Climate Change and Child Health: A Nigerian Perspective*

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Abstract

The detrimental effects of climate change are causing it to be an important topic of economic research and policy decisions. The negative impact of a changing climate on the health outcomes of children is especially concerning. We investigate the impact of a changing climate, in terms of changes in the monthly maximum average near-surface temperature ($^{\circ}C$) and total monthly precipitation (mm), on the nutritional status of children in Nigeria. This is done by combining LSMS-ISA survey data with high-resolution gridded climate data. Malnutrition in children is seen in the form of stunting, underweight and wasting. The results indicate that climate change is correlated with a higher probability of malnourished children in Nigeria. This paper supports the notion of the need for climate-friendly policies to mitigate the long-term effect of malnourishment.

Key words: Climate Change, Malnutrition, Stunting, Underweight, Nigeria, Spatial Analysis
JEL Classification: Q54, I12, I15

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1 Introduction

Reduction of malnutrition is key to allowing children to live, play, develop, and contribute to society in the future (United Nations Children's Fund (UNICEF) et al., 2020). Proper nourishment is shown to be a key determinant of a child's development including educational attainment with malnutrition reducing development. Climate and environment have been shown to be a determinant of childhood nutrition with rising temperature and droughts negatively affecting welfare and nutrition of young children (Grace et al., 2015). Individuals that experienced malnourishment in childhood have a higher probability of impaired health and productivity in adulthood (Alderman, 2006). Furthermore, the effects of malnutrition can be intergenerational that causes households to remain trapped in poverty (Pena & Bacallao, 2002).

Ahdoot et al. (2015) notes that humans are vulnerable to climate changes due to stress, decreased air quality, or other related factors affecting physical and mental health. Climate change can also affect disease patterns, cause extreme weather events, or food security. Children are especially vulnerable to the consequences of climate change due to their dependence on caregivers and immature physiology. Furthermore, Lobell and Field (2007) notes that erratic temperatures and precipitation caused by climate change affect agriculture production (productivity) and thus food security. (Davenport et al., 2017) notes that food insecurity is a factor that reduces child nutrition, human capital investment, and living standards. Furthermore, the children in households that are dependent on agriculture are most susceptible to chronic malnutrition due to climate change (Brown & Funk, 2008).

Although Black et al. (2008) found that poor children are often at considerable risk for malnutrition and stunting, in agriculture-dependent countries like Nigeria, all children are susceptible. Given Nigeria's composition, we expect urban as well as rural children to be vulnerable to changes in weather patterns since they are dependent on low-cost and locally grown foods (Davenport et al., 2017). In Nigeria, the cornerstone of the economy remains agriculture regardless of the availability of oil. Agriculture employs 36.5% of the entire labour force (World Bank Group, 2019) and contributes roughly a quarter of Nigeria's GDP (African Development Bank, 2019). Around 88% of farmers in Nigeria are considered small family farms (World Bank Group, 2019) and half of Nigeria's population is rural (FAO, 2019). All this indicates that malnutrition will become an even more substantial concern in Nigeria with a changing climate.

Stunting can arise due to poor nutrition in-utero and early childhood which is worse due to poor sanitation, unclean water and lack of hygiene (Grace et al., 2017). Children who suffer from stunting may never reach their full possible height, and may have suboptimal brain development that negatively affects children's cognitive development; educational attainment and economic productivity during adulthood (Beegle & Christiaensen, 2019; Feinstein, 2003; United Nations Children's Fund (UNICEF) et al., 2020). The first 1,000 days of life of a child is a critical phase of rapid physical and mental development (De Onis and Branca, 2016). Empirical evidence from both developing and developed countries suggest that taller siblings from the same mothers perform better on cognitive tests, and have better health, economic, and educational outcomes (Case and Paxson, 2010; Glewwe and Jacoby, 1995). Stunting can also cause decades of harmful effects and can undermine the development of a country, the average per capita income penalty from stunting in developing countries is about 7% (Galasso & Wagstaff, 2019).

Wasting is the short-term life-threatening result of poor nutrition or disease. These children suffer from weakened immunity and have an increased risk of death when wasting is severe (United Nations Children's Fund (UNICEF) et al., 2020). Underweight acts as a composite indicator of stunting and wasting. Underweight and malnourished children have an increased mortality rate, depending on the severity of the condition. The effects of this malnutrition vary but, it can undermine health and development, limit learning ability, diminish immune systems, reduce adult work performance and productivity, and increase the chance of giving birth to underfed babies (Jankowska et al., 2012). Grace et al. (2012) further notes that children have a lower likelihood of completing secondary school. Therefore, malnutrition has negative ramifications for a population's health and development in the short- and long-term.

The effect of climate change on child nutrition is easily observable in less developed countries. Research has shown that long-term improvement of economic development, such as higher human capital and economic growth in Africa may hinge, at least partially, on decreasing child malnutrition (Davenport et al., 2017). Chronic malnutrition leads to stunting in a third of all children under five years of age born in developing countries (Beegle & Christiaensen, 2019; Costello et al., 2009). Developing countries are worse off to deal with a changing climate due to a lack of resources and their dependence on agriculture (Balk et al., 2005). Sub-Saharan Africa is especially prone to malnutrition in children as it already has a history of "chronic food insecurity, poor health outcomes and, more recently, increased temperatures and decreased rainfall" (Davenport et al., 2017).

This study investigates the impact of changing temperatures and precipitation on child health indicators - stunting and underweight. We specifically focus on the monthly maximum average near-surface temperature ($^{\circ}C$) and total monthly precipitation (mm). We find empirical evidence that supports the notion that temperature has a direct effect on child malnutrition and precipitation an indirect effect (Ahdoot et al., 2015; Cooper et al., 2019). This support is seen by making use of the lagged temperature variable and a three-year lagged precipitation variable. We are not the first to consider the effects of temperature and/or precipitation on children's health outcomes. Although, many of these studies use predictive changes in temperature or rainfall to measure what the effect ought to be. The contribution of this paper is by making use of the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) that allows us to form a panel dataset to investigate if the actual changes in temperature and precipitation impact children's health outcomes.

Our results indicate that increasing temperatures and decreasing precipitation lead to a higher probability of malnutrition among children. The effect of these changing climate conditions is more severe in rural than in urban areas. Therefore, results suggest that the government must initiate climate-friendly policies to help avert related health consequences. Improvement in public infrastructure (Bassolé, 2007), access to electricity (Davenport et al., 2017), as well as improved educational and social institutions (Grace et al., 2012) are shown to be effective against a changing climate. Lastly, given the importance of the agriculture sector in sub-Saharan Africa, Opiyo et al. (2015) notes that improved livestock mobility, an increase in security, more livestock markets, and an expansion of transport and communication infrastructure are mechanisms to mitigate the negative effects of climate change.

The rest of this paper is set out as follows. Section 2 introduces the data used, the methodology, and the descriptive statistics. Section 3 sets out the empirical results with regards to temperature, precipitation, as well as the combined effect. Section 4 offers discussion points and policy implications. Section 5 concludes and offers some policy recommendations.

2 Data and Methodology

2.1 Measures of Child Malnutrition

Three waves of the Nigerian LSMS-ISA data are used to analyze the temperature and precipitation effects on child health for the period 2010-2011, 2012-2013, and 2015-2016. The LSMS-ISA project is a multi-topic, nationally representative household panel survey, with a focus on agriculture-related data. It is constructed in collaboration with the Nigerian National Bureau of Statistics. Multiple topics are covered and designed to improve the understanding of the links between agriculture, socioeconomic status, and non-farm income activities (Osabohien, 2018).

The LSMS-ISA data is sampled in two-stages: the post-planting stage, which occurs between August and October, and the post-harvest stage, which occurs between February and April. To measure the panel-effect of climate change, we use data on children that are in all three waves and below the age of seven. This restriction means children in our sample are aged between zero and two in wave one (2010-2011), between two and four in wave two (2012-2013) and between five and seven in wave three (2015-2016).

The analysis uses various malnutrition measures such as stunting, underweight, and wasting to understand the effects of climate change on child malnutrition. These variables are dichotomous and constructed following the standards of the World Health Organization (WHO) for all children under 7 years of age. First, we calculate height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height z-scores. The z-scores represents the number of standard deviations by which the child's anthropometric measurements deviates from the median child growth standard of WHO (World Health Organization, 2010).

Second, a z-score cut-off point of -2 is used to generate a binary indicator for stunting (a long-term child malnutrition status measure), underweight, and wasting (a short term indicator of acute malnutrition). A z-score of less than -2 identifies children who have low height-for-age or stunted children, low weight-for-age or underweight children, and low weight-for-height or wasted children (Organization et al., 1995). Children for whom we have incomplete or implausible anthropometry data are excluded from the analysis. We expect all the factors to affect the overall development of the child, but some research, namely Balk et al. (2005), have shown that stunting is a more robust indicator of chronic child malnutrition.[1]

2.2 Measures of Climate Variability

Temperature and precipitation data are from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia (Harris et al., 2014)[2]. The temperature and precipitation variables measure average near-surface maximum temperature in degree Celsius and total precipitation in millimetres, respectively. We use these two variables to keep this paper comparable to the literature (Davenport et al., 2017; Grace et al., 2015) as well as to take in account the dangers of increases in the daily maximum temperatures as noted by Buis (2020).

Table 1 shows how we calculated the varying values for temperature and precipitation. All the temperatures and precipitation are calculated as the monthly averages. The use of these periods is so that the climate variability span both the post-planting and post-harvesting stages of the LSMS-ISA dataset. The expectation is that the lagged values have more explanatory power in predicting the influence of climate change on the malnutrition of children (Grace et al., 2012).

[1] Results for wasting is available on request or in the online appendix.

[2] The downscaled version that corrects for bias, which is produced by WorldClim (Fick & Hijmans, 2017), is used.

Furthermore, changing temperature is the main contributor to the direct consequences of climate change, such as heat stress, diseases, and air quality, on child health (Ahdoot et al., 2015). We also find a strong correlation between the monthly maximum temperatures in the year of the survey with the different control variables. Therefore, the focus is on the temperature of the year preceding the survey.

Table 1: Timeline of Measures of Climate Variability

	Wave 1 (2010-2011)	Wave 2 (2012-2013)	Wave 3 (2015-2016)
Year of Survey Temperature/Precipitation	July 2010 - June 2011	July 2012 - June 2013	July 2015 - June 2016
Lagged Year of Survey Temperature/Precipitation	June 2009 - July 2010	July 2011 - June 2012	July 2014 - June 2015
Two Year Lagged Temperature/Precipitation	July 2008 - June 2009	July 2010 - June 2011	July 2013 - June 2014
Three Year Lagged Temperature/Precipitation	July 2007 - June 2008	July 2009 - June 2010	July 2012 - June 2013
Five Year Lagged Temperature/Precipitation	July 2005 - June 2006	July 2007 - June 2008	July 2010 - June 2011
Three-Year Average Temperature/Precipitation	July 2008 - June 2011	July 2010 - June 2013	July 2013 - June 2016
Five-Year Average Temperature/Precipitation	July 2006 - June 2011	July 2008 - June 2013	July 2011 - June 2016

Cooper et al. (2019) found that precipitation's effect on child stunting takes even longer to affect the health of a child. They use a Standardized Precipitation–Evapotranspiration Index (SPEI) and found that using a twenty-four-month lag, has the most notable effect in child nutrition. They also note that these effects are indirect in most cases and changing temperatures leads to changing precipitation. As Myers and Bernstein (2011) notes, indirect effects such as water scarcity, displacement, uncertainty, and food security is a substantial threat and can cause long-lasting damage. Therefore, we investigate the consequences of a three-year lagged precipitation's impact on child health outcomes.[3]

2.3 Control Variables

The variables included in the regressions were selected based on related literature.[4] In all estimations, we include several control variables including distance to markets, cities (a population of twenty thousand or more people), number of meals to children, plot size, number of market and production shocks, access to public and private services such as access to credit, agricultural extension service, electricity and characteristics of the household head. Asset ownership (an asset index compromised of whether they have a bicycle, motorcycle, car/other vehicles (vans), tractor, computer, telephone, cellular, radio, television, refrigerator, and stove), the tropical livestock unit, land size and soil quality variables are used as a proxy for the wealth of households.

[3] The effect of a one year lagged precipitation is also checked and available on request or in the online appendix.
[4] A full list and explanation of control variables are available in the technical appendix.

Children's education and age are proxies to their human capital. Household size, educational attainment and gender of household head are used to control taste, preference, and income-related heterogeneity between children. We use additional controls that measure the area's soil quality (Fischer et al., 2008) and the distance to freshwater. Freshwater data are from two sources, namely the Global Lakes and Wetlands Database (Lehner & Döll, 2004) and AQUAMAPS (FOA, 2019). We consider freshwater as water in the form of lakes, reservoirs, rivers, freshwater marshes, floodplains, and intermittent wetlands or lakes.[5]

2.4 Estimation Strategy

Let m^z be an indicator for childhood malnutrition where superscript $z = s, w,$ and u represent an indicator that is specific to stunting, wasting, or underweight, respectively. Let X be a vector of the control variables defined in section 2.3. Then we have the following models,

$$m_{it}^z = \alpha + \delta_1 lagged\_tmp + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it} \tag{1}$$

$$m_{it}^z = \alpha + \delta_2 three\_year\_lagged\_pre + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it} \tag{2}$$

$$\begin{aligned} m_{it}^z = {} & \alpha + \delta_3 lagged\_tmp + \delta_4 three\_year\_lagged\_pre \\ & + \theta(lagged\_tmp \times three\_year\_lagged\_pre) + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it} \end{aligned} \tag{3}$$

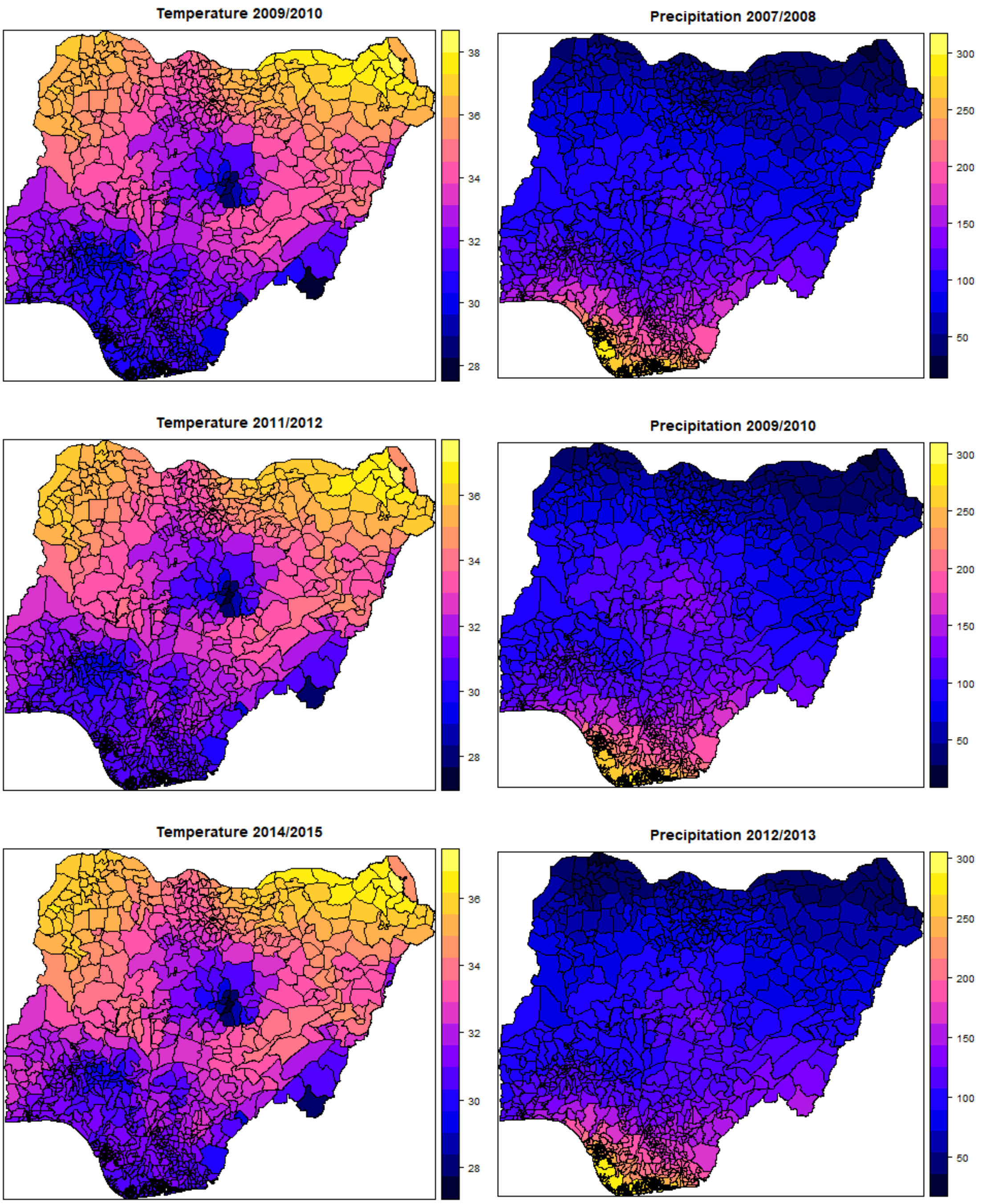
We estimate equations 1- 3 using a Logit model with panel techniques where $\bar{X}_i$ is time-average variable for i and allows for the estimation of the correlated random effects model as described by Wooldridge (2012). Estimation of equation 3 is a robustness check for the expectation that the interaction of temperature and precipitation affect child malnutrition.

2.5 Summary Statistics

The different climate zones across Nigeria are apparent in Figure 1. The northern portion of Nigeria is typically dryer, experiencing less precipitation, and has higher average temperatures than the South. The south-most point of Nigeria is the concentration point of precipitation. The specific regions experiencing these favourable climate conditions are South-South and South-East zones. The regions most affected by dry and warm areas are North-East and North-West.[6]

[5] More information on data sources and merging is available in the technical appendix.
[6] Table B1 in Appendix B shows climate variables by zone.

Figure 1: Maps of Temperature and Precipitation[7]



[7]Lagged temperature and three year lagged precipitation for each wave are shown since these are the variables used in the analysis. Note that the figure includes all of the households in the LSMS-ISA dataset across the three

Across the different waves, there is variation in the overall temperatures and precipitation.[8] P-values of these variations rejecting the null that the mean of these different variables is the same across the years, substantiate our claim. Overall, there is a small increase in the average maximum temperatures as well as a decrease in the average total precipitation. These patterns seen in our sample are similar to the climate changes of Nigeria noted by the World Bank Group (2020). Even with the dispersion in the location of urban and rural households, one can still see differences across these two areas.[9] The rural areas experience warmer temperatures than the urban areas. On average, urban households experience more precipitation. Even though a decrease in precipitation occurs over the three waves in urban areas, these households still receive more than their rural counterparts.

In our sample, 29.9% of children are stunted in the first wave, 13.2% in the second wave, and 19% in the third wave.[10] There is an improvement in the rate of stunting between the first and second wave but a deterioration between the second and third wave. Although the prevalence of underweight children in our sample is less than stunting, the pattern is similar to that of the prevalence of stunting. For wasting, the percentage of children in our sample suffering from wasting decreases from 12.9% in wave one to 6.8% in wave three. Note that a decrease in the prevalence of malnutrition, in the second wave, coincide with colder temperatures and more precipitation in the year of the second wave and the year preceding it. Overall, malnutrition of children improves in our sample but the persistent nature of stunting is alarming.

3 Empirical Results

We present the results in three stages. First, we present the effects of temperature on stunting and underweight for all children under 7 years of age. Second, we discuss the effects of precipitation on stunting and underweight. The tandem effect of temperature and precipitation on child nutrition follows. For brevity, discussion of the result focuses on excerpts of the standard logit estimations and the marginal effects of temperature (Tables 2 and 3) and precipitation (Tables 4 and 5) with the full standard logit estimations in Appendix C.[11] To measure the difference in impact on rural and urban areas, the marginal effects at the means by areas of residence are calculated as well.[12]

waves.

[8] See Table B2 in Appendix B.

[9] See Tables B3 & B4 in Appendix B.

[10] See Table B6 in Appendix B.

[11] The increasing or decreasing effect can be discerned from the coefficient signs, but the marginal effects are more informative, the marginal effects are at the mean values of all the control variables.

[12] Calculations of the average marginal effects lead to similar results.

3.1 Temperature

Table 2 presents the effects of preceding temperature on stunting and underweight for all children under 7 years of age, with Panel A specific to stunting and Panel B to underweight. The first column uses only the preceding temperature and CRE techniques and then columns 2-6 gradually add additional regional and location controls. Finally, columns 7-9 accounts for the education of the head of household. In both panels, the temperature has a positive effect on stunting and underweight. The result is robust to adding household demographics and regional characteristics.[13]

Table 3 displays the marginal effects of the average monthly maximum lagged temperature. These marginal effects quantify the effect of temperature on child malnutrition. Panel A displays the impact of changing temperatures on stunting at the average value of all the control variables. A one degree Celsius increase will increase the probability of a child suffering from stunting by between 16.1% and 23.2%. These effects are significant and robust to adding household demographics and regional characteristics. This positive correlation implies that the increase in temperature has a detrimental effect on human capital accumulation in Nigeria. Of policy concern, low human development of children that can be manifested in the form of stunting at an early age can result in a poverty trap when remediation of child stunting is partly or mostly irreversible (Barrett et al., 2016; Beegle & Christiaensen, 2019).

Focussing on Panel C in Table 3, the probability of a child being underweight increases by between 12.3% and 14.6% with a one-degree increase in the average monthly maximum temperature in the previous year. Investigating the differences of these changes over urban and rural areas delivers results as expected. In Panel B and Panel D, one can see that the effect on stunting and underweight is higher in rural areas than in urban areas. There is especially a big difference in the change of probability of a child suffering from stunting with an increase in temperature between the sectors, as seen in Panel B. The effect in rural areas is approximately more than 6 percentage points greater than in urban areas. For underweight, this difference decreases to about 4 percentage points, though, it is still clear that rural areas are more susceptible to temperature changes.

[13] Movement of households across areas (internal migration) may affect the results. However, we couldn't verify using the available data. In our data, only 14 households moved from urban to rural (9 total) or inversely (5 total) change their area of residence in our subset of the data making it empirically impossible to estimate.

Table 2: Logit Regressions' Coefficients - Lagged Temperature

Panel A: Stunted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.179***	1.123***	1.184***	1.732***	1.702***	1.740***	1.758***	1.782***	1.775***
Survey Temperature	(0.220)	(0.211)	(0.215)	(0.253)	(0.249)	(0.253)	(0.282)	(0.281)	(0.283)
Primary							-0.211	-0.165	-0.198
Education Complete							(0.261)	(0.266)	(0.260)
Secondary							0.032	0.065	0.038
Education Complete							(0.444)	(0.459)	(0.442)
University/Higher							-0.046	-0.220	-0.041
Education Complete							(0.790)	(0.806)	(0.797)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.046	0.033	0.036	0.062	0.059	0.056	0.091	0.096	0.086
Panel Level sd.	0.399	0.336	0.351	0.468	0.454	0.442	0.574	0.593	0.555
Chi-Squared	76.08	99.33	89.38	145.55	158.02	147.73	115.66	125.55	115.82

Panel B: Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.541***	1.483***	1.536***	2.026***	2.008***	2.025***	2.249***	2.281***	2.248***
Survey Temperature	(0.241)	(0.232)	(0.236)	(0.278)	(0.279)	(0.278)	(0.327)	(0.331)	(0.328)
Primary							-0.282	-0.305	-0.283
Education Complete							(0.283)	(0.286)	(0.283)
Secondary							-0.817	-0.870	-0.819
Education Complete							(0.525)	(0.534)	(0.524)
University/Higher							-0.052	-0.107	-0.078
Education Complete							(0.886)	(0.887)	(0.898)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.204	0.191	0.198	0.160	0.152	0.158	0.198	0.179	0.195
Panel Level sd.	0.919	0.881	0.902	0.793	0.768	0.786	0.902	0.848	0.893
Chi-Squared	64.10	78.95	68.53	153.88	156.57	154.96	131.44	136.40	131.40

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Marginal Effect - Lagged Temperature

Panel A: Stunted (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.172***	0.161***	0.172***	0.231***	0.225***	0.232***	0.223***	0.223***	0.225***
Survey Temperature	(0.030)	(0.029)	(0.029)	(0.032)	(0.031)	(0.032)	(0.033)	(0.033)	(0.033)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel B: Marginal Effect of Lagged Temperature on Stunting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.164***	0.149***	0.125***	0.183***	0.184***	0.161***	0.169***	0.174***	0.147***
	(0.029)	(0.027)	(0.026)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
Rural	0.175***	0.165***	0.188***	0.246***	0.237***	0.255***	0.240***	0.237***	0.250***
	(0.031)	(0.029)	(0.032)	(0.034)	(0.033)	(0.034)	(0.036)	(0.035)	(0.037)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel C: Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.129***	0.123***	0.128***	0.145***	0.142***	0.145***	0.146***	0.145***	0.145***
Survey Temperature	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Panel D: Marginal Effect of Lagged Temperature on Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.122***	0.118***	0.096***	0.112***	0.115***	0.104***	0.114***	0.117***	0.104***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.020)	(0.021)	(0.024)
Rural	0.131***	0.124***	0.139***	0.155***	0.150***	0.158***	0.156***	0.154***	0.159***
	(0.019)	(0.018)	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)	(0.022)	(0.022)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

3.2 Precipitation

Table 4 reports regression results for Equation 2 for stunting and underweight using three year lags of precipitation.[14] The results indicate that precipitation has a negative and significant effect

[14]The results for the one year lag are in the Online Appendix and support for the results found by Skoufias and Vinha (2012) and mentioned in Phalkey et al. (2015). Comparison of the one and three lagged results support research that precipitation has an indirect effect on child nutrition.

on child stunting. This effect implies an increase in rain, drizzle, or condensation three years before the survey, will decrease the probability of a child suffering from stunting. This effect remains robust to the different model specifications. Looking at Panel B, the effect the three years lagged precipitation has on underweight is not significant. But the impact of an increase in the precipitation level on underweight prevalence in children is still negative.

This finding supports the notion that precipitation has an indirect effect on child nutrition and corroborate the empirical evidence documented by Skoufias and Vinha (2012). The indirect effect of precipitation implies a change in the pattern of rain, drizzle or any other form of precipitation takes time to affect the nutritional status of children. More specifically, water is still available from dams or nearby water sources which causes the impact of dry seasons to take time to influence crops and food security. As noted by Phalkey et al. (2015), the effect of precipitation works its way through many demographic and economic variables.

Table 5 displays the marginal effects of the three year lagged precipitation at the means. The marginal effects are relatively small compared to temperature. Looking at Panel C, the impact of changing precipitation three years prior is not significant on children being underweight when not controlling for household demographics. Although small, the marginal effects are significant when controlling for household demographics and robust to regional characteristics. These marginal effects imply a 1mm increase in the monthly precipitation three years ago, decreases the probability of children suffering from stunting by between 0.4% and 0.7%.

A change in the precipitation level of 10mm or more will lead to greater changes in the probability of children suffering from stunting and being underweight. The most notable distinction is between the urban and rural areas as shown in Panel B and Panel D. Regardless of the small magnitude, there still exists a difference between rural and urban areas. Rural areas are affected more severely than urban areas. Especially in the case of stunting, the marginal effects increases from -0.005 to -0.008 when moving from urban to rural areas (Table 5, Column 9).

Table 4: Logit Regressions' Coefficients- Three Year Lagged Precipitation

Panel A: Stunted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.024**	-0.024**	-0.028**	-0.042***	-0.040***	-0.043***	-0.049***	-0.048***	-0.052***
Precipitation (mm)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Primary							-0.144	-0.090	-0.130
Education Complete							(0.253)	(0.256)	(0.250)
Secondary							0.172	0.197	0.181
Education Complete							(0.432)	(0.442)	(0.427)
University/Higher							0.184	0.061	0.179
Education Complete							(0.773)	(0.780)	(0.778)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.000	0.000	0.000	0.022	0.023	0.009	0.028	0.037	0.015
Panel Level sd.	0.008	0.017	0.009	0.274	0.279	0.175	0.310	0.354	0.220
Chi-Squared	49.47	82.22	57.26	122.13	139.63	123.64	109.17	122.34	110.02

Panel B: Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.019*	-0.019*	-0.021*	-0.022*	-0.020	-0.022*	-0.024	-0.021	-0.024
Precipitation (mm)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.016)	(0.015)	(0.016)
Primary							-0.153	-0.174	-0.155
Education Complete							(0.278)	(0.281)	(0.277)
Secondary							-0.548	-0.567	-0.549
Education Complete							(0.513)	(0.521)	(0.511)
University/Higher							0.121	0.085	0.083
Education Complete							(0.865)	(0.869)	(0.877)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.115	0.112	0.107	0.085	0.077	0.078	0.083	0.064	0.075
Panel Level sd.	0.655	0.643	0.628	0.554	0.524	0.528	0.546	0.475	0.517
Chi-Squared	28.40	40.93	30.34	127.22	130.72	128.86	116.44	122.16	116.81

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Marginal Effect - Three Year Lagged Precipitation

Panel A: Stunted (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.004	-0.004	-0.004	-0.006***	-0.006***	-0.006***	-0.007***	-0.006***	-0.007***
Monthly Precipitation (mm)	(0.014)	(0.031)	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel B: Marginal Effect of Three Year Lagged Precipitation on Stunting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	-0.003	-0.003	-0.003	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***	-0.005***
	(0.010)	(0.044)	(0.081)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	-0.004	-0.004	-0.004	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.008***
	(0.009)	(0.026)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel C: Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.002*	-0.002*	-0.002*	-0.002*	-0.002	-0.002*	-0.002	-0.002	-0.002
Monthly Precipitation (mm)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Panel D: Marginal Effect of Three Year Lagged Precipitation on Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	-0.002*	-0.002*	-0.001*	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	-0.002*	-0.002*	-0.002*	-0.002*	-0.002	-0.002*	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

3.3 Climate

It is noted in the literature that temperature and precipitation work in tandem to influence child nutrition (Davenport et al., 2017; Grace et al., 2012). Table 6 present an excerpt of the standard logit results as set out in equation 3.[15] Looking at Panel A, the effect of these climate variables on stunting is statistically significant and remains prominent throughout all of the different model specifications.

[15] Note that the difference between Columns 4-6 and Columns 7-9 is the addition of the household head's education.

Table 6: Logit Regressions' Coefficients - Climate Variables

Panel A: Stunted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	2.414***	2.305***	2.387***	3.214***	3.130***	3.194***	3.394***	3.344***	3.388***
Survey Temperature	(0.544)	(0.526)	(0.535)	(0.510)	(0.497)	(0.512)	(0.620)	(0.603)	(0.621)
Three Year Lagged	0.575***	0.533***	0.562***	0.688***	0.657***	0.679***	0.755***	0.717***	0.750***
Monthly Precipitation (mm)	(0.184)	(0.177)	(0.181)	(0.176)	(0.170)	(0.176)	(0.212)	(0.206)	(0.212)
Temperature ×	-0.017***	-0.016***	-0.017***	-0.021***	-0.020***	-0.021***	-0.023***	-0.022***	-0.023***
Precipitation	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.053	0.044	0.041	0.080	0.079	0.073	0.109	0.111	0.103
Panel Level sd.	0.427	0.391	0.374	0.536	0.531	0.509	0.635	0.641	0.615
Chi-Squared	87.78	101.60	97.88	155.77	164.97	157.55	121.04	130.08	121.14

Panel B: Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.070**	1.081**	1.102**	1.805***	1.825***	1.794***	1.941***	1.984***	1.929***
Survey Temperature	(0.465)	(0.456)	(0.456)	(0.580)	(0.573)	(0.580)	(0.706)	(0.695)	(0.708)
Three Year Lagged	-0.201	-0.192	-0.185	-0.103	-0.095	-0.106	-0.160	-0.156	-0.162
Monthly Precipitation (mm)	(0.179)	(0.177)	(0.175)	(0.220)	(0.220)	(0.220)	(0.265)	(0.265)	(0.266)
Temperature ×	0.006	0.006	0.006	0.003	0.003	0.003	0.005	0.005	0.005
Precipitation	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.186	0.181	0.179	0.140	0.131	0.136	0.185	0.160	0.181
Panel Level sd.	0.866	0.853	0.847	0.730	0.703	0.719	0.864	0.793	0.853
Chi-Squared	87.91	94.56	89.52	164.37	166.81	166.44	136.49	143.54	136.77

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Looking at Table 7, it is clear from all of the different panels that the effect of the lagged temperature dominates in the case of stunting and underweight. The precipitation three years before the survey does not significantly affect the probability of a child being stunted or underweight. However, these two variables work in tandem as higher temperatures as well as less precipitation seems to increase the probability of children being stunted or underweight. comparing this combined effect with temperature alone, the marginal effects of temperature on underweight are of similar magnitude. Although, when adding the impact of precipitation, the marginal effect of temperature is of smaller magnitude in the case of stunting.

As documented in the earlier analysis where we investigate the separate effect of temperature and precipitation, there still exists a gap between the impact in rural and urban areas. Children in rural areas are more susceptible to increases in temperatures as the probability that these children are either stunted or underweight is approximately, on average, 5-6 percentage points higher than those children in urban areas. These results show that children in rural areas are more susceptible to changing climate patterns than those in urban areas.

In the case of including the one year lagged precipitation with the one year lagged temperature and its interaction, the results for stunting remain similar.[16] That is, the lagged temperature still dominates the effect of children suffering from stunting. Notwithstanding, the impact on children suffering from underweight is different when looking solely at the regression tables. The lagged precipitation is negative and significant, while the temperature is positive but insignificant. The picture changes, though, when looking at the marginal effects at the means. Then once again, an increase in temperature leads to a significant change in the probability of a child being underweight. A change in precipitation does not significantly affect the probability that a child suffers from being underweight.

Furthermore, the results concerning the difference between urban and rural areas are still robust. That is, children in rural areas are more vulnerable to climate changes than those in urban areas. However, note that although children in rural areas are more susceptible to climate changes, those in urban areas are still negatively affected. That is, climate change does have a significant impact on the probability of these children being malnourished as well.

[16]Tables are available in the online appendix.

Table 7: Marginal Effect - Climate Variables

Panel A: Stunted (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.066^{**}	0.069^{**}	0.067^{**}	0.106^{***}	0.108^{***}	0.107^{***}	0.080^{**}	0.088^{**}	0.081^{**}
Survey Temperature	(0.032)	(0.031)	(0.031)	(0.035)	(0.035)	(0.035)	(0.037)	(0.037)	(0.037)
Three Year Lagged	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Monthly Precipitation (mm)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel B: Marginal Effects of Climate Variables on Stunting (At Means)

Urban (Temperature)	0.073^{**}	0.075^{***}	0.064^{***}	0.115^{***}	0.117^{***}	0.108^{***}	0.093^{***}	0.101^{***}	0.089^{***}
	(0.029)	(0.028)	(0.022)	(0.030)	(0.030)	(0.027)	(0.032)	(0.032)	(0.028)
Rural (Temperature)	0.107^{***}	0.110^{***}	0.112^{***}	0.169^{***}	0.169^{***}	0.172^{***}	0.145^{***}	0.153^{***}	0.148^{***}
	(0.029)	(0.028)	(0.030)	(0.037)	(0.036)	(0.038)	(0.041)	(0.040)	(0.042)
Urban (Precipitation)	0.000	0.000	-0.000	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural (Precipitation)	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel C: Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.140^{***}	0.140^{***}	0.137^{***}	0.143^{***}	0.142^{***}	0.144^{***}	0.149^{***}	0.146^{***}	0.149^{***}
Survey Temperature	(0.025)	(0.027)	(0.025)	(0.027)	(0.028)	(0.027)	(0.030)	(0.031)	(0.030)
Three Year Lagged	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Monthly Precipitation (mm)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Panel D: Marginal Effects of Climate Variables on Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban (Temperature)	0.141^{***}	0.144^{***}	0.114^{***}	0.143^{***}	0.148^{***}	0.132^{***}	0.157^{***}	0.166^{***}	0.146^{***}
	(0.022)	(0.023)	(0.022)	(0.024)	(0.025)	(0.026)	(0.029)	(0.030)	(0.031)
Rural (Temperature)	0.148^{***}	0.145^{***}	0.155^{***}	0.183^{***}	0.182^{***}	0.186^{***}	0.198^{***}	0.200^{***}	0.201^{***}
	(0.021)	(0.020)	(0.022)	(0.026)	(0.026)	(0.027)	(0.030)	(0.030)	(0.030)
Urban (Precipitation)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural (Precipitation)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

4 Discussion

The results set out in Section 3 coincide with those found in the literature (Davenport et al., 2017; Grace et al., 2012; Grace et al., 2015). Childhood malnutrition has remained a major public health challenge in Nigeria, in both urban and rural areas, but especially in the rural area. The overall rising temperatures and decreasing precipitation is harming food security and agriculture production. As seen, these changes contain serious negative consequences for children and increase the prevalence of malnutrition in children all over the country. Grace et al. (2012) notes that social factors such as education and health can help mitigate the impact of a changing climate on human health.

Children in rural areas are more likely to suffer from climate-changing conditions, which will lead to a decrease in their ability to improve their living standards as adults. This trap of malnutrition and low human capital accumulation will lead to a vicious cycle of "trapped malnutrition". This suggests that policies in Nigeria should focus on improving the standards in rural areas as well as urbanization. That is, policies should focus on improving the standards in rural areas as well as urbanization. For instance, improvement in household head's education is correlated with a decrease in malnutrition in children, although we did not find a statistically significant result in this study. Therefore, creating education opportunities can help mitigate the effect of climate change. Government policy also can promote human capital accumulation and mitigate the effect of climate change through nutritional programs at schools or by implication more comprehensive policies improving access to clean water and safe sanitation. Access to electricity and expanding health care is another way in which the government can improve malnutrition status of children.

Furthermore, policies should ensure the impact of a changing climate on agriculture productivity is minimal. Farmers need equipment and knowledge to adapt to changing weather patterns. Nigeria is fairly rich with water sources (Lohdip & Gongden, 2013). This water availability can contribute to the fact that changing temperatures have a more immediate effect on child nutrition than a changing pattern of precipitation. Lohdip and Gongden (2013) though, warns that an increase in temperature is causing desertification, especially in the north of Nigeria. The access to clean water is increasingly becoming a major issue with the depletion of Nigeria's water sources due to a changing climate. And as seen by this paper, these changes have serious negative consequences on the nutrition of children. The first step for improving and preserving the available water sources is formulating policies that protect Nigeria's water bodies. These policies would enable children to have access to clean water and to mitigate the effects of dry seasons on their nutrition.

Adegbehin et al. (2016) also notes that Nigeria is dependent on fossil fuels for energy generation. Certain fossil fuel and oil projects contaminate Nigeria's rivers which makes access to safe drinking water limited. Stricter policy rules and enforcement are required to ensure the safety of all water sources. There have been hydroelectric projects going up across Nigeria, but these are dependent on water sources. With a drying climate and increasing temperatures, supplying electricity to a population of nearly 200 million will be extremely difficult. The implications are that electricity in households helps to reduce the malnutrition in children. Children will be able to mitigate some effects of climate change with access to electricity. The changing climate patterns, though, will cause children to be vulnerable to indirect effects.

All of these changes and policies can help improve the prevalence of stunting in Nigeria and is needed to improve adult productivity and future human capital accumulation. Although this will help improve the situation of malnutrition, it will not eradicate the malnutrition problem in children, as United Nations Children's Fund (UNICEF) et al. (2020) intends it to be. To eradicate malnutrition, specifically stunting, an improvement in social factors needs to coincide with an improvement in policies regarding climate change. The government needs to ensure the sustainable use of water sources. The economy needs to move from a fossil fuel energy base to more climate-friendly techniques.

5 Conclusion

Achieving the goal of all children being free of malnutrition (United Nations Children's Fund (UNICEF) et al., 2020) is extremely difficult given the range of factors that influence child nutrition. In this paper, it is shown that there is a need to address the changing climate. This study made use of the LSMS-ISA database that allowed us to investigate the effect of actual changes in the patterns of temperature and precipitation. Previous studies used cross-sectional techniques to make predictive changes on the impact that climate change has on the malnutrition rate of children. We specifically focused on Nigeria since, although it is present in other sub-Saharan studies, not a lot of literature covers the effect of climate change on child health solely in Nigeria. Given that Nigeria contains several different climate structures with a good split between rural and urban households, it is an also ideal candidate to be the focus of this study.

The study provides a shred of empirical evidence that an increase in the monthly average maximum temperature increases the probability of a child to suffer from stunting and underweight in Nigeria. An increase in the average monthly precipitation decreases the probability of a child being malnourished. The study also illustrates that an increase in temperature has a more immediate impact on the prevalence of stunting and underweight than changes in precipitation. These effects are more pronounced in rural areas than in urban areas. Changes in precipitation mostly occur through indirect effects. This can be due to the rich water sources in Nigeria. Although Nigeria has sufficient water bodies at present, changing climate patterns, unsustainable water usage and the delayed impact of decreasing precipitation is of great concern. As illustrated, child malnutrition will worsen if nothing changes regarding climate-friendly policies.

The first step to mitigating the effect of climate change on the malnutrition rate in children is to ensure that child-orientated policies are in place (Lawler & Patel, 2012). These policies will set the course for children in many years to come. Such policies will improve the response to climate change and ensure a sustainable future for the next generations. Furthermore, taking care of children now will decrease the number of long-lasting effects of malnutrition and allow children to flourish in adulthood. They will be able to accumulate human capital and better care for their children. Their productivity will be higher and they will not fall into a "malnutrition trap".

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A Technical Appendix

A.1 Climate Data

Temperature and precipitation data is from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia (Harris et al., 2014).[17] This version is a gridded time-series dataset which covers the period 1960-2018. The spatial resolution is 2.5 minutes which is roughly $21km^2$. The variables available are average near-surface minimum temperature ($^{\circ}C$), average near-surface maximum temperature ($^{\circ}C$) and total precipitation (mm). For this paper, we focus on the effects that changes in average maximum near-surface temperature ($^{\circ}C$) and the total precipitation (mm) has on child nutrition.

A.2 Agriculture and Geographical Factors

Soil quality data is from the Harmonized World Soil Database version 1.2. This dataset is a 30 arc-second (about $1km^2$) raster database with over 15 000 different soil mapping units that combine existing regional and national updates of soil information worldwide with the information contained within the 1:5 000 000 scale FAO-UNESCO Soil Map of the World (Fischer et al., 2008). The variables used to measure the soil quality is the "Nutrient availability", "Nutrient retention capacity", "Rooting conditions", "Oxygen availability to roots", "Excess salts", "Toxicity", and "Workability (constraining field management)" of the soil. These vary on a scale from 0-7 where 0 - Ocean, 1 - No or slight limitations, 2 - Moderate limitations, 3 - Severe limitations, 4 - Very severe limitations, 5 - Mainly non-soil, 6 - Permafrost area, and 7 - Waterbodies.

Lastly, freshwater data sources are from the Global Lakes and Wetlands Database (Lehner & Döll, 2004). This database draws on a variety of existing data to create a global scale of large lakes, reservoirs, water bodies, and wetlands. This paper utilizes freshwater in the form of lakes, reservoirs, rivers, freshwater marshes, floodplains, and intermittent wetlands or lakes. A second source used for freshwater data is AQUAMAPS. AQUAMAPS is a global spatial database on water and agriculture which is produced by the Food and Agriculture Organization of the United Nations (FOA). From this database, freshwater sources include water bodies, rivers and dams in Africa (FOA, 2019).

A.3 Combining the Demographic and Climate Data

The households in the LSMS-ISA dataset have GPS references which are offset by two kilometres in urban areas, five kilometres in rural areas and extreme rural cases (1%) are offset by

[17] The downscaled version that corrects for bias, which is produced by WorldClim (Fick & Hijmans, 2017), is used.

10km. We used the households' GPS references to create a five-kilometre buffer around each of these points. This buffer allows us to assume, with relative certainty, that the specific household point is in that buffer zone without the zone being too big. We then used these five-kilometre buffer and georeferencing techniques to merge the climate data in this buffer with each specific household.

Merging these two datasets at the relevant spatial and temporal scales is crucial to ensure a thorough analysis of household health and climate changes (Grace et al., 2012). Very few studies adopt this approach and, by utilizing this approach, this paper contributes to the literature. Furthermore, this method of combination ensures we capture the individual-level effects across our panel data and ensures consistency throughout.

Given that the spatial resolution of the climate data is $21km^2$, households are combined with their GPS locations to the specific climate conditions ascribed by the resolution. Since the maximum distance a household is offset by is 10km, we can assign these households the climate conditions with relative confidence that it will be the climate conditions the household experience. Although households close to each other can experience different climate conditions, this barely happens and depends on the breakdown of the grid that contains the climate data.

A.4 Control Variables

There are quite a few different characteristics that influence the impact climate change can have on malnutrition in children. In the model, it is critical to control for the distance of households to the nearest fresh water source. Access to freshwater, markets, and cities are crucial determinants of child malnutrition. The expectation is that access to these sources reduces malnutrition rates. Therefore, a dummy of whether the community has a market is in the analysis. Furthermore, controls for the distance to the closest market and city, with a population of twenty thousand or more people, is added. We also include controls of household size, the age of children in months, the gender of the child, and the log of consumption per capita of the household.

The livestock of households determines the tropical livestock unit for each household Otte and Chilonda (2002). Calculations of this unit of measurement are for the beginning of the period (post-planting stage), and the end of the year (post-harvesting stage). Due to the correlation, we only use the TLU at the end of the survey period. A household's asset index compromise of whether they have a bicycle, motorcycle, car/other vehicles (vans), tractor, computer, telephone, cellular, radio, television, refrigerator, and stove. Therefore, this asset index ranges from zero to eleven, where eleven indicates a household that owns all of the assets.

A control for education expenditure is necessary, as the literature expect more education reduces the chance of malnutrition. We also control for the number of meals the children in the household receive and the number of time adults restrict their consumption to allow children to eat. Each household experiences market and production shocks and we account for the number of times these occur. Since the plot size of a household influences agriculture production, a control for the aggregate plot size of each household is necessary. We use the log form of plot size and assign a value of zero to those households who do not have a plot.

Agriculture productivity depends on soil quality. Hence, it is beneficial to control for the mean of soil workability and nutrient availability of the soil. Each household has a five-kilometre buffer while the soil quality is approximately on a $1km^2$ grid. Therefore, the mean of these indications of soil quality in the five-kilometre buffer is the closest approximation to the household's actual level of soil quality. A high mean value of these soil quality indicators implies better soil quality, as previously discussed.

Given the importance of the parent's education, we expect the household head to influence the level of malnutrition of the children due to the prominent role of the household head. Since the expectation is that mothers are more nurturing than their male counterparts, there is a control for the gender of the household head. Furthermore, we control for the level of education of the household head. The education level is in four categories: no education, completed primary education, completed secondary education, and completed tertiary or higher education.

The financial status of households can influence the nutritional status of children as well. Hence, the use of several controls, which indicates the household's financial aspects, is in order. These controls include borrowing money from formal and informal institutions as well as friends and family. Also included is whether the household has a non-farm enterprise, receiving any assistance from the government, or receiving any agri-extension information, be it from government or private institutions.

The final control used is whether the household has electricity in the dwelling they live in As previously noted, electricity can be a proxy for different social infrastructures. The use of dummies for the regions of Nigeria is in some models of the analysis. The motivation being the dispersion seen in Figure B1. These regions are North-Central, North-West, North-East, South-South, South-East, and South-West. The use of a dummy for urban and rural areas is in the analysis as well given the interest of this paper of the effects between rural and urban areas.

B Descriptive Statistics

Table B1: Temperature and Precipitation Across Zones

Columns by: zone	North-Central	North-East	North-West	South-East	South-South	South-West	P-value
n (%)	2392 (16.6)	2217 (15.4)	2661 (18.5)	2331 (16.2)	2319 (16.1)	2489 (17.3)	
Temperature							
Year of Survey Monthly Maximum Temperature (°C), mean (sd)	32.03 (1.67)	34.22 (1.43)	33.89 (1.39)	31.36 (0.66)	31.00 (0.43)	31.26 (0.83)	0.00
Year before Survey Monthly Maximum Temperature (°C), mean (sd)	32.16 (1.69)	34.48 (1.51)	34.12 (1.44)	31.40 (0.66)	31.03 (0.43)	31.33 (0.84)	0.00
Two Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.14 (1.68)	34.46 (1.49)	34.10 (1.39)	31.42 (0.66)	31.06 (0.43)	31.29 (0.82)	0.00
Three Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.07 (1.70)	34.38 (1.52)	34.04 (1.48)	31.29 (0.67)	30.94 (0.44)	31.21 (0.87)	0.00
Five Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.14 (1.68)	34.51 (1.46)	34.12 (1.41)	31.39 (0.66)	31.03 (0.42)	31.29 (0.82)	0.00
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.11 (1.68)	34.39 (1.47)	34.04 (1.40)	31.39 (0.66)	31.03 (0.42)	31.29 (0.82)	0.00
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.07 (1.67)	34.37 (1.45)	33.99 (1.39)	31.35 (0.65)	30.99 (0.42)	31.24 (0.83)	0.00
Average Temperature in the Wettest Quarter (°C), mean (sd)	24.74 (1.30)	25.36 (1.07)	25.59 (1.27)	25.03 (0.72)	25.24 (0.50)	25.28 (1.09)	0.00
Precipitation							
Year of Survey Monthly Precipitation (mm), mean (sd)	105.17 (15.07)	77.33 (23.42)	75.54 (15.88)	160.24 (19.64)	204.67 (41.62)	121.61 (23.48)	0.00
Year before Survey Monthly Precipitation (mm), mean (sd)	106.55 (16.14)	66.80 (20.29)	70.06 (19.82)	160.86 (19.85)	204.72 (41.89)	123.45 (18.63)	0.00
Two Years before Survey Monthly Precipitation (mm), mean (sd)	104.10 (16.52)	69.55 (20.09)	73.43 (16.54)	162.39 (20.94)	210.12 (42.77)	127.30 (26.67)	0.00
Three Years before Survey Monthly Precipitation (mm), mean (sd)	109.03 (13.48)	71.66 (20.84)	73.23 (18.01)	158.05 (17.97)	199.83 (39.39)	127.45 (21.30)	0.00
Five Years before Survey Monthly Precipitation (mm), mean (sd)	105.21 (14.61)	68.89 (19.86)	72.03 (15.55)	160.81 (19.57)	205.86 (41.08)	127.17 (26.18)	0.00
Three Year Average Monthly Precipitation (mm), mean (sd)	105.27 (15.04)	71.23 (20.23)	73.01 (16.98)	161.16 (19.86)	206.51 (41.38)	124.12 (20.94)	0.00
Five Year Average Monthly Precipitation (mm), mean (sd)	106.48 (14.48)	71.85 (20.42)	73.30 (16.98)	161.43 (19.83)	206.93 (41.29)	125.57 (20.27)	0.00
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	225.10 (30.27)	188.59 (38.41)	197.91 (35.66)	282.53 (28.88)	353.59 (65.10)	206.32 (46.61)	0.00
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	209.82 (30.80)	188.81 (39.76)	186.97 (29.76)	261.03 (23.30)	275.92 (46.22)	196.86 (16.81)	0.00

Table B2: Temperature and Precipitation Across Waves

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016	P-value
n (%)	4998 (34.7)	4799 (33.3)	4613 (32.0)	
Temperature				
Year of Survey Monthly Maximum Temperature (°C), mean (sd)	32.38 (1.79)	32.28 (1.79)	32.24 (1.61)	0.00
Year before Survey Monthly Maximum Temperature (°C), mean (sd)	32.74 (1.97)	32.21 (1.76)	32.32 (1.66)	0.00
Two Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.46 (1.93)	32.40 (1.79)	32.41 (1.65)	0.24
Three Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.03 (1.70)	32.76 (1.97)	32.21 (1.74)	0.00
Five Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.53 (1.90)	32.40 (1.79)	32.33 (1.75)	0.00
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.53 (1.89)	32.30 (1.78)	32.32 (1.64)	0.00
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.34 (1.81)	32.43 (1.85)	32.27 (1.67)	0.00
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.21 (1.08)	25.22 (1.08)	25.21 (1.07)	0.86
Precipitation				
Year of Survey Monthly Precipitation (mm), mean (sd)	125.70 (54.84)	121.43 (48.53)	122.31 (51.98)	0.00
Year before Survey Monthly Precipitation (mm), mean (sd)	120.35 (50.50)	122.41 (56.43)	120.91 (55.74)	0.15
Two Years before Survey Monthly Precipitation (mm), mean (sd)	129.67 (56.38)	125.38 (55.06)	115.27 (53.86)	0.00
Three Years before Survey Monthly Precipitation (mm), mean (sd)	124.36 (53.39)	120.15 (50.67)	122.64 (48.08)	0.00
Five Years before Survey Monthly Precipitation (mm), mean (sd)	117.08 (53.54)	123.99 (53.56)	126.82 (54.51)	0.00
Three Year Average Monthly Precipitation (mm), mean (sd)	125.24 (53.66)	123.08 (53.13)	119.49 (53.37)	0.00
Five Year Average Monthly Precipitation (mm), mean (sd)	125.29 (53.88)	123.74 (53.18)	120.97 (52.73)	0.00
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	240.53 (72.03)	240.73 (71.92)	242.43 (71.22)	0.37
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	222.01 (50.51)	219.92 (47.26)	214.95 (44.81)	0.00

Table B3: Temperature and Precipitation Across Waves in Urban Areas

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016	P-value
n (%)	1618 (35.2)	1501 (32.6)	1480 (32.2)	
Temperature				
Year of Survey Monthly Maximum Temperature (°C), mean (sd)	32.04 (1.58)	31.92 (1.54)	31.95 (1.40)	0.08
Year before Survey Monthly Maximum Temperature (°C), mean (sd)	32.33 (1.74)	31.84 (1.51)	32.03 (1.45)	0.00
Two Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.04 (1.71)	32.04 (1.54)	32.11 (1.44)	0.34
Three Years before Survey Monthly Maximum Temperature (°C), mean (sd)	31.71 (1.51)	32.32 (1.69)	31.88 (1.53)	0.00
Five Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.13 (1.68)	32.04 (1.54)	31.99 (1.52)	0.05
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.14 (1.68)	31.93 (1.53)	32.03 (1.43)	0.00
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	31.98 (1.60)	32.03 (1.59)	31.95 (1.46)	0.37
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.18 (1.06)	25.20 (1.06)	25.17 (1.05)	0.74
Precipitation				
Year of Survey Monthly Precipitation (mm), mean (sd)	133.87 (49.01)	126.95 (43.49)	121.52 (48.15)	0.00
Year before Survey Monthly Precipitation (mm), mean (sd)	124.56 (44.03)	128.38 (50.59)	129.87 (48.93)	0.01
Two Years before Survey Monthly Precipitation (mm), mean (sd)	137.93 (50.33)	134.65 (49.45)	117.99 (48.73)	0.00
Three Years before Survey Monthly Precipitation (mm), mean (sd)	133.81 (47.53)	125.29 (44.43)	127.77 (43.02)	0.00
Five Years before Survey Monthly Precipitation (mm), mean (sd)	119.30 (47.79)	134.56 (47.89)	135.64 (49.01)	0.00
Three Year Average Monthly Precipitation (mm), mean (sd)	132.12 (47.48)	129.99 (47.62)	123.13 (47.98)	0.00
Five Year Average Monthly Precipitation (mm), mean (sd)	132.07 (47.68)	130.82 (47.44)	125.31 (47.35)	0.00
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	236.86 (68.74)	238.51 (69.06)	239.65 (68.83)	0.52
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	216.84 (45.12)	215.61 (41.94)	211.64 (40.06)	0.00

Table B4: Temperature and Precipitation Across Waves in Rural Areas

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016	P-value
n (%)	3380 (34.5)	3298 (33.6)	3132 (31.9)	
Temperature				
Year of Survey Monthly Maximum Temperature (°C), mean (sd)	32.55 (1.86)	32.44 (1.86)	32.38 (1.68)	0.00
Year before Survey Monthly Maximum Temperature (°C), mean (sd)	32.94 (2.04)	32.38 (1.84)	32.46 (1.74)	0.00
Two Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.65 (1.99)	32.57 (1.88)	32.55 (1.72)	0.05
Three Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.19 (1.76)	32.96 (2.06)	32.37 (1.82)	0.00
Five Years before Survey Monthly Maximum Temperature (°C), mean (sd)	32.72 (1.97)	32.57 (1.88)	32.49 (1.82)	0.00
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.71 (1.96)	32.46 (1.86)	32.46 (1.71)	0.00
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.51 (1.87)	32.61 (1.93)	32.41 (1.75)	0.00
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.22 (1.09)	25.23 (1.09)	25.23 (1.09)	0.97
Precipitation				
Year of Survey Monthly Precipitation (mm), mean (sd)	121.80 (57.02)	118.92 (50.46)	122.61 (53.59)	0.01
Year before Survey Monthly Precipitation (mm), mean (sd)	118.33 (53.20)	119.70 (58.70)	116.61 (58.12)	0.09
Two Years before Survey Monthly Precipitation (mm), mean (sd)	125.71 (58.66)	121.17 (56.94)	113.92 (55.98)	0.00
Three Years before Survey Monthly Precipitation (mm), mean (sd)	119.83 (55.42)	117.81 (53.11)	120.16 (50.02)	0.15
Five Years before Survey Monthly Precipitation (mm), mean (sd)	116.01 (56.06)	119.18 (55.29)	122.58 (56.34)	0.00
Three Year Average Monthly Precipitation (mm), mean (sd)	121.95 (56.08)	119.93 (55.18)	117.71 (55.55)	0.01
Five Year Average Monthly Precipitation (mm), mean (sd)	122.04 (56.33)	120.52 (55.30)	118.86 (54.88)	0.07
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	242.28 (73.50)	241.73 (73.16)	243.64 (72.10)	0.56
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	224.49 (52.73)	221.88 (49.37)	216.49 (46.80)	0.00

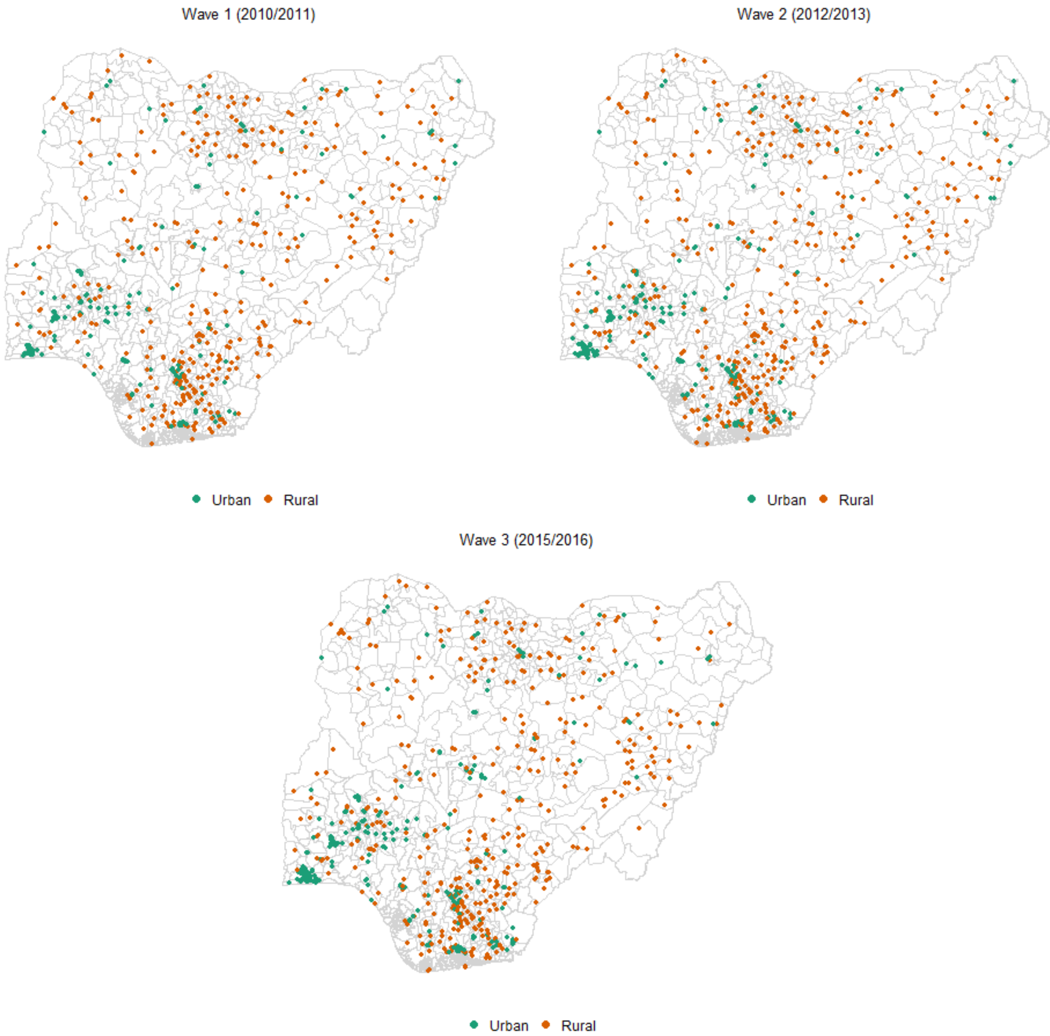
Table B5: Control Variables at Household Level

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016	P-value
n (%)	4998 (34.7)	4799 (33.3)	4613 (32.0)	
Varying Control Variables				
Distance to Closest Water Source (km), mean (sd)	4.60 (3.20)	4.58 (3.22)	4.64 (3.30)	0.74
Distance to Closest Market(km), mean (sd)	66.67 (43.82)	66.96 (43.49)	67.71 (43.61)	0.49
Distance to Closest City (km), mean (sd)	19.74 (19.97)	18.54 (15.41)	23.85 (20.19)	0.00
Log of Education Expenditure, mean (sd)	5.05 (3.93)	5.12 (3.97)	5.54 (4.00)	0.00
Log of Consumption per Capita, mean (sd)	11.32 (0.76)	11.36 (0.75)	11.64 (0.75)	0.00
Number of People in Household, mean (sd)	5.63 (3.22)	6.11 (3.86)	5.72 (3.37)	0.00
Number of Children in HH (Less than 5 Years of age), mean (sd)	2.94 (1.43)	2.98 (1.54)	2.20 (2.12)	0.00
Number of Meals to Children, mean (sd)	2.92 (1.80)	2.77 (2.18)	2.02 (1.87)	0.00
Restricted Meals so Children can Eat, mean (sd)	0.38 (0.99)	0.38 (1.08)	0.34 (0.93)	0.11
Household Asset Index, mean (sd)	2.85 (1.93)	3.06 (1.84)	3.17 (1.72)	0.00
Number of different Production Shocks Reported, mean (sd)	0.09 (0.33)	0.12 (0.35)	0.07 (0.28)	0.00
Number of different Market Shocks Reported, mean (sd)	0.10 (0.39)	0.10 (0.35)	0.18 (0.48)	0.00
Log of Aggregate Plot Size, mean (sd)	8.32 (1.63)	8.43 (1.33)	8.41 (1.47)	0.01
Tropical Livestock Units as of the time of survey, mean (sd)	2.33 (35.37)	1.90 (38.92)	1.12 (5.26)	0.15
Soil Workability (constraining field management) (mean), mean (sd)	1.50 (0.74)	1.50 (0.74)	1.49 (0.71)	0.75
Soil Nutrient availability (mean), mean (sd)	1.92 (0.90)	1.92 (0.90)	1.94 (0.88)	0.67
Binary Control Variables				
Borrow Food, or Rely on Friend/Relative? (Yes), n (%)	442 (9.3)	411 (8.9)	412 (9.0)	0.84
Borrow from Microfinance/Credit Associations/Bank (Yes), n (%)	192 (3.8)	283 (6.0)	324 (7.0)	0.00
Borrow from Friends/Relatives/Money Lenders (Yes), n (%)	1234 (24.7)	1219 (25.8)	298 (6.5)	0.00
Borrow from Informal Institution (Yes), n (%)	768 (15.4)	794 (16.8)	146 (3.2)	0.00
Has Non-Farm Enterprise (Yes), n (%)	2321 (46.4)	2608 (54.3)	2443 (53.0)	0.00
Agri-extension (Government/Private Sector) (Yes), n (%)	221 (4.4)	109 (2.3)	119 (2.6)	0.00
Government Assistance (food/cash/otherwise) (Yes), n (%)	81 (1.6)	152 (3.2)	96 (2.1)	0.00
Does HH have Electricity in Dwelling? (Yes), n (%)	2420 (49.4)	2454 (51.6)	2431 (53.0)	0.00
Gender of Household Head, n (%)				
Female, n (%)	754 (15.1)	689 (14.6)	577 (14.2)	
Male, n (%)	4242 (84.9)	4044 (85.4)	3487 (85.8)	0.48
Sector, n (%)				
Urban, n (%)	1618 (32.4)	1501 (31.3)	1480 (32.1)	
Rural, n (%)	3380 (67.6)	3298 (68.7)	3132 (67.9)	0.49
Categorical Control Variables				
Ordered Level of Household Head's Completed Education, n (%)				
None/Less than Primary, n (%)	1955 (45.5)	1769 (45.9)	1524 (44.7)	
Primary School Complete, n (%)	1262 (29.3)	1077 (28.0)	952 (27.9)	
Secondary School Complete, n (%)	828 (19.3)	752 (19.5)	700 (20.5)	
University or Higher Education Complete, n (%)	256 (6.0)	253 (6.6)	234 (6.9)	0.34
Region, n (%)				
North Central, n (%)	800 (16.0)	795 (16.6)	797 (17.3)	
North East, n (%)	800 (16.0)	774 (16.1)	643 (13.9)	
North West, n (%)	900 (18.0)	879 (18.3)	882 (19.1)	
South East, n (%)	800 (16.0)	772 (16.1)	759 (16.5)	
South South, n (%)	800 (16.0)	768 (16.0)	751 (16.3)	
South West, n (%)	898 (18.0)	811 (16.9)	780 (16.9)	0.10

Table B6: Variables for Children in the Sample

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016	P-value
n (%)	1274 (33.3)	1273 (33.3)	1274 (33.3)	
Continuous Variables				
Age in Months, mean (sd)	21.36 (17.29)	38.56 (14.08)	62.66 (19.90)	0.00
Weight (kg), mean (sd)	10.25 (5.41)	14.06 (2.99)	18.81 (4.41)	0.00
Length (cm), mean (sd)	72.13 (26.96)	94.29 (14.90)	109.17 (14.13)	0.00
Length/Height-for-age Z-score (WHO), mean (sd)	-0.30 (2.55)	-0.15 (1.82)	-0.30 (1.93)	0.27
Weight-for-age Z-score (WHO), mean (sd)	-0.21 (2.07)	-0.07 (1.42)	-0.15 (1.53)	0.20
Weight-for-Height/Length Z-score (WHO), mean (sd)	0.01 (1.88)	-0.09 (1.38)	-0.11 (1.51)	0.30
Binary Variables				
Gender, n (%)				
Female, n (%)	617 (48.4)	622 (48.9)	623 (48.9)	
Male, n (%)	657 (51.6)	651 (51.1)	651 (51.1)	0.97
Is Child Stunted? (Yes), n (%)	172 (29.9)	111 (13.2)	137 (19.0)	0.00
Is Child Wasted? (Yes), n (%)	93 (12.9)	70 (7.7)	47 (6.8)	0.00
Is Child Underweight? (Yes), n (%)	155 (18.8)	60 (6.6)	65 (8.5)	0.00
Does HH have Electricity in Dwelling? (Yes), n (%)	525 (41.4)	562 (44.3)	548 (43.0)	0.34
Gender of Household Head, n (%)				
Female, n (%)	48 (3.8)	51 (4.0)	79 (6.3)	
Male, n (%)	1225 (96.2)	1221 (96.0)	1174 (93.7)	0.00
Categorical Variables				
Ordered Level of Household Head's Completed Education, n (%)				
None/Less than Primary, n (%)	436 (41.7)	452 (44.2)	447 (44.3)	
Primary School Complete, n (%)	328 (31.4)	286 (28.0)	279 (27.7)	
Secondary School Complete, n (%)	229 (21.9)	216 (21.1)	225 (22.3)	
University or Higher Education Complete, n (%)	53 (5.1)	68 (6.7)	57 (5.7)	0.35

Figure B1: Maps of Urban and Rural Split



C Regression Results

C.1 Stunting and Lagged Temperature

Table C1: Logit Regressions - Lagged Temperature and Stunting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.179***	1.123***	1.184***	1.732***	1.702***	1.740***	1.758***	1.782***	1.775***
Survey Temperature	(0.220)	(0.211)	(0.215)	(0.253)	(0.249)	(0.253)	(0.282)	(0.281)	(0.283)
Distance to Closest				-0.375	-0.395	-0.382	-0.278	-0.370	-0.296
Water Source (km)				(0.733)	(0.688)	(0.698)	(0.664)	(0.629)	(0.631)
Distance to				-0.008	-0.011	-0.009	0.010	0.012	0.010
Closest Market (km)				(0.031)	(0.032)	(0.030)	(0.041)	(0.042)	(0.040)
Distance to				0.003	0.003	0.003	0.006	0.005	0.006
Closest City (km)				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Number of People				0.043	0.060	0.040	0.026	0.048	0.024
in Household				(0.070)	(0.069)	(0.070)	(0.085)	(0.085)	(0.085)
Log of Education				-0.026	-0.026	-0.026	-0.023	-0.023	-0.023
Expenditure				(0.032)	(0.032)	(0.032)	(0.036)	(0.036)	(0.036)
Household Asset				0.226***	0.225***	0.222***	0.256***	0.259***	0.254***
Index				(0.078)	(0.078)	(0.078)	(0.090)	(0.091)	(0.090)
Log of Consumption				-0.063	-0.041	-0.072	-0.124	-0.094	-0.136
per Capita				(0.169)	(0.169)	(0.168)	(0.194)	(0.196)	(0.193)
Number of Meals				0.056	0.056	0.057	0.078	0.084	0.075
to Children				(0.056)	(0.056)	(0.056)	(0.069)	(0.069)	(0.069)
Restricted Meals				-0.020	-0.023	-0.020	-0.068	-0.084	-0.069
so Children can Eat				(0.104)	(0.103)	(0.104)	(0.117)	(0.117)	(0.117)
Number of				0.112	0.103	0.117	0.126	0.092	0.135
Production Shocks				(0.188)	(0.192)	(0.187)	(0.209)	(0.216)	(0.208)
Number of Market				-0.115	-0.105	-0.116	-0.061	-0.062	-0.065
Shocks				(0.163)	(0.163)	(0.163)	(0.188)	(0.190)	(0.187)
Tropical				0.091**	0.093**	0.091**	0.126**	0.134**	0.127**
Livestock Units				(0.041)	(0.040)	(0.041)	(0.054)	(0.053)	(0.055)
Log of Plot Size				-0.070*	-0.068*	-0.071*	-0.052	-0.053	-0.054
of All Households				(0.040)	(0.039)	(0.039)	(0.050)	(0.050)	(0.049)

Soil Workability		-3.267	-3.456*	-3.247	-1.276	-1.641	-1.345
(mean)		(2.111)	(2.052)	(2.091)	(3.111)	(3.022)	(2.896)
Soil Nutrient		1.270	1.513	1.320	-1.119	-0.724	-0.953
Availability (mean)		(2.278)	(2.272)	(2.234)	(3.920)	(3.808)	(3.627)
Age in Months		0.009*	0.008*	0.009*	0.007	0.006	0.007
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Gender of		0.244	0.201	0.237	0.618	0.551	0.599
Household Head		(0.852)	(0.863)	(0.849)	(0.933)	(0.961)	(0.932)
Gender		0.789	0.696	0.810	1.085	0.980	1.121
		(1.447)	(1.514)	(1.376)	(1.489)	(1.554)	(1.426)
Borrow from Microfinance/		-0.068	-0.060	-0.074	0.134	0.166	0.132
Credit Associations/Bank		(0.444)	(0.448)	(0.448)	(0.511)	(0.521)	(0.518)
Borrow from Friends/		-0.198	-0.211	-0.187	-0.238	-0.262	-0.227
Relatives/Money Lenders		(0.190)	(0.192)	(0.190)	(0.225)	(0.229)	(0.224)
Borrow Food, or		-0.041	-0.014	-0.042	-0.392	-0.369	-0.394
Rely on Friend/Relative?		(0.308)	(0.311)	(0.309)	(0.366)	(0.375)	(0.367)
Is there a Market		-0.018	-0.063	-0.011	-0.003	-0.023	0.001
in the Community?		(0.201)	(0.205)	(0.201)	(0.228)	(0.232)	(0.229)
Does HH have		0.074	0.124	0.070	0.129	0.169	0.127
Electricity in Dwelling?		(0.318)	(0.322)	(0.316)	(0.365)	(0.369)	(0.363)
Has Non-Farm		0.071	0.066	0.060	0.175	0.128	0.174
Enterprise		(0.238)	(0.236)	(0.238)	(0.299)	(0.300)	(0.300)
Government Assistance		0.659	0.655	0.672	0.963**	0.947**	0.992**
(food/cash/otherwise)		(0.426)	(0.426)	(0.425)	(0.467)	(0.473)	(0.466)
Agri-extension		0.210	0.237	0.211	0.056	0.129	0.059
(Government/Private Sector)		(0.398)	(0.398)	(0.397)	(0.498)	(0.502)	(0.499)
North-East	0.174		0.195			-0.110	
	(0.200)		(0.258)			(0.296)	
North-West	0.471**		0.558**			0.466*	
	(0.194)		(0.250)			(0.283)	
South-East	-1.060***		-0.727**			-0.684*	
	(0.293)		(0.366)			(0.395)	

South-South		-0.280			-0.165			-0.107	
		(0.249)			(0.336)			(0.365)	
South-West		-0.144			0.126			0.065	
		(0.305)			(0.398)			(0.439)	
Rural			0.520***			0.409*			0.473*
			(0.155)			(0.213)			(0.266)
Primary							-0.211	-0.165	-0.198
Education Complete							(0.261)	(0.266)	(0.260)
Secondary							0.032	0.065	0.038
Education Complete							(0.444)	(0.459)	(0.442)
University/Higher							-0.046	-0.220	-0.041
Education Complete							(0.790)	(0.806)	(0.797)
Constant	-9.837***	-5.127***	-9.815***	-8.380***	-6.377**	-8.860***	-7.180**	-6.251*	-7.929**
	(1.130)	(1.672)	(1.118)	(2.883)	(2.952)	(2.916)	(3.419)	(3.475)	(3.506)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.046	0.033	0.036	0.062	0.059	0.056	0.091	0.096	0.086
Panel Level sd.	0.399	0.336	0.351	0.468	0.454	0.442	0.574	0.593	0.555
Chi-Squared	76.08	99.33	89.38	145.55	158.02	147.73	115.66	125.55	115.82

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

C.2 Underweight and Lagged Temperature

Table C2: Logit Regressions - Lagged Temperature and Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.541***	1.483***	1.536***	2.026***	2.008***	2.025***	2.249***	2.281***	2.248***
Survey Temperature	(0.241)	(0.232)	(0.236)	(0.278)	(0.279)	(0.278)	(0.327)	(0.331)	(0.328)
Distance to Closest				-0.042	-0.156	-0.050	0.038	-0.047	0.025
Water Source (km)				(0.410)	(0.408)	(0.405)	(0.504)	(0.465)	(0.496)
Distance to				0.019	0.015	0.018	0.034	0.019	0.032

Closest Market (km)	(0.043)	(0.039)	(0.043)	(0.064)	(0.051)	(0.062)
Distance to Closest City (km)	0.015*	0.015*	0.015*	0.022**	0.022**	0.022**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Number of People in Household	-0.246***	-0.234***	-0.247***	-0.240**	-0.228**	-0.241**
	(0.084)	(0.083)	(0.084)	(0.105)	(0.103)	(0.105)
Log of Education Expenditure	-0.033	-0.031	-0.033	-0.047	-0.043	-0.048
	(0.038)	(0.038)	(0.038)	(0.046)	(0.044)	(0.046)
Household Asset Index	0.037	0.040	0.036	-0.005	-0.002	-0.005
	(0.088)	(0.089)	(0.088)	(0.108)	(0.110)	(0.108)
Log of Consumption per Capita	-0.478**	-0.467**	-0.480**	-0.510*	-0.485*	-0.513*
	(0.224)	(0.221)	(0.224)	(0.263)	(0.257)	(0.262)
Number of Meals to Children	0.120**	0.119*	0.120**	0.162*	0.161*	0.161*
	(0.061)	(0.061)	(0.061)	(0.087)	(0.085)	(0.088)
Restricted Meals so Children can Eat	0.083	0.081	0.083	0.131	0.127	0.131
	(0.117)	(0.116)	(0.117)	(0.121)	(0.121)	(0.121)
Number of Production Shocks	0.712***	0.687***	0.708***	0.859***	0.818***	0.858***
	(0.213)	(0.214)	(0.213)	(0.247)	(0.245)	(0.246)
Number of Market Shocks	0.205	0.190	0.205	0.371	0.351	0.367
	(0.203)	(0.201)	(0.203)	(0.241)	(0.239)	(0.241)
Tropical Livestock Units	-0.005	-0.005	-0.005	0.011	0.012	0.011
	(0.034)	(0.027)	(0.036)	(0.051)	(0.051)	(0.051)
Log of Plot Size of All Households	-0.088**	-0.089**	-0.087**	-0.052	-0.057	-0.052
	(0.045)	(0.045)	(0.044)	(0.058)	(0.058)	(0.057)
Soil Workability (mean)	-2.169	-2.285	-2.164	-1.327	-1.410	-1.311
	(2.581)	(2.692)	(2.530)	(3.070)	(3.463)	(2.989)
Soil Nutrient Availability (mean)	-0.357	-0.161	-0.309	-1.464	-1.307	-1.420
	(3.378)	(3.486)	(3.309)	(4.064)	(4.529)	(3.951)
Age in Months	0.017***	0.016***	0.017***	0.017***	0.016**	0.017***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of Household Head	0.376	0.382	0.370	1.018	1.103	0.998
	(1.103)	(1.124)	(1.096)	(1.295)	(1.342)	(1.288)
Gender	-2.464*	-2.297	-2.478*	-2.739	-2.544	-2.738
	(1.477)	(1.489)	(1.483)	(1.917)	(1.956)	(1.943)

Borrow from Microfinance/			0.612	0.623	0.606	0.986*	0.977	0.986*
Credit Associations/Bank			(0.572)	(0.588)	(0.574)	(0.581)	(0.605)	(0.580)
Borrow from Friends/			0.111	0.097	0.115	-0.162	-0.161	-0.161
Relatives/Money Lenders			(0.235)	(0.234)	(0.235)	(0.275)	(0.273)	(0.275)
Borrow Food, or			-0.703**	-0.692*	-0.705**	-0.839**	-0.841**	-0.842**
Rely on Friend/Relative?			(0.358)	(0.360)	(0.358)	(0.401)	(0.401)	(0.401)
Is there a Market			0.155	0.128	0.153	0.226	0.194	0.222
in the Community?			(0.239)	(0.239)	(0.239)	(0.291)	(0.290)	(0.290)
Does HH have			0.287	0.280	0.286	0.382	0.376	0.383
Electricity in Dwelling?			(0.352)	(0.352)	(0.350)	(0.420)	(0.417)	(0.417)
Has Non-Farm			0.358	0.352	0.353	-0.003	-0.052	-0.000
Enterprise			(0.265)	(0.264)	(0.265)	(0.336)	(0.333)	(0.335)
Government Assistance			0.142	0.178	0.149	-0.162	-0.138	-0.150
(food/cash/otherwise)			(0.707)	(0.706)	(0.707)	(0.826)	(0.828)	(0.827)
Agri-extension			-0.676	-0.687	-0.668	-0.912	-0.932	-0.901
(Government/Private Sector)			(0.495)	(0.492)	(0.496)	(0.588)	(0.591)	(0.588)
North-East	0.050			-0.109			-0.448	
	(0.249)			(0.304)			(0.360)	
North-West	0.398			0.125			-0.177	
	(0.243)			(0.291)			(0.337)	
South-East	-0.712**			-0.419			-0.435	
	(0.355)			(0.447)			(0.495)	
South-South	-0.214			-0.278			-0.019	
	(0.326)			(0.426)			(0.470)	
South-West	0.324			0.698			0.829*	
	(0.355)			(0.444)			(0.482)	
Rural		0.425**			0.204			0.259
		(0.202)			(0.287)			(0.333)
Primary						-0.282	-0.305	-0.283
Education Complete						(0.283)	(0.286)	(0.283)
Secondary						-0.817	-0.870	-0.819
Education Complete						(0.525)	(0.534)	(0.524)

University/Higher							-0.052	-0.107	-0.078
Education Complete							(0.886)	(0.887)	(0.898)
Constant	-8.426***	-5.593***	-8.406***	-5.843	-5.915	-6.116*	-6.870*	-8.348**	-7.297*
	(1.407)	(2.145)	(1.406)	(3.688)	(3.896)	(3.699)	(4.067)	(4.226)	(4.116)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.204	0.191	0.198	0.160	0.152	0.158	0.198	0.179	0.195
Panel Level sd.	0.919	0.881	0.902	0.793	0.768	0.786	0.902	0.848	0.893
Chi-Squared	64.10	78.95	68.53	153.88	156.57	154.96	131.44	136.40	131.40

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

C.3 Stunting and Three Year Lagged Precipitation

Table C3: Logit Regressions - Three Year Lagged Precipitation and Stunting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.024**	-0.024**	-0.028**	-0.042***	-0.040***	-0.043***	-0.049***	-0.048***	-0.052***
Monthly Precipitation (mm)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Distance to Closest				-0.283	-0.278	-0.293	-0.202	-0.257	-0.222
Water Source (km)				(0.479)	(0.452)	(0.448)	(0.454)	(0.447)	(0.415)
Distance to				-0.015	-0.019	-0.014	0.003	0.006	0.004
Closest Market (km)				(0.033)	(0.034)	(0.032)	(0.046)	(0.048)	(0.043)
Distance to				0.010	0.009	0.010	0.013*	0.012*	0.013*
Closest City (km)				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Number of People				-0.014	-0.002	-0.017	-0.044	-0.027	-0.045
in Household				(0.066)	(0.066)	(0.066)	(0.077)	(0.079)	(0.077)
Log of Education				-0.015	-0.017	-0.016	-0.017	-0.019	-0.017
Expenditure				(0.031)	(0.031)	(0.031)	(0.034)	(0.035)	(0.034)
Household Asset				0.187**	0.185**	0.180**	0.210**	0.209**	0.203**
Index				(0.077)	(0.077)	(0.077)	(0.088)	(0.088)	(0.088)
Log of Consumption				-0.067	-0.042	-0.079	-0.140	-0.113	-0.154

per Capita	(0.166)	(0.168)	(0.165)	(0.191)	(0.193)	(0.188)
Number of Meals to Children	-0.034 (0.054)	-0.032 (0.054)	-0.035 (0.054)	-0.003 (0.066)	0.001 (0.066)	-0.010 (0.066)
Restricted Meals so Children can Eat	-0.055 (0.098)	-0.054 (0.098)	-0.056 (0.098)	-0.096 (0.109)	-0.108 (0.108)	-0.101 (0.108)
Number of Production Shocks	0.013 (0.184)	0.007 (0.187)	0.022 (0.182)	0.076 (0.200)	0.045 (0.207)	0.092 (0.197)
Number of Market Shocks	-0.100 (0.160)	-0.099 (0.162)	-0.100 (0.159)	-0.055 (0.182)	-0.059 (0.186)	-0.059 (0.180)
Tropical Livestock Units	0.082** (0.038)	0.083** (0.038)	0.083** (0.038)	0.120** (0.049)	0.126** (0.049)	0.121** (0.049)
Log of Plot Size of All Households	-0.055 (0.039)	-0.055 (0.038)	-0.057 (0.038)	-0.042 (0.048)	-0.044 (0.048)	-0.045 (0.047)
Soil Workability (mean)	-3.014 (1.999)	-3.288* (1.756)	-2.938 (2.053)	-1.206 (1.868)	-1.667 (1.826)	-1.214 (1.716)
Soil Nutrient Availability (mean)	2.276 (2.261)	2.705 (1.994)	2.225 (2.332)	0.024 (2.477)	0.646 (2.391)	0.071 (2.281)
Age in Months	-0.005 (0.004)	-0.005 (0.004)	-0.004 (0.004)	-0.006 (0.005)	-0.007 (0.005)	-0.006 (0.005)
Gender of Household Head	0.170 (0.843)	0.146 (0.858)	0.157 (0.838)	0.563 (0.938)	0.519 (0.964)	0.533 (0.935)
Gender	1.121 (1.549)	1.043 (1.544)	1.201 (1.471)	1.374 (1.592)	1.288 (1.604)	1.458 (1.514)
Borrow from Microfinance/ Credit Associations/Bank	0.056 (0.440)	0.072 (0.438)	0.061 (0.439)	0.197 (0.509)	0.253 (0.519)	0.199 (0.509)
Borrow from Friends/ Relatives/Money Lenders	-0.184 (0.183)	-0.187 (0.185)	-0.168 (0.181)	-0.175 (0.213)	-0.188 (0.217)	-0.157 (0.211)
Borrow Food, or Rely on Friend/Relative?	0.168 (0.290)	0.182 (0.291)	0.164 (0.289)	-0.178 (0.342)	-0.162 (0.349)	-0.175 (0.342)
Is there a Market in the Community?	-0.174 (0.192)	-0.206 (0.195)	-0.167 (0.191)	-0.172 (0.216)	-0.181 (0.218)	-0.171 (0.216)
Does HH have Electricity in Dwelling?	0.009 (0.322)	0.043 (0.321)	0.014 (0.319)	0.004 (0.369)	0.028 (0.367)	0.010 (0.365)

Has Non-Farm				-0.275	-0.284	-0.288	-0.135	-0.186	-0.141
Enterprise				(0.223)	(0.221)	(0.222)	(0.283)	(0.284)	(0.282)
Government Assistance				0.416	0.442	0.425	0.666	0.690	0.680
(food/cash/otherwise)				(0.415)	(0.422)	(0.414)	(0.440)	(0.448)	(0.440)
Agri-extension				0.221	0.259	0.222	0.058	0.120	0.058
(Government/Private Sector)				(0.376)	(0.376)	(0.372)	(0.461)	(0.465)	(0.459)
North-East		0.185			0.173			-0.086	
		(0.200)			(0.260)			(0.290)	
North-West		0.500***			0.521**			0.371	
		(0.190)			(0.249)			(0.278)	
South-East		-0.860***			-0.612			-0.552	
		(0.315)			(0.379)			(0.403)	
South-South		0.068			0.057			0.103	
		(0.317)			(0.404)			(0.432)	
South-West		-0.175			0.050			-0.067	
		(0.303)			(0.398)			(0.438)	
Rural			0.509***			0.493**			0.535**
			(0.149)			(0.211)			(0.259)
Primary							-0.144	-0.090	-0.130
Education Complete							(0.253)	(0.256)	(0.250)
Secondary							0.172	0.197	0.181
Education Complete							(0.432)	(0.442)	(0.427)
University/Higher							0.184	0.061	0.179
Education Complete							(0.773)	(0.780)	(0.778)
Constant	-0.287*	-0.975***	-0.741***	-2.542	-3.273	-2.801	-1.296	-1.717	-1.632
	(0.168)	(0.336)	(0.208)	(2.216)	(2.251)	(2.228)	(2.604)	(2.658)	(2.637)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.000	0.000	0.000	0.022	0.023	0.009	0.028	0.037	0.015
Panel Level sd.	0.008	0.017	0.009	0.274	0.279	0.175	0.310	0.354	0.220

Chi-Squared	49.47	82.22	57.26	122.13	139.63	123.64	109.17	122.34	110.02

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

C.4 Underweight and Three Year Lagged Precipitation

Table C4: Logit Regressions - Three Year Lagged Precipitation and Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	-0.019*	-0.019*	-0.021*	-0.022*	-0.020	-0.022*	-0.024	-0.021	-0.024
Monthly Precipitation (mm)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.016)	(0.015)	(0.016)
Distance to Closest				-0.110	-0.209	-0.126	-0.134	-0.188	-0.152
Water Source (km)				(0.355)	(0.348)	(0.349)	(0.420)	(0.378)	(0.410)
Distance to				0.008	0.005	0.007	0.040	0.030	0.038
Closest Market (km)				(0.039)	(0.036)	(0.038)	(0.063)	(0.054)	(0.062)
Distance to				0.020***	0.019**	0.020***	0.025***	0.025***	0.025***
Closest City (km)				(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)
Number of People				-0.327***	-0.320***	-0.328***	-0.324***	-0.316***	-0.324***
in Household				(0.082)	(0.081)	(0.082)	(0.098)	(0.097)	(0.098)
Log of Education				-0.024	-0.023	-0.025	-0.044	-0.041	-0.045
Expenditure				(0.037)	(0.037)	(0.037)	(0.043)	(0.042)	(0.043)
Household Asset				-0.019	-0.018	-0.021	-0.051	-0.050	-0.055
Index				(0.087)	(0.088)	(0.087)	(0.104)	(0.104)	(0.104)
Log of Consumption				-0.544**	-0.532**	-0.548***	-0.559**	-0.543**	-0.565**
per Capita				(0.213)	(0.210)	(0.212)	(0.247)	(0.241)	(0.246)
Number of Meals				0.024	0.020	0.023	0.057	0.052	0.055
to Children				(0.061)	(0.061)	(0.061)	(0.079)	(0.077)	(0.080)
Restricted Meals				0.049	0.043	0.048	0.097	0.088	0.097
so Children can Eat				(0.106)	(0.105)	(0.106)	(0.110)	(0.109)	(0.110)
Number of				0.574***	0.562***	0.569***	0.746***	0.724***	0.746***
Production Shocks				(0.199)	(0.198)	(0.197)	(0.223)	(0.220)	(0.221)
Number of Market				0.241	0.229	0.240	0.351	0.338	0.345
Shocks				(0.184)	(0.182)	(0.183)	(0.214)	(0.212)	(0.213)
Tropical				-0.002	-0.002	-0.001	0.006	0.006	0.007

Livestock Units		(0.033)	(0.027)	(0.034)	(0.045)	(0.045)	(0.045)
Log of Plot Size		-0.069	-0.071	-0.069	-0.037	-0.040	-0.037
of All Households		(0.044)	(0.044)	(0.043)	(0.054)	(0.053)	(0.053)
Soil Workability		-1.793	-1.848	-1.740	-1.169	-1.136	-1.105
(mean)		(1.584)	(1.649)	(1.546)	(1.528)	(1.691)	(1.486)
Soil Nutrient		1.532	1.751	1.515	0.972	1.115	0.926
Availability (mean)		(2.068)	(2.130)	(2.015)	(2.064)	(2.254)	(2.007)
Age in Months		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of		0.421	0.446	0.408	1.112	1.203	1.083
Household Head		(1.050)	(1.105)	(1.039)	(1.254)	(1.312)	(1.243)
Gender		-1.778	-1.703	-1.772	-1.983	-1.903	-1.970
		(1.699)	(1.698)	(1.726)	(2.021)	(2.053)	(2.062)
Borrow from Microfinance/		0.798	0.824	0.797	1.087**	1.109**	1.092**
Credit Associations/Bank		(0.524)	(0.543)	(0.524)	(0.537)	(0.562)	(0.534)
Borrow from Friends/		0.088	0.090	0.093	-0.094	-0.093	-0.091
Relatives/Money Lenders		(0.224)	(0.223)	(0.223)	(0.252)	(0.248)	(0.251)
Borrow Food, or		-0.500	-0.490	-0.502	-0.649*	-0.638*	-0.645*
Rely on Friend/Relative?		(0.338)	(0.339)	(0.337)	(0.378)	(0.379)	(0.378)
Is there a Market		0.001	-0.008	-0.001	0.065	0.056	0.059
in the Community?		(0.226)	(0.226)	(0.225)	(0.267)	(0.266)	(0.266)
Does HH have		0.219	0.219	0.223	0.247	0.239	0.253
Electricity in Dwelling?		(0.359)	(0.355)	(0.356)	(0.413)	(0.408)	(0.409)
Has Non-Farm		-0.024	-0.042	-0.031	-0.382	-0.421	-0.378
Enterprise		(0.250)	(0.249)	(0.250)	(0.316)	(0.315)	(0.315)
Government Assistance		-0.256	-0.216	-0.253	-0.509	-0.482	-0.506
(food/cash/otherwise)		(0.653)	(0.648)	(0.652)	(0.728)	(0.721)	(0.727)
Agri-extension		-0.599	-0.608	-0.585	-0.842	-0.843	-0.827
(Government/Private Sector)		(0.448)	(0.447)	(0.446)	(0.543)	(0.548)	(0.542)
North-East	0.051		-0.170			-0.332	
	(0.249)		(0.303)			(0.339)	
North-West	0.371		0.033			-0.182	
	(0.241)		(0.300)			(0.338)	

South-East		-0.477			-0.142			-0.211	
		(0.379)			(0.462)			(0.497)	
South-South		0.238			0.340			0.421	
		(0.425)			(0.484)			(0.512)	
South-West		0.265			0.698*			0.669	
		(0.332)			(0.410)			(0.434)	
Rural			0.388**			0.299			0.310
			(0.186)			(0.275)			(0.312)
Primary							-0.153	-0.174	-0.155
Education Complete							(0.278)	(0.281)	(0.277)
Secondary							-0.548	-0.567	-0.549
Education Complete							(0.513)	(0.521)	(0.511)
University/Higher							0.121	0.085	0.083
Education Complete							(0.865)	(0.869)	(0.877)
Constant	-1.283***	-1.653***	-1.627***	-1.289	-1.278	-1.548	-2.648	-2.223	-2.924
	(0.211)	(0.448)	(0.255)	(2.635)	(2.641)	(2.639)	(2.998)	(2.957)	(3.008)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.115	0.112	0.107	0.085	0.077	0.078	0.083	0.064	0.075
Panel Level sd.	0.655	0.643	0.628	0.554	0.524	0.528	0.546	0.475	0.517
Chi-Squared	28.40	40.93	30.34	127.22	130.72	128.86	116.44	122.16	116.81

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

C.5 Stunting and Climate Variables

Table C5: Logit Regressions - Climate Variables and Stunting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	2.414***	2.305***	2.387***	3.214***	3.130***	3.194***	3.394***	3.344***	3.388***
Survey Temperature	(0.544)	(0.526)	(0.535)	(0.510)	(0.497)	(0.512)	(0.620)	(0.603)	(0.621)
Three Year Lagged	0.575***	0.533***	0.562***	0.688***	0.657***	0.679***	0.755***	0.717***	0.750***

Monthly Precipitation (mm)	(0.184)	(0.177)	(0.181)	(0.176)	(0.170)	(0.176)	(0.212)	(0.206)	(0.212)
Temperature × Precipitation	-0.017***	-0.016***	-0.017***	-0.021***	-0.020***	-0.021***	-0.023***	-0.022***	-0.023***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Distance to Closest Water Source (km)				-0.443	-0.443	-0.448	-0.328	-0.391	-0.344
				(0.721)	(0.671)	(0.691)	(0.609)	(0.584)	(0.572)
Distance to Closest Market (km)				-0.014	-0.016	-0.014	-0.003	-0.001	-0.003
				(0.032)	(0.033)	(0.031)	(0.044)	(0.046)	(0.043)
Distance to Closest City (km)				0.007	0.006	0.007	0.009	0.008	0.009
				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Number of People in Household				0.031	0.044	0.029	-0.003	0.018	-0.005
				(0.069)	(0.069)	(0.069)	(0.084)	(0.084)	(0.084)
Log of Education Expenditure				-0.019	-0.021	-0.019	-0.016	-0.017	-0.017
				(0.033)	(0.033)	(0.033)	(0.036)	(0.036)	(0.036)
Household Asset Index				0.223***	0.223***	0.218***	0.258***	0.261***	0.255***
				(0.079)	(0.080)	(0.080)	(0.091)	(0.091)	(0.091)
Log of Consumption per Capita				0.010	0.022	-0.001	-0.030	-0.018	-0.045
				(0.175)	(0.175)	(0.174)	(0.203)	(0.204)	(0.201)
Number of Meals to Children				0.071	0.072	0.071	0.093	0.097	0.089
				(0.057)	(0.058)	(0.057)	(0.070)	(0.070)	(0.071)
Restricted Meals so Children can Eat				-0.038	-0.040	-0.039	-0.080	-0.092	-0.084
				(0.106)	(0.105)	(0.105)	(0.118)	(0.118)	(0.118)
Number of Production Shocks				0.162	0.154	0.167	0.183	0.144	0.196
				(0.195)	(0.198)	(0.194)	(0.217)	(0.222)	(0.216)
Number of Market Shocks				-0.086	-0.088	-0.089	-0.026	-0.031	-0.033
				(0.164)	(0.164)	(0.163)	(0.190)	(0.191)	(0.189)
Tropical Livestock Units				0.097**	0.099**	0.098**	0.133**	0.139**	0.135**
				(0.040)	(0.040)	(0.040)	(0.055)	(0.054)	(0.055)
Log of Plot Size of All Households				-0.067*	-0.067*	-0.067*	-0.049	-0.051	-0.050
				(0.041)	(0.041)	(0.040)	(0.052)	(0.052)	(0.050)
Soil Workability (mean)				-3.432	-3.517	-3.446	-0.263	-0.695	-0.373
				(2.832)	(2.726)	(2.772)	(3.909)	(3.747)	(3.744)
Soil Nutrient Availability (mean)				-0.498	-0.274	-0.362	-4.812	-4.158	-4.584
				(3.093)	(3.070)	(2.990)	(5.247)	(5.041)	(5.028)

Age in Months		0.008*	0.008	0.008*	0.005	0.005	0.005
		(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Gender of Household Head		0.142	0.133	0.129	0.523	0.506	0.495
		(0.913)	(0.925)	(0.906)	(1.073)	(1.097)	(1.070)
Gender		0.840	0.746	0.889	1.129	1.024	1.186
		(1.575)	(1.602)	(1.501)	(1.592)	(1.625)	(1.521)
Borrow from Microfinance/ Credit Associations/Bank		-0.013	0.003	-0.025	0.202	0.241	0.190
		(0.451)	(0.454)	(0.457)	(0.509)	(0.518)	(0.518)
Borrow from Friends/ Relatives/Money Lenders		-0.167	-0.172	-0.157	-0.166	-0.179	-0.154
		(0.193)	(0.194)	(0.192)	(0.231)	(0.235)	(0.230)
Borrow Food, or Rely on Friend/Relative?		-0.024	-0.008	-0.023	-0.346	-0.336	-0.341
		(0.315)	(0.318)	(0.316)	(0.375)	(0.384)	(0.376)
Is there a Market in the Community?		-0.104	-0.137	-0.099	-0.083	-0.095	-0.082
		(0.208)	(0.210)	(0.208)	(0.235)	(0.237)	(0.237)
Does HH have Electricity in Dwelling?		0.075	0.098	0.078	0.117	0.132	0.123
		(0.334)	(0.335)	(0.333)	(0.391)	(0.390)	(0.391)
Has Non-Farm Enterprise		0.062	0.063	0.045	0.150	0.122	0.143
		(0.244)	(0.243)	(0.244)	(0.311)	(0.311)	(0.311)
Government Assistance (food/cash/otherwise)		0.532	0.535	0.543	0.779*	0.784*	0.798*
		(0.419)	(0.422)	(0.417)	(0.463)	(0.467)	(0.461)
Agri-extension (Government/Private Sector)		0.233	0.249	0.233	0.173	0.205	0.177
		(0.409)	(0.410)	(0.407)	(0.515)	(0.521)	(0.515)
North-East	0.073		0.099			-0.250	
	(0.217)		(0.279)			(0.321)	
North-West	0.351		0.426			0.284	
	(0.214)		(0.276)			(0.315)	
South-East	-1.017***		-0.691*			-0.672	
	(0.334)		(0.408)			(0.437)	
South-South	-0.253		-0.197			-0.232	
	(0.397)		(0.492)			(0.522)	
South-West	-0.142		0.113			-0.005	
	(0.323)		(0.423)			(0.470)	

Rural			0.518***			0.463**			0.539*
			(0.159)			(0.225)			(0.282)
Primary							-0.214	-0.174	-0.199
Education Complete							(0.270)	(0.274)	(0.269)
Secondary							0.093	0.104	0.104
Education Complete							(0.463)	(0.476)	(0.459)
University/Higher							-0.095	-0.229	-0.095
Education Complete							(0.801)	(0.814)	(0.803)
Constant	-9.060***	-8.419**	-9.338***	-12.677***	-12.160**	-12.378***	-14.251***	-14.461**	-14.307***
	(3.135)	(3.641)	(3.085)	(4.358)	(4.762)	(4.376)	(5.182)	(5.625)	(5.196)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.053	0.044	0.041	0.080	0.079	0.073	0.109	0.111	0.103
Panel Level sd.	0.427	0.391	0.374	0.536	0.531	0.509	0.635	0.641	0.615
Chi-Squared	87.78	101.60	97.88	155.77	164.97	157.55	121.04	130.08	121.14

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

C.6 Underweight and Climate Variables

Table C6: Logit Regressions - Climate Variables and Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	1.070**	1.081**	1.102**	1.805***	1.825***	1.794***	1.941***	1.984***	1.929***
Survey Temperature	(0.465)	(0.456)	(0.456)	(0.580)	(0.573)	(0.580)	(0.706)	(0.695)	(0.708)
Three Year Lagged	-0.201	-0.192	-0.185	-0.103	-0.095	-0.106	-0.160	-0.156	-0.162
Monthly Precipitation (mm)	(0.179)	(0.177)	(0.175)	(0.220)	(0.220)	(0.220)	(0.265)	(0.265)	(0.266)
Temperature ×	0.006	0.006	0.006	0.003	0.003	0.003	0.005	0.005	0.005
Precipitation	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Distance to Closest				-0.040	-0.166	-0.049	0.031	-0.059	0.019
Water Source (km)				(0.412)	(0.400)	(0.405)	(0.503)	(0.454)	(0.493)
Distance to				0.022	0.018	0.021	0.038	0.024	0.037

Closest Market (km)	(0.044)	(0.038)	(0.043)	(0.065)	(0.051)	(0.063)
Distance to	0.014*	0.014*	0.014*	0.021**	0.021**	0.021**
Closest City (km)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Number of People	-0.233***	-0.225***	-0.234***	-0.229**	-0.215**	-0.229**
in Household	(0.082)	(0.082)	(0.082)	(0.104)	(0.103)	(0.104)
Log of Education	-0.033	-0.032	-0.033	-0.048	-0.044	-0.049
Expenditure	(0.038)	(0.038)	(0.038)	(0.046)	(0.044)	(0.046)
Household Asset	0.031	0.035	0.031	-0.013	-0.011	-0.014
Index	(0.088)	(0.089)	(0.088)	(0.108)	(0.110)	(0.108)
Log of Consumption	-0.494**	-0.483**	-0.496**	-0.531**	-0.508**	-0.534**
per Capita	(0.222)	(0.218)	(0.221)	(0.259)	(0.252)	(0.258)
Number of Meals	0.121*	0.121*	0.120*	0.167*	0.167**	0.166*
to Children	(0.063)	(0.062)	(0.062)	(0.087)	(0.085)	(0.088)
Restricted Meals	0.078	0.080	0.077	0.124	0.123	0.124
so Children can Eat	(0.114)	(0.114)	(0.115)	(0.121)	(0.121)	(0.120)
Number of	0.695***	0.673***	0.688***	0.849***	0.806***	0.848***
Production Shocks	(0.213)	(0.212)	(0.212)	(0.246)	(0.243)	(0.245)
Number of Market	0.205	0.196	0.205	0.367	0.350	0.362
Shocks	(0.201)	(0.200)	(0.201)	(0.242)	(0.240)	(0.242)
Tropical	-0.005	-0.004	-0.005	0.010	0.011	0.010
Livestock Units	(0.030)	(0.025)	(0.032)	(0.050)	(0.050)	(0.050)
Log of Plot Size	-0.088**	-0.090**	-0.087**	-0.054	-0.061	-0.054
of All Households	(0.044)	(0.044)	(0.044)	(0.057)	(0.058)	(0.057)
Soil Workability	-2.137	-2.216	-2.129	-1.333	-1.468	-1.311
(mean)	(2.488)	(2.565)	(2.414)	(2.980)	(3.310)	(2.871)
Soil Nutrient	0.108	0.269	0.167	-0.697	-0.471	-0.669
Availability (mean)	(3.333)	(3.441)	(3.228)	(4.048)	(4.487)	(3.899)
Age in Months	0.017***	0.017***	0.017***	0.018***	0.017***	0.018***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of	0.407	0.420	0.398	1.050	1.170	1.027
Household Head	(1.092)	(1.139)	(1.080)	(1.260)	(1.317)	(1.249)
Gender	-2.454	-2.359	-2.469	-2.682	-2.506	-2.685
	(1.498)	(1.496)	(1.511)	(1.996)	(2.041)	(2.021)

Borrow from Microfinance/			0.591	0.623	0.583	0.938	0.944	0.937
Credit Associations/Bank			(0.572)	(0.591)	(0.574)	(0.581)	(0.607)	(0.581)
Borrow from Friends/			0.081	0.075	0.083	-0.206	-0.203	-0.206
Relatives/Money Lenders			(0.235)	(0.235)	(0.234)	(0.280)	(0.279)	(0.279)
Borrow Food, or			-0.676*	-0.685*	-0.675*	-0.827**	-0.838**	-0.826**
Rely on Friend/Relative?			(0.349)	(0.352)	(0.349)	(0.393)	(0.395)	(0.393)
Is there a Market			0.163	0.142	0.161	0.240	0.203	0.235
in the Community?			(0.238)	(0.239)	(0.238)	(0.290)	(0.291)	(0.289)
Does HH have			0.303	0.308	0.299	0.425	0.426	0.422
Electricity in Dwelling?			(0.359)	(0.356)	(0.356)	(0.420)	(0.417)	(0.418)
Has Non-Farm			0.380	0.358	0.373	0.027	-0.027	0.030
Enterprise			(0.263)	(0.263)	(0.264)	(0.335)	(0.333)	(0.335)
Government Assistance			0.172	0.192	0.186	-0.123	-0.113	-0.109
(food/cash/otherwise)			(0.710)	(0.712)	(0.711)	(0.842)	(0.840)	(0.844)
Agri-extension			-0.651	-0.684	-0.638	-0.924	-0.950	-0.908
(Government/Private Sector)			(0.488)	(0.491)	(0.489)	(0.590)	(0.596)	(0.590)
North-East	-0.057			-0.309			-0.628	
	(0.275)			(0.330)			(0.385)	
North-West	0.260			-0.098			-0.363	
	(0.272)			(0.328)			(0.380)	
South-East	-0.540			-0.200			-0.339	
	(0.423)			(0.499)			(0.542)	
South-South	0.110			0.149			0.167	
	(0.535)			(0.574)			(0.607)	
South-West	0.361			0.743			0.821*	
	(0.378)			(0.453)			(0.494)	
Rural		0.394**			0.257			0.271
		(0.198)			(0.288)			(0.335)
Primary						-0.288	-0.318	-0.291
Education Complete						(0.278)	(0.281)	(0.278)
Secondary						-0.831	-0.874*	-0.830
Education Complete						(0.518)	(0.527)	(0.517)

University/Higher Education Complete							-0.119	-0.160	-0.153
							(0.891)	(0.895)	(0.905)
Constant	-6.346*	-5.363	-6.733*	-6.421	-6.837	-6.409	-9.855	-11.301*	-10.017*
	(3.803)	(4.582)	(3.767)	(5.356)	(5.828)	(5.345)	(6.068)	(6.418)	(6.040)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.186	0.181	0.179	0.140	0.131	0.136	0.185	0.160	0.181
Panel Level sd.	0.866	0.853	0.847	0.730	0.703	0.719	0.864	0.793	0.853
Chi-Squared	87.91	94.56	89.52	164.37	166.81	166.44	136.49	143.54	136.77

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Online Appendix
Climate Change and Child Health: A Nigerian Perspective*

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Abstract

The detrimental effects of climate change are causing it to be an important topic of economic research and policy decisions. The negative impact of a changing climate on the health outcomes of children are especially concerning. We investigate the impact of a changing climate, in terms of changes in the monthly maximum average near-surface temperature ($^{\circ}C$) and total monthly precipitation (mm), on the nutritional status of children in Nigeria. This is done by combining LSMS-ISA survey data with high-resolution gridded climate data. Malnutrition in children are seen in the form of stunting, underweight and wasting. The results indicate that climate change is correlated with a higher probability of malnourished children in Nigeria. This paper supports the notion of the need for climate-friendly policies to mitigate the long-term effect of malnourishment.

Key words: Climate Change, Malnutrition, Stunting, Underweight, Nigeria, Spatial Analysis
JEL Classification: Q54, I12, I15

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1 Lagged Temperature and Wasting

Table 1: Logit Regressions - Lagged Temperature

	(1) Wasted	(2) Wasted	(3) Wasted	(4) Wasted	(5) Wasted	(6) Wasted	(7) Wasted	(8) Wasted	(9) Wasted
Year Preceding	0.545***	0.592***	0.548***	0.387	0.404	0.397	0.740**	0.751**	0.753**
Survey Temperature	(0.206)	(0.216)	(0.206)	(0.299)	(0.312)	(0.300)	(0.352)	(0.371)	(0.353)
Primary							-0.255	-0.288	-0.254
Education Complete							(0.371)	(0.373)	(0.370)
Secondary							-0.619	-0.668	-0.638
Education Complete							(0.635)	(0.642)	(0.636)
University/Higher							-1.715	-1.426	-1.787*
Education Complete							(1.065)	(1.070)	(1.078)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.027	0.000	0.026	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.301	0.007	0.296	0.006	0.003	0.006	0.005	0.004	0.004
Chi-Squared	7.44	28.09	7.94	106.74	122.76	108.29	103.42	118.25	105.88

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: Logit Regressions - Lagged Temperature and Wasting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.545***	0.592***	0.548***	0.387	0.404	0.397	0.740**	0.751**	0.753**
Survey Temperature	(0.206)	(0.216)	(0.206)	(0.299)	(0.312)	(0.300)	(0.352)	(0.371)	(0.353)
Distance to Closest				-0.998**	-0.920**	-1.004***	-1.174***	-1.170**	-1.185***
Water Source (km)				(0.389)	(0.426)	(0.379)	(0.430)	(0.455)	(0.416)
Distance to				-0.056	-0.058	-0.054	-0.052	-0.061	-0.050
Closest Market (km)				(0.073)	(0.079)	(0.071)	(0.104)	(0.107)	(0.100)
Distance to				0.009	0.010	0.009	0.008	0.010	0.008
Closest City (km)				(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)
Number of People				0.129	0.129	0.130	0.217**	0.197*	0.217*
in Household				(0.098)	(0.101)	(0.099)	(0.109)	(0.114)	(0.111)
Log of Education				0.001	0.005	0.000	-0.010	-0.004	-0.012
Expenditure				(0.039)	(0.039)	(0.040)	(0.048)	(0.047)	(0.048)
Household Asset				0.043	0.046	0.040	0.047	0.057	0.039
Index				(0.097)	(0.101)	(0.098)	(0.113)	(0.121)	(0.114)

Log of Consumption	0.192	0.199	0.187	0.418	0.433	0.404
per Capita	(0.245)	(0.249)	(0.245)	(0.283)	(0.284)	(0.282)
Number of Meals	-0.083	-0.083	-0.084	-0.085	-0.094	-0.089
to Children	(0.091)	(0.097)	(0.092)	(0.105)	(0.114)	(0.107)
Restricted Meals	0.209	0.210	0.212*	0.231	0.235	0.234
so Children can Eat	(0.128)	(0.128)	(0.129)	(0.142)	(0.144)	(0.143)
Number of	-0.360	-0.364	-0.347	-0.117	-0.123	-0.100
Production Shocks	(0.286)	(0.289)	(0.286)	(0.301)	(0.310)	(0.301)
Number of Market	-0.178	-0.128	-0.173	-0.497*	-0.416	-0.492*
Shocks	(0.232)	(0.238)	(0.232)	(0.266)	(0.280)	(0.267)
Tropical	0.056***	0.050***	0.055***	0.067**	0.054**	0.067**
Livestock Units	(0.018)	(0.017)	(0.018)	(0.027)	(0.026)	(0.027)
Log of Plot Size	0.077	0.072	0.076	0.116*	0.108*	0.115*
of All Households	(0.055)	(0.055)	(0.054)	(0.064)	(0.065)	(0.063)
Soil Workability	2.387	2.776	2.234	2.858	4.265**	2.630
(mean)	(1.656)	(1.767)	(1.624)	(1.977)	(2.110)	(1.946)
Soil Nutrient	-8.289	-9.060	-7.889	-17.966**	-22.399**	-16.924**
Availability (mean)	(6.883)	(8.299)	(6.463)	(8.418)	(9.097)	(8.328)
Age in Months	-0.017***	-0.019***	-0.017***	-0.018***	-0.019***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of	-0.754	-0.718	-0.759	-0.940	-0.831	-0.942
Household Head	(1.254)	(1.197)	(1.246)	(1.414)	(1.336)	(1.417)
Gender	-4.214***	-4.745***	-4.294***	-3.284*	-3.808*	-3.412*
	(1.547)	(1.680)	(1.530)	(1.788)	(2.001)	(1.783)
Borrow from Microfinance/	-0.771*	-0.798	-0.766*	-0.541	-0.580	-0.520
Credit Associations/Bank	(0.463)	(0.492)	(0.464)	(0.577)	(0.624)	(0.578)
Borrow from Friends/	-0.030	0.017	-0.026	-0.270	-0.205	-0.267
Relatives/Money Lenders	(0.246)	(0.248)	(0.246)	(0.273)	(0.277)	(0.273)
Borrow Food, or	0.490	0.523	0.478	0.523	0.510	0.511
Rely on Friend/Relative?	(0.360)	(0.367)	(0.361)	(0.413)	(0.420)	(0.413)
Is there a Market	0.189	0.212	0.179	0.317	0.332	0.298
in the Community?	(0.255)	(0.254)	(0.254)	(0.283)	(0.280)	(0.281)
Does HH have	0.568	0.547	0.573	0.791	0.717	0.798
Electricity in Dwelling?	(0.394)	(0.382)	(0.392)	(0.498)	(0.484)	(0.493)
Has Non-Farm	0.093	0.041	0.084	0.189	0.198	0.196
Enterprise	(0.270)	(0.273)	(0.270)	(0.340)	(0.345)	(0.341)
Government Assistance	-0.303	-0.370	-0.312	-0.487	-0.592	-0.475

(food/cash/otherwise)				(0.650)	(0.695)	(0.654)	(0.732)	(0.799)	(0.734)
Agri-extension				0.357	0.261	0.368	0.145	-0.121	0.175
(Government/Private Sector)				(0.697)	(0.725)	(0.697)	(0.888)	(0.951)	(0.891)
North-East		-0.554**			-0.551*			-0.618*	
		(0.250)			(0.290)			(0.329)	
North-West		-1.141***			-1.364***			-1.674***	
		(0.268)			(0.291)			(0.360)	
South-East		-0.619**			-0.732*			-0.498	
		(0.287)			(0.383)			(0.423)	
South-South		0.103			0.117			0.379	
		(0.240)			(0.330)			(0.368)	
South-West		-0.225			-0.505			-0.205	
		(0.305)			(0.436)			(0.469)	
Rural			0.132			0.337			0.449
			(0.175)			(0.253)			(0.307)
Primary							-0.255	-0.288	-0.254
Education Complete							(0.371)	(0.373)	(0.370)
Secondary							-0.619	-0.668	-0.638
Education Complete							(0.635)	(0.642)	(0.636)
University/Higher							-1.715	-1.426	-1.787*
Education Complete							(1.065)	(1.070)	(1.078)
Constant	-1.429	-5.976***	-1.425	2.448	1.062	1.947	-0.824	-3.741	-1.684
	(1.192)	(1.871)	(1.193)	(3.061)	(3.529)	(3.065)	(3.807)	(4.464)	(3.860)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.027	0.000	0.026	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.301	0.007	0.296	0.006	0.003	0.006	0.005	0.004	0.004
Chi-Squared	7.44	28.09	7.94	106.74	122.76	108.29	103.42	118.25	105.88

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3: Marginal Effect - Lagged Temperature

Panel A: Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.044***	0.046	0.044***	0.026	0.025	0.026	0.044	0.041	0.045
Survey Temperature	(0.016)	(3.222)	(0.016)	(0.227)	(0.594)	(0.233)	(0.658)	(1.411)	(0.899)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Panel B: Marginal Effect of Lagged Temperature on Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.044***	0.049	0.041***	0.024	0.023	0.021	0.038	0.033	0.033
	(0.017)	(3.244)	(0.016)	(0.239)	(0.625)	(2.472)	(0.701)	(0.735)	(0.976)
Rural	0.044***	0.045	0.045***	0.026	0.026	0.028	0.046	0.043	0.049
	(0.016)	(3.210)	(0.017)	(0.223)	(0.583)	(0.440)	(1.276)	(1.377)	(1.686)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

2 Three Year Lagged Precipitation and Wasting

Table 4: Logit Regressions - Three Year Lagged Precipitation

	(1) Wasted	(2) Wasted	(3) Wasted	(4) Wasted	(5) Wasted	(6) Wasted	(7) Wasted	(8) Wasted	(9) Wasted
Three Years	0.018	0.018	0.018	0.012	0.013	0.012	0.019	0.021	0.018
before Survey Monthly Precipitation (mm)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)	(0.014)	(0.016)	(0.016)	(0.016)
Primary							-0.236	-0.313	-0.238
Education Complete							(0.371)	(0.373)	(0.370)
Secondary							-0.647	-0.669	-0.662
Education Complete							(0.650)	(0.644)	(0.651)
University/Higher							-1.603	-1.339	-1.674
Education Complete							(1.075)	(1.071)	(1.090)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.020	0.000	0.020	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.262	0.007	0.256	0.006	0.004	0.006	0.005	0.004	0.005
Chi-Squared	4.59	23.55	5.28	106.19	123.51	107.27	100.26	120.16	101.58

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Logit Regressions - Three Year Lagged Precipitation and Wasting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	0.018	0.018	0.018	0.012	0.013	0.012	0.019	0.021	0.018
Monthly Precipitation (mm)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)	(0.014)	(0.016)	(0.016)	(0.016)
Distance to Closest				-1.027***	-0.940**	-1.029***	-1.211***	-1.154***	-1.214***
Water Source (km)				(0.356)	(0.383)	(0.350)	(0.391)	(0.413)	(0.383)
Distance to				-0.047	-0.046	-0.046	-0.029	-0.034	-0.028
Closest Market (km)				(0.069)	(0.068)	(0.067)	(0.088)	(0.092)	(0.086)
Distance to				0.010	0.011	0.010	0.011	0.013	0.011
Closest City (km)				(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)
Number of People				0.092	0.092	0.092	0.156	0.133	0.155
in Household				(0.096)	(0.099)	(0.097)	(0.108)	(0.112)	(0.109)
Log of Education				-0.003	0.003	-0.004	-0.017	-0.006	-0.018
Expenditure				(0.039)	(0.040)	(0.040)	(0.048)	(0.048)	(0.048)
Household Asset				0.030	0.028	0.027	0.027	0.027	0.020
Index				(0.097)	(0.102)	(0.098)	(0.114)	(0.123)	(0.115)
Log of Consumption				0.168	0.168	0.163	0.350	0.363	0.339
per Capita				(0.244)	(0.245)	(0.243)	(0.277)	(0.276)	(0.277)
Number of Meals				-0.106	-0.101	-0.106	-0.130	-0.122	-0.133
to Children				(0.091)	(0.097)	(0.092)	(0.106)	(0.114)	(0.107)
Restricted Meals				0.218*	0.211	0.219*	0.239*	0.234	0.241*
so Children can Eat				(0.130)	(0.130)	(0.131)	(0.146)	(0.146)	(0.146)
Number of				-0.370	-0.383	-0.361	-0.159	-0.165	-0.147
Production Shocks				(0.280)	(0.279)	(0.280)	(0.297)	(0.297)	(0.297)
Number of Market				-0.167	-0.102	-0.163	-0.470*	-0.374	-0.465*
Shocks				(0.234)	(0.237)	(0.234)	(0.269)	(0.280)	(0.269)
Tropical				0.054***	0.050***	0.053***	0.062**	0.052**	0.061**
Livestock Units				(0.017)	(0.017)	(0.017)	(0.025)	(0.025)	(0.025)
Log of Plot Size				0.078	0.073	0.077	0.122*	0.114*	0.121*
of All Households				(0.055)	(0.054)	(0.055)	(0.064)	(0.062)	(0.063)
Soil Workability				2.125	2.518	1.999	2.121	3.368	1.906
(mean)				(1.486)	(1.588)	(1.475)	(1.816)	(2.099)	(1.824)
Soil Nutrient				-7.243	-7.401	-6.952	-12.897*	-16.238**	-11.958
Availability (mean)				(5.114)	(6.053)	(4.811)	(7.389)	(8.118)	(7.357)
Age in Months				-0.019***	-0.021***	-0.019***	-0.022***	-0.023***	-0.022***
				(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of				-0.626	-0.597	-0.631	-0.648	-0.507	-0.649

Household Head			(1.260)	(1.218)	(1.253)	(1.466)	(1.437)	(1.465)
Gender			-4.347***	-5.011***	-4.406***	-3.609**	-4.300**	-3.690**
			(1.547)	(1.693)	(1.534)	(1.803)	(2.049)	(1.802)
Borrow from Microfinance/			-0.693	-0.721	-0.687	-0.395	-0.420	-0.380
Credit Associations/Bank			(0.462)	(0.491)	(0.463)	(0.579)	(0.620)	(0.578)
Borrow from Friends/			-0.030	0.013	-0.026	-0.280	-0.223	-0.277
Relatives/Money Lenders			(0.249)	(0.250)	(0.249)	(0.277)	(0.279)	(0.278)
Borrow Food, or			0.491	0.567	0.483	0.510	0.568	0.506
Rely on Friend/Relative?			(0.360)	(0.369)	(0.361)	(0.418)	(0.431)	(0.418)
Is there a Market			0.157	0.194	0.148	0.274	0.310	0.257
in the Community?			(0.253)	(0.252)	(0.252)	(0.278)	(0.279)	(0.277)
Does HH have			0.597	0.577	0.601	0.834*	0.751	0.844*
Electricity in Dwelling?			(0.393)	(0.386)	(0.392)	(0.499)	(0.496)	(0.497)
Has Non-Farm			-0.011	-0.021	-0.018	0.062	0.118	0.065
Enterprise			(0.255)	(0.263)	(0.255)	(0.333)	(0.344)	(0.333)
Government Assistance			-0.312	-0.333	-0.320	-0.468	-0.634	-0.471
(food/cash/otherwise)			(0.655)	(0.673)	(0.658)	(0.710)	(0.753)	(0.710)
Agri-extension			0.392	0.339	0.400	0.119	-0.063	0.144
(Government/Private Sector)			(0.698)	(0.716)	(0.698)	(0.879)	(0.921)	(0.880)
North-East	-0.371			-0.436			-0.440	
	(0.249)			(0.297)			(0.323)	
North-West	-0.957***			-1.318***			-1.621***	
	(0.256)			(0.302)			(0.360)	
South-East	-0.582*			-0.669			-0.408	
	(0.317)			(0.409)			(0.452)	
South-South	0.212			0.322			0.707	
	(0.370)			(0.418)			(0.440)	
South-West	-0.260			-0.496			-0.177	
	(0.309)			(0.433)			(0.454)	
Rural		0.127			0.254			0.341
		(0.175)			(0.250)			(0.304)
Primary						-0.236	-0.313	-0.238
Education Complete						(0.371)	(0.373)	(0.370)
Secondary						-0.647	-0.669	-0.662
Education Complete						(0.650)	(0.644)	(0.651)
University/Higher						-1.603	-1.339	-1.674
Education Complete						(1.075)	(1.071)	(1.090)

Constant	-2.574***	-1.602***	-2.681***	2.097	4.941*	1.869	0.225	3.041	-0.134
	(0.214)	(0.420)	(0.273)	(2.578)	(2.721)	(2.583)	(3.152)	(3.336)	(3.179)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.020	0.000	0.020	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.262	0.007	0.256	0.006	0.004	0.006	0.005	0.004	0.005
Chi-Squared	4.59	23.55	5.28	106.19	123.51	107.27	100.26	120.16	101.58

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6: Marginal Effect - Three Year Lagged Precipitation

Panel A: Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Three Year Lagged	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Monthly Precipitation (mm)	(0.001)	(0.056)	(0.001)	(0.011)	(0.027)	(0.010)	(0.021)	(0.030)	(0.021)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Panel B: Marginal Effect of Three Year Lagged Temperature on Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.057)	(0.001)	(0.010)	(0.024)	(0.031)	(0.018)	(0.024)	(0.015)
Rural	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.055)	(0.001)	(0.011)	(0.028)	(0.011)	(0.022)	(0.031)	(0.022)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

3 Climate Variables and Wasting

Table 7: Logit Regressions - Climate Variables

	(1) Wasted	(2) Wasted	(3) Wasted	(4) Wasted	(5) Wasted	(6) Wasted	(7) Wasted	(8) Wasted	(9) Wasted
Year Preceding Survey Temperature	0.553	0.544	0.561	0.253	0.169	0.239	0.804	0.685	0.815
	(0.460)	(0.458)	(0.468)	(0.654)	(0.658)	(0.658)	(0.724)	(0.720)	(0.731)
Three Year Lagged Monthly Precipitation (mm)	-0.064	-0.073	-0.062	-0.095	-0.121	-0.104	-0.050	-0.072	-0.049
	(0.177)	(0.183)	(0.179)	(0.243)	(0.251)	(0.245)	(0.256)	(0.266)	(0.258)
Temperature × Precipitation	0.003	0.003	0.003	0.003	0.004	0.004	0.003	0.003	0.003
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.023	0.003	0.028	0.004	0.004	0.002	0.004	0.002	0.004
Chi-Squared	26.18	44.49	26.70	114.87	128.92	115.16	114.11	130.10	114.61

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Logit Regressions - Climate Variables and Wasting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding Survey Temperature	0.553	0.544	0.561	0.253	0.169	0.239	0.804	0.685	0.815
	(0.460)	(0.458)	(0.468)	(0.654)	(0.658)	(0.658)	(0.724)	(0.720)	(0.731)
Three Year Lagged Monthly Precipitation (mm)	-0.064	-0.073	-0.062	-0.095	-0.121	-0.104	-0.050	-0.072	-0.049
	(0.177)	(0.183)	(0.179)	(0.243)	(0.251)	(0.245)	(0.256)	(0.266)	(0.258)
Temperature × Precipitation	0.003	0.003	0.003	0.003	0.004	0.004	0.003	0.003	0.003
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Distance to Closest Water Source (km)				-1.036***	-1.009**	-1.037***	-1.270***	-1.283***	-1.269***
				(0.387)	(0.424)	(0.379)	(0.439)	(0.456)	(0.429)
Distance to Closest Market (km)				-0.063	-0.065	-0.061	-0.059	-0.070	-0.058
				(0.079)	(0.078)	(0.077)	(0.102)	(0.106)	(0.099)
Distance to Closest City (km)				0.009	0.010	0.009	0.009	0.011	0.009
				(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Number of People in Household				0.144	0.143	0.145	0.241**	0.215*	0.239**
				(0.101)	(0.103)	(0.103)	(0.113)	(0.118)	(0.115)
Log of Education Expenditure				-0.007	-0.003	-0.008	-0.021	-0.012	-0.022
				(0.039)	(0.040)	(0.040)	(0.047)	(0.047)	(0.048)

Household Asset Index	0.053	0.049	0.050	0.057	0.056	0.050
	(0.098)	(0.103)	(0.099)	(0.115)	(0.125)	(0.116)
Log of Consumption per Capita	0.158	0.163	0.152	0.367	0.382	0.357
	(0.244)	(0.243)	(0.243)	(0.279)	(0.271)	(0.278)
Number of Meals to Children	-0.093	-0.088	-0.093	-0.105	-0.098	-0.106
	(0.091)	(0.097)	(0.092)	(0.109)	(0.116)	(0.110)
Restricted Meals so Children can Eat	0.223*	0.216*	0.225*	0.245*	0.238	0.248*
	(0.132)	(0.130)	(0.133)	(0.148)	(0.147)	(0.149)
Number of Production Shocks	-0.355	-0.354	-0.346	-0.122	-0.112	-0.111
	(0.288)	(0.290)	(0.288)	(0.302)	(0.308)	(0.302)
Number of Market Shocks	-0.197	-0.149	-0.193	-0.516*	-0.449	-0.510*
	(0.232)	(0.238)	(0.232)	(0.264)	(0.281)	(0.264)
Tropical Livestock Units	0.052***	0.049***	0.051***	0.062**	0.055**	0.061**
	(0.017)	(0.017)	(0.017)	(0.026)	(0.026)	(0.026)
Log of Plot Size of All Households	0.080	0.071	0.078	0.119*	0.106*	0.118*
	(0.057)	(0.055)	(0.056)	(0.065)	(0.063)	(0.064)
Soil Workability (mean)	2.372	3.038*	2.218	3.108	4.662**	2.898
	(1.672)	(1.788)	(1.652)	(2.005)	(2.215)	(1.995)
Soil Nutrient Availability (mean)	-9.674	-9.996	-9.273	-20.484**	-24.741***	-19.449**
	(6.909)	(7.987)	(6.597)	(8.765)	(9.458)	(8.741)
Age in Months	-0.017***	-0.018***	-0.017***	-0.017***	-0.018***	-0.017***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of Household Head	-0.672	-0.646	-0.679	-0.788	-0.672	-0.793
	(1.180)	(1.156)	(1.174)	(1.312)	(1.280)	(1.315)
Gender	-4.669***	-5.255***	-4.734***	-3.809**	-4.382**	-3.890**
	(1.671)	(1.824)	(1.674)	(1.885)	(2.184)	(1.911)
Borrow from Microfinance/ Credit Associations/Bank	-0.714	-0.755	-0.707	-0.428	-0.463	-0.410
	(0.487)	(0.515)	(0.490)	(0.619)	(0.656)	(0.621)
Borrow from Friends/ Relatives/Money Lenders	-0.015	0.030	-0.009	-0.271	-0.214	-0.267
	(0.251)	(0.251)	(0.251)	(0.280)	(0.282)	(0.280)
Borrow Food, or Rely on Friend/Relative?	0.444	0.520	0.437	0.417	0.486	0.409
	(0.371)	(0.377)	(0.373)	(0.431)	(0.437)	(0.431)
Is there a Market in the Community?	0.196	0.225	0.186	0.326	0.353	0.305
	(0.258)	(0.258)	(0.257)	(0.290)	(0.289)	(0.289)
Does HH have Electricity in Dwelling?	0.642	0.618	0.647	0.923*	0.844*	0.926*
	(0.397)	(0.389)	(0.396)	(0.505)	(0.503)	(0.502)
Has Non-Farm	0.071	0.050	0.064	0.166	0.186	0.172

Enterprise				(0.273)	(0.277)	(0.273)	(0.348)	(0.356)	(0.349)
Government Assistance				-0.204	-0.210	-0.206	-0.370	-0.475	-0.365
(food/cash/otherwise)				(0.654)	(0.684)	(0.655)	(0.747)	(0.790)	(0.747)
Agri-extension				0.358	0.315	0.369	0.109	-0.050	0.141
(Government/Private Sector)				(0.695)	(0.716)	(0.694)	(0.870)	(0.924)	(0.871)
North-East		-0.304			-0.307			-0.362	
		(0.255)			(0.303)			(0.335)	
North-West		-0.855***			-1.137***			-1.443***	
		(0.287)			(0.310)			(0.369)	
South-East		-0.428			-0.491			-0.211	
		(0.316)			(0.408)			(0.439)	
South-South		0.599			0.763*			1.152**	
		(0.393)			(0.445)			(0.457)	
South-West		-0.035			-0.294			0.086	
		(0.318)			(0.447)			(0.469)	
Rural			0.145			0.326			0.422
			(0.175)			(0.259)			(0.320)
Primary							-0.276	-0.350	-0.281
Education Complete							(0.384)	(0.388)	(0.383)
Secondary							-0.716	-0.739	-0.733
Education Complete							(0.669)	(0.670)	(0.670)
University/Higher							-1.652	-1.482	-1.732
Education Complete							(1.087)	(1.102)	(1.099)
Constant	8.648**	7.169	8.729**	12.353**	14.603***	12.458**	10.498*	12.730*	10.266*
	(4.038)	(4.615)	(4.054)	(5.098)	(5.578)	(5.102)	(5.944)	(6.513)	(5.952)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.023	0.003	0.028	0.004	0.004	0.002	0.004	0.002	0.004
Chi-Squared	26.18	44.49	26.70	114.87	128.92	115.16	114.11	130.10	114.61

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 9: Marginal Effects - Climate Variables

Panel A: Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.092	0.088	0.092***	0.055	0.052	0.057	0.090	0.080	0.091
Survey Temperature	(0.077)	(2.417)	(0.035)	(0.856)	(1.575)	(3.614)	(1.997)	(6.760)	(1.645)
Three Year Lagged	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.003	0.003
Monthly Precipitation (mm)	(0.008)	(0.073)	(0.002)	(0.031)	(0.063)	(0.131)	(0.110)	(0.189)	(0.045)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Panel B: Marginal Effects of Climate Variables on Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban (Temperature)	0.075*	0.079	0.068**	0.047	0.048	0.043	0.074	0.070	0.065
	(0.044)	(1.991)	(0.029)	(1.000)	(1.255)	(2.666)	(1.454)	(6.586)	(1.544)
Rural (Temperature)	0.070*	0.070	0.072***	0.049	0.048	0.051	0.082	0.078	0.086
	(0.037)	(2.509)	(0.027)	(1.223)	(1.465)	(2.413)	(1.823)	(6.700)	(1.383)
Urban (Precipitation)	0.002	0.002 0.002*	0.001	0.001	0.001	0.002	0.002	0.002	
	(0.004)	(0.102)	(0.001)	(0.023)	(0.031)	(0.101)	(0.060)	(0.260)	(0.055)
Rural (Precipitation)	0.002	0.002	0.003*	0.002	0.002	0.002	0.003	0.003	0.003
	(0.004)	(0.066)	(0.001)	(0.042)	(0.058)	(0.114)	(0.093)	(0.257)	(0.072)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

4 Lagged Precipitation, Stunting and Underweight

Table 10: Logit Regressions - Lagged Precipitation

Panel A: Stunted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding Survey Precipitation	0.020** (0.009)	0.020** (0.008)	0.020** (0.008)	0.020** (0.010)	0.018* (0.010)	0.020** (0.010)	0.026** (0.011)	0.024** (0.011)	0.026** (0.011)
Primary Education Complete							-0.155 (0.248)	-0.103 (0.252)	-0.143 (0.246)
Secondary Education Complete							0.090 (0.426)	0.112 (0.436)	0.096 (0.422)
University/Higher Education Complete							0.085 (0.763)	-0.043 (0.771)	0.078 (0.768)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.001	0.001	0.000	0.013	0.014	0.001	0.017	0.027	0.005
Panel Level sd.	0.064	0.044	0.006	0.205	0.213	0.055	0.241	0.303	0.135
Chi-Squared	50.75	82.83	58.72	117.95	136.22	119.59	104.49	117.47	105.95

Panel B: Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding Survey Precipitation	0.035*** (0.009)	0.033*** (0.009)	0.034*** (0.009)	0.035*** (0.012)	0.035*** (0.012)	0.035*** (0.012)	0.044*** (0.014)	0.044*** (0.014)	0.044*** (0.014)
Primary Education Complete							-0.184 (0.269)	-0.209 (0.273)	-0.187 (0.268)
Secondary Education Complete							-0.674 (0.495)	-0.700 (0.504)	-0.675 (0.493)
University/Higher Education Complete							-0.065 (0.851)	-0.078 (0.853)	-0.105 (0.862)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.116	0.110	0.108	0.071	0.063	0.064	0.057	0.037	0.049
Panel Level sd.	0.655	0.639	0.630	0.502	0.472	0.474	0.446	0.355	0.410
Chi-Squared	34.02	44.95	35.89	128.51	132.07	130.22	117.84	124.97	118.36

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Logit Regressions - Lagged Precipitation and Stunting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.020**	0.020**	0.020**	0.020**	0.018*	0.020**	0.026**	0.024**	0.026**
Survey Precipitation	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Distance to Closest				-0.279	-0.294	-0.287	-0.258	-0.311	-0.270
Water Source (km)				(0.373)	(0.371)	(0.347)	(0.382)	(0.381)	(0.354)
Distance to				-0.012	-0.016	-0.011	0.008	0.010	0.009
Closest Market (km)				(0.033)	(0.034)	(0.032)	(0.044)	(0.047)	(0.043)
Distance to				0.010	0.009	0.010	0.012*	0.012*	0.012*
Closest City (km)				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Number of People				-0.019	-0.006	-0.022	-0.033	-0.016	-0.035
in Household				(0.066)	(0.067)	(0.066)	(0.078)	(0.080)	(0.078)
Log of Education				-0.019	-0.021	-0.020	-0.021	-0.023	-0.021
Expenditure				(0.030)	(0.031)	(0.030)	(0.034)	(0.034)	(0.034)
Household Asset				0.185**	0.183**	0.179**	0.201**	0.200**	0.195**
Index				(0.076)	(0.076)	(0.076)	(0.086)	(0.087)	(0.086)
Log of Consumption				-0.104	-0.076	-0.116	-0.160	-0.124	-0.173
per Capita				(0.163)	(0.165)	(0.161)	(0.186)	(0.189)	(0.184)
Number of Meals				-0.047	-0.046	-0.048	-0.012	-0.009	-0.018
to Children				(0.056)	(0.056)	(0.056)	(0.068)	(0.069)	(0.069)
Restricted Meals				-0.045	-0.045	-0.046	-0.091	-0.104	-0.095
so Children can Eat				(0.098)	(0.097)	(0.098)	(0.108)	(0.107)	(0.108)
Number of				-0.012	-0.014	-0.003	0.020	-0.006	0.033
Production Shocks				(0.181)	(0.185)	(0.179)	(0.198)	(0.206)	(0.196)
Number of Market				-0.100	-0.099	-0.099	-0.081	-0.086	-0.083
Shocks				(0.157)	(0.159)	(0.156)	(0.179)	(0.183)	(0.178)
Tropical				0.082**	0.083**	0.083**	0.120**	0.126**	0.121**
Livestock Units				(0.039)	(0.039)	(0.039)	(0.050)	(0.050)	(0.050)
Log of Plot Size				-0.053	-0.053	-0.055	-0.039	-0.041	-0.041
of All Households				(0.038)	(0.038)	(0.037)	(0.047)	(0.047)	(0.046)
Soil Workability				-1.886	-2.099	-1.900	-0.249	-0.749	-0.235
(mean)				(1.525)	(1.364)	(1.584)	(1.506)	(1.470)	(1.419)
Soil Nutrient				2.320	2.727	2.274	0.851	1.511	0.838
Availability (mean)				(2.076)	(1.735)	(2.225)	(2.094)	(1.927)	(2.041)
Age in Months				-0.003	-0.004	-0.003	-0.004	-0.005	-0.004
				(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Gender of				0.295	0.267	0.287	0.731	0.669	0.714

Household Head			(0.821)	(0.831)	(0.816)	(0.907)	(0.932)	(0.904)
Gender			1.086	1.009	1.185	1.377	1.314	1.477
			(1.469)	(1.459)	(1.421)	(1.547)	(1.560)	(1.506)
Borrow from Microfinance/			0.098	0.113	0.101	0.240	0.293	0.243
Credit Associations/Bank			(0.429)	(0.428)	(0.429)	(0.495)	(0.506)	(0.495)
Borrow from Friends/			-0.239	-0.242	-0.225	-0.246	-0.259	-0.231
Relatives/Money Lenders			(0.183)	(0.186)	(0.182)	(0.213)	(0.217)	(0.211)
Borrow Food, or			0.099	0.111	0.098	-0.282	-0.267	-0.277
Rely on Friend/Relative?			(0.283)	(0.285)	(0.283)	(0.332)	(0.339)	(0.332)
Is there a Market			-0.177	-0.214	-0.172	-0.178	-0.193	-0.178
in the Community?			(0.189)	(0.192)	(0.188)	(0.213)	(0.216)	(0.213)
Does HH have			0.096	0.131	0.104	0.114	0.139	0.128
Electricity in Dwelling?			(0.318)	(0.317)	(0.315)	(0.361)	(0.360)	(0.359)
Has Non-Farm			-0.276	-0.287	-0.289	-0.131	-0.185	-0.137
Enterprise			(0.221)	(0.219)	(0.221)	(0.278)	(0.280)	(0.278)
Government Assistance			0.422	0.449	0.432	0.695	0.723	0.707
(food/cash/otherwise)			(0.412)	(0.420)	(0.410)	(0.441)	(0.452)	(0.440)
Agri-extension			0.221	0.257	0.222	0.027	0.088	0.027
(Government/Private Sector)			(0.370)	(0.370)	(0.366)	(0.452)	(0.455)	(0.450)
North-East	0.181			0.197			-0.038	
	(0.200)			(0.258)			(0.286)	
North-West	0.503***			0.546**			0.425	
	(0.189)			(0.249)			(0.276)	
South-East	-0.875***			-0.647*			-0.605	
	(0.316)			(0.379)			(0.402)	
South-South	0.051			0.004			0.049	
	(0.321)			(0.403)			(0.430)	
South-West	-0.163			0.105			0.002	
	(0.298)			(0.386)			(0.421)	
Rural		0.480***			0.446**			0.442*
		(0.146)			(0.206)			(0.252)
Primary						-0.155	-0.103	-0.143
Education Complete						(0.248)	(0.252)	(0.246)
Secondary						0.090	0.112	0.096
Education Complete						(0.426)	(0.436)	(0.422)
University/Higher						0.085	-0.043	0.078
Education Complete						(0.763)	(0.771)	(0.768)

Constant	-0.381**	-1.024***	-0.802***	-2.478	-3.298	-2.723	-1.529	-2.057	-1.815
	(0.156)	(0.313)	(0.198)	(2.194)	(2.221)	(2.205)	(2.579)	(2.627)	(2.608)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.001	0.001	0.000	0.013	0.014	0.001	0.017	0.027	0.005
Panel Level sd.	0.064	0.044	0.006	0.205	0.213	0.055	0.241	0.303	0.135
Chi-Squared	50.75	82.83	58.72	117.95	136.22	119.59	104.49	117.47	105.95

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 12: Logit Regressions - Lagged Precipitation and Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.035***	0.033***	0.034***	0.035***	0.035***	0.035***	0.044***	0.044***	0.044***
Survey Precipitation	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Distance to Closest				-0.137	-0.227	-0.150	-0.198	-0.228	-0.213
Water Source (km)				(0.367)	(0.350)	(0.363)	(0.383)	(0.332)	(0.373)
Distance to				0.012	0.010	0.012	0.051	0.040	0.049
Closest Market (km)				(0.038)	(0.034)	(0.037)	(0.059)	(0.049)	(0.057)
Distance to				0.018***	0.018**	0.018***	0.024***	0.023***	0.024***
Closest City (km)				(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Number of People				-0.308***	-0.302***	-0.309***	-0.289***	-0.282***	-0.289***
in Household				(0.082)	(0.081)	(0.081)	(0.098)	(0.096)	(0.097)
Log of Education				-0.028	-0.028	-0.029	-0.047	-0.045	-0.048
Expenditure				(0.037)	(0.036)	(0.037)	(0.042)	(0.041)	(0.042)
Household Asset				-0.017	-0.015	-0.019	-0.057	-0.054	-0.061
Index				(0.087)	(0.088)	(0.087)	(0.104)	(0.105)	(0.104)
Log of Consumption				-0.545***	-0.533**	-0.550***	-0.540**	-0.526**	-0.548**
per Capita				(0.210)	(0.207)	(0.209)	(0.242)	(0.237)	(0.241)
Number of Meals				0.018	0.015	0.017	0.055	0.052	0.052
to Children				(0.064)	(0.063)	(0.064)	(0.081)	(0.079)	(0.082)
Restricted Meals				0.047	0.041	0.045	0.091	0.083	0.090
so Children can Eat				(0.107)	(0.106)	(0.107)	(0.110)	(0.109)	(0.110)
Number of				0.498**	0.486**	0.494**	0.643***	0.618***	0.642***
Production Shocks				(0.195)	(0.195)	(0.194)	(0.217)	(0.214)	(0.216)
Number of Market				0.260	0.249	0.259	0.346*	0.337	0.341

Shocks		(0.180)	(0.179)	(0.179)	(0.210)	(0.209)	(0.210)
Tropical		-0.003	-0.003	-0.002	0.004	0.003	0.004
Livestock Units		(0.031)	(0.027)	(0.033)	(0.045)	(0.045)	(0.045)
Log of Plot Size		-0.066	-0.067	-0.066	-0.034	-0.037	-0.034
of All Households		(0.044)	(0.044)	(0.044)	(0.054)	(0.053)	(0.053)
Soil Workability		-0.531	-0.570	-0.458	0.037	0.067	0.143
(mean)		(1.441)	(1.466)	(1.423)	(1.252)	(1.354)	(1.229)
Soil Nutrient		1.672	1.826	1.632	1.372	1.499	1.280
Availability (mean)		(1.860)	(1.881)	(1.835)	(1.724)	(1.821)	(1.708)
Age in Months		0.002	0.002	0.002	0.003	0.002	0.003
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of		0.405	0.430	0.395	1.132	1.222	1.106
Household Head		(1.076)	(1.126)	(1.065)	(1.318)	(1.366)	(1.310)
Gender		-1.968	-1.874	-1.964	-2.152	-2.049	-2.147
		(1.910)	(1.911)	(1.947)	(2.250)	(2.295)	(2.305)
Borrow from Microfinance/		0.752	0.777	0.750	1.027*	1.034*	1.032**
Credit Associations/Bank		(0.526)	(0.544)	(0.526)	(0.529)	(0.556)	(0.526)
Borrow from Friends/		0.043	0.047	0.049	-0.152	-0.144	-0.149
Relatives/Money Lenders		(0.226)	(0.225)	(0.225)	(0.253)	(0.249)	(0.252)
Borrow Food, or		-0.575*	-0.569*	-0.574*	-0.766**	-0.759**	-0.759**
Rely on Friend/Relative?		(0.342)	(0.343)	(0.341)	(0.379)	(0.380)	(0.379)
Is there a Market		-0.014	-0.024	-0.015	0.036	0.026	0.031
in the Community?		(0.223)	(0.222)	(0.222)	(0.262)	(0.261)	(0.261)
Does HH have		0.260	0.253	0.267	0.291	0.274	0.303
Electricity in Dwelling?		(0.354)	(0.350)	(0.351)	(0.404)	(0.399)	(0.402)
Has Non-Farm		-0.012	-0.025	-0.020	-0.361	-0.393	-0.359
Enterprise		(0.244)	(0.244)	(0.245)	(0.304)	(0.304)	(0.303)
Government Assistance		-0.274	-0.234	-0.270	-0.451	-0.418	-0.449
(food/cash/otherwise)		(0.644)	(0.640)	(0.643)	(0.725)	(0.717)	(0.722)
Agri-extension		-0.682	-0.695	-0.665	-0.939*	-0.946*	-0.922*
(Government/Private Sector)		(0.450)	(0.451)	(0.448)	(0.537)	(0.543)	(0.534)
North-East	0.039		-0.177			-0.328	
	(0.249)		(0.304)			(0.335)	
North-West	0.333		-0.018			-0.237	
	(0.240)		(0.303)			(0.337)	
South-East	-0.458		-0.144			-0.209	
	(0.382)		(0.468)			(0.501)	

South-South		0.258			0.299			0.381	
		(0.434)			(0.490)			(0.514)	
South-West		0.282			0.685*			0.674	
		(0.330)			(0.403)			(0.425)	
Rural			0.367**			0.284			0.296
			(0.185)			(0.273)			(0.308)
Primary							-0.184	-0.209	-0.187
Education Complete							(0.269)	(0.273)	(0.268)
Secondary							-0.674	-0.700	-0.675
Education Complete							(0.495)	(0.504)	(0.493)
University/Higher							-0.065	-0.078	-0.105
Education Complete							(0.851)	(0.853)	(0.862)
Constant	-1.387***	-1.684***	-1.706***	-1.323	-1.235	-1.570	-2.785	-2.232	-3.052
	(0.195)	(0.417)	(0.241)	(2.618)	(2.626)	(2.620)	(2.962)	(2.916)	(2.970)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.116	0.110	0.108	0.071	0.063	0.064	0.057	0.037	0.049
Panel Level sd.	0.655	0.639	0.630	0.502	0.472	0.474	0.446	0.355	0.410
Chi-Squared	34.02	44.95	35.89	128.51	132.07	130.22	117.84	124.97	118.36

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 13: Marginal Effect - Lagged Precipitation

Panel A: Stunted (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.003**	0.003**	0.003	0.003**	0.002*	0.003**	0.003**	0.003**	0.004**
Survey Precipitation	(0.001)	(0.001)	(0.024)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel B: Marginal Effect of Lagged Precipitation on Stunting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.003**	0.003**	0.002	0.002**	0.002*	0.002**	0.003**	0.003**	0.002**
	(0.001)	(0.001)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	0.003**	0.003	0.003	0.003**	0.003*	0.003*	0.004**	0.003**	0.004**
	(0.001)	(0.003)	(0.025)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel C: Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
Survey Precipitation	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Panel D: Marginal Effect of Lagged Precipitation on Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.003***	0.003***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

5 Lagged Precipitation and Wasting

Table 14: Logit Regressions - Lagged Precipitation

	(1) Wasted	(2) Wasted	(3) Wasted	(4) Wasted	(5) Wasted	(6) Wasted	(7) Wasted	(8) Wasted	(9) Wasted
Year Preceding Survey Precipitation	0.004	0.006	0.004	0.005	0.012	0.005	-0.007	-0.002	-0.007
	(0.010)	(0.011)	(0.010)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)
Primary Education Complete							-0.228	-0.309	-0.231
							(0.371)	(0.372)	(0.370)
Secondary Education Complete							-0.615	-0.652	-0.632
							(0.650)	(0.642)	(0.651)
University/Higher Education Complete							-1.572	-1.331	-1.646
							(1.079)	(1.071)	(1.093)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.018	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.246	0.007	0.239	0.005	0.003	0.006	0.005	0.004	0.004
Chi-Squared	2.66	26.17	3.09	109.45	134.12	110.64	100.06	129.15	102.11

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 15: Logit Regressions - Lagged Precipitation and Wasting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding Survey Precipitation	0.004	0.006	0.004	0.005	0.012	0.005	-0.007	-0.002	-0.007
	(0.010)	(0.011)	(0.010)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)
Distance to Closest Water Source (km)				-0.997***	-0.895**	-0.999***	-1.174***	-1.110***	-1.179***
				(0.364)	(0.382)	(0.357)	(0.411)	(0.422)	(0.400)
Distance to Closest Market (km)				-0.045	-0.042	-0.044	-0.033	-0.035	-0.031
				(0.066)	(0.064)	(0.064)	(0.090)	(0.092)	(0.087)
Distance to Closest City (km)				0.010	0.011	0.010	0.011	0.013	0.011
				(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Number of People in Household				0.102	0.109	0.103	0.153	0.139	0.153
				(0.095)	(0.098)	(0.096)	(0.106)	(0.110)	(0.108)
Log of Education Expenditure				-0.002	0.003	-0.003	-0.015	-0.004	-0.016
				(0.039)	(0.039)	(0.039)	(0.048)	(0.048)	(0.048)
Household Asset				0.037	0.040	0.033	0.030	0.036	0.023

Index	(0.097)	(0.101)	(0.098)	(0.114)	(0.123)	(0.115)
Log of Consumption per Capita	0.185	0.193	0.180	0.352	0.378	0.342
	(0.247)	(0.248)	(0.246)	(0.282)	(0.280)	(0.281)
Number of Meals to Children	-0.106	-0.104	-0.107	-0.121	-0.116	-0.124
	(0.092)	(0.097)	(0.092)	(0.106)	(0.114)	(0.107)
Restricted Meals so Children can Eat	0.214*	0.208	0.215*	0.236	0.231	0.238
	(0.129)	(0.129)	(0.130)	(0.145)	(0.145)	(0.145)
Number of Production Shocks	-0.381	-0.411	-0.372	-0.155	-0.180	-0.143
	(0.282)	(0.281)	(0.282)	(0.300)	(0.301)	(0.300)
Number of Market Shocks	-0.180	-0.124	-0.177	-0.469*	-0.382	-0.465*
	(0.236)	(0.239)	(0.236)	(0.271)	(0.281)	(0.271)
Tropical Livestock Units	0.054***	0.050***	0.054***	0.063**	0.052**	0.062**
	(0.018)	(0.017)	(0.018)	(0.025)	(0.025)	(0.025)
Log of Plot Size of All Households	0.079	0.076	0.078	0.120*	0.114*	0.119*
	(0.055)	(0.054)	(0.054)	(0.064)	(0.063)	(0.063)
Soil Workability (mean)	2.067	2.552*	1.952	1.929	3.402*	1.742
	(1.517)	(1.546)	(1.503)	(1.841)	(2.008)	(1.827)
Soil Nutrient Availability (mean)	-6.945	-6.993	-6.673	-13.484*	-16.852**	-12.548*
	(5.058)	(5.698)	(4.728)	(7.478)	(8.040)	(7.414)
Age in Months	-0.020***	-0.021***	-0.019***	-0.023***	-0.024***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of Household Head	-0.682	-0.682	-0.687	-0.721	-0.628	-0.722
	(1.260)	(1.218)	(1.254)	(1.439)	(1.397)	(1.439)
Gender	-4.208***	-4.848***	-4.270***	-3.421**	-4.032**	-3.510**
	(1.561)	(1.724)	(1.546)	(1.726)	(2.004)	(1.724)
Borrow from Microfinance/ Credit Associations/Bank	-0.735	-0.755	-0.728	-0.460	-0.499	-0.441
	(0.463)	(0.490)	(0.464)	(0.580)	(0.616)	(0.579)
Borrow from Friends/ Relatives/Money Lenders	-0.031	-0.001	-0.028	-0.261	-0.215	-0.260
	(0.247)	(0.247)	(0.247)	(0.275)	(0.277)	(0.275)
Borrow Food, or Rely on Friend/Relative?	0.495	0.569	0.488	0.538	0.583	0.532
	(0.360)	(0.368)	(0.360)	(0.416)	(0.429)	(0.416)
Is there a Market in the Community?	0.158	0.191	0.150	0.286	0.314	0.270
	(0.252)	(0.252)	(0.251)	(0.277)	(0.277)	(0.275)
Does HH have Electricity in Dwelling?	0.579	0.564	0.585	0.797	0.711	0.807
	(0.394)	(0.389)	(0.393)	(0.495)	(0.495)	(0.493)
Has Non-Farm Enterprise	-0.002	-0.013	-0.009	0.066	0.115	0.069
	(0.255)	(0.263)	(0.254)	(0.332)	(0.342)	(0.332)

Government Assistance (food/cash/otherwise)				-0.339	-0.366	-0.347	-0.500	-0.646	-0.501
				(0.658)	(0.679)	(0.660)	(0.714)	(0.757)	(0.713)
Agri-extension (Government/Private Sector)				0.352	0.240	0.360	0.133	-0.098	0.157
				(0.700)	(0.726)	(0.700)	(0.882)	(0.925)	(0.884)
North-East		-0.403			-0.491*			-0.476	
		(0.249)			(0.297)			(0.325)	
North-West		-0.979***			-1.370***			-1.632***	
		(0.253)			(0.298)			(0.352)	
South-East		-0.571*			-0.675*			-0.408	
		(0.321)			(0.409)			(0.452)	
South-South		0.229			0.315			0.705	
		(0.375)			(0.418)			(0.438)	
South-West		-0.296			-0.532			-0.215	
		(0.308)			(0.435)			(0.455)	
Rural			0.132			0.259			0.348
			(0.174)			(0.251)			(0.304)
Primary Education Complete							-0.228	-0.309	-0.231
							(0.371)	(0.372)	(0.370)
Secondary Education Complete							-0.615	-0.652	-0.632
							(0.650)	(0.642)	(0.651)
University/Higher Education Complete							-1.572	-1.331	-1.646
							(1.079)	(1.071)	(1.093)
Constant	-2.539***	-1.583***	-2.649***	2.181	5.133*	1.949	0.324	3.136	-0.052
	(0.204)	(0.395)	(0.264)	(2.575)	(2.698)	(2.579)	(3.153)	(3.304)	(3.181)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.018	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.246	0.007	0.239	0.005	0.003	0.006	0.005	0.004	0.004
Chi-Squared	2.66	26.17	3.09	109.45	134.12	110.64	100.06	129.15	102.11

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 16: Marginal Effect - Lagged Precipitation

Panel A: Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.000	0.000	0.000	0.000	0.001	0.000	-0.000	-0.000	-0.000
Survey Precipitation	(0.001)	(0.010)	(0.001)	(0.004)	(0.025)	(0.004)	(0.013)	(0.004)	(0.015)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Panel B: Marginal Effect of Lagged Temperature on Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban	0.000	0.000	0.000	0.000	0.001	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.010)	(0.001)	(0.003)	(0.023)	(0.003)	(0.010)	(0.003)	(0.008)
Rural	0.000	0.000	0.000	0.000	0.001	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.010)	(0.001)	(0.004)	(0.025)	(0.004)	(0.014)	(0.004)	(0.016)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

6 Climate Variables with Lagged Precipitation

Table 17: Logit Regressions - Climate Variables

Panel A: Stunted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.739**	0.717**	0.794**	1.342***	1.320***	1.366***	1.285***	1.353***	1.321***
Survey Temperature	(0.342)	(0.326)	(0.329)	(0.432)	(0.411)	(0.428)	(0.497)	(0.486)	(0.496)
Year Preceding	-0.152	-0.153	-0.133	-0.160	-0.162	-0.150	-0.171	-0.155	-0.160
Survey Precipitation	(0.133)	(0.123)	(0.132)	(0.180)	(0.166)	(0.179)	(0.201)	(0.188)	(0.199)
Temperature ×	0.005	0.005	0.004	0.005	0.005	0.005	0.006	0.005	0.005
Precipitation	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.038	0.034	0.028	0.049	0.050	0.041	0.070	0.079	0.063
Panel Level sd.	0.360	0.341	0.307	0.411	0.418	0.374	0.497	0.532	0.472
Chi-Squared	103.27	114.12	111.24	154.64	164.70	157.33	123.85	133.02	124.64

Panel B: Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.350	0.376	0.370	0.637	0.650	0.644	0.727	0.773	0.732
Survey Temperature	(0.382)	(0.373)	(0.383)	(0.467)	(0.467)	(0.466)	(0.549)	(0.556)	(0.546)
Year Preceding	-0.487***	-0.472***	-0.478***	-0.619***	-0.616***	-0.614***	-0.626***	-0.619***	-0.621***
Survey Precipitation	(0.151)	(0.145)	(0.152)	(0.207)	(0.208)	(0.207)	(0.231)	(0.234)	(0.230)
Temperature ×	0.015***	0.015***	0.015***	0.019***	0.019***	0.019***	0.020***	0.019***	0.020***
Precipitation	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.199	0.197	0.193	0.150	0.145	0.147	0.192	0.174	0.188
Panel Level sd.	0.903	0.897	0.886	0.762	0.746	0.754	0.885	0.832	0.872
Chi-Squared	92.32	99.11	93.54	159.34	161.91	160.96	136.07	142.10	136.72

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 18: Logit Regressions - Climate Variables and Stunting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.739**	0.717**	0.794**	1.342***	1.320***	1.366***	1.285***	1.353***	1.321***
Survey Temperature	(0.342)	(0.326)	(0.329)	(0.432)	(0.411)	(0.428)	(0.497)	(0.486)	(0.496)
Year Preceding	-0.152	-0.153	-0.133	-0.160	-0.162	-0.150	-0.171	-0.155	-0.160

Survey Precipitation	(0.133)	(0.123)	(0.132)	(0.180)	(0.166)	(0.179)	(0.201)	(0.188)	(0.199)
Temperature × Precipitation	0.005 (0.004)	0.005 (0.004)	0.004 (0.004)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.006 (0.006)	0.005 (0.006)	0.005 (0.006)
Distance to Closest Water Source (km)				-0.390 (0.761)	-0.421 (0.727)	-0.396 (0.716)	-0.333 (0.667)	-0.414 (0.635)	-0.348 (0.626)
Distance to Closest Market (km)				-0.008 (0.032)	-0.011 (0.033)	-0.008 (0.031)	0.012 (0.042)	0.015 (0.043)	0.012 (0.040)
Distance to Closest City (km)				0.002 (0.006)	0.002 (0.006)	0.003 (0.006)	0.005 (0.007)	0.005 (0.007)	0.005 (0.007)
Number of People in Household				0.048 (0.068)	0.062 (0.068)	0.046 (0.068)	0.028 (0.082)	0.050 (0.083)	0.026 (0.083)
Log of Education Expenditure				-0.027 (0.032)	-0.028 (0.032)	-0.027 (0.032)	-0.026 (0.036)	-0.026 (0.036)	-0.025 (0.036)
Household Asset Index				0.223*** (0.078)	0.222*** (0.078)	0.219*** (0.078)	0.252*** (0.089)	0.255*** (0.090)	0.250*** (0.089)
Log of Consumption per Capita				-0.069 (0.168)	-0.054 (0.169)	-0.078 (0.167)	-0.133 (0.193)	-0.111 (0.195)	-0.143 (0.191)
Number of Meals to Children				0.049 (0.057)	0.051 (0.057)	0.049 (0.057)	0.078 (0.069)	0.084 (0.069)	0.073 (0.070)
Restricted Meals so Children can Eat				-0.022 (0.103)	-0.023 (0.103)	-0.022 (0.102)	-0.073 (0.115)	-0.086 (0.116)	-0.074 (0.115)
Number of Production Shocks				0.079 (0.190)	0.071 (0.194)	0.085 (0.189)	0.081 (0.212)	0.042 (0.218)	0.093 (0.211)
Number of Market Shocks				-0.100 (0.163)	-0.099 (0.163)	-0.100 (0.163)	-0.065 (0.188)	-0.071 (0.190)	-0.068 (0.187)
Tropical Livestock Units				0.091** (0.040)	0.094** (0.040)	0.092** (0.040)	0.126** (0.054)	0.134** (0.053)	0.127** (0.054)
Log of Plot Size of All Households				-0.062 (0.040)	-0.062 (0.040)	-0.064 (0.039)	-0.045 (0.050)	-0.048 (0.051)	-0.048 (0.049)
Soil Workability (mean)				-2.963 (2.110)	-3.138 (2.026)	-2.935 (2.116)	-0.801 (2.828)	-1.189 (2.775)	-0.855 (2.591)
Soil Nutrient Availability (mean)				1.729 (2.254)	1.972 (2.230)	1.738 (2.228)	-0.519 (3.673)	-0.155 (3.577)	-0.414 (3.345)
Age in Months				0.010** (0.005)	0.010** (0.005)	0.011** (0.005)	0.008 (0.005)	0.008 (0.005)	0.009 (0.005)
Gender of Household Head				0.217 (0.893)	0.202 (0.899)	0.205 (0.884)	0.626 (1.001)	0.589 (1.021)	0.599 (0.993)

Gender				0.721	0.614	0.766	1.038	0.950	1.085
				(1.450)	(1.479)	(1.382)	(1.470)	(1.517)	(1.413)
Borrow from Microfinance/ Credit Associations/Bank				-0.128	-0.120	-0.135	0.046	0.080	0.044
				(0.442)	(0.443)	(0.447)	(0.503)	(0.512)	(0.511)
Borrow from Friends/ Relatives/Money Lenders				-0.208	-0.215	-0.198	-0.251	-0.266	-0.240
				(0.190)	(0.192)	(0.189)	(0.224)	(0.228)	(0.223)
Borrow Food, or Rely on Friend/Relative?				-0.070	-0.053	-0.070	-0.456	-0.440	-0.454
				(0.307)	(0.312)	(0.308)	(0.363)	(0.375)	(0.364)
Is there a Market in the Community?				0.001	-0.039	0.006	0.016	-0.006	0.018
				(0.204)	(0.207)	(0.204)	(0.232)	(0.235)	(0.232)
Does HH have Electricity in Dwelling?				0.099	0.130	0.098	0.145	0.163	0.148
				(0.320)	(0.321)	(0.319)	(0.364)	(0.364)	(0.364)
Has Non-Farm Enterprise				0.086	0.077	0.072	0.200	0.159	0.194
				(0.233)	(0.233)	(0.233)	(0.293)	(0.297)	(0.294)
Government Assistance (food/cash/otherwise)				0.583	0.586	0.600	0.861*	0.871*	0.888*
				(0.421)	(0.425)	(0.420)	(0.464)	(0.471)	(0.463)
Agri-extension (Government/Private Sector)				0.156	0.180	0.159	-0.015	0.035	-0.007
				(0.397)	(0.399)	(0.395)	(0.492)	(0.499)	(0.492)
North-East		0.087			0.095			-0.228	
		(0.216)			(0.278)			(0.318)	
North-West		0.366*			0.439			0.319	
		(0.213)			(0.273)			(0.311)	
South-East		-1.054***			-0.779*			-0.753*	
		(0.337)			(0.405)			(0.431)	
South-South		-0.290			-0.293			-0.319	
		(0.397)			(0.483)			(0.510)	
South-West		-0.200			0.038			-0.056	
		(0.321)			(0.415)			(0.460)	
Rural			0.500***			0.445**			0.484*
			(0.153)			(0.216)			(0.270)
Primary Education Complete							-0.230	-0.185	-0.218
							(0.261)	(0.266)	(0.259)
Secondary Education Complete							0.035	0.055	0.044
							(0.441)	(0.457)	(0.438)
University/Higher Education Complete							-0.117	-0.251	-0.124
							(0.784)	(0.801)	(0.791)
Constant	-8.314***	-7.674**	-8.540***	-10.417***	-10.251**	-10.155**	-11.276**	-11.727**	-11.344**

	(2.791)	(3.211)	(2.758)	(3.962)	(4.298)	(3.979)	(4.595)	(5.002)	(4.607)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599
Rho	0.038	0.034	0.028	0.049	0.050	0.041	0.070	0.079	0.063
Panel Level sd.	0.360	0.341	0.307	0.411	0.418	0.374	0.497	0.532	0.472
Chi-Squared	103.27	114.12	111.24	154.64	164.70	157.33	123.85	133.02	124.64

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 19: Logit Regressions - Climate Variables and Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.350	0.376	0.370	0.637	0.650	0.644	0.727	0.773	0.732
Survey Temperature	(0.382)	(0.373)	(0.383)	(0.467)	(0.467)	(0.466)	(0.549)	(0.556)	(0.546)
Year Preceding	-0.487***	-0.472***	-0.478***	-0.619***	-0.616***	-0.614***	-0.626***	-0.619***	-0.621***
Survey Precipitation	(0.151)	(0.145)	(0.152)	(0.207)	(0.208)	(0.207)	(0.231)	(0.234)	(0.230)
Temperature ×	0.015***	0.015***	0.015***	0.019***	0.019***	0.019***	0.020***	0.019***	0.020***
Precipitation	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Distance to Closest				-0.016	-0.123	-0.025	0.009	-0.052	-0.004
Water Source (km)				(0.381)	(0.372)	(0.375)	(0.455)	(0.407)	(0.445)
Distance to				0.025	0.021	0.024	0.049	0.033	0.048
Closest Market (km)				(0.040)	(0.035)	(0.039)	(0.063)	(0.050)	(0.061)
Distance to				0.012	0.011	0.012	0.018**	0.018**	0.018**
Closest City (km)				(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Number of People				-0.215***	-0.210**	-0.217***	-0.211**	-0.204**	-0.212**
in Household				(0.083)	(0.082)	(0.082)	(0.102)	(0.102)	(0.102)
Log of Education				-0.047	-0.045	-0.047	-0.062	-0.057	-0.063
Expenditure				(0.038)	(0.037)	(0.038)	(0.046)	(0.044)	(0.046)
Household Asset				0.031	0.034	0.030	-0.004	-0.004	-0.006
Index				(0.088)	(0.090)	(0.089)	(0.109)	(0.111)	(0.109)
Log of Consumption				-0.521**	-0.512**	-0.523**	-0.564**	-0.544**	-0.568**
per Capita				(0.219)	(0.216)	(0.219)	(0.256)	(0.250)	(0.256)
Number of Meals				0.102	0.101	0.102	0.152*	0.152*	0.150*
to Children				(0.064)	(0.063)	(0.063)	(0.088)	(0.086)	(0.089)
Restricted Meals				0.082	0.084	0.082	0.122	0.121	0.124
so Children can Eat				(0.116)	(0.116)	(0.116)	(0.122)	(0.122)	(0.121)

Number of		0.616***	0.604***	0.611***	0.747***	0.720***	0.745***
Production Shocks		(0.214)	(0.214)	(0.213)	(0.246)	(0.244)	(0.245)
Number of Market		0.219	0.210	0.219	0.351	0.335	0.346
Shocks		(0.202)	(0.201)	(0.202)	(0.244)	(0.243)	(0.244)
Tropical		-0.007	-0.006	-0.007	0.003	0.003	0.004
Livestock Units		(0.025)	(0.024)	(0.027)	(0.050)	(0.050)	(0.050)
Log of Plot Size		-0.077*	-0.081*	-0.076*	-0.048	-0.056	-0.047
of All Households		(0.045)	(0.045)	(0.045)	(0.057)	(0.057)	(0.056)
Soil Workability		-1.810	-1.942	-1.774	-1.159	-1.285	-1.091
(mean)		(2.187)	(2.251)	(2.127)	(2.313)	(2.542)	(2.229)
Soil Nutrient		1.862	2.025	1.861	1.460	1.588	1.426
Availability (mean)		(2.894)	(2.983)	(2.807)	(3.119)	(3.421)	(3.002)
Age in Months		0.022***	0.021***	0.022***	0.022***	0.021***	0.022***
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of		0.379	0.390	0.371	1.105	1.224	1.081
Household Head		(1.152)	(1.193)	(1.142)	(1.315)	(1.355)	(1.304)
Gender		-2.591	-2.487	-2.601	-2.949	-2.786	-2.947
		(1.607)	(1.620)	(1.622)	(2.031)	(2.081)	(2.058)
Borrow from Microfinance/		0.469	0.508	0.460	0.852	0.857	0.849
Credit Associations/Bank		(0.570)	(0.585)	(0.573)	(0.570)	(0.593)	(0.569)
Borrow from Friends/		0.067	0.061	0.070	-0.202	-0.197	-0.203
Relatives/Money Lenders		(0.239)	(0.238)	(0.239)	(0.283)	(0.280)	(0.282)
Borrow Food, or		-0.833**	-0.846**	-0.835**	-1.045**	-1.062**	-1.046**
Rely on Friend/Relative?		(0.369)	(0.371)	(0.369)	(0.416)	(0.417)	(0.416)
Is there a Market		0.159	0.138	0.157	0.210	0.176	0.205
in the Community?		(0.242)	(0.243)	(0.242)	(0.294)	(0.296)	(0.293)
Does HH have		0.274	0.272	0.271	0.343	0.337	0.343
Electricity in Dwelling?		(0.354)	(0.351)	(0.352)	(0.409)	(0.407)	(0.408)
Has Non-Farm		0.388	0.370	0.382	0.032	-0.013	0.035
Enterprise		(0.259)	(0.259)	(0.260)	(0.322)	(0.321)	(0.321)
Government Assistance		-0.009	0.002	0.002	-0.366	-0.369	-0.359
(food/cash/otherwise)		(0.718)	(0.720)	(0.719)	(0.859)	(0.858)	(0.860)
Agri-extension		-0.807	-0.836	-0.790	-1.093*	-1.120*	-1.073*
(Government/Private Sector)		(0.515)	(0.518)	(0.516)	(0.615)	(0.622)	(0.614)
North-East	0.001		-0.221			-0.490	
	(0.275)		(0.333)			(0.384)	
North-West	0.253		-0.115			-0.400	

		(0.277)			(0.336)			(0.381)	
South-East		-0.461			-0.199			-0.342	
		(0.429)			(0.506)			(0.551)	
South-South		0.207			0.131			0.135	
		(0.541)			(0.581)			(0.615)	
South-West		0.397			0.732			0.827*	
		(0.379)			(0.456)			(0.495)	
Rural			0.371*			0.236			0.276
			(0.199)			(0.287)			(0.331)
Primary							-0.322	-0.350	-0.325
Education Complete							(0.280)	(0.284)	(0.280)
Secondary							-0.893*	-0.939*	-0.892*
Education Complete							(0.513)	(0.524)	(0.512)
University/Higher							-0.229	-0.215	-0.260
Education Complete							(0.891)	(0.894)	(0.903)
Constant	-5.837	-4.603	-6.172*	-4.364	-4.849	-4.378	-7.933	-9.281	-8.112
	(3.570)	(4.280)	(3.538)	(5.174)	(5.553)	(5.160)	(5.689)	(5.948)	(5.658)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873
Rho	0.199	0.197	0.193	0.150	0.145	0.147	0.192	0.174	0.188
Panel Level sd.	0.903	0.897	0.886	0.762	0.746	0.754	0.885	0.832	0.872
Chi-Squared	92.32	99.11	93.54	159.34	161.91	160.96	136.07	142.10	136.72

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 20: Marginal Effect - Climate Variables

Panel A: Stunted (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.170***	0.165***	0.168***	0.221***	0.219***	0.222***	0.208***	0.207***	0.209***
Survey Temperature	(0.033)	(0.032)	(0.033)	(0.041)	(0.041)	(0.041)	(0.045)	(0.044)	(0.044)
Year Preceding	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Survey Precipitation	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel B: Marginal Effect of Climate Variables on Stunting

Urban (Temperature)	0.168***	0.160***	0.125***	0.179***	0.181***	0.155***	0.160***	0.162***	0.137***
	(0.035)	(0.034)	(0.030)	(0.039)	(0.040)	(0.038)	(0.041)	(0.041)	(0.039)
Rural (Temperature)	0.171***	0.167***	0.183***	0.235***	0.231***	0.244***	0.223***	0.221***	0.233***
	(0.033)	(0.032)	(0.035)	(0.043)	(0.042)	(0.044)	(0.046)	(0.046)	(0.047)
Urban (Precipitation) 0.001	0.001	0.001	0.001	0.001 0.001	0.001	0.001	0.001		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural (Precipitation)	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	2135	2135	2135	1960	1960	1960	1599	1599	1599

Panel C: Underweight (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.150***	0.151***	0.148***	0.170***	0.169***	0.170***	0.165***	0.161***	0.164***
Survey Temperature	(0.022)	(0.023)	(0.022)	(0.026)	(0.027)	(0.026)	(0.029)	(0.029)	(0.029)
Year Preceding	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Survey Precipitation	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Panel D: Marginal Effect of Climate Variables on Underweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban (Temperature)	0.151***	0.157***	0.120***	0.144***	0.147***	0.132***	0.139***	0.140***	0.127***
	(0.022)	(0.025)	(0.024)	(0.028)	(0.029)	(0.030)	(0.031)	(0.032)	(0.033)
Rural (Temperature)	0.150***	0.150***	0.157***	0.178***	0.176***	0.182***	0.172***	0.168***	0.176***
	(0.022)	(0.023)	(0.023)	(0.027)	(0.028)	(0.028)	(0.029)	(0.030)	(0.030)
Urban (Precipitation)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural (Precipitation)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2505	2505	2505	2306	2306	2306	1873	1873	1873

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 21: Logit Regressions - Climate Variables

	(1) Wasted	(2) Wasted	(3) Wasted	(4) Wasted	(5) Wasted	(6) Wasted	(7) Wasted	(8) Wasted	(9) Wasted
Year Preceding	0.076	0.058	0.090	0.025	-0.122	0.032	0.459	0.146	0.458
Survey Temperature	(0.393)	(0.391)	(0.398)	(0.544)	(0.518)	(0.546)	(0.605)	(0.579)	(0.606)
Year Preceding	-0.200	-0.216	-0.195	-0.137	-0.178	-0.135	-0.154	-0.248	-0.157
Survey Precipitation	(0.145)	(0.148)	(0.147)	(0.169)	(0.166)	(0.170)	(0.186)	(0.187)	(0.187)
Temperature ×	0.006	0.007	0.006	0.004	0.006	0.004	0.004	0.007	0.004
Precipitation	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.029	0.003	0.034	0.005	0.004	0.004	0.004	0.002	0.004
Chi-Squared	26.63	49.70	27.00	121.49	144.93	121.72	111.25	138.49	112.20

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 22: Logit Regressions - Climate Variables and Wasting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.076	0.058	0.090	0.025	-0.122	0.032	0.459	0.146	0.458
Survey Temperature	(0.393)	(0.391)	(0.398)	(0.544)	(0.518)	(0.546)	(0.605)	(0.579)	(0.606)
Year Preceding	-0.200	-0.216	-0.195	-0.137	-0.178	-0.135	-0.154	-0.248	-0.157
Survey Precipitation	(0.145)	(0.148)	(0.147)	(0.169)	(0.166)	(0.170)	(0.186)	(0.187)	(0.187)
Temperature ×	0.006	0.007	0.006	0.004	0.006	0.004	0.004	0.007	0.004
Precipitation	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Distance to Closest				-1.024**	-1.004**	-1.023**	-1.224**	-1.285***	-1.230***
Water Source (km)				(0.416)	(0.444)	(0.406)	(0.493)	(0.495)	(0.476)
Distance to				-0.064	-0.063	-0.061	-0.070	-0.080	-0.067
Closest Market (km)				(0.078)	(0.077)	(0.076)	(0.113)	(0.115)	(0.108)
Distance to				0.010	0.011	0.010	0.010	0.012	0.010
Closest City (km)				(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)
Number of People				0.146	0.151	0.146	0.222**	0.207*	0.221*
in Household				(0.102)	(0.104)	(0.103)	(0.112)	(0.116)	(0.114)
Log of Education				-0.006	-0.004	-0.008	-0.019	-0.013	-0.021
Expenditure				(0.039)	(0.039)	(0.039)	(0.048)	(0.047)	(0.048)
Household Asset				0.057	0.061	0.053	0.057	0.065	0.050

Index	(0.098)	(0.103)	(0.099)	(0.115)	(0.125)	(0.115)
Log of Consumption per Capita	0.157	0.161	0.152	0.353	0.363	0.343
	(0.245)	(0.244)	(0.244)	(0.283)	(0.276)	(0.282)
Number of Meals to Children	-0.100	-0.098	-0.100	-0.096	-0.095	-0.098
	(0.092)	(0.097)	(0.092)	(0.108)	(0.116)	(0.110)
Restricted Meals so Children can Eat	0.211	0.204	0.214	0.235	0.228	0.239
	(0.131)	(0.129)	(0.132)	(0.148)	(0.147)	(0.149)
Number of Production Shocks	-0.371	-0.390	-0.363	-0.112	-0.126	-0.102
	(0.292)	(0.295)	(0.292)	(0.308)	(0.316)	(0.308)
Number of Market Shocks	-0.204	-0.158	-0.201	-0.508*	-0.444	-0.504*
	(0.233)	(0.236)	(0.232)	(0.265)	(0.279)	(0.265)
Tropical Livestock Units	0.052***	0.049***	0.051***	0.063**	0.055**	0.063**
	(0.017)	(0.017)	(0.017)	(0.025)	(0.025)	(0.025)
Log of Plot Size of All Households	0.080	0.074	0.078	0.116*	0.106*	0.116*
	(0.056)	(0.055)	(0.055)	(0.065)	(0.064)	(0.064)
Soil Workability (mean)	2.055	2.946*	1.917	2.366	4.400**	2.184
	(1.744)	(1.742)	(1.711)	(2.148)	(2.209)	(2.097)
Soil Nutrient Availability (mean)	-9.214	-9.490	-8.781	-20.994**	-25.965***	-19.964**
	(7.192)	(8.106)	(6.768)	(9.365)	(9.840)	(9.227)
Age in Months	-0.017***	-0.019***	-0.017***	-0.018***	-0.019***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender of Household Head	-0.753	-0.760	-0.761	-0.910	-0.825	-0.917
	(1.161)	(1.140)	(1.156)	(1.269)	(1.239)	(1.272)
Gender	-4.478***	-5.044***	-4.538***	-3.516**	-4.095**	-3.604**
	(1.605)	(1.766)	(1.611)	(1.667)	(1.975)	(1.685)
Borrow from Microfinance/ Credit Associations/Bank	-0.761	-0.801	-0.752	-0.504	-0.554	-0.481
	(0.490)	(0.518)	(0.495)	(0.620)	(0.658)	(0.623)
Borrow from Friends/ Relatives/Money Lenders	-0.005	0.021	0.000	-0.238	-0.203	-0.236
	(0.248)	(0.249)	(0.248)	(0.277)	(0.280)	(0.278)
Borrow Food, or Rely on Friend/Relative?	0.442	0.508	0.432	0.469	0.499	0.455
	(0.367)	(0.374)	(0.368)	(0.422)	(0.432)	(0.423)
Is there a Market in the Community?	0.185	0.210	0.174	0.334	0.351	0.314
	(0.257)	(0.258)	(0.255)	(0.285)	(0.285)	(0.283)
Does HH have Electricity in Dwelling?	0.624	0.605	0.629	0.862*	0.783	0.863*
	(0.400)	(0.394)	(0.399)	(0.503)	(0.505)	(0.501)
Has Non-Farm Enterprise	0.061	0.036	0.053	0.160	0.177	0.166
	(0.272)	(0.276)	(0.272)	(0.345)	(0.349)	(0.345)

Government Assistance				-0.262	-0.286	-0.267	-0.429	-0.544	-0.426
(food/cash/otherwise)				(0.652)	(0.682)	(0.653)	(0.740)	(0.779)	(0.740)
Agri-extension				0.294	0.173	0.305	0.133	-0.122	0.158
(Government/Private Sector)				(0.696)	(0.729)	(0.695)	(0.878)	(0.937)	(0.879)
North-East		-0.317			-0.349			-0.391	
		(0.255)			(0.303)			(0.337)	
North-West		-0.866***			-1.189***			-1.478***	
		(0.285)			(0.309)			(0.365)	
South-East		-0.414			-0.507			-0.205	
		(0.321)			(0.404)			(0.440)	
South-South		0.630			0.735*			1.125**	
		(0.395)			(0.436)			(0.450)	
South-West		-0.016			-0.306			0.090	
		(0.317)			(0.445)			(0.467)	
Rural			0.134			0.326			0.424
			(0.176)			(0.261)			(0.320)
Primary							-0.249	-0.330	-0.255
Education Complete							(0.384)	(0.389)	(0.383)
Secondary							-0.638	-0.679	-0.659
Education Complete							(0.673)	(0.671)	(0.672)
University/Higher							-1.576	-1.416	-1.657
Education Complete							(1.098)	(1.110)	(1.109)
Constant	6.983*	5.616	7.062*	10.609**	13.108**	10.712**	7.967	10.280*	7.741
	(3.591)	(4.174)	(3.605)	(4.688)	(5.183)	(4.690)	(5.559)	(6.190)	(5.569)
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	No	No	Yes	No	No	Yes	No
Urban/Rural	No	No	Yes	No	No	Yes	No	No	Yes
Number of Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743
Rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel Level sd.	0.029	0.003	0.034	0.005	0.004	0.004	0.004	0.002	0.004
Chi-Squared	26.63	49.70	27.00	121.49	144.93	121.72	111.25	138.49	112.20

Robust Standard Errors in Parentheses. Rho is the proportion of the total variance contributed by the panel-level variance component. CRE denotes Correlated Random Effects Model. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 23: Marginal Effects - Climate Variables

Panel A: Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year Preceding	0.078***	0.078	0.078***	0.043	0.040	0.043	0.078	0.073	0.079
Survey Temperature	(0.030)	(1.972)	(0.029)	(0.725)	(1.223)	(0.946)	(1.686)	(19.446)	(1.383)
Year Preceding	0.000	0.000	0.000	0.000	0.001	0.000	-0.001	-0.000	-0.001
Survey Precipitation	(0.003)	(0.010)	(0.002)	(0.008)	(0.034)	(0.006)	(0.025)	(0.065)	(0.019)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Panel B: Marginal Effects of Climate Variables on Wasting (At Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban (Temperature)	0.083**	0.087	0.077**	0.042	0.041	0.038	0.068	0.064	0.059
	(0.033)	(3.589)	(0.030)	(0.465)	(1.511)	(0.727)	(2.282)	(19.531)	(1.079)
Rural (Temperature)	0.076***	0.075	0.078***	0.043	0.040	0.044	0.080	0.075	0.084
	(0.030)	(2.050)	(0.028)	(0.679)	(1.155)	(0.815)	(3.051)	(19.248)	(2.282)
Urban (Precipitation)	0.000	0.000	-0.000	0.000	0.001	0.000	-0.001	-0.000	-0.001
	(0.001)	(0.004)	(0.001)	(0.006)	(0.023)	(0.005)	(0.034)	(0.101)	(0.023)
Rural (Precipitation)	0.000	0.000	0.000	0.000	0.001	0.001	-0.001	-0.000	-0.001
	(0.004)	(0.014)	(0.002)	(0.010)	(0.037)	(0.007)	(0.023)	(0.108)	(0.032)
Observations	2321	2321	2321	2142	2142	2142	1743	1743	1743

Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Climate Smart Agriculture and Welfare *

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Abstract

There is a resurgence of interest in climate-smart agriculture as a strategy to deal with food security in the context of a changing climate in Africa. However, the empirical evidence base to justify the promotion of many of climate-smart agriculture practices is scant. This paper aims to fill in this gap and contribute to the agricultural policy disclosure through providing pragmatic evidence on the effects of a set of potentially climate smart agricultural practices, namely intercropping, improved seed use and their combination, on the welfare of small-scale rural farming households. We used panel survey data from LSMS-ISA, merged with geo-referenced historical rainfall and temperature data, as well as data pertaining to soil conditions to evaluate the impact of intercropping, improved seed and their combination on household consumption. The data were mainly analysed using Multinomial Endogenous Switching Regression model that address potential endogeneity and selection bias. Results reveal that adoption of intercropping and improved seed methods, independently, have positive and significant effects on per capita adult equivalent consumption of farming households. Similarly, adoption of the combination of these CSA methods has a positive effect. However, this effect is lower than the effect of adopting improved seed only. These results validate that CSA practices may be substantial contributors to the resilience of farming households despite rising food insecurity due to climate change. However, scaling up technology

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such as adoption of improved seed will significantly contribute to rural household resilience against the adverse effect of climate change though enhancing consumption and food security.

Key words: intercropping , improved seed , consumption, rural Nigeria

JEL Classification: D60, Q12 , Q16

1 Introduction

Sub-Saharan Africa is highly dependent on its vegetation and its agricultural systems. These systems not only contribute to a large share of its Gross Domestic Production, but they also contribute to the welfare of the population as a consequence of its heavy reliance on its food systems for their internal food supply (OECD, 2015). Climate change affects the agricultural sector in sub-saharan African countries disproportionately through reducing crop yield and food security (Collier et al., 2008; Mendelsohn, 2008). Nigeria is situated in the humid tropics of the continent and its mainstream agricultural production is rain-fed. Climate change leaves Nigeria's population vulnerable to food insecurity and aggravates the poverty challenges especially among small-scale farming households.[1] Despite Nigeria's reliance on the exporting of its oil, the agricultural sector remains a crucial medium of occupation and food supply for over 36 percent of the country's population – making it a significant sector in the economy (WHO, 2018). [2] Within the agricultural sector 88 percent of total farmers are small scale family farmers, and of those farmers 72 percent fall below the $1.9 per day poverty line (Schenck, 2018). Crop farmers plant five main crops: maize, cassava, yams, beans, and millet, whereby all these crops are rain dependent and require a substantial amount of moisture (WHO, 2018; Idowu et al., 2011).

Climate change effects have begun to manifest in Nigeria as seen through the Niger Delta province floods, and the droughts in Northern part of the country (Apata, 2011). The increased temperatures brought about by global warming, as well as amplified unpredictability of rainfall patterns make the crop production in Nigeria a great concern (Nwajiuba et al., 2015). The Nigerian agricultural sector primarily comprises of small-scale farmers whose livelihood depends on the performance of their farms, and these farms also provide employment in the rural regions of the country (Note, 2014). Considering all these alterations in the average functioning of the climate, they are likely to significantly affect agricultural systems considering that these systems are highly reliant on the weather conditions.

[1] Nigeria is the most populated country in Africa, boasting 186 million inhabitants in 2016 (WorldBank, 2020). Approximately 52 percent of its population resides in rural areas (WorldBank, 2020), indicating that over half the Nigerian population's welfare would be severely affected by unfavourable weather conditions such as drought and floods.

[2] The Nigerian National Bureau of Statistics (2017) reported that the agricultural sector contributed 24.4 percent to the economy's Gross Domestic Product, with crop production occupying 91.9 percent of the agricultural sector.

Climate change will pose a severe threat on food security in a country as agriculturally dependent as Nigeria, thus aggravating the hunger and poverty challenges that already exist. This challenge requires adequate adaptation methods that will reduce the vulnerability of the agricultural and food systems to climate change (Gregory et al., 2005). The options available that may allow for this adaptation, is an investment in structures that will prioritize the assessment of vulnerabilities of food systems, and thus aid with the formulation of strategies and institutions that will facilitate a smooth transition into sturdy agricultural and food systems (Change, 2016).

Climate smart agricultural practices (CSA) is one of the most advocated methods in mitigating the risks associated with the adverse effects of climate change, especially for developing countries that most population relies on subsistence farming (Fentie and Beyene, 2019; Arslan et al., 2015; Tiamiyu et al., 2018; Terdoo et al., 2014; Schenck, 2018; Sova et al., 2018). CSA explicates specialized type of agricultural practices that offer the prospect to concurrently increase productivity, enhance resistance, and alleviate carbon emissions (Rome, 2010). Nwajiuba et al. (2015) eloquently review the definition of CSA as agricultural practices that improve productivity as well as the resilience to adverse climate change effects, and aid in the lessening and eradication of greenhouse gas emissions. CSA practices such as intercropping, crop diversification, crop rotation, organic fertilizer and improved seeds aim not only to improve yields of crops, but also lessen the adverse effects associated with climate change through increasing agricultural production and incomes of rural households (Fentie and Beyene, 2019; Teklewold et al., 2017). Thus, enumerating the effects of these practices on the welfare of those that employ them will provide policymakers the empirical evidence to enhance the welfare of individuals and households that hinge on rural farming. However, quantifying the impacts of these innovative practices requires rigorous study. By focusing on two popular CSA practices and using a robust impact evaluation econometrics to addresses selection bias, this study aims to contribute to the scant empirical evidence by studying their impact on household welfare in Nigeria. Nigeria's agriculture depends heavily on rainfall; droughts (subsequent of climate change) have intensified the need to turn to climate-smart agricultural practices, in order to provide climate change resilient agricultural systems. These systems will potentially improve household welfare as well as offset the risks associated with climate change, like food insecurity.

While assessment of the impact of good agricultural practices on welfare of rural households has a long story in the development and agricultural economics literature, the impact of CSA receives interest only in contemporary work. Tolesa et al. (2014) looks into the effects of row planting on wheat production. Their study document that row planting has significant and positive effects on crop yield for farmers in highlands and no noteworthy effects on farmers in the lowlands in the Amhara region of Ethiopia. Similarly, Fentie and Beyene (2019) find that row planting significantly increased the income per hectare and consumption per capita within the two regions of Ethiopia. In Zambia, intercropping considerably increases yields of maize, and fertilizer emerges as a key driver of improvement in maize yields. Improved seed overall yielded an average positive impact on yields though it was discovered to be highly dependent on climatic conditions Arslan et al., 2015.

This study aims to evaluate the effects of adoption of two potentially CSA practices (namely, intercropping, improved seed and their combination) using nationally representative data from Nigeria combining it with innovative climate variables data and employing a Multinomial Endogenous Switching Regression (MESR) model. This study makes two important contributions to the literature. First, most studies rely on unrepresentative data which limit the external validity of the existing evidence (Lovo and Veronesi, 2019; Sibhatu et al., 2018). We utilize rich nationally representative survey data merged with geo-referenced weather data that allows to control for the effects of a variety of household and individual characteristics, climatic and agro-ecological conditions and institutional characteristics on crop choice and nutrition. We also use rigorous methods that tackle unobserved heterogeneity and selection bias. Second, unlike previous studies we compare the impacts of two potentially climate smart practices, intercropping and improved seed use, both separately and jointly. Although a growing body of literature tries to understand the impact on CSA on yield and welfare improvement, not enough is known about the joint effects of CSA practices, and this warrants further research.

Results reveal that adoption of intercropping and improved seed methods, independently, have positive and significant effects on per capita adult equivalent consumption of farming households. Similarly, adoption of the combination of these CSA methods has a positive effect. However, this effect is lower than the effect of adopting improved seed only. These results validate that CSA practices may be substantial contributors to the resilience of farming households despite rising food insecurity due to climate change. However, scaling up technology such as adoption of improved seed will significantly contribute to rural household resilience against the adverse effect of climate change though enhancing consumption and food security.

Our results show farming households that adopt CSA have significantly higher per capita adult equivalent consumption than households that do not adopt either of the two CSA practices, intercropping and improved seeds. This results are inline with the existing empirical evidence in Ethiopia and Zambia. Fentie and Beyene (2019), Arslan et al. (2015) and Manda et al. (2016) document that row planting and improved seed have a positive effect on welfare and yield in Ethiopia and Zambia, respectively. Similarly, adoption of the combination of these CSA methods has a positive effect. However, effect of adopting both improved seeds and intercropping have a lower than the effect of adopting improved seed only. Households that adopt improved seeds have highest consumption gain than households that use neither of the two CSA practices, as well as households that adopt intercropping only. These results, especially noting the inclusion of novel climatic variables and soil data, illustrates that policymakers should create finance streams that support CSA adoption especially in the rural and low-income parts of Nigeria that depend on farming. This would have significant effects crop yields, which would inherently boost food security and welfare midst increasing climate uncertainties.

The rest of this paper is structured as follows. Section 2 briefly reviews the literature. Section 3 discusses the data and presents the descriptive statistics for the variables of interest. Section 4 the estimation strategy. Section 5 discusses the findings. The last section concludes the study and point out some policy implications of the results.

2 Literature Review

Nigeria is largely an agricultural country. Adejuwon (2006) evaluated the potential crop production in Nigeria provided the potential effects of climate change. His results projected a decreasing yield of major crops in the case of continued global warming as a consequence to lack of minimum and maximum temperature tolerance of the modelled crops (maize, millet, sorghum, rice and cassava). However, limited literature exists that focuses on the welfare impacts of climate smart agriculture practices. Nwajiuba et al. (2015) emphasize that small-scale Nigerian farmers already utilize some CSA practices unknowingly, with their main objective to solely increase production. Some CSA practices that these farmers already use are drought-resistant seeds, improved seeds and legume crops as well as reduced tillage. CSA practices are a key to improving both productivity and profits within poor Nigerian households whose livelihood is dependent on agriculture. When combinations of CSA practices are employed, they can significantly increase yield and income of farm households (Manda et al., 2016).

Nyasimi et al. (2014) compile a comprehensive study that deciphers currently existing CSA technologies and practices in Africa. The CSA practices have been documented through various case studies and have positive impact on farmers welfare. Their study focuses on CSA practices that have been proven to succeed in what they call the 'triple win' – food security, climate change adaptation and climate change mitigation. Some of the key findings were taken from three different projects. The Drought Tolerant Maize for Africa (DTMA) Project that was launched in 2006, which developed and distributed "drought tolerant, high yielding, locally adapted varieties of maize" has increased farmer yields by 10 to 34 percent. The Water Efficient Maize for Africa Project that was launched in 2008, developed "drought-tolerant, early maturing and disease resistant" maize hybrids increased crop yields by 20 to 35 percent in a drought environment. The Sustainable Agricultural Development of Highlands Project in North Africa launched in 2013, initiated the no-tillage farming method in Morocco as a practice to preserve water use in agriculture has increased wheat yield by 25 percent with a reported case of 300 percent yield boost.

Using primary data from 808 households in southern Malawi Amadu et al. (2020) analysed the adoption of CSA and its impact on maize yield, they examined the CSA practices implemented by the Wellness, Agriculture for Life Advancement (WALA) program in Malawi. The project was an aid for the dryer parts of Malawi that were highly susceptible to food insecurity due to climate change. The impact of watershed treatment, which is a watershed conservation method that conserves water and facilitates healthy soil for crops, was studied using the endogenous switching method. The study found that maize yields for farmers that adopted all the CSA practices was 53 percent higher than those who did not adopt the CSA practices. Their result also suggest that the adoption of inorganic fertilizer may boost crop yields in dryland areas like Malawi.

Joshi (2005) and Njeru (2013) found crop diversification as one of the most potentially CSA practice that improves crop yield, profit margins, as well as food security. By focusing on the three CSA objectives (food security, climate change adaptation and climate change mitigation), they tackle Nigeria's fundamental challenges of declining agricultural productivity which affects the food security, as well as the high levels of carbon emissions (Nwajiuba et al., 2015). Njeru

(2013) compiles and examines literature and studies that have focused on crop diversification as a potentially effective CSA practice because of its cost-effectiveness and mainly its resilience in terms of being able to re-establish to its initial productive state once it has been disturbed.

Arslan et al. (2015) study a suite of possibly climate smart agricultural practices (comprising of reduced tillage, crop rotation and legume intercropping, combined with the use of improved seeds and inorganic fertiliser) and estimate the impact of all the practices on maize production in Zambia. They utilized panel data from the Rural Incomes and Livelihoods Surveys combined with a collection of climatic variables (rainfall and temperature) to examine how the effectiveness of these CSA practices change based on climate conditions. Their results showed that intercropping considerably increases yields of maize, and identified fertilizer as one of the most robust causal factors of yields. Improved seeds and fertilizers are highly reliant on climatic variables though their average impact on yields is positive. Crop rotations and minimum soil disturbance had no noteworthy effect on yields in their study.

Fentie and Beyene (2019) provided experimental evidence on the impact of one particular climate-smart agricultural practice which is row-planting. Examining 260 households in two regions within Ethiopia, using Propensity Score Matching methodology, their model found that the CSA practice of row planting had a substantial and positive effect on consumption per capita and income per hectare within these regions. The outcomes of this study endorse the prospective role of climate-smart agricultural practices (in this case, row planting) in advancing climate change resilience for small-scale farmers, as well as the welfare of their households and combatting food insecurity. Tolesa et al. (2014) employ Propensity Score Matching methodology on 248 randomly selected farmers to study the impact of wheat row planting in Ethiopia. Using a logit model and cross-sectional data, they found that row planting had a positive and significant effect on the yields of wheat for farmers in the highlands, but no significant impact was observed for farmers in the lowlands. Additionally, farmers in the highlands that utilized the row planting method for wheat production experienced higher yields, on average 13.9 per cent higher than farmers that used the conventional planting methods.

In Nigeria, there is limited research conducted to see the effects of potentially climate smart agricultural practises. Majority of available studies on CSA address the determinants of the willingness of farmers to adopt climate smart agricultural practices (Tiamiyu et al., 2018; Nwajiuba et al., 2015; Onyeneke et al., 2018). This is the reason this study focus on providing empirical evidence on potentially climate smart agricultural practises in Nigeria, with the purpose of resolving the shortcomings of the climate smart agriculture research especially in Nigeria that is relevant in safeguarding welfare of farmers and alleviating the adverse effects of climate change.

3 Data

3.1 Sample

We used the Nigerian General Household Survey, panel wave 3 from 2015-2016.[3] The survey is a panel study that is a nationally representative survey of approximately 5,000 households, which are indicative of rural and urban areas as well as all geopolitical zones. All the surveys are nationwide, and they use household, individual and community units of measurement. Agricultural households and non-agricultural households were approached biannually, after the planting season between August and October and after the harvest season between February and April (WorldBank, 2020). This survey helps improve the accuracy of estimations of trends, as well as allowing for a more far-reaching evaluation of poverty indicators and other socioeconomic characteristics.

Data on soil conditions was source from the FAO Harmonized World Soil Database version 1.2 (FAO, 2020). This database consists of over 15 000 various soil mapping components which are merged with current national and regional upgrades of international soil data. Variables that have been used to quantify soil quality are "soil workability", "soil nutrient retention capacity", and "soil nutrient availability" which all vary at a scale from 0 to 7.

Data pertaining to climatic variables was sourced from the Climatic Research Unit Time-Series version 4.03 of the University of East Anglia. The abridged version of the data is used, which is also adjusted for bias through the WorldClim data website, version 2.1 climate data for 1960 to 2018 (Wor, 2020). This dataset is time series data which is gridded over the period. The measure of the minimum object that can be determined by the sensor (spatial resolution) is roughly 21 kilometres squared. The temperature variables used from this data are "monthly temperature", "three-year average monthly temperature", "five-year average monthly temperature" and the "average monthly temperature in the wettest quarter"- all measured in °C. The precipitation variables used

[3] 2018 data is available, but access to it is restricted

are “year of survey monthly precipitation”, “previous year precipitation”, “three-year average monthly precipitation”, ”five-year average monthly precipitation” and “monthly precipitation in the wettest quarter” – all measured in millimetres. The monthly averages were calculated per wave from July to June.

The sample size was 2252 rural households within Nigeria that are located within rural areas. The survey gathered information on individual characteristics (gender, education level, age), household attributes (number of household members, household consumption,combined income, the value of assets, zone), agricultural characteristics (livestock holding, farmland size, labour allocated to farm, soil workability, distance to plots, distance to a water source, distance to market), agricultural practices (fertilizer use, improved seed use, intercropping), and climatic characteristics (average monthly temperature, monthly rainfall). Information regarding access to formal financial services and extension services was also collected. This survey allows us to perform an impact evaluation of potentially climate smart agricultural practices on the welfare of small-scale farming households.

3.2 Descriptive Statistics

Variables that were included in this study were directed by related literature and studies. Table 1 shows the main explanatory variables and statistics used for our analysis, subdivided by treatment type. In our sample, the average household consumption per adult equivalent was 166 689.10. Overall, the consumption of the treated farming households was higher than that of the untreated households. As seen in Table 4.1, farming households that adopted both programs/treatments (improved seed and intercropping) showed the greatest consumption levels, farming households that used improved seed only followed. Those that made use of intercropping only had the lowest consumption levels, even lower than the untreated ones. Of the total sample households, 80% of household heads were male, with the remaining 20% being women, with an average age 48 years old. Most of our sample household heads had no education at 39.34%. The majority of the sample farming households hailed from the North West zone (34%). Farming households that selected the intercropping method only were mainly situated in the North West zone, those that mostly selected improved seed use only were situated in the North Central zone. Those that mostly utilized a combination of the two treatments were mainly from the North West Zone, those that chose neither treatments were situated typically in the South South zone of Nigeria.

The average size of households in these farming households was 8 members. The consumption of those using both treatments was highest among the groups, followed by those that use improved seed only. Households that use intercropping only had the lowest consumption among all groups, as well as lower than the sample average. The value of assets of the households was highest for households that use improved seed only, followed by households that adopted both methods and then those that used neither. Households that use intercropping only had the lowest value of assets among all groups, as well as lower than the sample average. Households that used both treatments had the lowest livestock holding, followed by those that used neither treatment - which were both lower than the sample average. Households that used improved seed had the highest livestock holding, followed by those that used intercropping only. The average farmland size was 1.21 hectares, with households that utilized neither of the treatments having the highest land size (1.68 hectares) , followed by those that used improved seed only (1.66 hectares) and intercropping only (1.07 hectares), respectively. Households that adopted both treatments had the lowest farmland size of 0.93 hectares.

Farm households that utilized both treatments had the least labour days allocated to the farm in the past year (both hired and family) with 444.52 days, households using improved seed only had the highest days allocated to the farm at 575.33 days, the average number of days for the sample was 538.73. Households that used both treatments together used the most fertilizer per hectare of land. Households that experienced lower average temperatures used improved seed only or both treatments (both averaging at 27 degrees Celsius). Households that experienced higher monthly rainfall in the wettest quarter did not utilize any treatments, followed by those that used improved seed only. The majority of households that experienced the least monthly rainfall in the wettest quarter were those that utilized intercropping only. The average sample distance to households' plots was 1.57 kilometres, where households closest to their plots were those that used both treatments (1.29 km), followed by those that do intercropping (1.51 km), and untreated households (1.85 km).Those households that use improved seeds only are the furthest from their plots(1.90 km). The average distance to the market was 70.59 kilometres for the sample, households that used both treatments were closest to the market (63.18 km) and the households that used no treatments were furthest from the market (77.60 km). Households that have the highest probability of access to any sort of financial services are those that use improved seed only, followed by those that use both treatments, and then those that do not use either treatment. Those households that used intercropping only have the lowest chance of accessing financial services. Households that use both treatments are the ones that have the best access to extension services followed by those that use only improved seed, while those that use intercropping and use neither are the ones with the least access.

Table 1 – Descriptive Statistics by Treatment Type

	Intercropping		**Improved seed**		**Both**		**Untreated**		**Total**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Main Outcome Variable:										
Yearly household consumption per adult equivalent (in logs)	11.49	0.56	11.61	0.60	11.69	0.65	11.58	0.67	11.54	0.60
Household Head characteristics:										
Female (1/0)	0.12	0.33	0.09	0.29	0.12	0.33	0.16	0.37	0.13	0.34
Age	48.19	26.35	43.27	16.90	45.68	14.10	47.13	15.54	47.45	22.72
Household Head Education:										
No education	0.57	0.50	0.44	0.50	0.45	0.50	0.42	0.49	0.51	0.50
Primary	0.22	0.41	0.23	0.42	0.26	0.44	0.26	0.44	0.23	0.42
Secondary	0.16	0.36	0.23	0.42	0.16	0.37	0.21	0.40	0.17	0.38
Above Secondary	0.06	0.23	0.11	0.31	0.13	0.34	0.12	0.32	0.08	0.28
Household Characteristics:										
Number of household members	8.09	3.46	7.90	3.57	8.20	3.46	7.85	3.33	8.05	3.43
Total Income (in logs)	12.22	1.42	12.43	1.38	12.46	1.29	12.40	1.47	12.30	1.41
Value of assets (in logs)	10.30	1.23	10.75	1.21	10.67	1.30	10.46	1.42	10.40	1.29
Livestock holdings	1.50	3.98	1.67	3.96	1.20	3.03	1.26	5.24	1.41	4.19
Farmland size (in hectares)	1.07	1.68	1.66	3.67	0.93	1.20	1.68	5.52	1.21	3.03
Zones:										
North Central	0.17	0.37	0.33	0.47	0.13	0.34	0.19	0.40	0.17	0.38
North East	0.17	0.37	0.26	0.44	0.07	0.26	0.18	0.38	0.16	0.37
North West	0.38	0.49	0.16	0.37	0.44	0.50	0.18	0.39	0.34	0.47
South East	0.15	0.35	0.07	0.25	0.15	0.36	0.04	0.19	0.12	0.32
South South	0.09	0.28	0.13	0.34	0.12	0.33	0.24	0.43	0.13	0.33
South West	0.05	0.23	0.06	0.23	0.08	0.27	0.17	0.38	0.08	0.28
Total labor days (hired +family) allocated to the farm in the past year	560.66	587.20	575.33	622.93	444.52	524.35	527.63	584.34	538.73	581.01
Rate of fertilizer application (kgs/ha) (household level)	182.17	482.36	111.03	223.73	279.39	647.03	176.89	1092.09	191.14	679.66
Household uses formal financial services	0.23	0.42	0.34	0.48	0.33	0.47	0.32	0.47	0.27	0.44
Household Reached by extension services	0.08	0.27	0.10	0.30	0.18	0.38	0.08	0.27	0.09	0.29
Soil Workability (mean)	1.57	0.71	1.36	0.67	1.36	0.55	1.41	0.63	1.50	0.68
Average Distance to Plots (in km)	1.51	5.59	1.90	3.23	1.29	2.05	1.85	5.09	1.57	5.08
Three Year Average Monthly Temperature (°C)	27.34	0.92	27.00	1.04	27.00	0.84	27.26	0.81	27.27	0.90
Distance to Closest Market (km)	68.93	37.66	82.78	46.69	63.18	38.92	77.60	44.66	70.59	40.10
Distance to Closest Water Source (km)	4.45	3.09	4.66	3.24	4.84	3.03	4.27	3.03	4.47	3.08
Monthly Rainfall in the Wettest Quarter (mm)	203.78	42.39	219.17	40.70	213.40	38.20	217.66	47.97	208.65	43.54
Number of observations	1400		79		292		481		2252	

4 Empirical Strategy

In order to derive the treatment effects of CSA adoption on household welfare, measured by consumption per adult equivalent, we used multinomial endogenous switching regression approach (MESR) and a propensity score matching (PSM) for multiple treatments. Given the fact that the propensity score matching does not capture the effects of unobserved heterogeneity, the PSM estimates are used for robustness check.

The biggest challenge in estimating the treatment effect of any non-random self-selected intervention is finding a credible estimate of the counterfactual: what would have happened to treated households, households that adopt CSA, if they had not adopted CSA practices. If treatment is randomly assigned, the difference in the outcome of untreated and treated households can be a good estimate of the treatment effect. However, in non-randomly assigned treatments such as using CSA practices, households that adopt CSA practices (treated) may have characteristics that differ from the ones that don't adopt CSA practices. Thus, the comparison of the outcome between the two groups will yield to biased estimates (Rubin, 1974). Without information on why households self-select to adopt or not to adopt CSA, the next best alternative is to construct a counterfactual which is as close as the treated households, such that those who adopt CSA would have had similar outcomes to those that do not adopt (comparison group) in the absence of treatment (Khandker et al., 2009; Rubin, 1974).

Let there are $(P{+}1)$ completely exclusive treatments whereby the possible treatments are denoted using $(Y_0, Y_1, \ldots, Y_P)$. For each households, only one state of the potential treatment is observed and the other states are counterfactuals. Adoption of a particular CSA(treatment) is donated by $T\ \{0,1,\ldots P\}$. There are $P+1$ potential outcomes for each household, but there is only a single state treatment is observed (T_i). Thus, for a household i, $T_i = t$, then $Y_i = Y_i[t]{=}\mu_{\ t}$. In the context we are working, in multiple treatment frameworks, we place emphasis on the comparative efficacy of all treatments jointly and severally.

In multiple treatment framework, the relative average treatment effect (ATE) of treatment t' relative to t" is the difference of average outcomes had all households been observed under a single treatment t versus had all households been observed under alternative treatment t (Wooldridge, 2010, Araar et al., 2019).

Formally, the average treatment effect ($\tau_{ate}^{t^{'}t^{''}}$) is given as follows:

$$\tau_{ATE}^{t^{'}t^{''}} = \mu_{t'} - \mu_{t''} \tag{1}$$

The average treatment on the treated (ATT) is the pairwise contrast of the effects of treatments $t^{'}$ and $t^{''}$ for households in either $t^{'}$ or $t^{''}$. Thus ATT is given:

$$\tau_{ATT}^{t^{'}t^{''}} = \mu_{t't''} - \mu_{t't'} \tag{2}$$

The relative ATT of treatment (t') among households that are treated with t" is the difference between the mean outcome of those who were treated with t" and those treated with t' would have had if they had been treated with treatment t" instead of t' (Araar et al., 2019;Wooldridge, 2010).

In a multiple treatment the choice of estimate, either ATT or ATE, depends on the research or policy question under investigation. In this study, we aim to identify a CSA practice which is most beneficial to improve the welfare(consumption) of farm households in Nigeria. Thus, estimates of both ATE and ATT provide relevant information policy making. ATE shed light on what would be the gain in welfare (the treatment effect) if a particular treatment is adopted by all farm households. Similarly, ATT provide information on the relative effectiveness of one treatment versus another treatment. Additionally, if the interest is to evaluate the appropriateness of a treatment on improving the welfare of a particular group, the ATT would provide relevant estimates (Araar et al., 2019).

With the objective of providing full information, we estimate both ATE and ATT as summarized in Table 2.

4.1 Multinomial endogenous switching regression approach for multiple treatments

A farming households' choice between intercropping, improved seed, or simultaneous adoption of both practices may be endogenous to observed and unobserved characteristics of households leading to self-selection bias. With the objective of addressing potential self-selection bias due to observed and unobserved characteristics of households, we use the multinomial endogenous switching regres-

Table 2 – Treatment effects (ATE and ATT) of multiple treatments*

	ATE	ATT		
		Intercropping (in)	Seed(se)	Both** (inse)
Intercropping vs. Seed	$\mu_{in} - \mu_{se}$	$\mu_{in,se} - \mu_{in,in}$	$\mu_{in,se} - \mu_{se,se}$	§
Intercropping vs. Both	$\mu_{in} - \mu_{inse}$	$\mu_{in,inse} - \mu_{in,in}$	§	$\mu_{inse,in} - \mu_{inse,inse}$
Improved seed vs. Both	$\mu_{se} - \mu_{inse}$	§	$\mu_{se,inse} - \mu_{se,se}$	$\mu_{inse,se} - \mu_{inse,inse}$

*ATE is computed in comparison to households that did not adopt any of the CSA practices.
** Simultaneous adoption of improved seed and intercropping
§nonsensical cases to estimate the ATT.

sion approach following Dubin and McFadden (1984). Thus, we first model the treatment decision (intercropping, improved seed, or a combination of intercropping and improved seed, or neither) using a multinomial logit selection model that accounts the interdependence between the treatments. Then the effects of each treatment on consumption per adult equivalent is assessed using linear regression with endogenous treatment effects. By using this approach, we are able to estimate treatment effect that are efficient and consistent.

4.1.1 Multinomial logit selection model

Within random utility theory, it is assumed that a representative household chooses a treatment that maximize her/his utility. Formally, a latent model (T_{ji}) describes household i's choice for CSA practice j over another alternate CSA practice p.

$$T_{ji} = \gamma_j z_i + \varepsilon_{ji} \tag{3}$$

Where z_i is the vector of observable characteristics of a household that affect choice of CSA practice and $\varepsilon\ _i$ is the unobservable characteristics that affects adoption decision. The utility of adopting an alternative CSA practice is not observed, while the actual adoption of a given practice is observed. A household's choice of an alternative CSA practice j over alternative practice m is given:

$$
T_{ji}^{*} = \begin{cases} 0 \; if \; T_{ji}^{*} > \max_{m \neq 1} T_{mi}^{*} \;\; or \; \omega_{0i} < 0 \\ \quad \quad . \quad \quad . \quad \quad . \\ \quad \quad . \quad \quad . \quad \quad . \\ \quad \quad . \quad \quad . \quad \quad . \\ J \; if \; T_{ji}^{*} > \max_{m \neq j} T_{mi}^{*} \;\; or \; \omega_{ji} < 0 \end{cases} \tag{4}
$$

Where $\omega_{ji} = \max_{m \neq j}(T_{mi} - T_{ji}) < 0$ (Bourguignon et al., 2007). Eq. 4 implies that household i chooses alternative CSA practice j over m if and only if the welfare gain from j is greater than that welfare obtained from m for $m \neq j$.

Assuming that ε is an iid, the probability that a household i will adopt a given CSA practice j given its characteristics z can be given as a multinomial logit model (McFadden et al., 1973).

$$
p_{ji} = pr(\omega_{ji} < 0 \,|z) = \frac{\exp{(\gamma_j z_i)}}{\sum_{m=1}^{J} \exp(\gamma_m z_i)} \qquad j = 1, 2, \ldots, J \tag{5}
$$

4.1.2 Multinomial endogenous switching regression

In order to evaluate the impact of each treatment on consumption per adult equivalent of farming households, we specify the following multinomial endogenous switching regressions as in Equations:

$$
c_{ni} = \beta_n x_i + u_{ni} \qquad if \quad T = 0 \tag{6a}
$$

$$
c_{ini} = \beta_{in} x_i + u_{ini} \qquad if \quad T = 1 \tag{6b}
$$

$$
c_{seedi} = \beta_{seed} x_i + u_{seedi} if \qquad if \quad T = 2 \tag{6c}
$$

$$
c_{inseedi} = \beta_{inseed} x_i + u_{inseedi} \qquad if \quad T = 3 \tag{6d}
$$

Due to possible confounding factor such as motivation to work and risk taking behavior that affects the outcome variable (6a)–(6d) and the selection equation, however, estimating Equations 6a-6d using OLS yields biased results. Hence, consistent estimates of the parameters in Eqs (6a)–(6d) require correction for selectivity. Bourguignon et al. (2007) argue that consistent estimates of the parameters are obtained by introducing a correction term, in the in Eqs. (6a)–(6d) given as follows

(Eqs. (7a)–(7d)):

$$c_{ni} = \beta_n x_i + \sigma_n \lambda_n + \xi_{ni} \qquad if \quad T = 0 \tag{7a}$$

$$c_{ini} = \beta_{in} x_{ji} + \sigma_{in} \lambda_{in} + \xi_{ini} \qquad if \quad T = 1 \tag{7b}$$

$$c_{seedi} = \beta_{seed} x_{ji} + \sigma_{tr} \lambda_{tr} + \xi_{tri} \qquad if \quad T = 2 \tag{7c}$$

$$c_{inseedi} = \beta_{inseed} x_{ji} + \sigma_{inseed} \lambda_{inseed} + \xi_{inseedi} \qquad if \quad T = 3 \tag{7d}$$

Where σ_u is the covariance between ε and u; λ is the correction term derived based on estimated probabilities from Eq. 5 and the correlation (ρ) between ε and u.

Following this, we estimate the expected consumption per adult equivalent for untreated farming households as follows:

$$E(c_{ni} T = 0) = \beta_n x_i + \sigma_n \lambda_n \tag{8a}$$

Similarly, the expected consumption per adult equivalent of households that adopt the CSA practice under investigation are given in Eqs.8b- 8d.

$$E(c_{ini} | T = 1) = \beta_{in} x_i + \sigma_{in} \lambda_{in} \tag{8b}$$

$$E(c_{seedi} | T = 2) = \beta_{seed} x_i + \sigma_{seed} \lambda_{seed} \tag{8c}$$

$$E(c_{inseedi} | T = 3) = \beta_{inseed} x_i + \sigma_{inseed} \lambda_{inseed} \tag{8d}$$

Comparably the counterfactuals for non-adopters had they adopt one or more CSA practices is:

$$E(c_{ji} | T = 0) = \beta_j x_i + \sigma_j \lambda_n \tag{9a}$$

Finally, the expected value of consumption per adult equivalent for CSA practice adopters had they not adopt any of the CSA practice is as follows:

$$E(c_{ni}|T = j) = \beta_n x_i + \sigma_n \lambda_j \tag{9b}$$

Given *t' and t" are treatments in j* the ATE and ATT are computed as follows :

$$ATE_j = E(c_{ji}|T = j) - E(y_{ni}|T = n) = \beta_j x_{ji} + \sigma_j \lambda_j - \beta_n x_{ni} + \sigma_n \lambda_n \tag{10a}$$

$$ATE_{t't''} = E(c_{t'}|T = t') - E(c_{t''}|T = t'') = \beta_j x_i + \sigma_j \lambda_j - \beta_n x_{ni} + \sigma_n \lambda_n \tag{10b}$$

$$ATT_j = E(c_{ji}|T = j) - E(c_{ni}|T = j) = (\beta_j x_i + \sigma_j \lambda_j) - (\beta_n x_i + \sigma_n \lambda_j) \tag{11a}$$

$$ATT_{t't''} = E(c_{t''}|T = t') - E(c_{t'}|T = t') = (\beta_{t''} x_i + \sigma_{t''} \lambda_{t'}) - (\beta_{t'} x_i + \sigma_{t'} \lambda_{t'}) \tag{11b}$$

4.1.3 Propensity Score matching for multiple treatments

In the literature there are a number of approaches to estimate the propensity score in the case of multiple treatments. In this paper we follow the approach suggested by Lechner (2001) and Imbens (2000). Practically this entails constructing a multinomial treatment variable as a dependent variable and estimate an MNL regression of the treatment variable on the set of regressors that potentially affects selection to the treatment.

Estimating the pairwise ATEs such as $(\mu_t - \mu_{t'})$ required a consistent estimates of the population means of the potential outcomes for each of the treatments (μ_t and $\mu_{t'}$). Given the probability (the propensity score, $p_t(X)$) that a household with pre-treatment characteristics $\mathbf{X}$ receives treatment t ($p_t(X) = pr(T[t] = 1|X)$), a consistent estimate of μ_t is given by the weighted mean in Eq.12, where the weights satisfy $w_i[t] = \frac{1}{p_t(X)}$.

$$\mu_t = \frac{\sum_{i=1}^{n} T_i[t] Y_i w_i[t]}{\sum_{i=1}^{n} T_i[t] w_i[t]} \tag{12}$$

Then we estimate the ATE for $\mu_t - \mu_{t'}$ as follows :

$$\tau_{ate}^{tt'} = \mu_t - \mu_{t'} \tag{13}$$

To estimate the pairwise ATT for one of the CSA practices t' (E.g., $\mu_{t',t''} - \mu_{t',t'}$), we need to estimates the mean of the potential outcomes for non-adopter households like those who adopted one or more CSA practices, the treatment $t^{'}$ had they received the other treatment conditions $t^{''}$. Given onditional Independence Assumption and common support hold, a consistent estimate of $\mu_{t',t''}$ and $\mu_{t',t'}$ is given by the weighted and unweighted mean in Equations (14a) and (14b),respectively.

$$\mu_{t',t''} = \frac{\sum_{i=1}^{n} T_i[t^{''}]Y_i w_i[t^{'}, t^{''}]}{\sum_{i=1}^{n} T_i[t^{''}]w_i[t^{'}, t^{''}]} \tag{14a}$$

$$\mu_{t',t'} = \frac{\sum_{i=1}^{n} T_i[t^{'}]Y_i}{\sum_{i=1}^{n} T_i[t^{'}]} \tag{14b}$$

The weight in Eq. (14a) is $w_i[t^{'}, t^{''}] = \frac{p_{t'}(X)}{p_{t''}(X)}$. Taking the difference between Eq. (14a) and Eq. (14b), one can estimate the ATT for $\mu_{t',t''} - \mu_{t',t'}$ as $\tau_{att}^{t^{'}t^{''}} = \mu_{t',t''} - \mu_{t',t'}$.

5 Results

This section focuses on answering our key research question, which aims to estimate the impact of CSA practices (intercropping, improved seed and the combination of the two) on the welfare of farming households in Nigeria, through looking at households consumption per adult equivalent, using a MESR model.

The results are shown in Tables 3 and 4 present the estimated treatment effects for all farming households within the sample. As discussed in 4 the ATE shows the difference in consumption per adult equivalent for all households who adopt a particular CSA practice compared with the alternative group if they had used adopt another CSA practice or had used none of the CSA practices. First, we estimate the ATE by comparing adopters and non-adopters households. Second, we compare the average treatment effect of each CSA practices to one another. Results in Tables 3 showed that adoption of intercropping and improved seeds separately and jointly had a positive and significant effect on per adult equivalent consumption of households, compared to those who used neither of the practices.

The increase in on per adult equivalent consumption is 1.5%, 4.8% and 12.8% higher for intercropping, improved seed and joint adoption of intercropping, improved seed compared with households that used neither of the CSA practices, respectively. This results are consistent with the scant empirical evidence that shows the positive effect of CSA practices on household welfare (consumption). For instance, Fentie and Beyene, 2019 and Tolesa et al. (2014) found that row planting resulted consumption gain in Ethiopia. They both argue that consumption growth emanate from yield improvement of CSA practices. similarly, Amadu et al. (2020) found a higher maize yield for farmers that adopted the CSA practices in zzz. In Zambia, Arslan et al. (2015) also found that intercropping considerably increases yields of maize.

Table 3 – ATE of multiple treatments–All

Outcome variable- Yearly household consumption per adult equivalent ATE - MESR			
Intercropping vs. Untreated	0.015***	Intercropping vs. Improved Seed	-0.112***
Improved Seed vs Untreated	0.128***	Intercropping vs. Both	-0.032**
Both vs Untreated	0.048***	Improved Seed vs. Both	0.079 ***

$*p < 0.1, **p < 0.05, ***p < 0.01$

The ATE for households that use intercropping only compared to those that use improved seed only, shows a decline in consumption by 11.2%, suggesting a higher welfare gain of using improved seeds compared to intercropping. Looking at households that use intercropping only compared to those that use both treatments result in a decrease in per adult equivalent consumption of 3.2% indicating complementary nature of using improved seed for intercropping. Households that use improved seed only compared to those that use both treatments experience a 7.9% improvement in per adult equivalent consumption. This finding is in line with the fingerings of Verkaart et al. (2017), they document using improved chickpea improved household income and reduced consumption poverty. Our result of highest impact from adopting only improved seed are similar with Arslan et al. (2015) who found that improved seeds are highly reliant on climatic variables though their average impact on yields is positive. On the other hand, this findings is in contrast to the findings ofManda et al. (2016) who found that suggested that employing a combination of CSA practices have the highest increase yield and revenue, compared to adopting a single CSA practice.

In Table 4, the ATT of moving from intercropping only to improved seed only yielded a positive and significant 12.9% increase in consumption. The ATT of moving from improved seed only to intercropping only, though insignificant, decreases consumption by 16%. The ATT of moving from improved seed to both treatments, though insignificant, increases consumption by 3.3%. The ATT of moving from both treatments to intercropping significantly and negatively decreases consumption by 79%. Our result suggests that households that adopt improved seed have adopted effective CSA practice to improve their consumption; since adopting the other CSA practices such as intercropping or a combination would have decreased their consumption. In contrast, those that adopt only intercropping only would have a better welfare if they have adopted improved seed or adopt intercropping and improved seed simultaneously.

Table 4 – ATT estimates of multiple treatments–All

Outcome variable- Yearly household consumption per adult equivalent			**ATT- MESR**
	Intercropping	**Improved Seed**	**Both**
Improved Seed vs. Intercropping	0.129***	-0.160	§
Both vs. Intercropping	-0.010	§	-0.790
Both vs. improved Seed	§	0.033	0.04*

$*p < 0.1 **p < 0.05 ***p < 0.01$
§These are nonsensical cases to estimate the ATT

6 Robustness Checks

In this section, we use the propensity score matching approach for multiple tenement to examine the consistency our treatment effect estimates using Multinomial endogenous switching regression approach. Table 5 presents our estimates. The PSM estimates show that the ATE of adopting intercropping or both intercropping and improved seed versus not using neither practises is positive but not significant. The PSM estimates of adopting improved seed versus being untreated is positive and significant – which is consistent with the MESR estimates. We didn't find any difference in treatment effect between the treatments.

Looking at Table 6, the ATT estimates from the PSM are consistent with those of the MESR estimates, though the PSM estimates are all insignificant. The ATT of moving from improved seed to both treatments, though insignificant, increases consumption. The ATT of moving from improved seed only to intercropping only, though insignificant, decreases consumption. The ATT of moving from both treatments to intercropping significantly and negatively decreases consumption.

Table 5 – ATE of multiple treatments–All

Outcome variable- Yearly household consumption per adult equivalent ATE - PSM			
Intercropping vs. Untreated	0.014	Intercropping vs. Improved Seed	-0.052
Improved Seed vs Untreated	0.066*	Intercropping vs. Both	-0.350
Both vs Untreated	0.049	Improved Seed vs. Both 0.017	

$*p < 0.1, **p < 0.05, ***p < 0.01$

These results substantiate that improved seed use only or a mixture of improved seed as well as intercropping positively affects welfare through increasing consumption compared to using neither of the practises. Although MESR and PSM are based on different underlining assumptions and produced somewhat different quantitative results, the qualitative findings are similar. Both estimates suggest a positive impact of CSA practices (improved seed, or combined intercropping and improved seed) on the welfare of farming households in rural Nigeria. Moreover, results in both the ATE and ATT estimations relative to other treatments are similar, suggesting that improved seeds followed by the concurrent adoption of intercropping and improved seed would improve the welfare of farming households the highest.

Table 6 – ATT estimates of multiple treatments–All

Outcome variable- Yearly household consumption per adult equivalent ATT- PSM			
	Intercropping	**Improved Seed**	**Both**
Improved Seed vs. Intercropping	0.040	-0.026	§
Both vs. Intercropping	0.018	§	0.072
Both vs. Improved Seed	§	0.059	0.007

$*p < 0.1 **p < 0.05 ***p < 0.01$

§These are nonsensical cases to estimate the ATT

7 Conclusions

Literature relating to empirical studies on the impacts of CSA practices is still limited, though it is picking up momentum, especially in developing countries. Climate smart agriculture has been extensively defined, assessed, and accepted; but due to lack of data and methodology challenges, quantifying the impacts of these practices is arduous.

This study uses rigorous methods that tackle selection bias to evaluate the effects of intercropping, improved seed and the combination of the two on welfare of small farm holders in Nigeria. Existing studies mainly evaluate either one or the combination of these methods; we compare the impact separately and jointly, also including novel climatic and soil quality variables. By utilizing nationally representative survey data, we use a Multinomial Endogenous Switching Regression (MESR) model to evaluate the impact of intercropping and improved seed adoption on the welfare of farming households through examining their per adult equivalent consumption.

The results of this study show that the adoption of all the CSA practices under investigation have notable and positive effects on per adult equivalent consumption of Nigeria's farming households. The estimation results from the MESR model suggest that farming households that adopt improved seed have higher consumption levels than those that use intercropping and the combination of the two practices.

The results of this study demonstrate that policymakers should create finance streams that support CSA adoption especially in the rural and low-income parts of Nigeria that depend on farming. This would have significant effects on crop yields, which would inherently boost welfare and food security and in the centre of intensifying climatic uncertainties.

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Appendix

Table A.1 – First stage regression: Multinomial logistic regression

	Untreated		Improved seed		Both	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Female-headed household	0.3601**	0.1727	-0.1601	0.4107	0.0384	0.2136
Age of household head	-0.0027	0.004	-0.016*	0.0089	-0.0073	0.005
Education of household head						
Primary	0.1101	0.1597	0.1101	0.3337	0.155	0.1888
Secondary	0.2414	0.1748	-0.0228	0.3636	-0.0072	0.2209
Above secondary	0.3396	0.2361	-0.0167	0.4667	0.504*	0.2712
Total income	-0.0556	0.0453	0.01	0.0979	0.0416	0.0538
Total value of assets (in log)	0.028	0.0495	0.1942*	0.1087	0.1235	0.0616
Tropical Livestock Unit	0.0084	0.0129	0.0164	0.0202	-0.0177	0.0216
Land size (in hectare)	0.0431*	0.0225	0.0424	0.0405	0.0061	0.0376
Total Labor	-0.0003**	0.0001	-0.0002	0.0002	-0.0001	0.0001
Inorganic fertilizer	0.0002	0.0001	-0.0002	0.0004	0.0001	0.0001
Formal financial services	0.0559**	0.1598	0.2858	0.3267	-0.04***	0.1842
Extension services	-0.1662	0.2222	0.2404	0.4096	0.7947	0.2033
Soil Workability	-0.3419***	0.0923	-0.4659**	0.2019	-0.4303***	0.1274
Average Distance to Plots (km)	0.0026	0.0095	-0.0028	0.0249	-0.0157	0.0227
Three Year Average Monthly Precipitation (mm)	0.1744**	0.0767	-0.2661**	0.1336	-0.3024***	0.0811
Distance to Closest Market (km)	-0.0014	0.0015	0.0026	0.003	-0.0043	0.002
Distance to Closest Water Source (km)	-0.0054	0.0186	-0.0246	0.0393	0.0544**	0.0223
Monthly Rainfall in the Wettest Quarter (mm)	0.0109***	0.0018	0.0097***	0.0034	0.0029	0.0024
Region						
North central	-1.2737***	0.2319	0.4851	0.5915	-0.7351**	0.3224
North east	-1.1891***	0.2357	0.3408	0.6125	-1.4043***	0.3664
North west	-2.1413***	0.2548	-0.9677	0.6881	-0.6519**	0.3284
South east	-3.7866***	0.3556	-1.6391**	0.7936	-0.9604**	0.392
South south	-1.6454***	0.288	-0.8894	0.7284	-0.6797*	0.3914
Intercept	-5.4767**	2.3972	1.6651	4.1985	5.8947**	2.5802
Log likelihood			2044.844			
$\chi_2(d.o.f)$			448.66			
P-value			0			
N			2252			

Intercropping is the base outcome

$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A.2 – Second step regression: Selectivity correction based on multinomial logit

	Untreated		Intercropping		Improved seeds		Both	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Female-headed household	0.1306	0.0807	-0.0108	0.0543	-0.2357	0.32	0.0291	0.1131
Age of household head	-0.0007	0.0017	-0.0001	0.0006	0.0022	0.0073	-0.0015	0.0029
Household size	-0.0826***	0.0065	-0.07***	0.0041	-0.0535*	0.0196	-0.0658***	0.0123
Education of household head								
Primary	0.0057	0.0582	0.107**	0.0373	0.0284	0.2495	-0.0902	0.1048
Secondary	0.1113	0.0581	0.1249***	0.0392	0.0228	0.2426	0.0323	0.1182
Above secondary	0.256*	0.099	0.1741*	0.0688	0.3755	0.2104	0.3422*	0.1473
Total income (in log)	0.0906***	0.0177	0.0494***	0.01	0.0791	0.0621	0.046	0.0242
Total asset value (in log)	0.1785***	0.0236	0.1446***	0.0181	0.1617*	0.0909	0.1493***	0.0339
Tropical Livestock Unit	-0.0034	0.0046	0.002	0.0047	0.0087	0.0172	-0.0057	0.0068
Farm size (in hectare)	0.0082	0.0059	0.0227*	0.01	0.0154	0.0525	0.006	0.0289
Region								
North central	-0.0514	0.1453	-0.0619	0.1046	0.5769	0.7652	-0.1029	0.2357
North east	-0.0928	0.1272	-0.1104	0.1013	0.1256	0.7996	-0.0022	0.2254
North west	-0.0728	0.1136	-0.115	0.107	0.6591	0.8026	0.122	0.2071
South east	0.1416	0.1704	0.0217	0.1434	0.7483	0.9908	0.3257	0.2266
South south	0.1519	0.1003	0.0586	0.0739	0.7165	0.7023	0.4473**	0.1685
ρ_0	-0.3349	0.3072	-0.8579	0.6003	0.4541	1.0105	0.8979	0.6475
ρ_1	-1.3825*	0.8479	-0.4687	0.3659	1.7479	1.2268	2.2322***	0.7515
ρ_2	-0.0005	1.1767	1.1295	1.0255	0.3255	0.2554	0.2539	1.3383
ρ_3	-1.1417*	0.5499	-1.0488*	0.4221	1.1528	0.9508	0.199	0.2538
Intercept	8.655***	0.3717	9.8096***	0.2423	10.0035***	3.1548	11.4933***	0.8075
Log likelihood	2044.8436							
$\chi_2(d.o.f)$	448.66							
P-value	0							
N	2252							

* p<0.05, ** p<0.01, *** p<0.001

Impact of Crop Diversification on Food and Nutrition Security of Rural Households in Nigeria[1]

Hiywot Girma[2], Eleni Yitbarek[3]

Abstract

Nigeria is one of the food insecure countries in sub Saharan Africa where it has Global Hunger Index score of 32.8, with at least 5% of the global burden of undernutrition and more than 14 million malnourished children (Von et al., 2015; FRN, 2017). Numerous socio-economic and climatic factors affect food security status of households in Nigeria though improving food availability, accessibility, stability and utilization are important to keep up with the high population growth rate (3.2% per annum) observed in the country. Volatility of global food prices that affect the import of important food items and recent changes in climate that have led many states to experience delayed rains and/or flooding are the some of the main factors that affect the national food security status of Nigeria (FMARD, 2017). Substantial and sustainable reduction in food insecurity in Nigeria remains as a challenge without the effective engagement of the agricultural sector where the sector is the main contributor to the economy. Hence agricultural development that takes into account the impacts of market forces, social and cultural constraints, and climate change in production decisions is required to develop nutrition-sensitive agricultural livelihoods. With the focus to achieve improved nutrition and food security in the face of climate and price uncertainties in the country, the Nigerian Agricultural Sector Food Security and Nutrition Strategy 2016 – 2025 (AFSNS) has been developed where diversification of household food production and consumption are one of its priority areas. Crop diversification, a climate smart agriculture, impacts nutrition security as it affects the resilience of production systems and rural livelihoods. Despite the anticipation on the impact of crop diversification, there is no conclusive evidence on the effectiveness of farm diversification as a strategy to achieve nutrition security under all situations. Mixed evidence is established through a number of studies conducted in sub Saharan Africa. The studies mainly differ in methods used to capture the impact of crop diversification, the choice of food security and production diversity indicator variables (Simpson's Index, animal species

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count, crop species count and production diversity score), level of analysis (women, children, households level); choice of cut offs in defining food security and crop diversity, data (cross sectional, panel surveys, country level representativeness), and choice of explanatory variables (like incorporation of climate variables). This study looked at the impact of crop diversification on food security status of farm households in Nigeria by using nationally representative panel data (Nigerian General Household Survey-panel of wave1 (2010/11), wave2 (2012/13), and wave 3 (2015/16)). The household level socio economic, agricultural and welfare variables are enriched by merging them with climate variables, temperature and precipitation, which is mostly lacking in other household level studies conducted in sub-Saharan Africa. A robust method of endogenous switching regression was used to analyse the impact of crop diversification on consumption, food insecure months and diet diversity of farming households. Results show impacts to differ depending on the food security measures used. Improvement in per adult equivalent consumption was found in response to adoption of crop diversification. In addition, food insecure months in a year were lessened due to crop diversification. In contrast to the above, the impact of crop diversification on consumption of diverse diets was insignificant, where diet diversity is captured as consumption of six or more food items on Household Diet Diversity Score (HDDS).

Key words: Climate smart agriculture, food security, diet diversity, crop diversification, farming practice impact assessment

1. Introduction

1.1 Country profile

Nigeria is the most populous country in Africa and the seventh most populous in the world, with an estimated 173 million people in 2013. As of 2015, Nigeria was the world's 20th largest economy, worth more than $500 billion and $1 trillion in terms of nominal GDP and purchasing power parity (PPP) respectively. The country presently operates a federal system consisting of 36 states plus the Federal Capital Territory (FCT) of Abuja. The 36 states are grouped into six distinct geo-political zones — North Central, North East, North West, South East, South South, and South West — which to a great extent reflect ethnic affinity. The states are also divided into 774 local government areas serving as administrative units and a third tier of government (FMARD, 2017). Though oil contributes significantly to the Nigerian economy, the country is mainly an agricultural based economy where the sector generates employment for two third of the population. Despite agriculture's importance to the economy, production has been rising less than 1 percent in value-added per capita annually for the last 20 years. Declining national food self-sufficiency also results due to mismatch between population growth and domestic food production. In addition, significant losses have been recorded in exports of many commodities like cotton, groundnut, cocoa and palm oil due to continuous decline in the production of those commodities. Nigeria produces the world's largest volume of cassava, cowpea, yam and sorghum, but it has been a net importer of food and major importer of wheat, rice, sugar and fish (FMARD, 2011, as cited in FMARD, 2017). The main factors undermining production include reliance on rainfed agriculture, smallholder land holding, and low productivity due to poor planting material, low fertilizer application, and a weak agricultural extension system amongst others.

The volatility of global food prices have similarly led to increases in the prices of imported foods. Paradoxically, agricultural households have among the highest levels of food insecurity. Indeed, more than 50% of foods consumed in households, including agricultural households are purchased. With Nigeria's population increasing at an alarming rate of 3.2% per annum, food availability, accessibility, stability and utilization must constantly be increased to prevent food insecurity (Bill & Melinda Gates Foundation, 2014; Global Food Security Index, 2014; Atehnkeng, et al., 2017).

1.2 Food security context

Moderate and severe food insecurity has been consistently increasing since 2014 globally. The percent of people undernourished (PoU) in Africa is more than twice the world average (8.9 percent) and is the highest among all regions. Undernourished people in Africa increase from 17.6 percent in 2014 to 19.1 percent of the population in 2019. This prevalence is more than twice the world average (8.9 percent) and is the highest among all regions. Evidence also reveals that the world is not on track to achieve the SDG 2.1 Zero Hunger target by 2030, with number of undernourished people exceeding 840 million in 2030. Much of the recent increase in food insecurity is related with conflicts exacerbated by climate-related shocks, and impacts related with economic slowdowns on food access by the poor (FAO et al., 2020). Nigeria is one of the food insecure countries in sub Saharan Africa where it has Global Hunger Index score of 32.8, though the country showed some improvements in severity of hunger (GHI of 47.7 in 1994) (Von et al., 2015). Other indicators of food security show the same picture. The country is food energy deficient (a 38kcal/person/day food energy) with critical shortage of nutrient-rich foods, with low dietary availability of iron from animal sources (1mg/person/day compared to global average of 2.9mg); low consumption level of quality protein (35g/person/day compared to global average of 68.6g); and unacceptable level of food consumption score in 29% of the poorest households and 15% of the richest households. In addition, foods are unaffordable and food expenditure takes significant proportion of household income, with 58% of total national expenditure. More than 80% of households that spend belong to the lowest wealth quintile and they spend more than 75% of their resources on food. Majority of households in Nigeria lack access to nutrient-rich foods and consume monotonous staple-based diets. Access to adequate food is affected by limited availability of such foods, lack of knowledge and/information, lack of demand, and conflict (in some parts of the country) (Kuku-Shittu, et al., 2013).

Malnutrition is a big problem in Nigeria where indicators of chronic, long-standing and acute malnutrition are manifested in big proportions. According to the 2013 Nigeria Demographic and Health survey, 37% of children under-five are stunted, indicating, 18% of children under the age of five years are wasted, with 12% severely wasted; 29% of Nigerian children are underweight. Malnutrition is also very prevalent among women 15 to 49 years old, where 11% are underweight, while 25% are overweight or obese (NPC & ICF International, 2014).

Malnutrition causes child death, and affects health, educational attainment, and economic productivity. Nigeria contributed 13% of global child deaths in 2013 (UN, 2013). Diet related Non-Communicable diseases (NCDs) such as obesity, diabetes mellitus, and cardiovascular diseases are also becoming public health concerns in the country. In Nigeria, diet related NCDs such as obesity, diabetes mellitus, and cardiovascular diseases are increasing public health concerns. In 2012, it was projected that about 5 million Nigerians would die of NCDs by the year 2015, and diabetes alone was projected to cause about 52% of the mortality in 2015. At present, about 8 million Nigerians suffer from hypertension and 4 million have diabetes (Ekpenyong, et al., 2012).

1.3 Agriculture and food/nutrition security

Agricultural production is an integral part of the food environment and defines the people's dietary choices and nutritional status there by affecting nutritional outcomes and food security. Importance of agriculture to food security and poverty reduction is well documented. In response to international agreements such as the Paris Climate Agreement and the United Nations Sustainable Development Goals (SDGs), which emphasize the importance of ensuring food security, as well as to national development agendas, countries have been developing strategies to maintain agricultural production and achieve food security. Improving the food security status of smallholder farmers is at the centre of the development agenda, as small holders constitute the food insecure and poorest segment of the population. In addition, smallholder agriculture constitutes a major share of agricultural output. Improving food security of smallholder farmers is also critical for climate change adaptation and development goals in many developing countries (Godfray et al. 2010; Vermeulen et al. 2012; van Wijk et al., 2020). Agriculture has assisted a number of countries in achieving the Millennium Development Goal (MDG) target 1c of halving the proportion of hungry people by half in 2015. In many sub Saharan countries, smallholder farmers produce for own consumption and income generation. Recent growth in agriculture has contributed to a decline in proportion of national food insecurity figures and reduction in poverty, though in absolute terms the number of people suffering from chronic food deprivation are still increasing and that demand for efforts to curb the problem (Goyal & Nash, 2017). Between 2000 and 2015 a decline in the number of undernourished people-from 28.1 to 20.8- is documented (FAO et al., 2017).

To achieve global development goals and targets for nutrition security, nutrition specific interventions alone, even if implemented at scale, have not proven to meet global targets for improving nutrition (Bhutta et al., 2013; WHO, 2014). Agriculture has strong potential to contribute to nutrition security as it can influence the underlying determinants of nutrition outcomes. Black et al. (2013) shows the contribution of agriculture in improving global food availability and access, and in enhancing household income, food security, dietary quality, and empowerment of women. A number of global and regional initiatives indicate the need for agriculture for better nutrition and health outcomes. The discussions leading up to the United Nations' 2030 Agenda for Sustainable Development (United Nations, 2017), and growing number of regional initiatives like the Comprehensive Africa Agriculture Development Programme investment plans (Rampa & Seters, 2013) indicate the importance of supporting countries to integrate nutrition interventions into their agricultural investment plans. In an effort to address nutrition security issues, the government of Nigeria has also taken key policy initiatives over the years like mandatory fortification of key staples with major micronutrients, iron and iodine, and bio fortification to mainstream nutrition into agriculture. While nutrition-specific interventions are necessary, they are not sufficient for achieving adequate nutrition. Nutrition-sensitive interventions in areas such as agriculture, social protection, and education are required. Nutrition-sensitive interventions address the underlying causes of malnutrition including poverty, food insecurity, inadequate health services and caregiving, and poor sanitation and hygiene. Consequently, ongoing efforts to transform the agricultural sector in Nigeria especially prioritize improved food security and nutrition as a fundamental outcome. To achieve improved nutrition and food security in the country, the Nigerian Agricultural Sector Food Security and Nutrition Strategy 2016 – 2025 (AFSNS) has been developed. This is with the intent to guide the activities of the Federal Ministry of Agriculture and Rural Development (FMARD) and the wider agricultural sector in Nigeria and to ensure effective mobilization of human, material, and financial resources. Towards achieving the goal of improved nutrition, eight priority areas are formulated in the strategy, where diversifying household food production and consumption, and increasing access to micronutrient rich foods is one of them (FRN, 2017).

Nutrition sensitive agriculture and nutrition-specific interventions are approaches used to address the problem of food insecurity and malnutrition. Micronutrient supplementation, food supplementation, fortification, promotion of exclusive breastfeeding and optimal complementary feeding, immunization, and sanitation and hygiene interventions are some of the nutrition-specific interventions to address the immediate causes of malnutrition (dietary intake and disease) (Ruel & Alderman, 2013). Though these approaches are not enough to address the full range of insecurity problems, they are indispensable in reducing malnutrition. Prediction on the effectiveness of the interventions in Nigeria show a 20% reduction in prevalence of stunting if nutrition-specific interventions are implemented with 90% coverage (Bhutta et al., 2013). Child stunting, underweight and anaemia are also reported to decrease by about 5.9%, 7.0% and 2.4% respectively in response to a 10% increase in per capita gross domestic product (GDP). The same increase in GDP is associated with reduction of maternal underweight and anaemia by 4.0% and 1.8% respectively (Lin, et al., 2013).

Agriculture provides several unique opportunities for improving nutrition. This is through developing nutrition-sensitive agricultural livelihoods and interventions with income generating activities for at-risk groups, and by making nutritious foods more accessible (available and affordable), more nutrient-dense, and culturally acceptable. Through its impact on production, food prices, income provision, access to quality and diverse diets, and women empowerment, nutrition sensitive agricultural livelihood has huge potential in addressing the underlying causes of malnutrition (Meeker & Haddad, 2013; UNSCN, 2014). Nutrition-sensitive agricultural interventions have leverage in addressing food security issues as agriculture is the source of food and is the major source of employment in rural areas where malnutrition is concentrated. In addition, agriculture is the main source of income for the rural population, which in turn affects food security variables of access to food and health care among others. Agricultural production also affects the supply and prices of agricultural commodities which in turn affects net buyers and sellers of food. Finally, yet importantly, agriculture has impact on women's empowerment, health and time, which in turn affects food security situation of a household. Hence, agricultural development that takes into account the impacts of market forces, social and cultural constraints, and climate change in production decisions is required to develop nutrition-sensitive agricultural livelihoods.

With at least 5% of the global burden of undernutrition in Nigeria, and more than 14 million malnourished children, the Government recognizes that addressing malnutrition is indispensable for economic and social development (FRN, 2017). Substantial and sustainable reduction in malnutrition in Nigeria remains a significant challenge without the effective engagement of the agricultural sector. Numerous socio-economic and climatic factors affect food security status of households in Nigeria though improving food availability, accessibility, stability and utilization are important to keep up with the high population growth rate (3.2% per annum) observed in the country. Volatility of global food prices that affect the import of important food items, recent changes in climate that have led many states to experience delayed rains and/or flooding, conflict and insurgency in some parts of the country affect the national food security status of Nigeria (FMARD, 2017).

Crop diversification, one of climate smart agriculture is a program that is adopted broadly to curb the problem of food insecurity in the Nigeria. It is timely to know the impact of this food security intervention in Nigeria and the associated constraints and/or favourable conditions related with its adoption by farming households.

1.4 Uncertainty in Agricultural Production and the need for Climate smart agriculture

Efforts to increase crop production are taking place under rapidly changing, often unpredictable, environmental and socio-economic conditions. One of the most crucial challenges is the need to adapt to climate change, which – through alterations in temperature, precipitation and pest incidence – affects types of crops grown, the time that they can grow, as well as their potential yields. In the near term, climate variability and extreme weather shocks are projected to increase, affecting all regions, with negative impacts on yield growth and food security particularly in sub-Saharan Africa and South Asia in the period up to 2030. In addition, rising food prices driven by population and income growth, and by reduced productivity pose a threat to the world food system. Between 2010 to 2050 real price increases of 59 percent for wheat, 78 percent for rice and 106 percent for maize are expected (Nelson et al., 2010). Declining quality of natural resources and climate change affects the vulnerable smallholder farmers, as they are dependent on ecosystem goods and services for provision of food, fuel and fibre for immediate household consumption and the market. Without taking action to improve the productivity of smallholder agriculture, addressing global food security is not likely. The exposure to climate change and variability is further exacerbated by lack of diversification. Lack of diversification compounded with lack of assets to buffer against such climate risks leads to exposure to risks of income variability, crop failure, and malnutrition. Climate change also impacts households negatively as increases in temperature affects land suitability for growing crops and their nutrient contents (WB, 2019).

Crop diversification, one of farm diversification strategies, increases crop production in the face of climate and price uncertainties. This secures the availability of food and regular flow of foods into households throughout the seasons there by improving food security (FAO, 1997).

1.4.1. Crop Diversification as a Climate smart agriculture (CSA)

Climate smart agriculture integrates efforts from the local to global levels for sustainably using agricultural systems to achieve food and nutrition security through the integration of necessary adaptation and capturing potential mitigation (McCarty et al., 2018). CSA has three main pillars to be considered at different spatial and temporal scales 1. achieve food security, 2. adapt and build resilience to climate change and 3. reduce greenhouse gas emissions to mitigate further climate change (FAO, 2018).

Crop diversification is one of CSA where the decisions to diversify or not by agricultural households affect the resilience of production systems and rural livelihoods and nutrition outcomes. Hence understanding the linkages between production decisions, resilience and nutrition is important. Specialization and diversification have different impacts on livelihoods, ecosystem resilience and nutrition. Their impacts are assessed through exploring the natural resource and ecosystem pathways, income pathways and food environment pathways. A number of studies show that both on farm specialization and diversification contribute to improved resilience to climate-related risks but agroecosystem resilience is higher in diversified production systems.

There are a number of climate change adaptation and mitigation options which can sustainably improve production and minimize environmental impacts of production in each crop system. Depending on the choice of adaptive and coping strategies, each farming household may well have different climate change adaptation and mitigation options. The management practices and technologies focus on adaptation and practices with greater space for reducing production risks and reducing emissions. Increasing diversity within the agricultural ecosystem involves diversity of crops or crop varieties at many spatial scales (landscape level, within farms and/or within the same crop), and over different time frames. The specific climate smart approaches to crop production include increasing diversity and complexity within the agricultural ecosystem, improving sustainable soil and land management, increasing energy use efficiency, promoting sustainable mechanization, and developing simple and robust scientific tools to guide the decision-making of farmers on seasonal and long-term basis (FAO, 2017).

1.5 Farm level Nutrition Agriculture pathways

Agriculture can influence food security/nutrition through income gains, modification of household's consumption patterns i.e. increase household consumption, or some combination of both. Gender relations in the household further mediate these mechanisms. Higher income alter the amount, composition and quality of food consumed at a household. In addition, it facilitates the purchase of health- and nutrition-related goods and services. Though agricultural income is important, it is not sufficient to improve nutrition. Evidence on commercialization of agriculture and the resulting shift away from staples to cash crops shows negative nutritional consequences on the poor and children (Von Braun & Kennedy, 1994; Ecker et al., 2011). Linkages between agricultural income and calorie consumption are complex and studies show the results to be inconsistent. Results range from showing an absence of response in calorie consumption among the very poor to income gains to near one where almost all additional income goes toward expanded calorie consumption (Strauss & Thomas, 1995). Evidence further shows elasticities of agricultural income to be high for very poor households but decline with income as household shift to diversified diets (Hoddinott & Wiesmann, 2010; Subramanian & Deaton, 1996).

The variation in the link between agricultural income and nutrition are explained in relation to intra-household allocation (gender roles) and mental accounting. People use mental accounting to decide on how to use funds – that is, people dedicate income from certain types of activities for specific types of expenditures. Producers tend to think of certain income sources as being dedicated to certain types of expenditures and, therefore, if these income sources decline or increase these specific types of expenditures change disproportionately (Villa et al., 2010). Promotion of agriculture, or even of a particular crop or livestock, may then alter the use of funds in specific ways that influence dietary intakes. The literature on intra-household dynamics shows that households respond differently to changes in income depending on who has control of the resources within a household (Quisumbing, 2003). If agricultural income accrues to household members more concerned with diet quality and nutrition, this may lead to more spending on goods and services linked to nutrition outcomes. Even beyond the individual accrual of income, the promotion of agriculture is likely to alter the allocation of resources within the household, particularly the time use of household members.

Consumption of own production is the other pathway linking agriculture to consumption. In addition to mental accounting and intra-household allocation, own consumption decision can be explained by market imperfections or failures (Villa et al., 2010). Not well functioning markets or high transaction cost create a wedge between buying and selling prices. This has influence on consumption of the agricultural output produced by the household. Imperfect markets in output, input, labor, credit or insurance markets lead to non-separable production and consumption decisions within an agricultural household (Singh, Squire, & Straus, 1986).

1.6 Literature Review

Using Malawi's Third Integrated Household Survey (2010–2011) Mazunda, et al. (2015) looked at the impact of crop diversification on dietary diversity and household level access to micronutrient access. They found positive and significant associations, where the strongest association was found between crop diversification and micronutrient access. The study used a standard treatment effect model that uses maximum likelihood to estimate the effect of an endogenously chosen crop diversity on continuous endogenous food security and nutritional variables. Muthini et al. (2020) assessed the effect of production diversity on women, children and the household dietary diversity in Kenya using count of crop species, animal species, production diversity score, and the Simpson's index as measures of farm production diversity. The study used the poisson model. The findings indicate that farm production diversity is significantly associated with the dietary diversity of women and that of the entire household, but is not associated with the dietary diversity of children, with different production diversity measures having different impacts on dietary diversity. Adjimoti & Kwadzo (2018) conducted a study to determine how crop diversification affected food security in a specific region in rural Benin using primary data collected in the Collines Region in Benin. They used principal component analysis (PCA) to construct multidimensional food security indices and a Simpson diversity index to measure the degree of crop diversification. They used linear regression model to determine the effect of crop diversification on household food security status. They found crop diversification to have a positive effect on household food security status. A study in Northern Namibia looked at the constraints and success factors related to diversification into crop and livestock enterprises, and the effect of the diversifications on food security. A Seemingly Unrelated Regression model was used to assess the joint factors that affect total farm diversification and a step-wise error correction model was used to evaluate the conditional effect of the crop and livestock diversification on food expenditure and dietary diversity. Past exposure to climate shocks and access to climate information were found to affect both crop and livestock diversification decisions. In addition, greater food security outcome was found to be affected by greater diversification into both crop and/or livestock production (Mulwa & Visser, 2020). Makate et al. (2016) looked at the impact of climate smart agriculture on productivity and household resilience (food security, income, and nutrition) in rural Zimbabwe. To correct for the selection bias arising from the voluntary nature of crop diversification, crop diversification and the outcome variables were estimated jointly within a recursive mixed process framework. The results from the study show improvement in crop productivity, income, food security and nutrition at household level following the increase in rate of crop diversification adoption. Sibhatu & Kibrom (2018) systematically reviewed 45 studies from 26 countries that have analyzed associations between production diversity, dietary diversity, and nutrition in smallholder households. They provided a meta-analysis of estimated effects. They found that less than 20% of the studies report consistently positive and significant associations, and around 60% of them report positive associations only for certain subsamples or indicators, while the rest of the studies found no significant associations at all. In addition, they found a small and positive average marginal effect of production diversity on dietary diversity, with mean effect of 0.062. This suggests that farms would have to produce 16 additional crop or livestock species to increase dietary diversity by one food group, where farms in sub-saharan Africa would have to produce around 9 additional species to increase diet diversity by one unit. The meta-analysis was conducted on studies that looked at associations among different measures of farm diversification and diet diversification measures. The same studies include production diversifications within mixed, crop, and livestock farming systems. The studies also considered different dietary measures like Household Dietary Diversity Score (HDDS), Women's Dietary Diversity Score (WDDS), Children Dietary Diversity Score (CDDS), calorie consumption, protein and micronutrients intake that measure nutrition outcomes at household as well as individual level (women and children).

Several studies have looked at the links between production diversity and diet diversity in farming households and results are context specific and mixed. A positive link between farm and diet diversity was found in 19 out of 21 studies reviewed by Jones (2017). Sibhatu et al. (2015) found positive associations between production and diet diversity in Indonesia and Malawi, but found no association in the case of Ethiopia and Kenya. Jones et al. (2014) found mixed results in Malawi farm households' cases, where they found positive and significant associations between production diversity and aggregate dietary diversity scores, but significant and positive associations were not found when they look at the associations between production diversity and the frequency of consumption of certain healthy food. Measuring production diversity in terms of simple species count and using regression model, Sibhatu & Qaim (2018) found positive association between production diversity and diet diversity in Indonesia, Kenya, and Uganda. But when they measure production diversity in terms of number of food groups produced, the association becomes insignificant.

The studies conducted in sub Saharan Africa differ mainly in the methods used to capture the impact of crop diversification; choice of food security and production diversity indicator variables (Simpson's Index, animal species count, crop species count and production diversity score); level of analysis (women, children, households level); choice of cut offs in defining food security and crop diversity; data (cross sectional, panel surveys, country level representativeness); and choice of explanatory variables (like incorporation of climate variables).

The studies conducted to look at the link between farm diversification and diet diversification show that there is no conclusive evidence on the effectiveness of farm diversification as a strategy to achieve nutrition security under all situations.

This study contributes to literature by looking at the impact of crop diversification on food security of farm households in Nigeria using nationally representative panel data. A robust method of endogenous switching regression method is also applied to correct for the bias that may arise from the voluntary nature of crop diversification. The paper also contributes to literature as it incorporated climate change variables(temperature and precipitation) into the food security analysis, which is mostly lacking in other household level studies conducted in sub-Saharan Africa. The study found a positive impact of crop diversification farming practice on food security in Nigeria. Significant improvements in consumption by farming households, and lessening of food insecure months farming households face in a year are observed in response to adoption of crop diversification. In contrast to the above, improvements in consumption of diverse diets could not be achieved due to crop diversification. Diet diversity is captured as consumption of 6 or more food items on Household Diet Diversity Score (HDDS).

2. Estimation strategy

The objective of the study is to investigate the causal effect of crop diversification on nutrition and food security. A common challenge in estimating the causal effect using observational data based on surveys is that there may be selection bias as well as unobserved heterogeneity that correlates with the right-hand side variable that bias estimates. That is, households may not randomly decide to diversify their crops rather they may self-select to diversify into crop diversification. Besides, development agencies such as extension workers may intentionally provide support and encourage some households to diversify their crop. Thus, the non-random process of selection could bias the causal effect estimate. Moreover, there may be structural differences among crop diversifiers and non-diversifiers that could bias estimates. Not least, there may also be endogeneity due to some unobserved factors that correlate with diversification decision. We address these problems utilizing available panel data and recent advance in panel econometric approach to address the aforementioned problems. Specifically, we apply a generalized panel data switching regression model with correlated unobserved effects (Malikov and Kumbhakar, 2014).

$$y_{it}^{r} = \begin{cases} x_{it}^{r}\beta^{r} + \alpha_{i}^{r} + u_{it}^{r} & \text{if } D_{it} = r \\ - & \text{Otherwise} \end{cases} \quad (1)$$

$$D_{it}^{r*} = w_{it}^{r}\gamma_{t}^{r} + \xi_{i}^{r} + \upsilon_{it}^{r} \quad (2)$$

where x^{r}_{it} and w_{it}^{r} are $1{\times}K_r$ and $1{\times}L_r$ vectors of exogenous covariates (which may overlap) with corresponding conformable parameter vectors β^{r} and γ_{t}^{r}. (a_i^{r},ξ_i^{r}) are individual-specific unobserved effects that are allowed to be correlated with right-handside covariates. The outcome variable y_{it}^{r} is observed only if the r^{th} regime is selected. The regime selection (switching) is governed by a latent variable D_{it}^{r*} with observable categorical realizations: $D_{it} = r$ if the r^{th} regime is selected. While the disturbances u^{r}_{it} and υ_{it}^{r} are orthogonal to (x^{r}_{it}, w_{it}^{r}), their distributions are however allowed to be correlated, namely $E[u^{r}_{it}\upsilon_{it}^{r} \mid x^{r}_{it}, w_{it}^{r}]$ 6= 0

The latent variable D_{it}^{r*} can naturally be thought of as measuring an individual's propensity to select the regime r. Hence, the r^{th} regime is said to be selected if and only if

$$D_{it} = r \Leftrightarrow D_{it}^{r*} > D_{jt}^{r*} \quad \forall j = 1, \ldots, R(j \neq r) \quad (3)$$

While one can treat the regime switching as a system of (R - 1) dichotomous decision rules, we follow an alternative approach by considering the former in the random utility framework. That is

$$D_{it} = r \Leftrightarrow D_{it}^{r*} > \max_{j=1,\ldots,R(j\neq r)} \{D_{jt}^{r*}\} \quad (4)$$

Substituting Eq. (4) in (6), we let

$$\epsilon_{it}^{r} \equiv \max_{j=1,\dots,R(j\neq r)} \left\{ w_{it}^{j}\gamma_{t}^{j} + w_{i}^{j}\delta_{t}^{j} + e_{it}^{j} \right\} - e_{it}^{r} \tag{5}$$

Then follows Eq. (8)

$$D_{it} = r \Leftrightarrow \epsilon_{it}^{r} < w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r} \tag{6}$$

Given that e^{r}_{it} is extreme value distributed, it follows that ϵ_{it}^{r} is multinomial logistically distributed over i with the corresponding marginal distribution $\Lambda_r(.)$

$$\begin{aligned} \mathbb{P}[D_{it} = r | x_i^r, w_i^r] &= \Lambda_r(w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r}) \\ &= \frac{exp(w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r})}{\sum_j exp(w_{it}^{j}\gamma_{t}^{j} + w_{i}^{j}\delta_{t}^{j})} \end{aligned} \tag{7}$$

For some strictly positive monotonic transformation $J_r(.)$, Eq.(8) is equivalent to Eq.(10)

$$D_{it} = r \Leftrightarrow J_r(\epsilon_{it}^{r}) < J_r(w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r}) \tag{8}$$

Now, we can look at Eq.(3) and Eq.(4) as a binary selection model, for each given regime r. That is, we can essentially replace the regime switching equation (4) for each r=1,...,R with its equivalent in Eq.(11) (Malikov and Kumbhakar, 2014).

$$\tilde{D_{it}^{r*}} = J_r(w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r}) - J_r(\epsilon_{it}^{r}) \tag{9}$$

where $\tilde{D}_{it}^{r*}$ is a transformed latent variable such that $D_{it} = r$ if and only if $\tilde{D}_{it}^{r*} > 0$. Following Lee (1983), $J_r(.) \equiv \Phi^{-1}[\Lambda_r(.)]$, where $\Phi(.)$ is the standard normal cdf. The advantage of such a transformation is that the random error $J_r(\epsilon_{it}^{r})$ in Eq.(9) is standard normal by construction, which would later enable us to make use of the truncated moments of the standard normal.

Given these and assumptions about the unobserved effects in Eq.(3) and dependence between the two disturbances in Eq.(3) and Eq.(4), the selection bias corrected outcome equations can be given as in Eq. (12)

$$\begin{aligned} \mathbb{E}[y_{it}^{r} | x_i^r, w_i^r, D_{it} = r] &= x_{it}^{r}\beta^{r} + \mathbb{E}[\alpha_i^r | x_i^r, w_i^r, D_{it} = r] + \mathbb{E}[u_{it}^{r} | x_i^r, w_i^r, D_{it} = r] \\ &= x_{it}^{r}\beta^{r} + x_i^r\varphi^r + w_i^r\omega^r + (\psi_t^r + \pi_t^r)\mathbb{E}[\epsilon_{it}^{\tilde{r}} | x_i^r, w_i^r, D_{it} = r] \\ &= x_{it}^{r}\beta^{r} + x_i^r\varphi^r + w_i^r\omega^r + \rho_t^r\mathbb{E}[\epsilon_{it}^{\tilde{r}} | \epsilon_{it}^{\tilde{r}} < J_r(w_{it}^{r}\gamma_{t}^{r} + w_{i}^{r}\delta_{t}^{r})] \end{aligned} \tag{10}$$

Given that $\epsilon_{it}^{\tilde{r}}$ is standard normal by construction, the expected value term in Eq. (12) equals the negative of the inverse Mills ratio (IMR) given in Eq. (13)

$$\mathbb{E}[\epsilon_{it}^{\tilde{r}} | \epsilon_{it}^{\tilde{r}} < J_r(.) = -\frac{\phi[J_r(.)]}{\Phi[J_r(.)]} = -\frac{\phi[J_r(.)]}{\Lambda_r(.)} \tag{11}$$

where $\varphi(.)$ is the standard normal pdf.

We can consistently estimate the model in two stages. In the first stage, we estimate γ_t^r and δ_t^r based on Eq. (9) via maximum likelihood for each time period t separately. The obtained estimates $\hat{\gamma}_t^r$ and $\hat{\delta}_t^r$ are then used to compute the selection bias correction term. In the second stage, we consistently estimate the main parameters of interest β^r via pooled least squares on Eq. (12) that includes the predicted inverse Mills ration for each regime, r, separately.

Treatment effect estimation

Once we consistently estimate the outcome equations, we can compute the counterfactual as well as average diversification effects following Carneiro et al. (2002). The average diversification effects are the expected outcomes (nutrition and food security) estimated from Eq.(12). The counterfactual is defined as the average outcome (nutrition and food security) of the diversifiers had they not diversified their crop production. For each regime, we can estimate the following conditional expectations for each outcome variable.

Non-diversifiers (actual):

$$E[yit0 \mid x0i, wi0, Dit = 0] = x0it\beta 0 + x0i\,\phi 0 + wi0\omega 0 + \rho 0t\,(-IMR) \quad (12)$$

Crop diversifiers (actual):

$$E[yit1 \mid x1i, wi1, Dit = 1] = x1it\beta 1 + x1i\,\phi 1 + wi1\omega 1 + \rho 1t\,(-IMR) \quad (13)$$

Crop non-diversifiers counterfactual:

$$E[yit0 \mid x0i, wi0, Dit = j] = x0it\beta j + x0i\,\phi j + wi0\omega j + \rho jt(-IMR) \quad (14)$$

Crop diversifiers counterfactual:

$$E[yitj \mid xji, wij, Dit = 0] = xjit\beta 0 + xji\phi 0 + wij\omega 0 + \rho 0t\,(-IMR) \quad (15)$$

Using the above conditional expectations, we can compute the average treatment effects on the treated (ATT) by taking the difference between actual and counterfactual outcomes. ATT for crop diversifiers:

$$ATT = E[yit1 \mid x1i, wi1, Dit = 1] - E[yit1 \mid x1i, wi1, Dit = 0] \quad (16)$$

Average treatment effect on the untreated (ATU):

$$ATU = E[yit0 \mid x0i, wi0, Dit = 0] - E[yit0 \mid x0i, wi0, Dit = j] \quad (17)$$

2.1 Data

2.1.1 Nigerian GHS Panel Data

The study used the Nigerian General Household Survey-panel of wave1 (2010/11), wave2 (2012/13), and wave 3 (2015/16). The General Household Survey (GHS) is a cross-sectional survey of 22,000 households carried out annually throughout the country. A sub-sample of the GHS forms a panel survey (GHS-Panel) and it applies to 5,000 households of the GHS, which collects additional data on multiple agricultural activities and on household consumption. This GHS-Panel Nigeria is part of a larger, regional project in Sub-Saharan

Africa. Nigeria is one of the seven countries being supported by the World Bank, through funding from the BMGF, to strengthen the production of household-level data on agriculture. This regional project, the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) is conducted with the objective of improving the understanding of agriculture in Sub-Saharan Africa. The GHS-Panel drew heavily on the Harmonized National Living Standards Survey (HNLSS – a multi-topic household survey) and the National Agricultural Sample Survey (NASS – the key agricultural survey). This sheds light on the role agriculture could have on households' economic wellbeing, and the effect could be monitored over time.

The GHS-Panel include agricultural data, welfare indicators and socio-economic characteristics. It is a nationally representative survey of 5,000 households, which are also representative of the geopolitical zones. The GHS-Panel is carried out every two years, and all the waves of the revised GHS-Panel are carried out in two visits-post planting and post-harvest time. All households were visited twice where some important factors such as labour, food consumption, and expenditures were collected during both visits. The post-planting visit occurred directly after the planting season to collect information on preparation of plots, labour used for planting, inputs used and others related to the planting season. The post-harvest visit occurred after the harvest season and information on labour used for cultivating and harvesting activities, types of crops harvested, and other issues related to the harvest cycle are collected. The panel survey was conducted using a multi-stage stratified sample design, where the samples comprised of 60 Primary Sampling Units (PSUs) or Enumeration Areas (EAs) that are chosen from each of the 37 states in Nigeria and a total of 2220 EAs nationally. Out of a sample of 22,200 households, 5,000 households from 500 EAs were selected for the panel component. (NNBS & WB, 2016; NNBS et al., 2014; NNBS et al., 2013).

2.1.2 GHS, Soil and Climate data

The GHS-Panel has three questionnaires. The household questionnaire gives information on demographics, education, health, labour, food and non-food expenditure, household nonfarm income-generating activities, food security and shocks, safety nets, housing conditions, assets, information and communication technology, and multitude sources of household income. The GHS-Panel Agriculture Questionnaire provides information on land ownership and land use, farm labour, inputs use, GPS land area measurement and coordinates of household plots, agricultural capital, irrigation, crop harvest and utilization, animal holdings and costs, and household fishing activities. The GHS-Panel Community Questionnaire solicits information on access to infrastructure, community organizations, resource management, changes in the community, key events, community needs, actions and achievements, and local retail price information.

Data on soil conditions are sourced from the FAO Harmonized World Soil Database version. This database is a 30 arc-second raster database consisting of over 15000 various soil mapping components which are merged with current national and regional upgrades of international soil data. Climate variables are obtained from the Climatic Research Unit (CRU) Time-Series (TS) version 4.03 of University of East Anglia. The abridged version of the data is used, which is also adjusted for bias through the WorldClim data website, version 2.1 climate data for 1960 to 2018. This dataset is time series data which is gridded over the period. The measure of the minimum object that can be determined by the sensor (spatial resolution) is roughly 21 kilometres squared. The temperature variables used from this data are "monthly temperature", "three-year average monthly temperature", "five-year average monthly temperature" and the "average monthly temperature in the wettest quarter"- all measured in degree Celsius. Precipitation variables used include "year of survey monthly precipitation", "previous year precipitation", "three-year average monthly precipitation"," five-year average monthly precipitation "and "monthly precipitation in the wettest quarter" – all measured in millimetres. The monthly averages were calculated per wave from July to June (CRUTS 4.03, 1960–2018 CE).

As Household location is geo-referenced in the GHS-Panel, it was convenient to link household level data with the climate and soil data sets.

2.2 Empirical Strategy

Endogenous switching regression approach is used to model the impact of crop diversification on food security status of households in Nigeria. The Stata commands xteregress and xtprobit are used to estimate the empirical model. The xteregress fits a random-effects linear regression model and accommodates endogenous covariates and treatment, and also accounts for correlation of observations within panels or within groups. It is applied to the continuous dependent variables that are used to measure food security i.e. per adult equivalent consumption and number of food insecure months. The xteprobit command fits a random-effects probit regression model and like the xteregress command accommodates the endogenous nature of crop diversification and accounts for correlation of observations within panels or within groups (StataCorp, 2019). The xtprobit command is used for the binary dependent variable in the study i.e. diet diversity. The use of probit model with an endogenous treatment and random-effects are discussed in Angrist (2001) and (Conway 1990) respectively.

3. Result

3.1 Descriptive Statistics

Table 1. Descriptive Statistics and Variable Definition

Variables	Variable Definition	Treatment Group Mean	Std. Dev.	Min	Max	Control Group Mean	Std. Dev.	Min	Max
peraeq_cons	Yearly HH consumption per adult equivalent (in log)	11.34	0.60	8.90	15.04	11.43	0.63	9.34	14.95
months_food_i~c	Number of Months a household was food insecure	0.34	0.93	0	6	0.42	1.04	0	6
hdds	Household dietary diversity index	7.92	1.78	2	14	8.28	2.03	0	13.52
sdipos	Shannon Diversity Index	1.22	0.23	0.83	2.35	0.39	0.31	0	0.83
fhh	Binary variable = 1 if household head is female; 0 otherwise	-	-	0	1	-	-	0	1
age	Completed age of a household head in years	50.87	14.32	6	98	51.88	15.29	16	98
hh_members	Number of Household Members	7.39	3.45	1	31	6.56	3.36	1	33
illiterate_hh	Binary variable = 1 if household head is illiterate; 0 otherwise	-	-	0	1	-	-	0	1
w_value_assets	Value of household assets owned by a household in #? (in log)	10.2	1.29	2.08	14.23	10.25	1.41	3.91	14.23
lvstck_holdin~u	Total Livestock holding by a household in TLU	2.20	22	0	1155	1.44	6.94	0	210.50
farm_size_agl~d	Land size including all plots in hectares	2.40	4.41	0	108.82	1.44	3.41	0	128.28
workab_mea	Soil workability mean	1.52	0.72	1	5.06	1.41	0.62	1	6.73
dist_market	Distance to the closest market in Kilo meter	69.07	36.16	0.46	214.34	71.26	39.82	0.28	214.36
labor_hired	Total hired labor allocated to the farm in the past year in days	190.63	8466	0	530000	35.25	91.25	0	2167

use_fin_serv_~t	Binary variable = 1 if household uses formal financial services ; 0 otherwise	-	-	0	1	-	-	0	1
ext_reach_pub~c	Binary variable = 1 if household is reached by extension services; 0 otherwise	-	-	0	1	-	-	0	1
three_year_av~p	Three Year Average Monthly Precipitation (mm)	33.01	1.75	27.61	37.55	32.38	1.91	27.61	37.55
three_year_av~e	Three Year Average Monthly Maximum Temperature (°C)	103.36	45.34	32.34	282.89	122.49	51.68	32.34	295.36
zone1	Binary variable=1 if household is located in zone 1; 0 otherwise	-	-	0	1	-	0.37	0	1
zone2	Binary variable=1 if household is located in zone 2; 0 otherwise	-	-	0	1	-	0.39	0	1
zone3	Binary variable=1 if household is located in zone 3; 0 otherwise	-	-	0	1	-	0.38	0	1
zone4	Binary variable=1 if household is located in zone 4; 0 otherwise	-	-	0	1	-	0.41	0	1
zone5	Binary variable=1 if household is located in zone 5; 0 otherwise	-	-	0	1	-	0.37	0	1
lagged_tmp	One year lag temperature in degree Celsius	33.06	1.79	27.57	37.94	32.43	1.96	27.57	37.94
sdipos_mean	The mean of Shannon Index of a state a household is located	0.90	0.25	0	1.29	0.71	0.27	0	1.29

Table 1 shows the description and summary statistics of the variables used in the analysis. The mean, standard deviation, minimum and maximum values of each variable for the treatment and control group within the panel of sample rural smallholder farmers is reported in the table.

The Shannon diversification index (SDI) is the variable used to measure crop diversification status of a household. It is calculated as a measure of proportional abundance, and is uded to express species evenness and richness. The index is calculated as:

$$H' = -\sum P_i ln\, P_i$$

where P_i is area share occupied by ith crop population (Meng et al., 1999). Households whose SDI scores are greater or equal to the median (0.8270326) are classified as adopters of crop diversification farming system. The minimum SDI is 0.83 while the maximum is 2.35 as shown in table 1. The Shannon index was originally used in information theory, but has been commonly applied to evaluate species diversity in ecological communities. It has also been widely used in the agronomic literature to transform qualitative traits into a scalar measure which can be compared over sets of varieties (Spagnoletti Zeuli and Qualset, 1987; Meng et al, 1999).

Consumption, number of food insecure months and household food diversity are the three indicators of food security that are used in the study. Consumption is measured as yearly per adult equivalent consumption level of a household where it incorporates consumption of both food and non-food items. The study used the logarithm of the yearly per adult equivalent consumption level of households, where the mean value is 11.34, and is the same for both adopters and non-adopters of crop diversification. The minimum and maximum log consumption values are 8.90 and15.04 for adopters, 9.34, and 14.95 for non-adopters respectively.

The average number months a household stayed food insecure was 0.34 for the treatment group, and 0.42 for the control group. Some households in both groups can stay up to 6 months without secure food access while others can remain secure all year round.

The extent of household food insecurity is measured by the household dietary diversity score (HDDS). The score measures the level of food insecurity in a household. The HDDS was computed following Kennedy et al. (2010). Foods included in HDDS-from different sources.

namely: (i) foods purchased outside the home and consumed in the home. (ii) home-produced foods (i.e. production for own consumption). (iii) foods received as gifts. and (iv) foods purchased and eaten outside the home). The value ranges between 0 and 14, where the lowest amount households consume in the treatment group is 2 on HDDS scale, the mean HDDS being almost equal for the two groups (~8). The study used a dummy variable to indicate status of food insecurity where a household is considered to consume diverse foods if the household consumes six or more of the food items in the HDDS scale. According Kennedy et al. (2010), there are no established cut-off points in terms of number of food groups to indicate adequacy of dietary diversity for the HDDS. Recommended ways involve using the mean or distribution of HDDS scores for analytical purposes. This study used both the mean HDDS and consumption of 6 diets and above as indicators of diet diversity).

Household characteristics were measured using age and literacy of a household head, household size, and household wealth indicators like asset and livestock ownership.

The mean age of household head is 51 years for all households, the oldest being 98 years old. Gender of the household takes a value of 1 if the head of the household is female and 0 if the head is male. Household size indicated by number of household members ranges between 1 and 33 with mean household size of 7. Literacy is measured as a binary variable where it takes the value of 1 when the head of household receives no education and 0 if the head takes any form of education. The value of asset owned by a household is expressed in monetary terms (naira?) and it has a mean value of 10 in log terms. The maximum value of owned asset (log) reaches 14.23, and the minimum is 2.08 and 3.91 for the treatment and control group respectively.

The average livestock holding by a household expressed in tropical livestock units is 2.2 for the treatment group whereas 1.44 for the control group.

Size of agricultural land includes all plots that are cultivated, left as fallow and pasturelands, and it is measured in hectares. The mean farm sizes are 2.4 and 1.44 for the treatment and control group respectively. Agricultural farmland owned by households in the treatment group can reach up to 108.82 hectares whereas for those in the treatment group reaches up to 128.28 hectares. Another farm input considered in the study is hired labor use that measures the total hired labor allocated to a farm in the past year and is indicated in labor days. The average labor days allocated to a farm is 190 days for the treatment group and 35.25 days in the case of the control group. The maximum labor days are observed in the treatment group amounting to 530000 days, and 2167 days in the control group.

Soil workability shows the health of soil and is measured by considering different soil characteristics such as soil structure, soil texture, soil organic matter content, soil consistence/bulk density, the occurrence of gravel in soil profile, the presence of continuous hard rock at shallow depth as well as rock outcrops (Fischer et al., 2008). The mean value of soil workability is used in the analysis.

The distance of an agricultural household to the closest market is measured in Kilometres. The average distance of households to the nearest market is 69.07 kilometre in the treatment group whereas those in the control group will have to travel 71.26 kilometres on average to reach the closest market. Some households in both groups travel as far as 214.34 to reach the closest market, while others travel only 0.28 kilometres.

Access to extension and financial services are binary variables where they take the value of 1 if a household receives the extension and financial services and takes a value of 0 if the household is not reached by these institutions.

Three Year Average Monthly Precipitation and three Year Average Monthly Maximum Temperature are used as climate change variables that affect farm operations and household food security. Precipitation is measured in millimetres while temperature is measured in degree Celsius. The mean average monthly precipitation is 33.01 mm, and it can reach to 37.55 mm and can be as low as 27.61 for areas under the treatment group, and precipitation for the control group lies between 27.61mm and 37.55 mm. The three Year Average Monthly Maximum averaged over treatment households reaches103.36 °C and varies between 32.34°C and 282.89°C. The control group has an average three Year Average Monthly Maximum value of 122.49°C, with maximum and minimum values of 32.34°C and 295.36°C respectively.

3.2 Econometric Results

This section presents the results of the endogenous switching regression model i.e. the impact of crop diversification, which is a climate smart agricultural practice, on food security status of agricultural households in rural Nigeria. The Average treatment effect and Average treatment effect on the treated from adopting crop diversity on three types of food security measures is given in Table2. The factors that affect crop diversity choices of households, and the corresponding food security measures i.e. adult equivalent consumption, number of food insecure months, and diet diversity are given in Tables A1, A2, and A3 (see Appendix A).

As shown in Table 2, the correlation between error terms of the three crop diversity equations and the corresponding outcome equations (adult equivalent consumption, number of food insecure months, and household nutrition (consumption of 6 types of diets on HDDS scale and above) are significant and hence the use of ESRM. The relationship between farm diversification and food security could be significantly positive or negative depending on whether there is foregone income benefits from specialization. In this study crop diversification has positive effect on welfare of agricultural households in Nigeria. Adult equivalent consumption, number of food insecure months and nutrition security measures are used as indicators of household welfare. On average, households that adopt crop diversification have 28 percent higher consumption level compared to those that did not adopt. The number of food insecure months also lessen on average by 18 percent for those households that adopt crop diversification. The nutrition impact is also significant for the adoptees as households that use crop diversification as a farming practice consume on average more than 6 food groups on the HDDS scale of 12. This is consistent with study results by Mazunda, et al. (2015) in Malawi, Muthini et al. (2020) in Kenya, and Makate et al. (2016) in Zimbabwe.

The magnitude of the crop diversity effect on food security differs according to the indicator used for measuring food security. Crop diversification plays significant role in increasing consumption and reducing the food insecure months that households normally face in a year, while it has a lesser effect on diet diversity. Crop diversity has positive contribution to welfare when adult equivalent consumption and number of food insecure months are used to measure food security, where the value is higher in the case of adult equivalent consumption. However, when an HDDS based diet diversity measure is used, the average effect of crop diversification on nutrition security becomes insignificant, but the average effect of adopting crop diversification on the treated (those that adopt crop diversification) is positive and significant at the margin. Crop diversification improves agricultural production, where the income gain from that can alter the amount, composition, and quality of the food consumed as well as facilitate the purchase of other welfare enhancing goods and services. Improvement in agricultural production also increases consumption from own production, where higher amounts are consumed in the presence of market imperfections.

Table 2: Treatment effects estimates of crop diversification on welfare

Outcome	ATE		ATT	
	Margin	Std. Err.	Margin	Std.Err.
Adult-equivalent consumption	0.2858***	0.0699	0.2486***	0.0995
Number of food insecure months	-0.1833***	0.074	-0.1727**	0.0758
Nutrition secure, (mean food groups cut-off)	0.0724	0 .0456	0.0777*	0.0459

* p<0.05, ** p<0.01, *** p<0.001

A number of household characteristics, farm level production and biophysical factors, institutional factors, climate change variables, and geographical location of households are found to affect food security and crop diversification decisions significantly (see Appendix A).

3.2.1 Determinants of Food security

Gender of household head is important in consumption decisions of households. Being headed by females increases consumption compared to households headed by males though the effect is small. Household size also affects consumption level of households. As the number of household members increases, adult equivalent consumption of a household decreases, keeping other factors constant. This could be that consumption requirement of households' increases with increase in number of people in a household, depleting and spreading the available resource base of a household among the bigger size of the household. However, household size is positively associated with nutrition as the probability of consuming more food items in a household increases with number of household members. This result should be considered with caution as the increase in number of people that consume diverse diet could have resulted from different members in a household having different preferences of food items in the HDDS scale. Illiteracy has the negative expected sign in all of the welfare measures and is significant in cases of consumption and nutrition equations. On top of other benefits, being literate assists people to be aware of wellbeing improving levels of energy, health expenditures and nutrition for health and vitality.

The higher the value of assets held by households, the higher the consumption level and nutrition intake as well as the lower the number of food insecure months faced by households. Assets act as insurance policies especially for vulnerable households that face production and price uncertainties. In times of income shortfalls or production loss, households can sell their assets and buy the required food and non-food items. Owning assets helps to reduce food insecure month as households can sell them at a time where food is scarce. Livestock holding and size of agricultural land seem to have minimal effect on consumption. They are not significantly associated with food insecure months and diet diversity measures of welfare.

Access to markets influences accessibility of goods and services, and households that are close to markets are assumed to have access to variety of food and non-food items. Those close to the market also face relatively lower costs compared to those that reside far from them. Households that are closer to the market have the opportunity to purchase food from the market, consume from own consumption, or a combination of both. The findings of this study also show that, the lesser the distance to the market the bigger the consumption is for households that adopt crop diversification. In addition to access to purchase cheaper food and non-food items, those who diversify and have better market access also have benefit from less transport cost and have good opportunities to engage in markets to sell agricultural produce and earn higher agricultural revenues. Access to markets; however, has no effect on reducing food insecure months in a year and nutrition status or diet diversity of households. This could be that a bigger proportion of food consumed by households is sourced from own production. Though access to market may lead to possibility of increased income, the decision taken by households in allocating the income gained determines if market access affects the consumption or nutrition aspects of household welfare. Significant proportion of the income could be spent for purchase of non-food items. The positive effect of market access on household welfare is documented in a number of studies-Kumar et.al. (2015), Johns (2017) and Sibhatu et.al. (2015).

Institutional factors like access to public extension and financial services have positive effect on consumption. Access to financial services is positively associated with both consumption and nutrition outcomes of households. Access to finance aids in availing scarce resources in times of need by households. Households smooth their consumption when their resources got depleted for a number of reasons. Income from a number of sources and own production may not be enough to cover the household needs. The same sources of income and own production could also be affected by a combination of natural, and socio economic factors.

Increase in temperature is associated with consumption and nutrition intake patterns of households. Higher temperature leads to lower levels of consumption and nutrition intake. Higher temperature affects farm production negatively making agricultural households vulnerable to climate change. Climate variables are negatively and significantly associated with household consumption. Variability in precipitation seems to affect only consumption negatively. Agriculture is impacted negatively by a rise in temperature and precipitation, and that impacts access and availability of consumption goods to a household. A change in temperature affects more those households that did not diversify compared to those that did. In addition, change in precipitation affects households negatively but the effect is more for non-adoptees. The magnitude of the negative response coefficients is larger for change in temperature compared to increase in precipitation. A study in Northern Nigeria also shows a decline in agricultural productivity resulting from a negative rainfall shock leading to a decrease in household consumption (Amare et.al, 2018). Other studies conducted in different areas in Nigeria also show decline in crop production in response to increase in temperature but show mixed evidence on the impact of precipitation (Agboola & Ojeleye (2007); Ayinde et al.(2011), and Jidauna et al. (2012)). Excessive heat and rainfall also affect consumption by causing post-harvest losses.

Households' locations (zones) also affect consumption behavior. Zones affect the different welfare indicators differently. Being located in zone 1, zone 2, zone 3, and zone 4 has a negative effect on consumption compared to being in zone 6. The probability of having food insecure months' increases in zone 4 compared to that of zone 6. Households located only in zone 5 have higher probability of consuming diverse diets.

3.2.2 Determinants of crop diversity

One year lagged temperature and mean crop diversity index of the state a household is located in the country are used as instruments for crop diversification. Household's decision to diversify depends on characteristics of households, availability of production inputs, physical and institutional factors, climate change factors, and geographical location of households.

Household size, agricultural land size, soil workability, three year average temperature and three year average precipitation affect crop diversity choice positively in all measures of welfare, whereas market access and hired labor use affect only the consumption measure. Livestock holding is an important determinant of crop diversification by households when food insecurity months is used as welfare measure. Being located in a specific zone does not seem to have strong effect on choices of farming practices. However, owning larger agricultural land increases the chance of crop diversification (see Appendix A). This result is consistent with findings by Ojo et al.(2014) and Muthini et al.(2020).

Increase in soil workability condition, three-year average temperature and precipitation contribute positively to crop diversification decisions by households. Increasing distance to input and output market for a household also increases the relative cost of crop diversification. The probability of adopting crop diversification is high for households located in zone 3 compared to those located in zone 6. Unobserved and omitted geographical variables in the other zones do not significantly affect choice of farming practices by households. This is in line with some studies in Nigeria which show presence of uniform farming system across the different ecological zones despite the existence of significant differences in annual rainfall, temperature and output (Sowunmi & Akinola, 2010).

Climate variability influences the risks faced by farmers, hence building adaptive capacity requires knowledge management. Institutions engaged in extension services among others play a significant role in dissemination of climate related information that will increase the decision-making abilities of farmers in their respective farming systems. Though a positive relationship between crop diversification and access to public extension services is expected, the study results do not show any significant relationship. A study in Namibia shows past exposure to climate shocks and access to climate information to be important determinants of diversification decisions (Mulwa & Visser, 2020).

Extended period is required to realize the benefits of climate smart agriculture (productivity increase and resilience). During the transition, the returns to agriculture can be low or even negative; hence, some form of financing is required during this period to support the transition. Transition cost is likely to be higher to poorer producers, making the challenge of delivering the benefits of climate smart agriculture to those most in need even higher. The capacity of producers to make required adjustments depends mostly on existence of policies and institution that can support their access to credit and insurance. Producers may consider climate smart agriculture as risky investment as farmers will need to learn new farming methods and as they do not have access to insurance. Financial constraints can affect adoption of climate smart agricultural practices like crop diversification particularly when initial investment costs are high and the benefits from such investments can only be realized after some time. A number of studies show that financial constraints and opportunity cost of land affect farmers' decisions to adopt climate smart agricultural practices. Hence, the decision to adopt crop diversification as one of climate smart farming practices is expected to be affected by access to financial institutions that can support farmers' access to credit especially in the absence of insurance. In this study we could not find significant effect of access to financial resources on crop diversification decisions. This could be associated with constraints to access adequate amount of finance, as there is widely available information on the growing financial need by small scale farmers, especially the poor.

Better soil workability condition, which indicates better soil moisture and soil health has positive effect on crop diversification decisions as expected.

Distance to the market determines the cost and benefit associated with any climate smart practice. The decisions to adopt crop diversification depends on availability of agricultural inputs through increasing returns to labor and land making stable and better prices for the market produce. Hence, access to improved market is a major determinant of crop diversification. This study also reveals the increase in the choice of crop diversification farming practice as distance to markets becomes lesser. A recent study in Malawi, among others, also reveals the positive effect of market access on crop diversification decision (Mazunda et. Al, 2015).

4. Summary and Conclusion

The study analysed the impact of crop diversification on welfare (nutrition security) of rural households in Nigeria, with the intention to understand how agriculture can become more nutrition-sensitive in particular situations. The Nigerian GHS Panel Data (first three waves), FAO Harmonized World Soil data, and the Climatic Research Unit (CRU) and WorldClim climate data were used. Per adult equivalent consumption, food insecure months and diet diversity were used as measures of food/nutrition security. To correct for bias that may arise from self-selection issue, the ESRM approach was used.

On farm crop diversification contributes to improvement of rural household consumption and reduction of food insecure months. Though consumption gains and reduced food insecure months can be achieved due to improvements in income and/or own production, diet diversity, which is consumption of six or more diets on the HDDS scale, could not be improved. Hence, consideration of only consumption and food insecure months as welfare indicators is not enough to show the whole picture of food security status of households in Nigeria.

Socio economic factors like gender of household head, household size, farm size of agricultural land and market access, and climate change variables like temperature and precipitation affect food security of households differently in crop diversifying and non-diversifying households. Increasing credit provision and asset ownership is an effective way to improve consumption and nutrition, as the two factors have larger effects. Simultaneous improvement in all welfare measures- consumption, food secure months, and diet diversity, is achieved when increasing asset ownership is targeted. Assets act as insurance policies especially for vulnerable households that face production and price uncertainties which are observed in the country. During times of income shortfalls or production loss, households sell their assets and buy the required food and nonfood items, hence improvement in household food security.

Access to market is necessary for raising rural consumption but less so for improving access to a diverse range of foods. Improving the transport or transaction cost aspects of market access do not have any impact on securing nutrition security and reduction of food insecure months but only consumption.

Consumption is also improved if women become heads of households, and smaller size of households could be maintained. In addition, educating household heads leads to improved consumption and nutrition diversity among households. Provision of health and diet related information through broader extension outreach, and availing financial resources in times of need are critical for achieving the required level of household consumption. More importantly, access to finance plays a significant role in achieving improvements in both consumption and nutrition diversity.

The exposure to climate variability i.e. variability in temperature and precipitation has significant negative impact on nutrition security and increase in consumption, where the impact on nutrition is more pronounced in cases where there is no on farm crop diversification. Unobserved geographical factors expressed in zones also influence households' level of consumption and diet intake, as well as food insecure months they face in a year.

The choice between on farm crop diversification or specialization is largely affected by considerations of climate variability. Household and farm characteristics as well as physical and institutional factors have minimal contribution towards choices of farming practices. Temperature and precipitation variability, and soil workability conditions on the other hand significantly lead to the decision of crop diversification. Market access has a significant role in crop diversification choice as well as consumption.

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APPENDIX A: ESR model Output of the Determinants of Food security and Crop Diversification

Table A1: Determinants of adult equivalent consumption and crop diversification

Variable	Adopters: adult-equivalent consumption		Non-adopters: adult-equivalent consumption		Selection equation	
	Coffe.	Std. Err.	Coffe.	Std. Err.	Coffe.	Std. Err.
Household characteristics						
fhh	0.0891*	0.0366	0.1031**	0.0348	0.0249	0.0625
age	-0.0002	0.0007	-0.0007	0.0008	0.0022	0.0014
hh_members	-0.0580***	0.0032	-0.0722***	0.0042	0.0146*	0.0064
illiterate_hh	-0.0974***	0.0218	-0.1255***	0.0261	-0.0235	0.0443
lnvalue_assets	0.1120***	0.0083	0.1290***	0.009	-0.023	0.0156
Production input						
lvstck_holding_tlu	-0.0003**	0.0001	0.0038**	0.0013	0.0014	0.0010
farm_size_agland	-0.0067**	0.0024	-0.0048	0.0043	0.0438**	0.0166
labor_hired	0.000	0.000	0.0006***	0.0001	0.0005*	0.0002
Biophysical factors						
workab_mea	-0.0121	0.0139	-0.0039	0.0177	0.1594***	0.0318
avg_dist_hh	-0.0001	0.0003	0.0000	0.0003	-0.0003	0.0005
dist_market	-0.0008**	0.0003	0.0000	0.0003	-0.0012*	0.0006
Institutional factors						
ext_reach_public	0.1043*	0.0453	0.1185*	0.0472	-0.139	0.0897
use_fin_serv_credit	0.2253*	0.0974	0.1995*	0.1004	0.0709	0.1805
Climate change						
three_year_avg_tmp	-0.0289**	0.0089	-0.0108	0.0087	0.8572***	0.1467
three_year_avg_pre	-0.0017**	0.0005	-0.0002	0.0005	0.0038***	0.0010
Regions						
zone1	-0.2376***	0.0548	-0.0947	0.0541	0.079	0.1019
zone2	-0.2913***	0.0591	-0.1381*	0.0609	0.0361	0.1119
zone3	-0.3562***	0.0600	-0.1620*	0.0634	0.2401*	0.1154
zone4	-0.1651**	0.0619	-0.0158	0.0580	-0.0029	0.1103
zone5	0.1341	0.0711	0.2023***	0.0609	0.0347	0.126
Instrumental variables						
lagged_tmp					-0.7478***	0.1440
sdipos_mean					1.6567***	0.1094
Constant	12.2722***	0.3519	10.8803***	0.3245	-5.3974***	0.6996
Regression Diagnosis						
corr(e.trt,e.lperaeq_c)			-0.2220**			
Log-likelihood			-9323.9163 ***			
N=nT			6,798			

* p<0.05, ** p<0.01, *** p<0.001

Table A2: Determinant of food insecure months and crop diversification

Variable	Adopters: Number of food insecure months		Non- Adopters: Number of food insecure months		Selection equation	
	Coffe	Std. Err.	Coffe	Std. Err.	Coffe	Std. Err.
Household characteristics						
fhh	0.0907	0.0720	0.007	0.0740	0.0037	0.059
age	-0.0017	0.0012	-0.0003	0.0014	0.0024	0.0014
hh_members	0.0159***	0.0044	0.0086	0.0056	0.0195**	0.006
illiterate_hh	-0.0112	0.0346	-0.067	0.0458	-0.0122	0.0423
Production input						
lnvalue_assets	-0.0534***	0.0131	-0.0459**	0.0140	-0.0198	0.0148
lvstck_holding_tlu	0.0002	0.0003	-0.0024	0.0013	0.0019**	0.0007
farm_size_agland	-0.0002	0.0022	0.0044	0.0044	0.0439**	0.0164
labor_hired	0.0000***	0.0001	-0.0001	0.0001	0.0003	0.0002
Biophysical factors						
workab_mea	-0.0360*	0.0182	0.0178	0.0272	0.1640***	0.0308
avg_dist_hh	-0.0004	0.0002	-0.0001	0.0002	-0.0004	0.0004
dist_market	0.0002	0.0004	-0.0015***	0.0004	-0.0009	0.0005
Institutional factors						
ext_reach_public	0.0261	0.0717	-0.0528	0.0638	-0.1036	-0.086
use_fin_serv_credit	-0.0439	0.1059	0.4315	0.2254	0.2132	0.1618
Climate change						
three_year_avg_tmp	-0.0239	0.0129	0.0389**	0.0122	0.2685*	0.1191
three_year_avg_pre	0.0012	0.0008	-0.001	0.0008	0.0038***	0.0009
Regions						
zone1	-0.1183	0.0867	0.0198	0.0641	-0.018	0.0912
zone2	-0.0644	0.0955	0.1592	0.0854	-0.0709	0.1031
zone3	-0.0315	0.1004	0.0417	0.0834	0.1259	0.1057
zone4	0.4546***	0.1066	0.7939***	0.0983	-0.0744	0.1002
zone5	-0.188	0.1225	0.2606**	0.0967	0.0278	0.1184
Instrumental variables						
lagged_tmp					-0.1725	0.1161
sdipos_mean					1.8700***	0.0969
Constant	1.5025**	0.5484	2.2125***	0.4778	-5.1922***	0.6703
Regression Diagnosis						
corr(e.trt,e.lperaeq_cons)			-0.1448***			
Log-likelihood			-14966.328 ***			
N=nT			6,798			

* p<0.05, ** p<0.01, *** p<0.001

Table A3: Determinant of nutrition security and crop diversification

Variable	Adopters: nutrition security		Non- Adopters: nutrition security		Selection equation	
	Coffe	Std. Err.	Coffe	Std. Err.	Coffe	Std. Err.
Household characteristics						
fhh	0.021	0.1002	0.1722	0.0995	0.0326	0.0626
age	-0.0012	0.0021	-0.0048	0.0025	0.0022	0.0014
hh_members	0.0258**	0.0097	0.0237*	0.0108	0.0183**	0.0064
illiterate_hh	-	0.0626	-0.1552*	0.0758	-0.018	0.0446
Production input						
lnvalue_assets	0.2532***	0.0232	0.2908***	0.0283	-0.0145	0.0156
lvstck_holding_tlu	0.0012	0.0008	0.0028	0.0049	0.0013	0.0009
farm_size_agland	0.0034	0.0060	0.0119	0.0092	0.0434*	0.0174
labor_hired	0.0002	0.0002	0.0001	0.0004	0.0004	0.0002
Biophysical factors						
workab_mea	-0.0475	0.0415	-0.0886	0.0573	0.1651***	0.0322
avg_dist_hh	-0.0025	0.0013	0.000	0.0005	-0.0003	0.0004
dist_market	-0.0014	0.0008	-0.0021*	0.0009	-0.0011	0.0006
Institutional factors						
ext_reach_public	0.1587	0.1386	0.2538	0.1619	-0.1536	0.0906
use_fin_serv_credit	0.6299*	0.2868	0.4649	0.3996	0.0909	0.1863
Climate change						
three_year_avg_tmp	-0.0953***	0.0245	-0.1189***	0.0284	0.3727**	0.1225
three_year_avg_pre	-0.0011	0.0015	-0.0034*	0.0015	0.0037***	0.0010
Regions						
zone1	-0.7361***	0.1485	-0.9327***	0.1440	0.0243	0.1004
zone2	-0.7306***	0.1595	-0.8373***	0.1715	-0.0293	0.1105
zone3	-0.8974***	0.1641	-1.3170***	0.1779	0.176	0.1132
zone4	0.2587	0.1697	0.6040***	0.1570	-0.0169	0.1103
zone5	0.6224**	0.2129	0.6065***	0.1748	0.0487	0.1274
Instrumental variables						
lagged_tmp					-0.2711*	0.1196
sdipos_mean					1.7825***	0.0986
Constant	1.2131	-0.953	1.9244	-1.0366	-5.3357***	0.7094
Regression Diagnosis						
corr(e.trt,e.lperaeq_cons)			-0.1999*			
Log-likelihood			-7832.6508			
N=nT			6,797			

* p<0.05, ** p<0.01, *** p<0.001

Crop diversity and welfare dynamics: Empirical Evidence from Nigeria *

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Abstract

Crop diversification is one of the most ecologically feasible and cost-effective climate adaptation agriculture practices. Agricultural development strategy in many Africa countries assumes that crop diversification leads to improved food and nutrition security. However, the direct causal link is far from simplistic, and the existing empirical evidence is mixed. In this study, we investigate crop diversification's effect on farm household's poverty dynamics in Nigeria. We take advantage of novel and unique nationally representative household panel survey data combined with geospatial information on agro-climatic conditions from Nigeria. To our knowledge, it is the first time that a welfare-based, micro-level dataset with spatial coverage has been assembled to examine the effect of climate-smart agriculture practice on poverty dynamics. Our analysis relies on an endogenous switching model that accounts for both initial condition bias and sample attrition bias. Results are consistent across different crop diversity measures, showing that adopting crop diversity is negatively associated with poverty entry but does not affect poverty persistence. Climate change captured as changes in the monthly maximum average near-surface temperature and total monthly precipitation are associated positively and negatively with poverty entry, respectively. Given the heterogeneous effects of crop diversity on short-term poverty (poverty entry) and long-term poverty (poverty persistence), other adaptations and mitigation strategies are suggested to help poor households escape poverty.

Key words: Crop diversification, nutrition security, poverty dynamics, Africa

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1 Motivation

Improving agricultural productivity has long been the foundation for poverty reduction, enhanced food security, and sustainable growth in developing countries, particularly in Sub Saharan Africa (Majid, 2004; Lin et al., 2001). In Africa, poverty is predominately a rural phenomenon (Beegle et al., 2016), such that agricultural development and growth is more crucial for immediate as well as sustainable poverty reduction (Majid, 2004; Lin et al., 2001). Sustainable agricultural growth would enhance food production and keep food prices within tolerable limits for both the urban and rural poor. Empirical evidence from developing countries has shown that 1 percent growth in agricultural yield corresponds to a 0.83 percent reduction in the number of people living in extreme poverty, defined as living on less than a dollar a day (Thirtle et al., 2001). In Africa only, a 1 percent increase in agriculture yields corresponds to 0.96 percent decreases in the percentage of the population living on less than $ 1 per day (Lin et al., 2001).

Despite the recent rapid economic growth and apparent improvements in the development of agriculture sector in Sub-Saharan Africa (SSA), about 33 percent of its population is malnourished and about 40 percent of SSA preschool children, under five years old, are chronically undernourished (Kidane et al., 2006; Remans et al., 2011).[1] The food security challenge will only become more difficult, as the region food demand is expected to increase 60 percent by 2050 (Xie et al., 2018). Recent evidence suggests that climate change manifested in the form of increasing temperatures, weather variability, invasive crops and pests, and more frequent extreme weather events among others, is emerging as one of the major threats to the development of the agriculture sector and might worsen food insecurity and malnutrition (Azzarri and Signorelli, 2020; Hope Sr, 2009; Nyasimi et al., 2014). It is expected that climate change affects smallholder farmers disproportionately, for instance, a moderate increase in temperatures will have a negative impact on the production of rice, maize, and wheat, which are mainly produced by smallholder farmers in SSA (Morton, 2007). Given the fact that many of the countries that will be adversely affected by climate change are in SSA that have a larger share of poor population whose livelihood depends on subsistence agriculture, there is an urgent public policy demand for identifying sustainable agricultural practices that can enhance agricultural productivity, improve poor household resilience from climate-related risks and shocks and reduce emissions.

[1] In the last decade, there has been a strong commitment from many African governments to invest in agriculture, the adoption of the Malabo Declaration and the Comprehensive Africa Agriculture Development Program (CAADP) are excellent examples. CAADAP is a continental effort that promotes a holistic approach to tackling hunger in Africa through agriculture-led economic growth. In order to achieve the CAADAP agenda, African governments have committed to increase public spending in agriculture and raise agricultural productivity by at least 6 percent.

Contemporary economics literature, has identified several climate-smart agriculture (CSA) practices such as minimum soil disturbance, crop rotation, crop diversification and intercropping as a potential agricultural practices to improve agricultural yield and improve food and nutrition security (Tesfaye and Tirivayi, 2020; Joshi, 2005; Manda et al., 2016). Similarly, the literature on nutrition and dietary diversity highlights the importance of consumption diversification and a well balanced diet to combat malnutrition (Ruel, 2003; Meenakshi et al., 2010; Mazunda and Pauw, 2015). Among the different CSA practices crop diversification is identified as one of the most ecologically feasible and cost-effective climate adaptation agriculture practice in many developing countries. The existing scant empirical evidence suggest that adopting crop diversification improves the consumption of the poorest and reduces poverty (Tesfaye and Tirivayi, 2020; Sibhatu and Qaim, 2018) and that this effect is due to greater availability of food for consumption and increased agricultural income. This strand of literature provides several plausible explanations on the effect of crop diversify on agricultural yield, household consumption and poverty. Nevertheless, studies has not moved down to an empirical analysis of how crop diversification affect poverty dynamics. Thus, this study aims to examine the impact of crop diversification on poverty dynamics using endogenous switching model, accounting for initial condition bias[2], attrition bias and household heterogeneity. The study focuses on Nigeria, where poverty and food insecurity is ubiquitous.[3]

Regardless of the particular welfare indicators such as income or consumption, poverty is not a static phenomenon.[4] Empirical evidence in both developing and developed countries show that a large proportion of individuals move into and out of poverty over time (Jalan and Ravallion, 1998; Baulch and Hoddinott, 2000b). The consensus from literature is that static view of poverty is an inappropriate vehicle with which to understand the determinants of poverty and that it diverts policymakers' attention on poverty's symptoms, rather than its causes (Addison et al., 2009; Cappellari and Jenkins, 2002; Jalan and Ravallion, 1998). For instance, an individual who is observed above a given minimum threshold at a point in time might be unable improve income further while another person below the minimum

[2]A bias that arises from the fact that a poverty spell may have already begun before the first observation of households in the data at hand and its correlation with unobserved characteristics such as 'ability' and 'motivation' Wooldridge, 2005

[3]In 2019, 40 percent of the total population, or about 83 million Nigerians, live below the country's poverty line of 137,430 Naira (USD 381.75) per year (https://www.worldbank.org/en/programs/lsms/brief/nigeria-releases-new-report-on-poverty-and-inequality-in-country).

[4]Because of the limited availability of data that might contain more than a single snapshot static poverty analysis was the norm in the literature. However, panel data is more available than it once was in many developing countries, and, therefore, more researchers have begun to examine the dynamics of poverty, rather than the statics poverty analysis (see Baulch and Hoddinott, 2000a; McKay and Lawson, 2003; Dercon and Shapiro, 2007; Baulch, 2011, for more discussion).

threshold is able to improve income further later on (Heckman, 1981; Dercon, 2001). This means that individuals with similar current command over resource may follow different long-term poverty trajectories and poverty frontiers go far beyond the category of the poor covered by a cross-section analysis.

Poverty dynamics analysis focuses on the understanding of why some individuals, households, and communities remain poor while others experience rapid welfare improvements. Considerable work has been undertaken from both theoretical and empirical perspective to understand if self-reinforcing mechanisms exist which can cause poverty to persist resulting in individuals or households to remain poor for long. However, our understanding of the factors that push individuals or households to enter, escape or remain in poverty is still incomplete. From a policy design point of view, it is precisely these factors that are crucial for designing poverty reduction policies. Improved understanding of the heterogeneous nature of poverty - whether it consists of more individuals or households that move in and move out of poverty (transient poor) or consists of more individuals or households that are poor for a long period (persistently poor) has a vital implication for public policy. If poverty is more of transient, then policies aimed at stabilizing income fluctuations (such as increasing access to financial services or providing social security programs) may be more appropriate. If poverty is more persistent public policy perhaps better be directed to structural and longer-term interventions that crowd in an investment like protection of productive assets, human capital accumulation, promote adoption of improved production technologies such as CSA, encourage entrepreneurial risk-taking and expansion of social protection provision (Ravallion, 1996; Dercon, 1998; Glauben et al., 2012; Barrett et al., 2016).

The dynamics of poverty stem from the combined dynamics of endowment accumulation (encompassing financial, human, natural, and social capital) and technology adoption (including both production such as crop diversification and exchange technologies such as market and non-market means of transacting and the institutions that support them) in the face of risk (Barrett et al., 2016). In neoclassical economic growth theory and its prediction of convergence towards a unique, dynamic equilibrium rate of steady state growth in wellbeing, the initially poor escape poverty if they accumulate enough productive endowments or adopt a rewarding technology. Hence, the initially poor have a strong incentive to accumulate and adopt (Barro and Sala-i Martin, 2004). In reality, poor initial conditions – commonly manifested in insufficient productive asset holdings, limited access to the financial market and the use of relatively inefficient technologies – instead induce behavioral changes that reinforce poverty. Thus, convergence to a single equilibrium might not occur, but both poor and non-poor equilibria instead co-exist (Barrett and Carter, 2013). At the macro level, geography, institutional and technology adoption failures for instance can hold countries and regions in poverty (see, for example Bloom et al., 1998 and Gallup et al., 1999 for geography, Acemoglu et al., 2001 and Tan, 2010 for institution and Azariadis and Stachurski, 2005 for technology adoption). At the meso level, social networks, norms, and culture can exclude households or individuals from accumulating their endowments and adopt remunerative technologies (Conley and Udry, 2010; Santos and Barrett, 2011; Chantarat and Barrett, 2012). At the micro level, a range of mechanisms including financial exclusion, uninsured risk and adoption of inefficient technologies such as traditional agricultural practices can force individuals and households to self-select to less rewarding livelihood strategies that reinforce poverty in the long-run (Rosenzweig and Binswanger, 1993; Morduch, 1995; Dercon, 1998; Barrett et al., 2001, 2006).

Crop diversification impacts poverty and food & nutrition security through two main channels. First, crop diversification cushion the problem of food and nutrition insecurity due to the most likely increase in yields that boost the production of crops for household consumption (Kankwamba et al., 2012; Immink and Alarcon, 1991; Jones et al., 2014; Mazunda and Pauw, 2015). Second, crop diversification brings yield stability and insurance effect, since if one crop fails, households can still depend on the other crop (Njeru, 2013; Smithson and Lenne, 1996). Third, crop diversification improves food security and nutrition by enhancing farm household's income. A consistent body of evidence from different settings suggest that the income realized from the sale of agricultural produce is positively related to food and nutrition security in farm households (Mazunda and Pauw, 2015; Smith and Haddad, 2000; Mukherjee and Benson, 2003; Joshi et al., 2004; Bhagowalia et al., 2012). Thus, the combination of various crops in agro-ecosystems in smallholder farming can contribute significantly to poverty reduction and food security of rural farm households. However, the pathway is not always direct and linear. Studies have shown that crop diversification to high-value cash crops among smallholder farmers does not necessarily lead to household food and nutrition security (Fleuret and Fleuret, 1980; Lappe et al., 1977). Specializing in high-value cash crop might displace food crops, which, in turn, lowers food security and dietary adequacy in households, particularly when household food availability does not change in response to improved farm household income from cash crops (Winters et al., 2006; Gwatkin et al., 2007).

In this study we investigate the impact of climate shocks (measured in terms of changes in the monthly maximum average near-surface temperature ($°C$) and total monthly precipitation (mm)) and crop diversification on poverty dynamics using rigorous econometric specifications and nationally representative panel data from Nigeria. The paper contributes to the existing literature on the effect of climate-smart agriculture practices, in particular, crop diversification studies in several ways. First, unlike previous studies that focus on static poverty (nutrition or consumption) analysis, this study focus on the dynamics of poverty. This allows us to capture the effects of crop diversification both in short and long run. Second, the study contributes to the growing literature on climate-smart agriculture and welfare of rural agricultural households in developing countries. But, it differs from existing studies that are based on cross-sectional data that suffer from endogeneity. This study utilizes rich panel survey and geo-referenced historical climate (rainfall and temperature) data from Nigeria which enables us to capture the dynamics in crop diversification and its implications on household welfare dynamics. By using endogenous switching model we are also able to control for the panel attrition in our sample and address initial condition bias. As a result, unlike other studies on poverty dynamics, the estimates presented in this study do not suffer from sample selection bias caused by limiting the analysis to balanced panel. Third, we measure the level of crop diversity using various crop diversity indices namely: Count, Shannon-Weaver and Composite entropy. Hence, we are able to study the different aspects of multi-cropping regimes and check the robustness of our results to different crop diversity measures.

Results show that both initial conditions and panel retention are endogenous to poverty transitions (dynamics) in Rural Nigeria. We find crop diversification has a negative effect on poverty entry. On the other hand, precipitation leads to a lower probability of entering into poverty. Similarly, increasing temperatures lead to a higher poverty entry. We also document that there is state dependence on poverty in rural Nigeria. The positive effect of crop diversification on poverty entry suggests that agricultural policies should have a greater focus on agricultural diversification in general and crop diversification, in particular, to mitigate the effect of climate change on household welfare in the short run. Although crop diversification exerts positive welfare gain by protecting households not to enter into poverty, we do not find evidence that crop diversification mitigates poverty persistence.

The remainder of the paper proceeds as follows. The next section summarize the literature. Section 3 describes the data and variables used. Section 4.1 presents the estimation strategy. Estimation results and its policy implication are discussed in Section 5. Section 6 concludes.

2 literature review

Since the seminal contribution of Heady (1952) who identify crop diversification as an agricultural practice to manage risk, there is growing empirical evidence on its role as an effective farm-level risk management strategy to climate variability (e.g., Asfaw et al., 2019; Asfaw et al., 2018; Seo and Mendelsohn, 2008). However, the empirical evidence that studies the effect of crop diversification on the welfare of smallholding farm household welfare is scant (Tesfaye and Tirivayi, 2020; Alobo Loison, 2015).

Crop diversification is centered around cultivating a variety of crops - that can either be from one species or different species - in a given area of farming land (Heal, 2000; Makate et al., 2016; Mango et al., 2018). The planting of these crops can be done either by intercropping or some form of crop rotation. Recent studies suggest that crop diversification is a cost-effective and feasible practice that can reduce agricultural uncertainties for small-scale farmers (Makate et al., 2016, Joshi, 2005). Lin (2011) and Truscott et al. (2009) ascertain that crop diversification prompts increased biodiversity of the agricultural land, improving soil fertility and controlling for pests, thus increases crop yield. According to Mango et al. (2018), crop diversification also enhances resilience, which is defined as the soil's ability to return to its initial agricultural state after it has been utilized. Makate et al. (2016) explains that this resilience results from reduced soil erosion, reduced parasites (weed and insects), and reduced chemical use to control pests and preserve soil fertility. In turn, the increased soil fertility allows for higher crop yields per unit of farming land. For small-scale farmers, Di Falco and Chavas (2009) affirm that the cultivating of various crops species helps farmers cope with uninsured shocks associated with fluctuating crop prices and production.

Sibhatu and Qaim (2018) take the inventory of the existing studies that analyzed the relationship between crop diversification and welfare of farm households in developing countries. Their study concludes that despite the increasing evidence on crop diversification's positive contribution to household consumption and nutrition, the existing empirical evidence is mixed and inconclusive. Akaakohol and Aye (2014) collect data from 120 farming households in Makurdi (Nigeria), aiming to quantify the welfare effects of diversification on farm households. They document that crop diversification has a positive and significant effect on households' per capita consumption. They also go further in explaining the determinants of crop diversification adoption in the farming household. Their study suggests that a male-headed household, households with higher education levels and credit access are more likely to adopt crop diversification. On the other hand, access to markets and increased farming experience tend to have a negative and significant relationship with crop diversification.

Asfaw et al. (2019) explore the empirical correlation between crop and livelihood diversification strategies with household welfare in Zambia, Malawi, and Niger. Through utilizing national representative household surveys and climate data from these countries, they find that effect of diversification on household income varies across countries, but what is most noteworthy is that the impact of crop and income diversification had a significant and positive effect on the household welfare of the poorer countries. This finding emphasizes the specific effects crop diversification can have on African countries, considering their food security challenges and malnutrition (especially in the rural areas). Mango et al. (2018) estimate the effects of crop diversification on nutrition and the income of rural households in central Malawi. After controlling for household heterogeneity, they find a positive and significant relationship between crop diversification and household income levels. Their findings show a positive relationship between crop diversification and their two dietary diversity indicators, Household Food Insecurity Access Score and Household Food Consumption Score. Makate et al. (2016) study the impacts of crop diversification in rural Zimbabwe. Using data from 500 small-scale farming households, their results show that crop diversification improves income, crop yield, and food security at the household level.

In Zambia, Kumar et al. (2015) investigated the correlation between crop diversification and children dietary status. Using household survey data collected from 3,040 households, they find a significant and positive relationship between crop diversification and nutritional variation in children between 6 and 23 months. They also find a positive correlation between crop diversification and children's dietary status between 24 to 56 months. Sibhatu et al. (2015), show evidence that crop diversification does indeed increase the welfare of farming households, but not always. Studies in Malawi, Indonesia, Ethiopia, and Kenya, showed that when crop diversity is high, its relationship with dietary diversity becomes negative due to specializing prior income benefits. This means that crop diversity will improve household's nutritional welfare that has not yet adopted agricultural diversity. These findings underline the importance of crop diversity adoption to improve the welfare of rural households. However, results are context-specific. More recently, Tesfaye and Tirivayi (2020) study the impact of crop diversification on the welfare of rural households in Ethiopia using national representative data. They found that crop diversity improves household welfare (dietary diversity and consumption expenditure) and enhances households' risk management in the short run. Using nationally representative data, we study the effect of crop diversification on welfare and nutrition dynamics in Nigeria. To the best of our knowledge, this is the first study that combines national representative panel data with geospatial climate indicators to analyze the effect of crop diversification on poverty and nutrition dynamics.

2.1 Crop diversity, Food production, and Climate change

Improving smallholder agricultural systems is a crucial response to climate change and food security, which are the most pressing global challenges today. Improving incomes and food security for the largest group of food-insecure households in the world requires strengthening agricultural production. This, in turn, calls for improving the resilience of the agriculture system to adapt to climate change (World Bank, 2010; Adger et al., 2003). Though studies suggest that average crop production will not drop by 2050, in SSA production is predicted to drop as the region is expected to face increased climate variability and extreme weather shocks (Xie et al., 2018; McCarthy et al., 2001; Smith et al., 2007). A study in 12 food-insecure regions of the world shows that changes in mean temperatures and rainfall, increased climate variability, and changes in pest and disease patterns could significantly impact agricultural production and food security by 2030 (Lobell et al., 2008). Parts of South Asia and Sub-Saharan Africa are expected to be hardest hit, with decreases in agricultural productivity between 15-35 percent (Fischer et al., 2002; Smith et al., 2007).

Environmental changes affect different aspects of agricultural production that influence food production and food security (Fuhrer, 2003; Parry et al., 2005). Climate change or fluctuations in temperature influence nutrient cycling, soil moisture, pest occurrences, and plant diseases. Diversified agroecosystems are important to build the resilience of agricultural systems through ensuring the maintenance of the system's functional capacity that results from an incomplete understanding of the effects of environmental change by humans (Elmqvist et al., 2003). The agricultural system's resilience can be improved by adopting crop diversity, which dampens pest outbreaks and pathogens, and buffers crop production from climate variability and extreme events. Recent studies indicate that it will not be feasible to meet future SSA food demand using yield gap closure alone; it requires increasing cropping intensity (increasing the number of crops grown per area) and other more complex practices such as an expansion of irrigated production area (Xie et al., 2018).

Several empirical studies have also shown high plant diversity within agricultural plots leading to higher production levels compared to agricultural systems with lower plant diversity (Tilman et al., 2006: Picasso et al., 2008: Smith et al., 2008). In contrast, few studies have found opposite results. Snapp et al. (2010), for instance, found that biodiverse rotational systems produced lower yield than integrated monocropped grain systems, despite the previous system producing higher quality. In this case, a choice of diverse systems depends on the premium the market pays for quality.

2.2 Pathway from diversification to poverty reduction

Crop diversification impacts poverty and food & nutrition security through various channels. One of the direct mechanisms through which crop diversification improves food security and nutrition is the production of crops for household consumption. Crop diversification towards nutrient dense crops has the potential to improve nutrition for farm households (Kankwamba et al., 2012). Immink and Alarcon (1991) examine the effect of crop diversification on nutrition in Guatemala and find an insignificant effect at both household and individual level. In contrast, Jones et al. (2014) and Mazunda and Pauw (2015) provide evidence that crop diversification improves dietary diversity and nutrition security among farming households in Malawi. Other similar studies document a positive association between the number of crops cultivated and household dietary diversity & consumption and negative association with poverty measures in developing countries (see Tesfaye and Tirivayi, 2020 in Uganda; Asfaw et al., 2018 in Niger Herforth, 2010 on Kenya and Tanzania; Torheim et al., 2004 on Mali; Remans et al., 2011 on Malawi, Mali, and Uganda). However, the link between crop diversification and nutrition is not simple and the existing empirical evidence is mixed (Sibhatu and Qaim, 2018).

The second main channel through which crop diversification improves food security and nutrition is through enhancing farm household's income. A consistent body of evidence from different settings suggest that the income realized from the sale of agricultural produce is positively related to food and nutrition security in farm households (Mazunda and Pauw (2015); Smith and Haddad, 2000; Mukherjee and Benson, 2003; Joshi et al., 2004; Bhagowalia et al., 2012). While income from the sale of agricultural produce improves the welfare of households in general and food security in particular, the pathway is not always direct and linear. The literature has shown that diversification to high-value cash crops among smallholder farmers is incompatible with improving household food and nutrition security (Fleuret and Fleuret, 1980; Lappe et al., 1977). This scant empirical evidence suggests that households will be affected though displacement of food crops by cash crops, which, in turn, lowers food security and dietary adequacy in households, particularly when household food availability does not change in response to improved farm household income from cash crops. Indeed, recent studies highlight the extent to which improved income from crop diversification affects household food and nutrition security depends on different socio-economic factors such as, characteristics of the food market, household knowledge about nutrition and individual preferences of consumption (Winters et al., 2006; Gwatkin et al., 2007).

3 Data

This paper takes advantage of a unique longitudinal dataset, the Nigerian General Household Survey (NGHS), a rich and representative geopolitical zone data (at both the urban and rural levels). The survey is administered by the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) program of the World Bank in collaboration with the

Nigerian National Bureau of Statistics (NBS). [5] It is a survey of 5,000 households and provides a rich array of information on household characteristics, income sources, household assets, consumption expenditure, shocks, coping strategies, food security, land holdings, crop production, and livestock ownership. The sample used for this empirical analysis is a panel of rural households collected in 2010/11 (Wave 1), 2012/13 (Wave 2), and 2015/16 (Wave 3). The time dimension of NGHS is long enough to allow estimating poverty transition than previous studies of poverty dynamic in Africa.

NGHS Georeferennce households which enables us to merge the household data with geospatial climate information. We extract historical temperature and precipitation data from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia (Harris et al., 2014).[6] We measure both temperature and precipitation at an average near-surface maximum temperature in degree Celsius and total precipitation in millimeters, respectively. Both temperatures and precipitation are calculated as the monthly averages. Our average calculation is motivated by the fact that climate variability span both the post-planting and post-harvesting stages of the LSMS-ISA dataset. We expect that the lagged values of temperature and precipitation have more explanatory power in predicting the influence of climate change on households' welfare than the same year temperature and precipitation data **?**. Thus, our focus is on the temperature and precipitation of three years preceding the survey in our empirical analysis.

Every analysis of the welfare dynamics draws on the microeconomic theory of utility maximization (see section 4 for detailed discussion). According to standard theory, a household's objective is to maximize utility subject to a budget constraint. Although the utility of households is not directly observable, it is a construct representing household welfare. In the literature, either income or consumption is used to proxy monetary welfare. For developing countries, consumption is preferred as a better approximation of 'utility' than income, due to high measurement errors in income (see Haughton and Khandker, 2009; Deaton, 1997; Ravallion, 1992 for detailed discussion). In rural Africa, income is more volatile and highly affected by seasonality; relying on income as an indicator of welfare might significantly under- or overestimate living standards. Consumption is also a better measure of long-term welfare because households' smooth consumption over time through borrowing, draw down savings, or receive public and private transfers. Accordingly, in this study, we

[5] The data is collected by the National Bureau of Statistics of Nigeria in collaboration with the Bill and Melinda Gates Foundation and the World Bank. More statistical addendum of NGHS is available on the Living Standards Measurement Study (LSMS) website of the World Bank. See http://go.worldbank.org/IFS9WG7EO0.

[6] The downscaled version that corrects for bias, which is produced by WorldClim Fick and Hijmans, 2017, is used.

use household consumption to proxy household utility levels. The definition of consumption is comprehensive in that it includes both food and non-food components. Food consumption includes the value of food purchased from markets and prepared food in-house. The non-food component includes expenditures on clothing, energy, education, kitchen equipment, contributions, health, education, transportation, and other non-durable items. Real total consumption then is divided by 'adult equivalents' to determine real per adult equivalent household consumption.

Our unit of analysis is a household, as defined in the first wave of NGHS. A household is deemed poor if adult equivalent consumption is below the country's absolute poverty line. The poverty line in Nigeria is estimated following the cost-of-basic-needs approach in two stages, using 3,000 calories as the expected minimum caloric intake for the average Nigerian. First, the food poverty line is estimated using the average quantities of a bundle of food basket most frequently consumed by households in the lower half of the expenditure distribution. Second, the poverty line's non-food component is estimated by dividing the food poverty line by the average food-share of households below the minimum calorie intake (NBS, 2010).[7]

Table 1 presents the descriptive statistics of covariates used in the empirical analysis. We have two types of variables. First, we have the outcome variable, the poverty status of households. As discussed above poverty status of the household is defined based on the Nigeria national poverty line and real household per adult equivalent consumption. Second, we have the determinants of poverty, control variables. The control variables are grouped into four main categories, namely: household head characteristics, household characteristics, climate variables, and crop diversity variables. We also needed additional variables to test the exclusion restrictions in the selection equations, initial poverty, and panel retention equations(see Section 4.1 for detailed discussion). We use the household head's parental socio-economic status (fathers' education and occupation) to instrument the households' initial poverty status. We created a set of binary variables to summarize fathers' engagement in the non-farm sector.[8] The basic argument is that parental background plays a vital role in a human capital accumulation of children, which determines the initial poverty status of the households but not transitions into and out of poverty (Stewart and Swaffield, 1999; Cappellari and Jenkins, 2002; Cappellari and Jenkins, 2004). As an instrument for sample retention, we used a binary variable indicating whether a household was a NGHS original sample member; this instrument is similar to that employed by Cappellari and Jenkins

[7] The national poverty line was 137,430 Naira (USD 381.75) per year in 2019.

[8] NGHS collects data on parents' education and occupation status regardless of whether parents are alive or, if alive, reside in the same household (see Azomahou and Yitbarek, 2020 for detail discussions).

(2002); Cappellari and Jenkins (2004) and is based on the argument that households in the first wave of NGHS is selected randomly from the population and it improves the chance of staying in the sample but not poverty transitions.

Table 1 – Descriptive Statistics of control variables

Variable	Mean	Std. Dev.	Min	Max
Female household head	0.089	0.284	0	1
Age of household head	45.602	11.047	16	65
Illiterate household head	0.465	0.499	0	1
Household size	6.282	2.997	1	23
Asset value (in log)	10.103	1.711	0	14
Livestock holding (TLU)	2.128	23.667	0	1155
Farm size	2.672	16.705	0	810
Access to credit	0.193	0.395	0	1
Access to agriculture extension service	0.110	0.313	0	1
Average 3 years annual temperature (°C)	32.747	1.879	28	37
Average three years annual rainfall (mm)	110.447	46.392	37	290
North central	0.194	0.396	0	1
North east	0.163	0.370	0	1
North west	0.314	0.464	0	1
South east	0.161	0.367	0	1
South south	0.090	0.286	0	1
South west	0.079	0.269	0	1
Observations (nT)	2088	2088	2088	2088

3.1 Context and poverty transition patterns

Despite government and other development actors' efforts, poverty has remained unabated in Nigeria. According to the recent NSB estimates, around 83 million Nigerians - roughly half the Nigerian population - live in extreme poverty in 2019. Between 1980 and 2010, the incidence of poverty in Nigeria rose from 27.2 percent to 69.0 percent (World Bank, 2012). Poverty is predominantly a rural phenomenon. Favorable climate, distance from the sea, and lack of pubic infrastructure in the Northern part are the primary determinant of poverty (World Bank, 2016). However, such one point-in-time (static) poverty estimate tends to obscure information on individual poverty experiences across time and space. The empirical literature in both developed and developing countries suggest that households do escape poverty during periods of an aggregate rise in poverty rates and enter into poverty during periods of aggregate decline in the poverty rate (Azomahou and Yitbarek, 2015 on Ethiopia; Dang and Dabalen, 2019 on 21 Sub-Saharan African countries (not including

Nigeria). We are not aware of any analysis of poverty dynamics in Nigeria and Africa's most part in the economic literature. Thus, we begin our analysis by looking at households' basic poverty transition between 2011 and 2016. Table 2 shows the raw poverty transition matrix for households we observe in all the waves or balanced panel in panel A and all households in Panel B.

The transition probabilities give the probability of households being poor or non-poor at wave t conditional on the previous wave's poverty status $(t-1)$. The table shows that the chance of being poor in rural Nigeria significantly differs depending on the household's poverty status in the previous years. Poor households have a higher chance of being poor than households that were non-poor in the earlier waves. Table 2 shows that households that were poor and non-poor at $t-1$ have 84 percent and 35 percent chance to stay in poverty and to enter into poverty at t, respectively. There is also a high persistence rate of both states, being poor or not poor. At earlier waves $(t-1)$, poor households are 84 percent likely to stay in poverty, while non-poor households during previous waves have a 65 percent chance to stay out of poverty at t. Moreover, the table shows lower transition probabilities for poor households to exit poverty in subsequent waves. The likelihood of getting out of poverty at t for those who were poor at $t-1$ is only 16 percent, while the probability of entering into poverty for non-poor households is 35 percent. Overall, the likelihood of poverty for poor households in the previous waves is about 49 percent higher than the poverty rate for non-poor to enter poverty in subsequent waves. The 49 percent measure the 'aggregate' poverty dependence in rural Nigeria without controlling for observed heterogeneity (such as education, asset, size of household members) and unobserved heterogeneity such as motivation and risk-taking behavior of household head and household members. Poverty dependence might also arise either because of over-representation of poor or non-poor households in the panel data (endogenous selection of households in the dataset over time) or due to true state dependence poverty that arises from the change in households' behavior because of experience poverty in the past. Our empirical analysis addresses these econometrical issues by accounting for both observed and unobserved determinants of a household.

Panel (B) of Table 2 shows the transition matrix constructed using all households we observe in the dataset, unbalanced panel. Note that data on consumption or poverty transition is not available for households we do not observe in two consecutive waves. The 'missing' column of the table shows the households' poverty status before leaving the panel. The column shows that household poverty status differs by attrition propensity. The attrition propensity of non-poor households (67%) is twice that of poor households (33%). This suggests that households' retention between 2009/10 and 2016/17 in NGHS is non-random phenomena and varies by our outcome variable, by households' poverty status. It is important to note that the panel attrition of NGHS is lower than similar dataset in developing countries, and the problem is not so much that the bulk of sample households' stayed in the dataset from one wave to the next, but that the retention rates differed by the poverty status of the households. This requires specification of household retention mechanism and joint estimation with the poverty transition equation to obtain unbiased estimates. We shall employ a poverty transition model that uses sample data with observations of six different types: each corresponding to each of the six cells of the panel (B) of Table 2 and incorporates household heterogeneity.

Table 2 – Poverty transition rates (in %), with and without missing, 2011-2016

Poverty status, wave $t-1$	Poverty status, wave t		
	Non-poor	Poor	Missing
(a)Balanced Panel			
Non-poor	65.07	34.93	
Poor	16.43	83.87	
All	23.98	76.02	
(b)All households (Unbalanced Panel)			
Non-poor	66.94	33.06	33.33
Poor	17.11	82.89	66.67
All	25.37	74.63	72.07

3.2 Crop diversification measures and patterns

Crop diversification at a farm level involves growing more than one crop to achieve self-sufficiency or risk diversification (Makate et al., 2016). There are various ways of measuring crop diversification at a farm level. This study uses the three most common crop diversity measures: the number of crops grown by the household, Shannon-Weaver, and Composite Entropy Index. The number of crops grown by the household is the most widely used measure of crop diversity. It merely measures crop diversity richness by counting the number of crops grown by household (Asfaw et al., 2018; Sibhatu et al., 2015). Because this measure assumes an equal contribution of all crops to the household's crop portfolio, we used two other crop diversity measures, the Shannon-Weaver index and Composite entropy index, that capture both richness and evenness. Shannon's (Shannon-Weaver) index assess the degree of concentration when crops are grouping into type reflecting the abundance of different crops (Saenz and Thompson, 2017). Its value ranges between 0 and 1, with a higher value indicating higher diversity. The composite entropy index gives due weighting to the total number of crops grown by the farm household. Its value is standard scale bounded by 0 and 1, where higher values indicate increased numbers of crops grown and more equitable land allocation across crops (Makate et al., 2016). Both Composite entropy and Shannon's indices are computed based on the proportion of gross cropped area under different crops cultivated in a particular geographical area. Table 3 summarizes the crop diversification measures used.

Table 3 – Definition of crop diversity indices

Index	Mathematical Construction	Explanation	Adaptation in this paper
Number of crops	D=S	Richness	A Household produced S number of crops
Shannon-Weaver	$D = -\Sigma p_i \ln p_I, D > 0$ $D > 0$	Proportional abundance and Richness	p_i is proportion, or relative abundance of a species
Composite Entropy	$D = -\sum_i^p p_i ln_s(p_i)(1 - 1/S)$, $0 \leqslant D \leqslant 1$	Proportional abundance and Richness	p_i is proportion, or relative abundance of a species

Table 4 summarizes the crop diversification pattern of Nigerian rural households between 2011 and 2016. Crop diversification in Nigeria is low but is increasing throughout the panel. On average, households grow three crops. The Shannon-Weaver index's average is higher than the Composite entropy index suggesting land is not equally distributed to different crops cultivated by the households. Overall, the results show that crop diversification is low in Nigeria, and it tends to increase over the survey period (2011-2016) slightly.

Table 4 – Crop diversity patter- mean values, by wave

	2011	2013	2016	Pooled
Number of crops	2.425	2.633	2.906	2.648
	1.582	1.608	1.519	1.584
Shannon-Weaver Index	0.738	0.828	0.865	0.810
	0.502	0.494	0.482	0.495
Composite Entropy Index	0.631	0.707	0.7295	0.692
	0.428	0.421	0.412	0.423
N	2408	2430	2438	

4 Conceptual framework

We assume households are heterogeneous, and their decision to engage in crop diversification is constrained by household resources, the availability of information, and their preferences (Foster and Rosenzweig, 2010). According to Winters et al. (2006), the main factors that drive household demand for crop diversification are managing risks, adapting to agroecological production conditions, meeting market demands, and food security. Households engage in crop diversification if the perceived benefits substantially outweigh the benefits derived from monocropping. Thus, it is plausible to view household decisions to diversify crops through the lens of constrained optimization, where the household chooses to diversify its crop production if diversification is expected to be beneficial (De Janvry et al., 2010). The expected benefit the i^{th} household derives from crop diversification at time t is determined by a set of household characterstics that are observable (X_{it}), those that are unobservable (η_{it}), and independently and identically distributed error term (ϵ_{it}). Denoting D_{it} as a binary indicator of crop diversification and $E(u^*)$ as the expected utility to be derived from crop diversification. A household engage in crop diversification if and only if the expected utility from diversification is higher i.e. if $E[u^*|D_{it} = 1] > E[u^*|D_{it} = 0]$.

The outcome variable Y_{it} is also a function of observed variables including household characteristics, system level factors and agro-ecological factors (Z_{it}), crop diversification status D_{it}, unobservables, such as innate ability and motivation to work (V_{it}), and independently and identically distributed errors (ξ_{it}). The crop diversification and outcome equations are represented as follows:

$$D_{it} = D_{it}(X_{it}, \eta_{it}, \upsilon_{it}) \tag{1}$$

$$Y_{it} = Y_{it}[Z_{it}, D_{it}(X_{it}, \eta_{it}, \upsilon_{it}), V_{it}, \xi_{it}] \tag{2}$$

The observed variables in the crop diversification equation (or the selection equation) and outcome equations (X, Z) and the unobserved variables (η_{it} and V_{it}) may share elements. Therefore, we need to investigate the interdependence between the decision to diversify and the discussed outcome (food and nutrition security). **we have to estimate things simultaneously!**

4.1 Estimation strategy

One of the main reasons for studying poverty dynamics is to identify households who are most likely to remain poor and identify factors that drive poverty persistence. Poverty may persist due to the materialization of shocks (covariate shocks such as climate change or idiosyncratic like unemployment or loss of working days due to illness) that erode physical and human capital of households. Households may also experience extended poverty because of particular characteristics of its member, because of observed or unobserved characteristics of household members.Lack of Human capital accumulation in the form of low educational attainment and poor health are good examples of observed heterogeneity while lack of ability or motivation to work are good example of unobserved characteristics of household members. Poverty may also persist due to behavioral change that follows the experience of poverty. This is called ‘genuine’ state dependence of poverty. Thus, empirical models of poverty dynamics need to account for the effects of households heterogeneity (both observed and unobserved) and genuine state dependence to understand the impact of crop diversification on poverty dynamics. In the literature, there are several models has been used to study poverty dynamics such as the ‘component’ approach (see Jalan and Ravallion (1998)) , the ‘spell’ approach (see xx), and the ‘transition’ approach (e.g., Bane and Ellwood, 1986; Stevens, 1994 and Devicienti, 2011). The most recent approach that consists of ‘Dynamic Random Effects Probit’ and ‘Endogenous Switching’ models model the poverty transition using first-order Markov process. Because an endogenous switching model that is due to Cappellari and Jenkins (2002, 2004) has the advantage of controlling for non-random panel attrition which is a characteristic of our data, we use endogenous switching model to investigate poverty dynamics among Nigerian rural households with an emphasis on the effects of crop diversification. To the best of our knowledge, these models are rarely used to study poverty dynamics in Africa.[9]

Endogeneous switching models poverty transitions between two consecutive years (waves), $t-1$ and t using a trivariate probit model. There are four parts of the model. First, the determination of poverty status at t. Second, the determination of household retention between $t-1$ and t. Third, the determination of poverty status at $t-1$ to account for the initial conditions problem. Forth, the correlations between the unobservables affecting all the three processes. The combination of all the four parts characterizes the determinants of poverty persistence and poverty entry rates which means poverty dynamics.

Let households be characterized by a latent poverty propensity p^*_{it-1} at $t-1$, of the following form:

$$p^*_{it-1} = \boldsymbol{\beta}'\mathbf{x}_{it-1} + u_{it-1} \tag{3}$$

We call Equation (3) the initial poverty status equation, where $i = 1, \cdots, N$ indexes households and $t = 1, \cdots, T_i$ time span, $\mathbf{x}_{it-1}$ is a vector of controls describing i's household characteristics (including our main interest variable- crop diversification index), $\boldsymbol{\beta}$ is a vector of parameters to be estimated and the error term $u_{it-1} = \delta_i + \mu_{it-1}$ (the sum of an household-

[9]Faye et al. (2011) and Azomahou and Yitbarek (2015) are the only exceptions. Faye et al. (2011) use endogenous switching model to study poverty dynamics in Nairobi slum. Azomahou and Yitbarek, 2015 used a data from Urban Ethiopia to study the effect of informal risk sharing on poverty dynamics.

specific effect and an orthogonal white noise error) follows the standard normal distribution ($u_{it-1} \sim N(0,1)$). p^*_{it-1} is the latent dependent variable and p_{it-1} is the observed counterpart defined as,

$$p_{it-1} = \mathbf{1}_{[p^*_{it-1}>0]} \tag{4}$$

where $\mathbf{1}_{[]}$ denotes the indicator function which takes on the value 1 if the corresponding latent variable is positive, and 0 otherwise. Assume r^*_{it} to be a $i's$ latent propensity of household retention between two consecutive waves and summarized by the relationship below:

$$r^*_{it} = \boldsymbol{\gamma}'\mathbf{w}_{it-1} + \varepsilon_{it} \tag{5}$$

where the error term $\varepsilon_{it} = \eta_i + \vartheta_{it}$ (the sum of an household-specific effect η_i plus an orthogonal white noise error ϑ_{it}) follows a normal distribution $\varepsilon_{it} \sim N(0,1)$. $\boldsymbol{\gamma}$ is a vector of parameters to be estimated and $\mathbf{w}_{it-1}$ is a vector of controls describing i's household characteristics. If i's latent retention propensity is less than some critical threshold (normalized to 0), then household is not observed at t, and hence household's poverty transition status is not also observed. Let r_{it} be a binary indicator of households retention between t and $t-1$ which is defined as follows:

$$r_{it} = \mathbf{1}_{[r^*_{it}>0]} \tag{6}$$

We call 5 retention equation. The third component of the model is the specification for poverty status at t, which we call ' poverty transition equation'. Assume the latent propensity of poverty be summarized by:

$$p^*_{it} = [(p_{it-1})\lambda'_1 + (1-p_{it-1})\lambda'_2]\,\mathbf{z}_{it-1} + \epsilon_{it} \tag{7}$$

where λ'_1, λ'_2 are parameter vectors to be estimated and $\mathbf{z}_{it-1}$ denotes vector of controls, and the error term $\epsilon_{it} = \tau_i + \xi_{it}$ (the sum of an household specific effect τ_i plus an orthogonal white noise error ξ_{it}) follows a normal distribution $\xi_{it} \sim N(0,1)$. Let's define the relation

$$p_{it} = \mathbf{1}_{[p^*_{it}>0]} \tag{8}$$

Note that p_{it} is only observed if we observe the households in two colliquative waves, at t and $t-1$ or when $r_{it} = 1$. Given this, the poverty transition equation can be specified as follows:

$$(p_{it}|p_{it-1}, r_{it} = 1) = \mathbf{1}_{\left[\{(p_{it-1})\lambda_1' + (1-p_{it-1})\lambda_2'\}\mathbf{z}_{it-1} + \epsilon_{it} < \kappa_t\right]} \tag{9}$$

Equation 9 indicates that p_{it} is conditional not only on p_{it-1} but also $r_{it} = 1$. Hence, the model allows the impact of the explanatory variables to differ based on whether the household was poor at $t-1$ ($p_{it-1} = 1$) or not ($p_{it-1} = 0$). Hence, the specification provides estimates of the poverty entry and persistence rate determinants separately. The model can be estimated jointly using multivariate probit regression. However, in order to identify the model exclusion restrictions (instrumental variables) are required for the initial poverty equation (Eq.3) and the retention equation (Eq.5). In other words, we need variables that affect the initial poverty and the retention of households but not poverty transitions of households between two consecutive waves, variables entering the $\mathbf{x}_{it-1}$ or $\mathbf{w}_{it-1}$ vectors but not $\mathbf{z}_{it-1}$.

The joint distribution of the error terms u_{it-1}, ε_{it} and ϵ_{it} is trivariate standard normal, and characterized by unrestricted (and estimable) correlations across the three equations: initial poverty status equation, retention equation and poverty transition equation. The following are the three estimable correlations :

$$\begin{aligned}
\rho_1 &\equiv \text{correlation between unobserved characteristics affecting } p_{it-1} \text{ and } r_{it} \text{ or } \mathrm{cov}(\delta_i, \eta_i) \\
\rho_2 &\equiv \text{correlation between unobserved factors affecting } (p_{it}|p_{it-1}) \text{ and } p_{it-1} \text{ or } \mathrm{cov}(\delta_i, \tau_i) \\
\rho_3 &\equiv \text{correlation between unobserved factors affecting } r_{it} \text{ and } (p_{it}|p_{it-1}) \text{ or } \mathrm{cov}(\eta_i, \tau_i)
\end{aligned}$$

Thus, the distribution of the unobserved households heterogeneity is parameterized via the cross-equation correlations. A positive sign of ρ_1 indicates that households who were more likely to be initially poor are more likely to remain in the panel of the subsequent waves compared to initially non-poor households. A positive sign of ρ_2 (correlation between the unobserved factors affecting initial poverty status (Eq.3) and poverty transition (Eq.7)) indicates poverty is more likely to persist among households who were initially poor compared to their non-poor peers. A negative (positive) ρ_3 indicates households that are observed in two successive waves are less (more) likely to remain poor or to fall into poverty compared to households that drop out from the panel.

Other things being equal, if the correlation between ρ_1 and ρ_3 are equal to zero, panel attrition is random and joint estimation of the retention equation (Eq.(5)) can be ignored. In such instances, the model reduces to a bivariate model. If the correlation of ρ_2 and ρ_1 is equal to zero, then the initial condition can be ignored as well, and past poverty experience can be treated as exogenous. Finally, if $\rho_1 = \rho_2 = \rho_3 = 0$ both initial poverty and sample attrition are exogenous, and the model reduces to a univariate probit model (Cappellari and Jenkins, 2002, 2004). If $\rho_1 = \rho_2 = \rho_3 \neq 0$ then all the equations should be estimated simultaneously. In this study the estimation of the model is performed using simulated maximum likelihood.

5 Results

We discuss the results in two stages. First, we test our estimation strategy's validity by evaluating the correlations between unobservables and testing the exogeneity of initial conditions and sample retention in our data. Second, we discuss each explanatory variable's estimated impact, particularly that of crop diversification on households' poverty status, the probability of poverty persistence, and the probability of poverty entry.

5.1 Validity of estimation strategy

To assess the exogeneity of initial conditions and panel retention in poverty dynamics, we tested for the separate and joint significance of the unobserved characteristics between retention and initial condition equations (see Eqs. 3 and 5). Panel (A) of Table 5 reports the estimates. The correlation between unobserved household-specific factors determining initial poverty status and panel retention of households between t and $t-1$ (ρ_1) is statistically insignificant, indicating there is no systematical difference in terms of initial poverty between households that remain in the sample and households that left the panel in subsequent waves.

Table 5 – Statistical tests for validity of estimation strategy

	Count		Shannon-Weaver Index		Composite entropy	
Parameters	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
A. Correlation coef.						
$\rho_1 = \text{cov}(\delta_i, \eta_i)$: initial poverty status, retention	-0.04	0.084	-0.04	0.084	-0.04	0.083
$\rho_2 = \text{cov}(\delta_i, \tau_i)$: initial poverty status, poverty transition	0.786***	0.062	0.789***	0.062	0.789***	0.062
$\rho_3 = \text{cov}(\eta_i, \tau_i)$: retention, poverty transition	0.405***	0.0624	0.406***	0.062	0.406***	0.062
	Chi-2	P-Value	Chi-2	P-Value	Chi-2	P-Value
B. Exogeneity Wald tests						
Exogeneity of initial conditions: $\rho_1 = \rho_2 = 0$	72.39	0.000	72.73	0.000	72.73	0.000
Exogeneity of sample retention: $\rho_1 = \rho_3 = 0$	1019.09	0.000	1024.37	0.000	1025.02	0.000
Joint exogeneity: $\rho_1 = \rho_2 = \rho_3 = 0$	1083.15	0.000	1089.44	0.000	1090.08	0.000
C. Instrumental validity						
Inclusion of fathers education	3.170	0.075	3.460	0.063	3.480	0.062
Inclusion of fathers participation in the manufacturing sector	0.210	0.649	0.190	0.660	0.190	0.661
Joint exclusion of fathers occupation and education	5.390	0.068	5.730	0.057	5.750	0.057
Inclusion of enumeration in 2010	7.300	0.007	7.240	0.007	7.240	0.007

The correlation between unobserved characteristics affecting a household's poverty status (poverty entry and poverty persistence) and unobservables affecting initial poverty (ρ_2) is positive and statistically significant. This suggests that unobservables that increase the probability of being in poverty initially also increase the probability of being poor currently. Thus, ignoring initial condition bias while estimating poverty entry will lead to biased poverty estimates, poverty entry rates will be underestimated. Similarly, estimating poverty persistence probability on a sample with a conditional poverty propensity higher than the relevant population will overestimate poverty persistence. This finding is in line with our previous observation in Table 2 that there is a state dependence of poverty in rural Nigeria, where poor households have a higher chance to stay in poverty than their non-poor counterparts.

The correlation between unobservables affecting household poverty transition and panel retention (ρ_3) is positive and significant, implying that households observed in two successive waves have a higher probability of experiencing poverty than households that leave the sample. This confirms our earlier observation in the raw poverty transition matrix (Table 2) that non-poor households have a higher chance (67%, twice that of poor households (33%)) to exit from the survey than their poor counterparts. The selective attrition of non-poor households in subsequent waves might lead to under-representation of non-poor households in the balanced panel data compared to the unbalanced panel data. This finding suggests that estimation without accounting for the sample attrition bias, relying on the balanced panel data, would yield biased results.

Panel (B) of Table 2 report the joint exogeneity tests. By testing the joint significance of $\rho_1 = \rho_2$, we show the endogeneity of the initial condition. Similarly, exogeneity of panel retention can be tested by the joint significance of $\rho_1 = \rho_3$. Results confirm our observation in the raw poverty matrix that panel attrition in the data set is not random; the joint significance is significantly different from zero. Finally, all the three correlation coefficients were jointly significant with a p-value of less than 1%. All the tests assert that both initial conditions and panel retention are endogenous poverty transition processes between t and $t-1$. Hence, poverty transition should be estimated simultaneously with the initial condition and the panel retention equations.

Panel (c) of Table 5 presents the validity of the execution restrictions (the instruments variables) in the two selection equations, initial poverty equation (Eq. 3) and retention equation (Eq. 5). We follow previous studies (Cappellari and Jenkins, 2004; Faye et al., 2011) and undertook a Wald test to check for the relevance of the instruments used both separately and jointly. Paternal education (years of schooling) could be excluded from the poverty transition equation separately and jointly with the paternal sector (engagement in a modern (non-farm) sector). The p-values for the separate and joint Wald test are 0.075, 0.649, and 0.068, respectively. Likewise, the inclusion of enumeration status in 2010 (first wave of the NGHS) in the retention equation is positive and significant; the p-value was 0.007 confirming its validity. Moreover, the exclusion of all variables is statistically significant in the two selection equations (Equation 3 and Equation 5) at a 1% significance level supporting the validity of the instruments we used for the data at hand.

All in all, all the tests confirm the estimation strategy fitted NGHS data and highlight the necessity of simultaneous estimation of the all the three equations namely; initial condition (Equation 3), retention (Equation 5) and poverty transition (Equation 9) equations to get unbiased results.

5.2 Effects of crop diversification on poverty dynamics

Table 6 and Table 7 present the effect of control variables on poverty transition probabilities, poverty entry and poverty persistence, respectively. Table 6 reports the effect of control variables (z) on the probability of poverty entry (Eq.8) for households that were non-poor at t, where the probability of the conditioning event (being poor) in the base year is held constant. Similarly, the second set reports the parameter estimates (λ_2) in the poverty persistence equation (Eq.9) for households that were poor at $t-1$.

From the household characteristics, larger households are more likely to experience a higher probability of poverty entry. Lack of human capital accumulation, having an illiterate household head, is substantially correlated with a higher probability of poverty persistence but not poverty entry suggesting that education is a good persistence poverty reduction leverage in rural Nigeria. This finding is in line with the scant empirical evidence in Africa. Azomahou and Yitbarek (2015) and Faye et al. (2011) document the same result in Ethiopia and Kenya, respectively. Female and older household heads are also less likely to be persistently poor, indicating the life cycle's role to accumulate assets (both physical and human) that play a vital role in protecting households to stay in poverty for an extended period. Both the age and gender of the household head do not make a difference in terms of poverty entry. Access to credit increases the probability of entering poverty but decreases the likelihood of persistent poverty. The positive effect might indicate access to credit after materialization of shocks provide insurance as long as households are not too 'poor.' The negative effect of credit on poverty persistence highlights the importance of promoting access to and using formal financial services by marginalized segments of the population to maximize welfare in the long run. Households residing in South Nigeria have a higher chance of entering into poverty while a household in the South part has a higher chance of staying in poverty, highlighting the north-south poverty divide in the country.

Table 6 – Multivariate Probit model: Poverty Entry

	Count		Shannon Weaver Index		Composite entropy Index	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household Head characteristics						
Sex: Female	-0.037	0.135	-0.0358	0.135	-0.0359	0.135
Age	0.001	0.004	0.001	0.003	0.001	0.003
Illiterate	0.113	0.102	0.112	0.102	0.112	0.102
Household characteristics						
Household size	-0.123***	0.016	-0.122***	0.016	-0.122***	0.016
Value of assets (In log)	0.030	0.026	0.0303	0.026	0.0304	0.026
Livestock holding(TLU)	-0.001	0.004	-0.001	0.003	-0.0001	0.001
Land Size (acres)	-0.001	0.003	-0.001	0.003	-0.001	0.003
Access to formal credit (1 = Yes)	0.237**	0.103	0.238**	0.103	0.238**	0.103
Access to agri. extension service (1=yes)	0.151	0.141	0.159	0.14	0.159	0.14
Climate change						
Three Year Lagged Temperature	0.052	0.035	0.052	0.035	0.052	0.035
Three Year Lagged Precipitation	-0.003*	0.002	-0.003*	0.002	-0.004*	0.001
Crop Diversification						
Crop Diversification	-0.552**	0.248	-0.172**	0.086	-0.202**	0.101
Regions						
North central	-0.053	0.177	-0.0635	0.177	-0.0641	0.177
North east	-0.272	0.215	-0.3	0.213	-0.301	0.213
North west	-0.554**	0.218	-0.573***	0.217	-0.574***	0.217
South east	0.367**	0.185	0.345*	0.184	0.343*	0.184
South south	0.325	0.211	0.317	0.211	0.315	0.211
Intercept	-1.549	1.265	-2.122*	1.226	-2.120*	1.226
Log likelihood	686.81		686.81		686.81	
χ_2(d.o.f)	686.81(70)		685.96(70)		685.99(70)	
P-value	0.000		0.000		0.000	
# Observations	2088		2088		2088	

The standard errors are robust.

Household is defined in the period when it is first observed (in 2010/11) and remains the same.

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 7 – Multivariate Probit model: Poverty Persistence

	Count		Shannon Weaver Index		Composite entropy Index	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household Head characteristics						
Sex: Female	-0.252**	0.123	-0.255**	0.123	-0.255**	0.123
Age	-0.00842**	0.004	-0.00834**	0.004	-0.00834**	0.004
Illiterate	0.189**	0.094	0.187**	0.094	0.187**	0.094
Household characteristics						
Household size	0.181***	0.015	0.180***	0.015	0.180***	0.015
Value of assets (In log)	-0.104***	0.025	-0.104***	0.025	-0.104***	0.025
Livestock holding(TLU)	0.00054	-0.002	0.001	-0.002	0.001	-0.002
Land Size (acres)	-0.002	0.002	-0.002	0.002	-0.002	0.002
Access to formal credit (1 = Yes)	-0.608***	0.094	-0.606***	0.094	-0.606***	0.094
Access to agri. extension service (1=yes)	0.0161	0.134	0.0155	0.134	0.0153	0.134
Climate change						
Three Year Lagged Temperature	0.0397	0.032	0.0392	0.032	0.0391	0.032
Three Year Lagged Precipitation	-0.001	0.002	-0.001	0.002	-0.001	0.002
Crop Diversification						
Crop Diversification	0.185	0.228	0.085	0.078	0.099	0.091
Regions						
North central	0.597***	0.154	0.589***	0.154	0.589***	0.154
North east	0.438**	0.185	0.439**	0.185	0.439**	0.185
North west	0.884***	0.187	0.873***	0.187	0.874***	0.187
South east	0.341**	0.163	0.345**	0.162	0.345**	0.162
South south	0.0465	0.187	0.0523	0.187	0.0528	0.187
Intercept	1.963*	1.148	2.138*	1.109	2.137*	1.109
Log likelihood	686.81		686.81		686.81	
χ_2(d.o.f)	686.81(70)		685.96(70)		685.99(70)	
P-value	0.000		0.000		0.000	
# Observations	2088		2088		2088	

The standard errors are robust.

Household is defined in the period when it is first observed (in 2010/11) and remains the same.

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Turning into our main poverty determinants, climate change, precipitation leads to a lower probability of entering poverty. Similarly, increasing temperatures lead to a higher poverty entry, but the estimate is not significant. Concerning the probability of poverty persistence, a significant difference does not appear due to our climate change variables. The relationship between crop diversity (count, crop groups, Shannon-weaver, and composite entropy) and poverty entry is negative and significant. The result implies that cultivating more crops reduces the chance of entering into poverty. This result shade light on the role of crop diversification for consumption smoothing mechanisms and suggest that crop diversification protects households not to enter into poverty due to shocks in the short run. Thus, agricultural policies should focus on agricultural diversification in general and crop diversification in particular to improve households' welfare in the short run. Although crop diversification, using all crop diversification measures, exerts a negative poverty entry effect, we do not find evidence that crop diversification reduces poverty persistence. This result suggests that crop diversification does not support households to escape poverty.

From policy perspectives, our findings suggest that policies that target to reduce poverty in the short run should focus on promoting crop diversification. Given the persistent nature of poverty in rural Nigeria, poor households have a 49 percent to stay in poverty compared to non-poor households (Table 2), poverty reduction programs that aim to prevent households from falling into poverty not only have a short-run effect but also help to reduce future poverty. However, given the possibility of the high opportunity cost of crop diversification and lack of effect on poverty persistence, our result suggests that further research is required to identify other agricultural policies and interventions that support rural households to mitigate the effect of climate change. The results further suggest that policies that target crop diversification as a welfare-enhancing strategy need to consider the social, economic, and agroecological conditions of poor households.

The estimates for initial poverty status and retention equations are provided in Table 8 and Table 9. Overall, more covariates are significantly different from zero in the initial poverty status equation than the poverty transition equation. It is plausible to argue that the covariates' weaker effect in poverty transition (poverty entry and poverty persistence) due to accounting for non-random panel attrition in our sample. We document having an illiterate household head, an increase in temperature, and residing in the Northwest of Nigeria increase the probability of being poor in the base period, 2010/2011. Conversely, having more assets, access to formal credit, and residing in southern (in south-south and South West) significantly reduces the propensity to be poor in the initial period. The instrument variables have expected signs; having educated fathers and fathers engaged in the modern sector reduces initial pottery. However, the effect of fathers' occupation is not significant

Table 8 – Multivariate Probit model: Selection equation, Initial condition

	Count		Shannon Weaver Index		Composite entropy Index	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household Head characteristics						
Sex: Female	-0.15	0.136	-0.15	0.136	-0.15	0.136
Age	-0.0014	0.004	-0.0015	0.004	-0.0015	0.004
Illiterate	0.306**	0.119	0.307***	0.119	0.307***	0.119
Household characteristics						
Value of assets (In log)	-0.157***	0.032	-0.156***	0.032	-0.156***	0.032
Household size	0.273***	0.021	0.273***	0.021	0.273***	0.021
Livestock holding(TLU)	0.00086	0.005	0.000868	0.004	0.000869	0.004
Land Size (acres)	-0.00312	0.003	-0.00308	0.002	-0.00307	0.002
Access to formal credit (1 = Yes)	-0.449***	0.110	-0.449***	0.110	-0.449***	0.110
Access to agri. extension service (1=yes)	-0.14	0.158	-0.141	0.158	-0.141	0.158
Climate change						
Three Year Lagged Temperature	0.0211	0.039	0.0218	0.039	0.0219	0.039
Three Year Lagged Precipitation	0.00275	0.002	0.00273	0.002	0.00273	0.002
Crop Diversification						
Crop Diversification	-0.011	0.273	-0.0128	0.095	-0.0148	0.111
Regions						
North central	0.279	0.184	0.278	0.184	0.277	0.184
North east	0.333	0.238	0.327	0.236	0.327	0.236
North west	0.659***	0.246	0.664***	0.246	0.663***	0.246
South east	-0.388**	0.189	-0.387**	0.187	-0.387**	0.187
South south	-0.390*	0.217	-0.389*	0.216	-0.389*	0.216
Instrumental variables						
Father years of schooling	-0.0228*	0.013	-0.0237*	0.013	-0.0238*	0.013
Father engaged in modern sector	-0.0589	0.130	-0.0568	0.129	-0.0565	0.129
Intercept	0.679	1.377	0.65	1.332	0.647	1.332
Log likelihood	686.81		686.81		686.81	
χ_2(d.o.f)	686.81(70)		685.96(70)		685.99(70)	
P-value	0.000		0.000		0.000	
# Observations	2088		2088		2088	

The standard errors are robust.

Household is defined in the period when it is first observed (in 2009/10) and remains the same.

Significance levels: $*$: 10% $**$: 5% $***$: 1%

separately, suggesting the exclusion of both variables from poverty transition equations.

Concerning the retention equation, increasing temperature and residing in regions other than the southwest reduce household retention in the subsequent waves. The effect of temperature highlights the possibility that families affected by climate change to move and find better opportunities. This is indeed obedient with the World Bank's estimation that climate change could cause more than 86 million people to migrate within Africa by 2050 alone (Rigaud et al., 2018).

Table 9 – Multivariate Probit model: Selection equation, Panel Retention

	Count		Shannon Weaver Index		Composite entropy Index	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household Head characteristics						
Sex: Female	-0.302	0.194	-0.301	0.194	-0.301	0.194
Age	-0.00314	0.00498	-0.00316	0.00498	-0.00316	0.00498
Illiterate	-0.187	0.121	-0.186	0.121	-0.186	0.121
Household characteristics						
Household size	0.0106	-0.0167	0.0106	-0.0167	0.0106	-0.0167
Value of assets	-0.0124	0.0288	-0.0124	0.0288	-0.0124	0.0288
Livestock holding(TLU)	0.000844	-0.00158	0.000844	-0.00158	0.000844	-0.00158
Land Size (acres)	-0.0006	0.00233	-0.0006	0.00234	-0.0006	0.00234
Access to formal credit (1 = Yes)	-0.0618	0.145	-0.0612	0.145	-0.0612	0.145
Access to agri. extension service (1=yes)	0.0615	0.200	0.0611	0.200	0.0611	0.200
Climate change						
Three Year Lagged Temperature	-0.200***	0.0536	-0.200***	0.0536	-0.200***	0.0536
Three Year Lagged Precipitation	0.00519	0.00317	0.00517	0.00317	0.00517	0.00317
Regions						
North central	1.389***	0.239	1.390***	0.239	1.390***	0.239
North east	0.776***	0.261	0.774***	0.261	0.774***	0.261
North west	2.078***	0.281	2.078***	0.281	2.078***	0.281
South east	1.065***	0.278	1.064***	0.278	1.064***	0.278
South south	0.566*	0.304	0.566*	0.304	0.566*	0.304
Instrumental variables						
Household is part of 2010/11 sample	0.0001***	-5.4E-07	0.0001***	-5.4E-07	0.0001***	-5.4E-07
Intercept	6.756***	(1.942	6.767***	-1.943	6.767***	-1.943
Log likelihood	686.81		686.81		686.81	
χ_2(d.o.f)	686.81(70)		685.96(70)		685.99(70)	
P-value	0.000		0.000		0.000	
# Observations	2088		2088		2088	

The standard errors are robust.

Household is defined in the period when it is first observed (in 2010/11) and remains the same.

Significance levels: $*$: 10% $**$: 5% $***$: 1%

6 Conclusion

Poverty is predominant in Sub-Saharan Africa. Agricultural diversification has been recognized as a strategy to reduce poverty and improve welfare, in addition to its vital role as a climate risk coping strategy. However, very little empirical evidence exists on the links between crop diversification and household poverty. The study contributes to the literature and the policy discourse by thoroughly investigating crop diversification's effect on poverty dynamics in rural Nigeria. We address three main research questions. First, what is the nature of poverty dynamics experienced by rural Nigerian households? Second, do climate change affect poverty transitions? Third, what is the impact of crop diversification on poverty dynamics? Providing answers to these questions is crucial for designing effective rural poverty alleviation policies in a rural settlement where the effect of volatile and extreme weather patterns is ubiquitous. The study uses three-wave panel data from the Nigerian General Household Survey (NGHS) that spans 2011-2016 and employs an endogenous switching regression model.

Our results show that both initial conditions and panel retention are endogenous to poverty transitions (dynamics) in Rural Nigeria. We find crop diversification has a negative effect on poverty entry. On the other hand, precipitation leads to a lower probability of entering into poverty. Similarly, increasing temperatures lead to a higher poverty entry. We also document that there is state dependence on poverty in rural Nigeria. The positive effect of crop diversification on poverty entry suggests that agricultural policies should have a greater focus on agricultural diversification in general and crop diversification, in particular, to mitigate the effect of climate change on household welfare in the short run. Although crop diversification exerts positive welfare gain by protecting households not to enter into poverty, we do not find evidence that crop diversification mitigates poverty persistence.

From policy perspectives, our findings suggest that policies that target to reduce poverty in the short run should focus on promoting crop diversification. Given the persistent nature of poverty in rural Nigeria, poverty reduction programs that aim to prevent households from falling into poverty not only have a short run effect but also help to reduce future poverty. However, given the possibly high opportunity cost of crop diversification and lack of effect on poverty persistence, our result suggests that further research is required to identify other agricultural policies and interventions that support rural households to mitigate the impact of climate change. The results suggest that policies that target crop diversification as a welfare-enhancing strategy need to consider the social, economic, and agroecological conditions of poor households.

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