the observed agricultural seasons, which varies across the two survey rounds. u_{phct} is a mean zero error term, with clustering at the plot- or household level. The same specification applies to the household panel analysis, dropping the subscript p for plots.

The choice of which control variables to include is not obvious. Following the recommendation in Dell et al. (2013) we only include regressors that can credibly be viewed as exogenous. Controlling for input use or crop choice when looking at agricultural yield would be problematic, since these variables are likely to be influenced by whether or not the household experiences a shock; in fact they may be important channels through which a household may adapt to climate risk. Angrist and Pischke (2008) calls this a "bad control problem" and shows that including regressors that are not exogenous to the weather variables we are interested in would bias the estimates of β_1 and β_2. X_{hct} consists therefore only of a set of control variables at the household level, more specifically the age and gender of household head and whether the households' plots were measured with GPS or not.

The coefficient β_1 can be interpreted as the effect of being exposed to a shock without having been exposed to shocks over the past 10-year period. The average effect of a shock is thus $\beta_1 + \beta_2 \times \mathrm{Prev\bar{S}hock}$ where $\mathrm{Prev\bar{S}hock}$ is the average number of shocks experienced. β_2 is thus the coefficient of main interest here. $\beta_2 < 0$ indicates that previous exposure to shocks makes the household less able to deal with a current shock (depletion), while $\beta_2 > 0$ indicates that households are able to learn from previous shock exposure to mitigate the impact of a current shock (adaptation). β_3 is interpreted as the effect of previous shock exposure when there is no current shock.

Since we are controlling for plot fixed effects, we are only exploiting variation within each plot over time. Any variation in the *PrevShock* variable is thus variation in the number of shocks a plot has been exposed to *between the first and the second survey round*, and *in the first years that enter into the 10-year period.* This means that an increase in previous shock exposure must come from experiencing a shock in the 2007/08 season and/or the 2008/09 season, whereas a decrease in shock exposure would occur if when moving the 10-year window forward results in a shock year dropping out. When estimating the coefficient on the interaction between previous shock exposure and experiencing a current shock, we are thus only looking at plots in the second survey round that experience a shock, and that have experienced a change in shock exposure between the two seasons.

We also capture the effect of previous shock exposure on the impact of a current shock through LastShock_{ct}, replacing PrevShock_{ct}. This variable is based on counting the number of years since a similar shock, i.e. rainfall in 10th, 15 or 20th percentile, occurred. As described above, we expect that the timing of previous shock exposure may matter for the impact of a current shock. For instance, having recently experienced a similar shock could magnify the negative effect of a contemporaneous shock if households have depleted their asset stock, and adaptation to a new shock is costly. As the time passes since the household last experienced a shock, their asset stock may be rebuilt, but knowledge of how to adapt to a shock may dissipate over time. We also include a squared term LastShock^2_{ct} interacted with the current shock, to test for a non-linear effect of the time since a previous shock on the impact of a current shock. Our second specification is as follows:

$$\begin{aligned} \text{Y}_{phct} = \alpha_p + \gamma_1 \text{Shock}_{ct} + \gamma_2 \text{Shock}_{ct} \times \text{LastShock}_{ct} \\ + \gamma_3 \text{Shock}_{ct} \times \text{LastShock}^2_{ct} + \gamma_4 \text{LastShock}_{ct} + \gamma_5 X_{hct} + u_{phct} \end{aligned} \tag{2}$$

where the average effect of a shock is $\gamma_1 + \gamma_2 \times \text{Last}\bar{\text{S}}\text{hock} + \gamma_3 \times \text{Last}\bar{\text{S}}\text{hock}^2$. We include the same control variables as in the first specification.

5.2 Child health outcomes

We employ a reduced form model to investigate the impact of shocks and their interaction with previous shocks on child health outcomes.

$$\text{Y}_{ihgrt} = \alpha_r + \lambda_1 \text{Shock}_{grt} + \lambda_2 \text{Shock}_{grt} \times \text{PrevShock}_{grt} + \lambda_3 \text{PrevShock}_{grt} + \lambda_4 X_{ihgrt} + u_{ihgrt} \tag{3}$$

where Y_{ihrt} is a measure of the nutritional status for child i in household h in grid cell c in region r at time t, and α_r is a region-specific intercept. We employ three outcomes: height-for-age (stunting), weight-for-age (wasting) and weight-for-height (underweight). X_{ihgrt} includes a set of child-specific characteristics on age and gender. As discussed above, precipitation may also have a direct effect on child short-term nutritional outcomes through its effect on the disease environment. We therefore include total precipitation in the month the child was interviewed to control for this in the regressions with weight-for-age and weight-for-height. This will vary across children within the same enumeration area. Shock_{grt} refers to the last agricultural season prior to child measurement in grid cell g in region r at time t We use region-level fixed effects rather then enumeration area fixed effects, as we are not using the entire sample of children from the second survey round. Note that one region can be covered by several grid cells.

$\lambda_2 < 0$ would indicate a depletion story, where repeated previous exposure to droughts makes child health increasingly vulnerable to recent shocks. For short-term nutritional outcomes, we expect the impact mechanism to be through the income of the household, where the impact on household consumption is increasing in previous shock exposure, perhaps due to asset depletion and lack of consumption smoothing mechanisms. $\lambda_2 > 0$ would, on the other hand, indicate that households are able to learn from previous shocks, through improved income- and consumption smoothing and/or through agricultural adaptation, depending on the sign of β_2 from specification 1.

For height-for-age, we expect $\lambda_2 = 0$ regardless of whether the household is able to learn from previous shocks, since this outcome reflects accumulated nutritional shocks. We expect a contemporaneous shock (rainfall below first or second decile) to have a negative impact ($\lambda_1 < 0$) on short-term nutritional outcomes, i.e. weight-for-age and weight-for-height, but less so for height-for-age as this measure does not react quickly to changes in consumption. On the other hand, previous exposure to shocks (in the child's lifetime) is expected to affect height-for-age negatively, which could imply $\lambda_3 < 0$ depending on when the previous shocks occurred.

6 Results

6.1 Agricultural yield

6.1.1 Plot panel results

We start off by presenting our results for agricultural outcomes, in line with the first empirical specification in eq. (1), using the plot-level panel. In tables 3, 4 and 5 we report the results from using log of total agricultural yield, cereal yield and maize yield, respectively, as the outcome variable. Plot-level fixed effects are included throughout, and we are therefore exploiting the within-plot level variation. When we only include the shock variables, we find that experiencing a negative precipitation shock defined as rainfall in the 10th, 15th and 20th percentile of the local historical precipitation distribution, on average results in lower yield. This holds for all three outcome variables, and is statistically significant at the 5 percent level for the two most severe shock definitions for all three outcomes, and at the 10 percent level for rainfall in the 20th percentile for total yield. Rainfall in the 10th decile results in a reduction in yield of between 23 and 28 percent depending on the outcome variable, with strongest effects found for cereals and maize. As expected, the impact magnitude is increasing in the severity of the shock, with an average 11 percent decrease in total yields with rainfall in the 20th percentile, 21 percent with rainfall in the 15th percentile, and a 23 percent decrease with rainfall in the 10th percentile.

Next, we include an interaction term between the number of shocks experienced and a shock this agricultural season, while controlling for the number of shocks experienced, thus estimating the full specification in eq. (1). The only case where both coefficients of interest are statistically significant is for log of total maize yield, when looking at the impact of precipitation in the 20th percentile this agricultural season, and previous experience with the same type of shocks. The effect of the shock is negative and statistically significant at the 10 percent level, and the magnitude indicates that a shock reduces maize yield by as much as 25 percent. However, the coefficient on the interaction term between a current shock and the number of previous shocks is positive. This corresponds to $\beta_1 < 0$ and $\beta_2 > 0$ in eq.(1) of our empirical specification, indicating that the negative effect of a shock on maize yields is less severe the more shocks the household has previously been exposed to. The coefficient on the interaction term is positive and statistically significant at the 1 percent level. Since we are only exploiting within plot variation we are essentially estimating the coefficient on the interaction term based on plots that experienced a shock between the two survey rounds.

Based on the results, it seems that plots that have recent shock experience are less affected by a current shock. The magnitude indicates that experiencing a shock between the survey rounds reduces the impact of a current shock by as much as 16 percentage points. This means that the impact of a current shock for those that recently experienced a shock is less than half of the impact for those with no recent shock experience. This could indicate that there is some adaptation or learning from recent shocks that enables farmers to better cope with new shocks. We also find a positive and statistically significant coefficient on the interaction term when looking at rainfall in the 20th percentile for cereal yield and the 15th percentile for maize yields, but the shock coefficient is not statistically significant in these specifications. The results are similar when defining rainfall shocks as rainfall in the lower percentiles of the rainfall distribution of the rainy season, as shown in tables A1-A3 in Appendix I.

The coefficient on the number of shocks experienced in the past (β_3 in eq. (1)) is positive in most specifications. This implies that past shock experience is positive for current yields and which is a finding that needs to be explored further. One potential explanation could be that plots are left fallow during droughts, which improves fertility in following seasons. Another potential explanation is that shocks cause local prices to increase, perhaps for a while after the shock, creating incentives to invest in crop production and increase yields. Alternatively, adaptation might be yield increasing (for instance adoption of improved, drought resistant varieties). These potential mechanisms are further discussed in Section 7.

Next we investigate whether and how the time lag since the plot last experienced a similar shock affects current agricultural yield, based on eq.(2). Results from this specification are reported in tables 6, 7 and 8. We saw previously that a rainfall shock results in reduced agricultural yield. When we include a variable capturing the time span since a similar shock occurred and its interaction with a contemporaneous shock, we find a negative shock impact and a positive coefficient on the interaction term in all specifications, but the coefficients are only statistically significant in the specification with total yield as the dependent variable and rainfall in the 20th percentile. The negative coefficient on the shock variable is statistically significant at the 5 percent level and the coefficient on the interaction term is significant at the 10 percent level, and correspond to $\lambda_1 < 0$ and $\lambda_2 > 0$ in eq. (2). The more time that has passed since the household last experienced rainfall in the 20th percentile, the smaller the impact of a shock in the current season, indicating that the households may need to rebuild its asset stock to be able to cope with another shock. There is no statistically significant coefficient on the squared interaction term (λ_3), and the results are not clear when looking at maize yields and cereal yields as outcome variables. Too little variation in a present-year shock may account for our inability to identify a robust effect.

The coefficient on the number of years since last shock is negatively signed, small in magnitude, and statistically significant at the 1 percent level. This pattern holds for all three measures of agricultural yield, with the exception of previous exposure to rainfall in the 10th percentile for total yield.

6.1.2 Household panel results

We also investigate the impact of shocks and its interaction with previous exposure using the household panel. This yields similar results, available upon request. However, the opposite of what we expected occur when including the interactions for total yield for the most severe shock – the shock appears to have a positive and significant effect on total yield while the interaction term is negative and significant. An on average higher average weight for more drought-tolerant crops, e.g. cassava - a typical crop, may be driving this result. At the household level, we observe yields from all plots, and in the case of a severe drought the household may cope by harvesting cassava, which is drought tolerant once established and can be harvested throughout the year (Barratt et al., 2006). If this is the case, the negative sign on the interaction term may reflect that the stock of cassava could be depleted if the household deals with several shocks in this way.

6.2 Child health outcomes

In tables 9, 10 and 11 we report the results on child anthropometric outcomes. Region-, birth month- and interview month- fixed effects are included but not reported. We are therefore comparing children within the same region, born in the same month (in part accounting for their exposure to rainfall shocks) and interviewed in the same month. We also control for the disease channel when investigating the impact of shocks on short-run nutritional outcomes, by including precipitation in the month of interview. The rainfall shocks are defined as precipitation in the 10th or 20th percentile of the local historical rainfall distribution in the months of the rainy season (the long rainy season in the bimodal areas).

We do not find any statistically significant effect of shocks in the rainy season before the child was measured on height-for-age, which is not unexpected since height-for-age is a measure of long run nutritional status. However, experiencing rainfall in the 10th percentile of the local historical rainfall distribution in the rainy season prior to being measured, has a negative impact on short nutritional outcome, measured by the weight-for-age Z-score of children 5 years and younger. The coefficient is negative and statistically significant at the 10 percent level and indicates that the most severe rainfall shock on average reduces weight-for-age by 0.22 standard deviations. We are not able to uncover any impact of less severe shocks (rainfall in the 20th percentile in the last rainy season), or any impact on the weight-for-height. This could be because households are able to avoid negative impacts of less severe shocks on children, or because we do not have enough within-region variation in shocks to estimate this coefficient. We do not find any statistically significant impact on the interaction between previous shocks and a current shock (γ_2 in eq. (3)) when it comes to weight-for-age Z-scores, but the coefficient on the interaction term is negative and significant in the specification with weight-for-height as dependent variable. If previous shock exposure makes children *more* vulnerable to current shocks, despite our findings of the opposite for agricultural outcomes, this could indicate that adaptation is somehow costly. If reducing the impact of shocks on yields is costly in terms of for instance time use, this could mean that the benefits of adaptation do not "trickle down" to children. This hypothesis requires further investigation.

7 Caveats and future work

7.1 Endogenous placement and selection issues

In the above analysis we have treated previous exposure as orthogonal to household characteristics. There are several reasons why this assumption could be problematic.

Households' adaptive behaviour may include migration, as documented by Munshi (2003) in the Mexican setting. The households we observe who are still in agriculture after several shocks may be different from the ones that have left agriculture or migrated. They may be better at agriculture, so that the coefficient on our interaction term is overestimated, or they may be less skilled, and thus unable to find other income sources. By comparing households that exit and stay in agricultural production across the two survey rounds, we can assess whether selection effects are driving our results. A more long term perspective on selection into migration might be analyzed using the urban samples of households that have migrated from rural areas. We will also investigate how common income diversification outside agriculture is.

A similar reasoning holds for the child health outcomes and the crops observed. The children we observe may be more resilient. They have survived several shocks, and have not been sent away to other family members. In order to address some of these concerns we will assess child mortality, based on reported deaths in the household over the past year and since the last survey round, and assess how common it is to send children away in response to shocks. Likewise, the crops we observe in our total yield variables are also "selected" – households may for instance harvest more cassava, which has a higher yield, after a drought. We will investigate how common it is to switch crops (in our case, the switch is between our two periods of data).

So far we have assumed that the household that experienced a contemporaneous shock, is the same household that experienced similar shocks over the past 10 years. The estimated learning effect from previous shock exposure will be downward biased if the household we observe in the panel is not the same household that operated the observed plots 10 years ago. Fortunately, the survey asks how long each individual has lived in the community, enabling us to assess to what extent this might be affecting our results.

We compare the characteristics of households based on their previous shock exposure over the past 10 years, dividing them into two groups: those that have experienced no shocks and those that have experienced at least one. If our results are driven by positive selection into agriculture, resulting in an overestimated interaction coefficient on adaptation, then the households who are still farming despite repeated exposure are expected to have among other higher levels of education and better housing. We investigate this by comparing households based on their previous shock exposure, and the results are shown in table 12. The results show that the households with no shock experience are on average larger, and a larger share is female headed. There is no significant difference in age of household head or years of education of the household head at the 5 percent level of significance. However, since these are characteristics of households *after* experiencing shocks, all household characteristics are essentially endogenous to the shocks. Especially in terms of household wealth, we could expect households that have experienced more negative shocks to be less wealthy. Indeed, our results show that households with no shock experience on average have better quality housing, measured by the share that has metal roofing. We would ideally like to observe households before they experience shocks to test whether households that experience shocks are different than those that do not. Since each cluster has the same probability of experiencing a shock, there should be no difference between households prior to the shock. We therefore investigate whether households that experienced shocks in 2010/11 were different in 2008/09. The results are shown in Table 13. We find that households that experience a shock "next season" on average have older and less educated household heads, and a larger share are female-headed. We find no significant difference in terms of housing quality before the shock occurs.

7.2 Climate data - satellite vs extrapolated

We intend to replicate our results using another source of climate data. More specifically, we intend to replicate the analysis using ERA Interim reanalysis data obtained from the European Centre for Medium-Term Weather Forecasting (ECMWF). This data has the advantage that it is less reliant on local rainfall gauge stations. A downside is that each grid cell covers 0.75x0.75 degrees, thus giving us less variation.

8 Conclusion

In this paper we have investigated to what extent previous shock exposure affects the impact of contemporaneous shocks on households. We focus on two outcome variables, crop yield and child health outcomes. We find that experiencing a drought, when defined as rainfall below the second decile, is less detrimental to cereal and maize yield given previous recent exposure of droughts of similar magnitude. This holds when controlling for plot-level time-invariant unobservables, and we also find suggestive results when using household fixed effects. In terms of child health outcomes, we find that experiencing a severe negative rainfall shock in the agricultural season preceding child measurement results in lower weight-for-age, whereas we find no effect on height-for-age or weight-for-height. We will in the future include the NPS3-2012/13 as soon as the data is made publicly available, and address the concerns discussed above.

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Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Plot level					
Total yield (kg/hect)	875.07	1050.29	18.42	11943.43	5416
Cereal yield (kg/hect)	889.74	930.95	29.16	5991.05	4313
Maize yield (kg/hect)	798.73	764.12	10.16	4447.90	3297
Household level					
Age hh head	48.695	15.345	19	105	2436
Female headed hh	0.25	0.433	0	1	2436
Year 2010/2011	0.5	0.5	0	1	2436
GPS measured plots	0.571	0.495	0	1	2436
Rainfall below 10th percentile this season	0.042	0.201	0	1	2436
No. of seasons with rainfall below 10th perc., last 10 yrs	1.166	1.071	0	4	2436
Rainfall below 10th perc. * No. of similar shocks last 10 yrs	0.095	0.484	0	3	2436
Years since rainfall below 10th percentile	9.362	9.638	1	41	2436
Rainfall below 10th perc. * Years since last similar shock	0.122	0.603	0	4	2436
Rainfall below 15th percentile this season	0.071	0.257	0	1	2436
No. of seasons with rainfall below 15th perc., last 10 yrs	1.625	1.277	0	5	2436
Rainfall below 15th perc. * No. of similar shocks last 10 yrs	0.198	0.804	0	4	2436
Years since rainfall below 15th percentile	6.273	6.675	1	35	2436
Rainfall below 10th perc. * Years since last similar shock	0.122	0.603	0	4	2436
Rainfall below 20th percentile this season	0.112	0.316	0	1	2436
No. of seasons with rainfall below 20th perc., last 10 yrs	2.418	1.552	0	7	2436
Rainfall below 20th perc. * No. of similar shocks last 10 yrs	0.337	1.085	0	5	2436
Years since rainfall below 20th percentile	3.622	3.265	1	20	2436
Rainfall below 20th perc. * Years since last similar shock	0.382	1.434	0	18	2436

Table 2: Summary statistics: Z-scores for children 0-59 months old

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Length/height-for-age Z-score	-1.618	1.527	-5.93	5.93	3189
Weight-for-age Z-score	-0.893	1.16	-5	5.43	3190
Weight-for-length/height Z-score	0.031	1.278	-5.58	5.65	3184
Age in months	35.58	20.6	0	77	4203
Female	0.503	0.5	0	1	4439
Year 2010/2011	0.461	0.499	0	1	4439
Unimodal/bimodal rainfall below 10th percentile season before child measured	0.083	0.276	0	1	4439
No. of seasons with rainfall below 10th perc., last 10 yrs	1.483	1.025	0	4	4439
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs	0.163	0.638	0	4	4439
Unimodal/bimodal rainfall below 20th percentile season before child measured	0.203	0.402	0	1	4439
No. of seasons with rainfall below 20th perc., last 10 yrs	2.567	1.381	0	6	4439
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs	0.524	1.275	0	6	4439

Table 3: Dep. var.: Total yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.231**	0.019				
	(0.108)	(0.251)				
No. of seasons with rainfall below 10th perc., last 10 yrs		0.095				
		(0.064)				
Rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.094				
		(0.129)				
Rainfall below 15th percentile this season			-0.208**	0.043		
			(0.086)	(0.219)		
No. of seasons with rainfall below 15th perc., last 10 yrs				0.215***		
				(0.045)		
Rainfall below 15th perc. * No. of similar shocks last 10 yrs				0.000		
				(0.074)		
Rainfall below 20th percentile this season					-0.106*	-0.042
					(0.060)	(0.125)
No. of seasons with rainfall below 20th perc., last 10 yrs						0.249***
						(0.045)
Rainfall below 20th perc. * No. of similar shocks last 10 yrs						0.047
						(0.046)
Number of Obs.	5416	5416	5416	5416	5416	5416
Mean of Dep. Var.	6.21	6.21	6.21	6.21	6.21	6.21

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported.

Table 4: Dep. var.: Total cereal yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.260**	-0.103				
	(0.103)	(0.260)				
No. of seasons with rainfall below 10th perc., last 10 yrs		0.149*				
		(0.077)				
Rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.035				
		(0.125)				
Rainfall below 15th percentile this season			-0.182**	-0.143		
			(0.092)	(0.286)		
No. of seasons with rainfall below 15th perc., last 10 yrs				0.286***		
				(0.050)		
Rainfall below 15th perc. * No. of similar shocks last 10 yrs				0.108		
				(0.094)		
Rainfall below 20th percentile this season					-0.106	-0.166
					(0.065)	(0.143)
No. of seasons with rainfall below 20th perc., last 10 yrs						0.308***
						(0.051)
Rainfall below 20th perc. * No. of similar shocks last 10 yrs						0.117**
						(0.052)
Number of Obs.	4313	4313	4313	4313	4313	4313
Mean of Dep. Var.	6.31	6.31	6.31	6.31	6.31	6.31

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported

Table 5: Dep. var.: Total maize yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.287**	-0.217				
	(0.116)	(0.285)				
No. of seasons with rainfall below 10th perc., last 10 yrs		0.239***				
		(0.090)				
Rainfall below 10th perc. * No. of similar shocks last 10 yrs		0.037				
		(0.141)				
Rainfall below 15th percentile this season			-0.207**	-0.513		
			(0.104)	(0.317)		
No. of seasons with rainfall below 15th perc., last 10 yrs				0.305***		
				(0.061)		
Rainfall below 15th perc. * No. of similar shocks last 10 yrs				0.239**		
				(0.105)		
Rainfall below 20th percentile this season					-0.092	-0.253*
					(0.070)	(0.152)
No. of seasons with rainfall below 20th perc., last 10 yrs						0.320***
						(0.061)
Rainfall below 20th perc. * No. of similar shocks last 10 yrs						0.163***
						(0.058)
Number of Obs.	3297	3297	3297	3297	3297	3297
Mean of Dep. Var.	6.22	6.22	6.22	6.22	6.22	6.22

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head GPS measurement of plot and average temperature in growing season included but not reported

Table 6: Dep. var.: Total yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and years since last shock.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.633	-2.416				
	(0.442)	(2.051)				
Years since rainfall below 10th percentile	-0.009	-0.009				
	(0.007)	(0.007)				
Rainfall below 10th perc. * Years since last similar shock	0.136	1.440				
	(0.132)	(1.436)				
Rainfall below 10th perc. * Years since last similar shock sq.		-0.218				
		(0.235)				
Rainfall below 15th percentile this season			-0.245**	-0.438**		
			(0.105)	(0.214)		
Years since rainfall below 15th percentile			-0.022***	-0.022***		
			(0.005)	(0.005)		
Rainfall below 15th perc. * Years since last similar shock			0.017	0.091		
			(0.014)	(0.071)		
Rainfall below 15th perc. * Years since last similar shock sq.				-0.002		
				(0.002)		
Rainfall below 20th percentile this season					-0.247**	-0.182
					(0.118)	(0.241)
Years since rainfall below 20th percentile					-0.038***	-0.038***
					(0.009)	(0.009)
Rainfall below 20th perc. * Years since last similar shock					0.059*	0.032
					(0.030)	(0.088)
Rainfall below 20th perc. * Years since last similar shock sq.						0.002
						(0.005)
Number of Obs.	5416	5416	5416	5416	5416	5416
Mean of Dep. Var.	6.21	6.21	6.21	6.21	6.21	6.21

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported

Table 7: Dep. var.: Cereal yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and years since last shock.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.451	0.116				
	(0.408)	(1.866)				
Years since rainfall below 10th percentile	-0.021***	-0.021***				
	(0.008)	(0.008)				
Rainfall below 10th perc. * Years since last similar shock	0.070	-0.344				
	(0.127)	(1.319)				
Rainfall below 10th perc. * Years since last similar shock sq.		0.069				
		(0.219)				
Rainfall below 15th percentile this season			-0.196*	-0.247		
			(0.119)	(0.231)		
Years since rainfall below 15th percentile			-0.027***	-0.027***		
			(0.005)	(0.005)		
Rainfall below 15th perc. * Years since last similar shock			0.014	0.034		
			(0.023)	(0.083)		
Rainfall below 15th perc. * Years since last similar shock sq.				-0.001		
				(0.003)		
Rainfall below 20th percentile this season					-0.190	-0.083
					(0.128)	(0.272)
Years since rainfall below 20th percentile					-0.043***	-0.043***
					(0.009)	(0.010)
Rainfall below 20th perc. * Years since last similar shock					0.044	0.001
					(0.034)	(0.102)
Rainfall below 20th perc. * Years since last similar shock sq.						0.002
						(0.006)
Number of Obs.	4313	4313	4313	4313	4313	4313
Mean of Dep. Var.	6.31	6.31	6.31	6.31	6.31	6.31

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported

Table 8: Dep. var.: Maize yield (log). Plot FE. Rainfall below 10th, 15th, 20th percentile this season and years since last shock.

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall below 10th percentile this season	-0.387	0.324				
	(0.449)	(2.298)				
Years since rainfall below 10th percentile	-0.032***	-0.032***				
	(0.009)	(0.009)				
Rainfall below 10th perc. * Years since last similar shock	0.045	-0.476				
	(0.139)	(1.650)				
Rainfall below 10th perc. * Years since last similar shock sq.		0.087				
		(0.274)				
Rainfall below 15th percentile this season			-0.046	-0.266		
			(0.131)	(0.254)		
Years since rainfall below 15th percentile			-0.028***	-0.028***		
			(0.008)	(0.008)		
Rainfall below 15th perc. * Years since last similar shock			-0.024	0.062		
			(0.026)	(0.090)		
Rainfall below 15th perc. * Years since last similar shock sq.				-0.003		
				(0.003)		
Rainfall below 20th percentile this season					-0.116	-0.107
					(0.144)	(0.318)
Years since rainfall below 20th percentile					-0.036***	-0.036***
					(0.010)	(0.010)
Rainfall below 20th perc. * Years since last similar shock					0.024	0.021
					(0.038)	(0.117)
Rainfall below 20th perc. * Years since last similar shock sq.						0.000
						(0.006)
Number of Obs.	3297	3297	3297	3297	3297	3297
Mean of Dep. Var.	6.22	6.22	6.22	6.22	6.22	6.22

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported

Table 9: Dep. Var.: Height-for-age Z-score

	(1)	(2)	(3)	(4)
Unimodal/bimodal rainfall below 10th percentile season before child measured	-0.125	-0.140		
	(0.115)	(0.152)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.028		
		(0.051)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		0.016		
		(0.062)		
Unimodal/bimodal rainfall below 20th percentile season before child measured			0.065	0.042
			(0.088)	(0.131)
No. of seasons with rainfall below 20th perc., last 10 yrs				-0.015
				(0.040)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.006
				(0.043)
Number of Obs.	3189	3189	3189	3189
Mean of Dep. Var.	-1.62	-1.62	-1.62	-1.62

Standard errors clustered at household level in parentheses. Sample: individuals aged 0-60 months from farming households.
Controls for age, sex, survey year, region, birth- and interview month included but not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Dep. Var.: Weight-for-age Z-score

	(1)	(2)	(3)	(4)
Rainfall (mm) in month of interview	0.001**	0.002**	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Unimodal/bimodal rainfall below 10th percentile season before child measured	-0.224**	-0.131		
	(0.107)	(0.133)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.092*		
		(0.050)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.064		
		(0.052)		
Unimodal/bimodal rainfall below 20th percentile season before child measured			0.109	0.076
			(0.096)	(0.118)
No. of seasons with rainfall below 20th perc., last 10 yrs				0.046
				(0.038)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.041
				(0.044)
Number of Obs.	2094	2094	2094	2094
Mean of Dep. Var.	-0.90	-0.90	-0.90	-0.90

Standard errors clustered at household level in parentheses. Sample: individuals aged 0-60 months from farming households.
Controls for age, sex, survey year, region, birth- and interview month included but not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Dep. Var.: Weight-for-height Z-score

	(1)	(2)	(3)	(4)
Rainfall (mm) in month of interview	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Unimodal/bimodal rainfall below 10th percentile season before child measured	-0.090	0.028		
	(0.111)	(0.124)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.094*		
		(0.049)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.086*		
		(0.051)		
Unimodal/bimodal rainfall below 20th percentile season before child measured			0.124	0.101
			(0.105)	(0.126)
No. of seasons with rainfall below 20th perc., last 10 yrs				0.072*
				(0.038)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.043
				(0.045)
Number of Obs.	2089	2089	2089	2089
Mean of Dep. Var.	0.09	0.09	0.09	0.09

Standard errors clustered at household level in parentheses. Sample: individuals aged 0-60 months from farming households.
Controls for age, sex, survey year, region, birth- and interview month included but not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Comparison of households by exposure to rainfall shocks

Variable	Risk exposure	N	Mean	St. Dev	p
Age hh head	No shock last 10 years	758	50.75	15.10	0.000
	At least one shock last 10 years	1678	47.77	15.37	
Household size	No shock last 10 years	758	5.72	2.90	0.126
	At least one shock last 10 years	1678	5.51	3.17	
Years of education hh head	No shock last 10 years	758	4.23	3.67	0.037
	At least one shock last 10 years	1678	4.54	3.24	
Female hh head	No shock last 10 years	758	0.26	0.44	0.449
	At least one shock last 10 years	1678	0.25	0.43	
Metal roof	No shock last 10 years	758	0.62	0.48	0.000
	At least one shock last 10 years	1678	0.44	0.50	

Households in balanced panel, "last 10 years" refers to 1997/98-2006/07 for the first survey year, and 1999/00-2008/09 for the second survey round. A shock is defined as rainfall in the 10th percentile of the local historical rainfall distribution.

Table 13: Comparison of households in first survey round by rainfall shock in second survey round

Variable	Risk exposure	N	Mean	St. Dev	p
Age hh head	Rainfall in 10th percentile 2009/10	28	48.04	18.79	0.891
	No shock	1190	47.64	15.21	
Household size	Rainfall in 10th percentile 2009/10	28	3.90	2.04	0.006
	No shock	1190	5.46	2.96	
Years of education hh head	Rainfall in 10th percentile 2009/10	28	4.07	3.41	0.506
	No shock	1190	4.5	3.37	
Female hh head	Rainfall in 10th percentile 2009/10	28	0.39	.50	0.068
	No shock	1190	0.24	0.43	
Metal roof	Rainfall in 10th percentile 2009/10	28	0.75	0.44	0.004
	No shock	1190	0.47	0.50	

Households in balanced panel, characteristics in 2008/09 survey. Shocks based on percentiles in local historical rainfall distribution. Results are similar for shocks defined as rainfall in 15th or 20th percentile.

Appendix I

Figure A1: Enumeration Areas from NPS1 2008/09

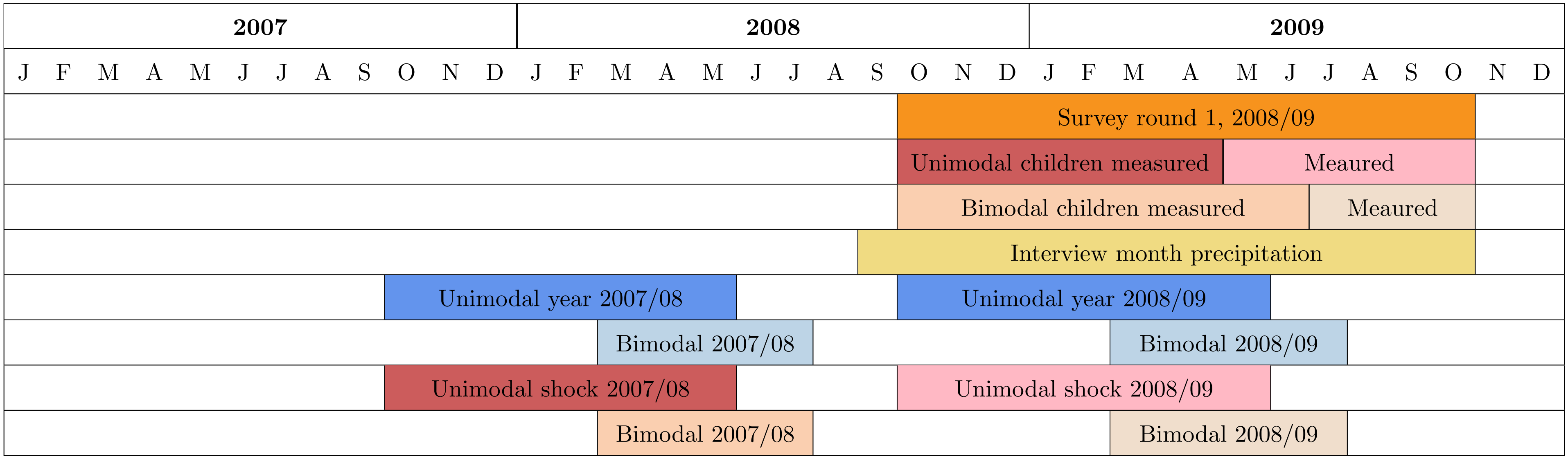

Figure A2: Timeline: child shock, survey round 1 (NPS1)

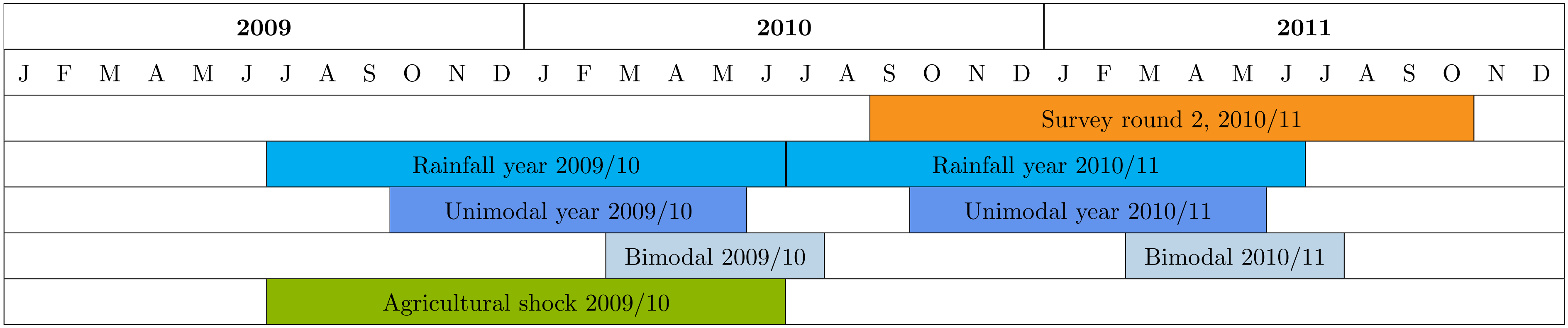

Figure A3: Timeline: agricultural shock, survey round 2 (NPS2)

Table A1: Dep. var.: Total yield (log). Plot FE. Rainfall below 10th/20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)
Unimodal/bimodal rainfall below 10th percentile this season	-0.289***	0.166		
	(0.092)	(0.225)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.145*		
		(0.079)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.156		
		(0.101)		
Unimodal/bimodal rainfall below 20th percentile this season			-0.109*	0.123
			(0.059)	(0.138)
No. of seasons with rainfall below 20th perc., last 10 yrs				0.302***
				(0.048)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.031
				(0.057)
Number of Obs.	5416	5416	5416	5416
Mean of Dep. Var.	6.21	6.21	6.21	6.21

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported.

Table A2: Dep. var.: Cereal yield (log). Plot FE. Rainfall below 10th/20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)
Unimodal/bimodal rainfall below 10th percentile this season	-0.217**	0.153		
	(0.101)	(0.242)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.346***		
		(0.089)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.052		
		(0.108)		
Unimodal/bimodal rainfall below 20th percentile this season			-0.124**	-0.207
			(0.063)	(0.154)
No. of seasons with rainfall below 20th perc., last 10 yrs				0.371***
				(0.052)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.174***
				(0.061)
Number of Obs.	4313	4313	4313	4313
Mean of Dep. Var.	6.31	6.31	6.31	6.31

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported.

Table A3: Dep. var.: Maize yield (log). Plot FE. Rainfall below 10th/20th percentile this season and past 10 seasons.

	(1)	(2)	(3)	(4)
Unimodal/bimodal rainfall below 10th percentile this season	-0.200*	0.329		
	(0.118)	(0.263)		
No. of seasons with rainfall below 10th perc., last 10 yrs		0.385***		
		(0.105)		
Unimodal/bimodal rainfall below 10th perc. * No. of similar shocks last 10 yrs		-0.131		
		(0.128)		
Unimodal/bimodal rainfall below 20th percentile this season			-0.102	-0.280*
			(0.069)	(0.167)
No. of seasons with rainfall below 20th perc., last 10 yrs				0.404***
				(0.063)
Unimodal/bimodal rainfall below 20th perc. * No. of similar shocks last 10 yrs				0.228***
				(0.071)
Number of Obs.	3297	3297	3297	3297
Mean of Dep. Var.	6.22	6.22	6.22	6.22

Standard errors clustered at plot level in parentheses.

Survey year, age and sex of household head, GPS measurement of plot and average temperature in growing season included but not reported.