Climate-Induced Agricultural Productivity Change and Child Nutritional Outcomes: Empirical Evidence from Nigeria Mulubrhan Amare Bedru Balana

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Abstract

This study examines the effect of climate-induced agricultural productivity change on child nutritional outcomes. We also examine heterogeneity in the effect of climate-induced agricultural productivity changes on child nutritional outcomes through market access and education. Using micro level multiple waves of farm household panel data from Nigeria, we first show that perception and high temperature (heat stress) reduces agricultural productivity. Secondly, using fixed effects instrumental variables (FE-IV) models, we show that climate-induced agricultural productivity change has a negative effect on child nutritional outcomes, measured by child height-for-age and weight-for-age. The results indicate that climate changes undermine the ability of smallholder farmers to increase agricultural productivity and improve nutritional outcomes. The main channel through which climate-induced agricultural productivity change affects child nutritional outcomes is by decreasing food production for own consumption. The results further show that households who have limited access to markets and lower educational level are more vulnerable climatic shocks. Thus, ex ante interventions and policies geared towards climate smart agriculture and ex-post measures are needed to cushion vulnerable households from falling into severe food insecurity and malnutrition. Such measures need to be complemented with strategies for improving farmers' access to markets and capacity strengthening to enhance smallholders' resilience to climatic shocks and improved nutritional outcomes.

JEL Codes: D13, D81, Q12, Q13, Q54

Key Words: Climate Change, Agricultural Productivity Change, Child Nutritional Outcomes

Climate-Induced Agricultural Productivity Change and Child Nutritional Outcomes: Evidence from Nigeria

1. Introduction

Agricultural research and development interventions focused on intensification of farming and the modernization of market channels for agricultural products can lead to agricultural productivity change and, thereby, reduce poverty as well as meet growing demands for food. Improving the productivity, profitability, and sustainability of smallholder agriculture is considered a key pathway out of poverty and food insecurity for many rural households (Ehui and Pender, 2005; Gulati, et al., 2012; Webb and Block, 2012). Byerlee, et al. (2009) emphasized the new paradigm of agriculture's role and its multiple functions for development, with a focus on the effects of rising productivity of smallholder agriculture on poverty reduction and household food and nutrition security. In this regard, smallholder-focused inclusive agricultural productivity change will play a key role not only for poverty reduction but also for structural transformation of the agricultural sector. An increased level of specialization and market-oriented production of high value crops by smallholders could be a salient feature of such a transformation. This could, ceteris paribus, increase overall productivity, create marketing opportunities, and provide additional income, thereby helping smallholders move out of poverty, enable them to afford more diversified diets, and improve their food security (Irz, et al., 2001, Minten and Barret, 2008; Christiaensen, 2011). However, agricultural productivity change may not necessarily translate into improved child nutritional outcomes (Berti, et al., 2004; Hawkes and Ruel, 2008). For instance, an increased level of commercialization and production of high-value crops may occur at the expense of growing diverse food crops, which may lead to a decrease in household's dietary diversity (Pingali and Rosegrant, 1995).

There is well-established evidence on the linkages between agricultural productivity change and poverty reduction. Among the possible pathways through which agricultural productivity can reduce poverty, for instance, are through increased incomes and increased household consumption (Minten and Barret, 2008; Schneider and Gugerty, 2011; Christiaensen, 2011). Agriculture also has the potential to reduce undernutrition. However, explicit evidence is thin on the linkages between agricultural productivity and nutritional outcomes, often due to a lack of reliable empirical data. Using Living Standards Measurement Study (LSMS) panel survey data from Nigeria, this study examines the key issue, not well explored in the literature, of how agricultural productivity changes and child nutritional outcomes are linked in the presence of unobserved heterogeneity, which could cause an endogeneity problem. We merge LSMS panel

data with satellite-based precipitation and temperature data to deal with unobserved heterogeneity and exploit exogenous variation in rainfall and temperature during the growing season to proxy for exogenous changes in agricultural productivity change. That is, we use exogenous variation in rainfall and temperature as an instrument for agricultural productivity change.

This identification strategy is based on the premise that variability in precipitation and temperature are exogenous to agricultural productivity change, and, thus, we examine the effects of climate-induced agricultural productivity change on the nutritional outcomes of children. Similar identification strategies have been applied in recent studies. For instance, Chaijaroen (2019) used changes in sea surface temperature as exogenous causes of variations in coral bleaching and its impact on incomes of coastal households in Indonesia. Emerick (2018) used increases in agricultural productivity caused by rainfall variability to examine its impact on sectoral reallocation of labor in India. Emerick extended this analysis to examine the distributional implication of agricultural productivity change on child nutritional outcomes by rural versus urban and geographical zones, obtaining insights for designing policies to both improve agricultural productivity and reduce child undernutrition.

We specify and estimate two-stage fixed effects models. In the first stage, we estimate agricultural productivity, specified in a Cobb-Douglas production functional form, using exogenous variations in precipitation and temperature among the other explanatory covariates. In the second stage, a fixed effects instrumental variable (FE-IV) model that links agricultural productivity and child nutritional outcomes was estimated using the estimated value agricultural productivity as an instrument (p-hat) with other household characteristics. Results from the first-stage model show that variability in precipitation and temperature strongly predicts agricultural productivity change, which implies the fitness of these exogenous factors as instruments. The results from the second stage FE-IV model indicate that an increase in climate-induced agricultural productivity change has a negative impact on child nutritional outcomes, as measured by child height-for-age and weight-for-age. These nutritional outcomes are obtained mainly through a 'food production – own consumption' causal pathway. Examining the heterogeneity in the impact of climate-induced agricultural productivity by education level and market access, our results show that child nutritional outcomes are weaker for households with higher education level and better access to market centers than the median values in the sample. This suggests that interventions and policies geared towards intensification of production need to be complemented with strategies for improving farmers' access to markets in order to induce incentives for increased production.

The remainder of the paper is organized as follows. Section 2 presents a concise review of literature on the linkages between agricultural productivity and nutritional outcomes. Section 3 describes data sources, the construction of variables, and the descriptive results. Empirical model development and identification strategies are presented in section 4. Section 5 reports the findings and discussions of the results. The final section concludes the paper with key policy messages.

2. Linkages Between Agricultural Productivity Change and Child Nutritional Outcomes

Issues connecting agricultural productivity to food and nutrition security outcomes are receiving increasing attention in Africa (Frison, et al., 2006; Headey, et al., 2012; Gómez and Ricketts, 2013; Kadiyala, et al., 2014; Kassie, et al., 2015; Abay and Hirvonen, 2016; Zeng, et al., 2017; Ruel, et al., 2018; Ecker, 2018; Tomich, et al., 2019). Several pathways that link agriculture to nutrition have been identified. These pathways are influenced by different actors and factors, such as climate change, agricultural practices, income changes, market and consumer demands, employment generation, rural nonfarm multiplier effects, food price effects, and nutrition-relevant policies and programs (Christiaensen, et al., 2011; Haddad and Meeker, 2013; Gollin, et al., 2014; Abay and Hirvonen, 2016; Zeng, et al., 2017; Ruel, et al., 2018; Ecker, 2018). Therefore, the pathways from agricultural production to nutrition outcomes are dynamic and may not necessarily be linearly connected (Haddad and Meeker, 2013; Kadiyala, et al., 2014; Yosef, et al., 2015).

Several studies have shown that investing in agricultural development is significant for poverty reduction, income growth, macro-economic transformation, household food security, and employment creation in the economies of sub-Saharan Africa (Gowing and Palmer, 2008; Christiaensen, et al., 2011; IMF, 2012; Collier and Dercon, 2014; Kassie, et al., 2015; FAO, 2016; World Bank, 2017; Matthew, et al., 2019). Despite the high potential and role that agriculture could play in the region, the productivity of the sector remains low (Collier and Dercon, 2014; Kassie, et al., 2015; World Bank, 2017; Matthew, et al., 2019). Major factors have been identified for low agricultural productivity in Africa, including poor investment in agricultural research; low application of improved agricultural inputs, such as fertilizer and high yield varieties; low adoption of improved technologies, e.g., mechanization; institutional constraints, such as land tenure insecurity; political or social instability; lack of access to agricultural extension services; poor access to credit facilities; low labor productivity due, in part, to low technical know-how; poor market access, and inadequate infrastructure (Ehui and Pender, 2005; Christiaensen, et al., 2011; Shiferaw, et al., 2014; Kassie, et al., 2014).

Besides the aforementioned factors, the impact of climate change on agricultural productivity should not be ignored. With agricultural production dependent mainly on rainfall, the

effects of abnormal rainfall patterns, whether shortages or excesses, and increase in temperature affect agricultural production and productivity in sub-Saharan Africa (Di Falco and Veronesi, 2013; Shiferaw, et al., 2014; Belloumi, 2014; Kassie, et al., 2014; Fisher, et al., 2015; Rippke, et al., 2016; Powlson, et al., 2016; Amare, et al., 2018a; Cooper, et al., 2019). The adverse effects of climate change on agricultural production can have negative effects on household food security and child nutrition outcomes through several pathways, including reduced yields, shifts in economic incentives, increases in food prices, changes in employment opportunities, changes in sources and distribution of income, and changes in the nutritional content of foods (Chijioke, et al., 2011; Belloumi, 2014; Cooper, et al., 2019). Studies in Nigeria have shown that rises in temperature and abnormal rainfall patterns as a result of climate change are negatively affecting agricultural productivity and consequentially affecting human and livestock health (Di Falco and Chavas, 2009; Chijioke, et al., 2011; Abidoye and Ayodele, 2015).

There are multiple pathways through which agricultural productivity can improve the nutrition and food security of farm households. The most fundamental and direct pathway is the **'production – household's own consumption' linkage**. Improvements in the quantity of food produced by the smallholder farming household can be used for its own consumption. Through this pathway, deficits in micronutrients or calories can be supplied by the increase in own-farm productivity (Potts and Nagujja, 2007; Masset, et al., 2011; Zeng, et al., 2017; Kassie, et al., 2015; Tomich, et al., 2019).

Second, the **income effects** due to increased sales or increased labor demand from improved agricultural production can positively influence nutrition outcomes indirectly through income and expenditure routes. For instance, income generated from agricultural wages earned as farm workers or from the sale of an increased quantity of produce can be used to purchase nutritious food not produced in the household (Webb and Block, 2012; Bhagowalia, et al., 2012; Du, et al., 2015; Tomich, et al., 2019). Headey (2011) and Webb and Block (2012) found that high agricultural growth rates in developing countries were found to reduce stunting rates, possibly because of the increased returns to agricultural production enabling greater household expenditure on food.

Third, agricultural productivity can influence nutrition through **women's empowerment**. Studies have shown that the nutrition and welfare effects due to increased income from higher agricultural productivity interacts with the empowerment of women in developing countries (Allendorf, 2007; Ghosh, 2007; Sauer, et al., 2016; de Jager, et al., 2017). Conceptually, the empowerment of women pathway couples increased income with women-friendly agricultural technologies and leads to increased intra-household bargaining power for women and

strengthened purchasing power. Hence, since women are mostly responsible for issues around household nutrition, especially for their children, this may facilitate increased consumption of nutritious food for children in the household (Hallman, et al., 2003; Allendorf, 2007; Ghosh, 2007).

Fourth, agricultural productivity can also affect nutrition outcomes through **food price effects**. Higher food crop productivity can result in downward pressure on food prices in local markets (Adhiguru and Ramasamy, 2003; Parasuraman and Rajaretnam, 2011; Webb and Kennedy, 2014). For net food consumers, a reduction in food prices enables greater accessibility to food and essential nutrients (Kadiyala, et al., 2014; Tomich et al., 2019). On the other hand, Tomich et al. (2019) noted that low food prices could have long-term negative effects on agriculture production stability, declines in productivity, lower availability of food crops, and, ultimately, may result in scarcity of major food crops and higher food prices. Studies have shown that high food prices play an important role in reducing dietary diversification and in adverse nutritional outcomes (Adhiguru and Ramasamy, 2003; Parasuraman and Rajaretnam, 2011; Gaiha, et al., 2012; Abay and Hirvonen, 2016). Thus, the food price effects pathway between agricultural productivity and nutritional outcomes may not yield a sustainable solution unless adequate policies are in place to stabilize prices and protect farmers from price volatility.

In principle, effective pro-poor growth approaches led by agriculture should be influenced by increased agricultural productivity linked to improved access to domestic and export markets (Lagakos and Waugh, 2013; Duranton, 2015; Tombe, 2015; Donaldson and Hornbeck, 2016; Donovan, 2017; Donaldson, 2018). Improved agricultural productivity without effective market access will hinder both expected short and long run outcomes of higher levels of production, such as increased incomes, livelihood diversification, and food and nutrition security (Donovan, 2017; Donaldson, 2018).

Human capital has also been identified as contributing beneficially to several pathways between agricultural productivity and improved nutrition, while also playing significant role in improving agricultural productivity. Enhancing farmers' knowledge and their exposure to technological innovations through training is a key input to improving agricultural productivity (Asfaw and Admassie 2004; Reimers and Klasen, 2012; Danso-Abbeam, et al., 2018; Mariyono, 2019; Anang, et al., 2020). Education may not only influence the decision of farmers to adopt new agricultural technology, but also affect their farming creativeness, innovative ability, and technical efficiency. Moreover, education can play an indirect role in improving agricultural productivity through enhancing off-farm employment opportunities, income diversification, and improving household resilience (Asfaw and Admassie 2004; Reimers and Klasen, 2012; Liu, et al., 2014;

Mutisya, et al., 2016). Therefore, education through its role in improving agricultural productivity can lead to improved child nutritional outcomes within farming households.

Against this backdrop, we empirically investigate the pathways linking agricultural productivity to the nutritional status of children within smallholder households in Nigeria.

3. Data and Descriptive Results

3.1. Data sources

The study uses two waves from the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) panel data set in Nigeria – wave 2 collected in 2012/13 and wave 3 collected in 2015/16.[1] The LSMS-ISA data sets are nationally representative and include detailed information on demographic and household characteristics, including on assets, agricultural production, nonfarm income and other sources of income, family and hired labor, and access to services. The agriculture module contains information on crop and livestock production, farm technologies employed, use of modern inputs, and the productivity of crops and livestock. The community-level instrument contains information on local infrastructure, basic public goods, local agricultural land, precipitation, and other factors that could affect agricultural productivity. Additionally, there is a module on healthcare utilization and child anthropometrics, in which information is collected on the age, height, and weight of preschool children in survey households. Given a general deficiency in the availability of high-quality agricultural data in Nigeria, the LSMS-ISA is the best nationally representative data set to use to understand the structure and performance of the agricultural sector.

In addition, georeferenced for the location of the survey enumeration areas are provided in the LSMS-ISA survey data set. This permits spatial data to be linked to the survey data on households and their farm plots. Based on this locational information, we merged the LSMS-ISA data with extract temperature data extracted from NASA MERRA-2 (Modern-Era Retrospective analysis for Research and Application). We develop monthly mean, maximum, and minimum temperatures in degrees Celsius over the 1986-2016 period of spatial resolution of 0.5 ° x 0.625 ° (~55km x 69km) (GMAO, 2015). Similarly, we extract the precipitation data from the Climate Hazards Group InfraRed Precipitation Station (CHIRPS) archives provided by the Climate Hazard

[1] Wave 4 (2017/2018) LSMS ISA data was released recently. However, we could not use this data because of the sample was rebalanced, leading to significant dropouts of sample households from Waves 2 and 3. This high rate of attrition is likely to create biasedness in any econometric estimation.

Group. It includes monthly rainfall in millimeters from 1981-2017 of spatial resolution of 0.050 X 0.050 (~ 5km x 5km) (Funk, et al., 2015; Novella and Thiaw, 2013).

3.2. Construction of variables

Anthropometric measures: we used the *Anthro* software of the World Health Organization for the computation of mean z-scores for height-for-age (HAZ), weight-for-age (WAZ), weight-for-height (WHZ) for all children under the age of five years in the survey sample. The assignment of anthropometric z-scores was based on the WHO Child Growth Standards and considered a child's sex, age, height in centimeters, and weight in kilograms (WHO Multicentre Growth Reference Study Group 2006). These z-scores were used to estimate the percentage of children who were stunted, wasted, or underweight.

Agricultural productivity: We used land productivity to measure changes in agricultural productivity among the farm households. We expressed the net value of crop production in monetary terms per unit land (measured in hectares).[2] Hence, agricultural productivity is referred to as net returns to land.[3]

Income aggregates: We generated household income aggregates by combining farm income and non-farm income. Farm income comprises crop income and livestock income, while non-farm income includes income from self-employment; fishing (artisanal); wages, including agricultural wages; and other income sources, such as rental incomes, transfers or remittances, and other revenue streams not captured elsewhere.

Income sources: Different methods were used to construct income based on source. We calculated *crop income* by using the total value of crop production minus total crop expenses; *livestock income* was generated from the value of livestock production and consumption minus livestock expenditures; *self-employment income* was computed from the profit of processed crops sold and from reported self-employment income; *wage income* was generated from wages earned

[2] As with other inputs, land productivity can be expressed in many units. Given that the land may be used to grow many different crops, a physical unit, such as metric ton or kilogram, may not be the best choice. Putting a monetary value on their respective output is often needed to aggregate the output of different crops.

[3] Net crop income is calculated as gross crop income minus crop expenses. The costs of agricultural production are the sum of all explicit crop expenses reported in each instrument. The value of harvest is the value of crop production. Crop production is valued either by the respondent's own valuation (if available) or by multiplying quantities produced by the sales prices observed by the head of household for each crop if he or she sold that crop. If the household did not sell a crop, the value per unit is imputed using the median per-unit value of observed sales at the smallest geographic unit for which we have at least 10 observations.

from work both in the agricultural and non-agricultural sector; and *other source of income* comprises the sum of investment income, rental income, and remittance income.

Climate change variables: we construct three measures of climate change variables: i) we follow the literature to construct deviation of log rainfall from average (DR) using spatial precipitation data (Maccini and Yang, 2009; Björkman-Nyqvist, 2013; Amare, et al., 2021). DR measures rainfall anomalies by first calculating the average total rainfall across the rainy months (March through October) in each survey enumeration area for a 30-year baseline period from 1986 to 2016.[4] The change in the rainfall variable is defined as the deviation of log rainfall from the average using: $\mathrm{DR}_{it} = \ln(\mathrm{R}_{it}) - \ln(\overline{\mathrm{R}}_i)$, where R_{it} indicates rainfall during a specific rainy season at the location of household i for year t. $\overline{\mathrm{R}_i}$ is the historical average rainfall over the period from 1986 to 2016 at the location of household i.

ii) Growing Degree Days (GDD): we follow agronomic literature, which suggests nonlinear transformations of temperature known as growing degree days (GDD) and harmful degree days (HDD) (Schlenker and Roberts 2006; Lobell, et al., 2011; Lobell, et al., 2013; Deryng, et al., 2014; Hendricks and Peterson, 2014; Jagnani, et al., 2019; Aragón, et al., 2021). These studies use GDD and HDD to estimate the impact of temperature on agricultural yield. We follow a similar procedure and calculated GDD and HDD using the cumulative exposure to temperatures between a lower bound (the standard base temperature of 10°C) up to an upper threshold 32°C. We calculate GDD for each month in the last 30 years (1985-2016) by subtracting the standard base temperature of 10°C from the mean temperature for each month of rainy season. We then subtract the average season GDD for the last 30 years for each crop cycle from the GDD for each of the waves of data collected. Thereby, we derive the GDD deviation for each wave during the respective rainy season for each survey household as $\mathrm{DGDD}_{it} = \ln(\mathrm{GDD}_{it}) - \ln(\overline{\mathrm{GDD}}_i)$.

iii) Harmful Degree Days (HDD): we defined degree days above 32°C (GDD>32) as harmful degree days (HDD) to capture days with heat stress that can reduce crop production physiologically. As in DGDD, we calculated the log HDD difference from the average (DHDD) which represent the deviation from the mean for harmful degree days. In essence, DHDDs are anomalies relative to mean of temperature over the 30-year period.

[4] It is usually between March and October in Nigeria. However, we captured difference between northern and southern Nigeria. For northern Nigeria, the effectiveness of weather variables can be well captured between May and October, while March to October is more accurate for southern Nigeria.

3.3. Descriptive results

Table 1 shows the nutritional status of children measured according to HAZ, WAZ and WHZ. The average HAZ for all children in the sample is −1.01. We found that about 31 percent of the children in our sample are stunted (HAZ < –2.0) and 16 percent are underweight (WAZ < –2.0). Children in rural households have a significantly higher mean HAZ and WAZ than children in urban households. The difference in HAZ, especially, is relatively large, which is also reflected in stunting prevalence rates. Meanwhile, the average WHZ for all the sample children is -0.03 and 11 percent of the children are wasted. Consistent with stunting and underweight, a higher rate of child wasting is observed in rural households than urban households.

Table 1 also presents the summary statistics of key variables used in the econometric models. It is important to note that values in the table were averages obtained from the two waves. The results show that the proxy for average agricultural productivity (land productivity) of real net crop income is USD 2,480 (PPP) per hectare. We recorded the deviation from the long-term mean of our instrumental variable of rainfall and temperature, as DGDD and DHDD – the deviation from the long-term mean for GDD and for HDD is 0.07and 0.02, respectively.[5]

[5] We restrict the data to farm households for which the agricultural questionnaire was completed and for which data on rainfall at the household level are available.

Table 1: Descriptive statistics of variables used in the econometric analysis, full sample

	Mean	Standard Deviation
Outcome variables		
Child nutritional outcomes		
Height-for-age z-score (HAZ)	-1.01	2.50
Weight-for-height z-score (WHZ)	-0.03	2.35
Weight-for-age z-score (WAZ)	-0.67	1.69
Child undernutrition prevalence rates		
Child stunting (HAZ < –2), 0/1	0.31	
Child wasting (WHZ < –2), 0/1	0.11	
Child underweight (WAZ < –2), 0/1	0.16	
Agricultural productivity		
Land productivity - real net crop income per hectare, PPP USD	2,479.8	3,190.7
Instruments		
DR – Deviation of log rainfall from average (long term mean)	-0.04	0.09
DGDD – Deviation of log Growing Degree Days from average (long term mean GDD)	0.07	0.33
DHDD – Deviation of log Harmful Degree Days from average (long term mean HDD)	0.02	0.02
Explanatory variables		
Boy child, 0/1	0.52	0.50
Age of child, months	31.2	17.53
Family size, adult equivalents	6.10	3.11
Female head of household, 0/1	0.06	
Educational attainment of household head, years	7.2	6.03
Age of household head, years	46.1	10.98
Total assets value, PPD USD	1,018.5	1,864.7
Livestock, Tropical Livestock Units	58.67	230.91
Wage non-agricultural income, PPP USD	1,395.3	4,150.5
Wage agricultural income, PPP USD	20.7	199.0
Self-employment income, PPP USD	2,081.4	4,432.2
Remittances, PPP USD	8.09	75.76
Access to finance (credit use), 0/1	0.02	
Used fertilizer, 0/1	0.40	
Used pesticides or herbicides, 0/1	0.27	
Access to agricultural extension, 0/1	0.07	
Distance to market, km	70.30	43.15
Number of observations	7,180	

Source: Authors' calculations based on Nigeria LSMS-ISA 2012 and 2015.
Note: Productivity, wealth, and income values are computed as purchasing power parity in U.S. dollars unit (PPP USD).

4. Empirical Strategies

Here we discuss our empirical approach to investigate the two main objectives of this study. First, we examine the effects of climatic factors on agricultural productivity change by controlling farmer's characteristics and input usages. Second, we address the implication of agricultural productivity change for child nutritional outcomes.

4.1. climate and agricultural productivity change

We measure agricultural productivity (P_{it}) as the real net crop income per ha. We use a Cobb-Douglas production function (equation 1):

$$\ln(P_{it}) = \gamma_{it} + \beta_x \ln(X_{it}) + \beta_h \ln(H_{it}) + \beta_r \mathrm{DR}_{it} + \beta_{rs} \mathrm{DR}^2{}_{it} + \beta_g \mathrm{DGDD}_{it} + \beta_h \mathrm{DHDD}_{it} + \nu_i + \nu_t + \varepsilon_{it}, \quad (1)$$

where X_{it} is a vector of quantities of inputs and plot characteristics, including labor inputs, seeds, fertilizer, and herbicide or pesticide by household i in year t. We expect all farm technology variables to contribute positively to productivity. H_{it} is a vector of household characteristics and wealth indicators, including household size, age, dependency ratio of the household, and income from remittances, wages, and self-employment for household i in year t. DR_{it}, DGDD_{it}, and DHDD_{it} are as defined in section 3.2 (i.e., deviations of log rainfall, log growing degree days, and log harmful degree days from their respective long-term averages for household i in year t, respectively). We also include higher order polynomial terms associated with these changes to control nonlinear effects of changes in rainfall. The variables ν_i and ν_t represent household and time-fixed effects, respectively. The variable ε is a mean zero, identically and independently distributed random error and is assumed to be uncorrelated to all the explanatory variables. The problem in estimating the drivers of agricultural productivity is that unobserved characteristics, e.g., information about inputs, managerial skill, ability, or additional dimensions of soil quality, are likely to be correlated with productivity and the variables of interest. This correlation could bias ordinary least squares (OLS) estimators (Wooldridge, 2010). We exploit the panel nature of the dataset to minimize such prospective bias. The fixed effects, ν_i and ν_t, help to ensure that the estimated effects of variables are not due to differences in common time shocks or technical progress, or due to household- and village-invariant unobserved characteristics, respectively.

4.2. Climate-induced agricultural productivity change and child nutritional outcomes

We estimate the impact of climate-induced agricultural productivity change on child nutritional outcomes using a functional form in equation 2:

$$C_{itv} = \gamma_0 + \gamma_p \ln(\mathrm{P}_{itv}) + \gamma_h \ln(\mathrm{H}_{itv}) + \varsigma_i + \lambda_p + \eta_{it}. \quad (2)$$

The dependent variable in equation 2 is the child nutritional outcomes (C_{it}) at village level v. The child nutritional outcome of interest is captured by the coefficients on P_{it}, which is agricultural productivity change. H and P are as defined above. Because similar intrinsic demographic characteristics can lead to different asset distribution patterns, a household fixed effect, ς_i, is

included to control for time-invariant unobserved demographic characteristics. Furthermore, a state-fixed effect, λ_p, is included to control for further geographic diversity in land quality and for covariate shocks affecting all provinces uniformly in each year. The variable η_i is the idiosyncratic error term.

However, agricultural productivity change, which is expected to be simultaneously determined with child nutritional outcomes could be an endogenous decision by farm households because of the joint decision of production and consumption in subsistence farming (de Janvry et al., 1991). Agricultural productivity change is also expected to be correlated with unobservable household characteristics that may affect child nutritional outcomes. Thus, OLS would cause upward- or downward-biased estimates (Bellemare, 2013; Hausman and Taylor, 1981).[6] More specifically, if a farmer's agricultural productivity change is measured with error, and the true value of the impact of agricultural productivity change is negative, the OLS estimate will be biased toward zero, even if that error has a mean of zero. Thus, the OLS estimate will be too small because of attenuation bias. The two sources of bias could apply simultaneously to the OLS estimation: the upward bias caused by omitted ability variables and the downward bias caused by measurement error in agricultural productivity (Wooldridge, 2010).

Because of this potential endogeneity problem, we investigate the implications of agricultural productivity change on child nutritional outcomes indicators by employing an instrumental variable (IV) estimation approach. Most studies of this sort exploit some exogenous variation in agricultural productivity change and aim to investigate its effect on child nutritional outcomes. We follow previous literature and use an instrumental variable constructed by matching our panel household data with satellite-based rainfall and temperature data (Chaijaroen, 2019; Emerick, 2018). We use deviation from the long average during the wet season. To exploit the panel nature of the dataset, we estimate the following fixed-effects (IV-FE) model for our second stage (equation 3).

$$C_{itv} = \gamma_0 + \gamma_p \ln(\widehat{\mathrm{P}}_{itv}) + \gamma_h \ln(\mathrm{H}_{itv}) + \varsigma_i + \lambda_p + \eta_{itv}, \quad (3)$$

$\widehat{\mathrm{P}}_{it}$ is the predicted value of agricultural productivity change from our first-stage regression. Other notations in Equation 3 are similar to those in equations 1 and 2.

[6] OLS would cause upward- or downward-biased estimates if all the unobservable characteristics have a negative effect on both productivity and the observed RHS variables. But unobservable characteristics can also have a negative impact. For example, consider the case where most of the people who adopt improved seeds live on slopes that reduce crop yield. If we do not observe the slope, we will underestimate the yield improvements associated with improved seed adoption.

5. Results and Discussions

5.1. First stage regression results

We first briefly report the results of the first stage estimates of the determinants of agricultural productivity change using a fixed-effects model (equation 1). Table 2 presents these results. The first stage estimation is mainly used in the later FE-IV analysis to explain child nutritional outcomes (equation 3). As expected, negative rainfall shock strongly affects agricultural productivity. In Table 2 we present both conditional and unconditional regressions of agricultural productivity change on measures of deviation of rainfall, growing degree days, and harmful degree days from average and their higher order polynomial terms. Our results show that climate variability strongly predicts agricultural productivity change. The relationship involves significant nonlinearities, indicating that these types of nonlinearities and dynamics are evident on agricultural productivity change. This is consistent with previous studies (e.g., Hendricks and Peterson, 2014; Jagnani, et al., 2019; Aragón, et al., 2021). The results show that high temperature (heat stress) reduces agricultural productivity change. A one percent increase in harmful degree days result in 4 percent decrease in agricultural productivity. This is consistent with the empirical evidence in Nigeria by (Chijioke, et al., 2011; Abidoye and Ayodele, 2015), shown that rises in temperature and abnormal rainfall patterns because of climate change are negatively affecting agricultural productivity and consequentially affecting human and livestock health.

The results also indicate that among household characteristics, education of the household head and livestock holdings significantly affect agricultural productivity change. The estimates also show the presence of an inverse relationship between farm size and land productivity robust to all estimation specifications and consistent with many other findings in the literature (Barrett, 1996; Carletto, et al., 2013). We find that fertilizer use, application of herbicides or pesticides, and access to extension all have a significant, positive association with agricultural productivity change. Our results are consistent with several studies that demonstrate that input use has a substantial effect on the agricultural performance of farmers (e.g., Amare, et al., 2012; de Janvry and Sadoulet, 2010; Mendola, 2007; Ravallion and Datt, 1999). Distance to markets increases transaction costs and access to information, which, in turn, affect agricultural productivity. This result suggests that better infrastructure may help to cut transaction costs, increasing the likelihood of adoption of market-provided inputs and, thus, increasing agricultural productivity.

366 **Table 2:** First stage regression: climatic factors and agricultural productivity change

	(1) Agricultural productivity	(2) Agricultural productivity
Deviation of rainfall from average	-0.087***	-0.082***
	(0.002)	(0.003)
Deviation of rainfall from average-squared	-0.120**	-0.273***
	(0.051)	(0.001)
Deviation of Growing Degree Days from average	0.911***	0.987***
	(0.211)	(0.212)
Deviation of Harmful Degree Days from average	-0.391***	-0.348***
	(0.092)	(0.088)
Education of head		0.089**
		(0.044)
Land size		-0.633***
		(0.024)
Livestock		0.555**
		(0.277)
Value of total assets		-0.042
		(0.037)
Wage income		-0.097***
		(0.019)
Self-employment income		-0.072***
		(0.019)
Transfer		0.041
		(0.066)
Credit use		0.125
		(0.250)
Extension		0.442**
		(0.193)
Fertilizer		1.413***
		(0.158)
Pesticides/herbicides		0.193**
		(0.090)
Distance to market		-0.255***
		(0.087)
2015	0.297***	0.149*
	(0.092)	(0.089)
Constant	5.773***	4.343***
	(0.517)	(0.613)
Fixed effects	Yes	Yes
Observations	7,180	7,180
Kleibergen–Paap rk Wald F statistic on selection instruments	18.23***	27.89***
F-test of excluded instruments: F (2, 6585)	36.01***	32.92***

367 Source: Based on LSMS–ISA W2-2012 and W3-2016 survey in Nigeria.
368 Note: All continuous variables are in log form. Enumeration area clustered standard errors in parentheses.
369 * p < 0.10, ** p < 0.05, *** p < 0.01.
370
371

372 **5.2. The impact of climate-induced agricultural productivity change**

373 Before turning to look at the impact of climate-induced agricultural productivity change on child
374 nutritional outcomes, we briefly discuss the quality of the selection of the instrument used. To
375 probe the validity of our instrument selection, we look at the weak identification test and the over-

identification tests. The test results support the choice of the instrument – deviation of rainfall, growing degree days, and harmful degree days from average, as do the F-test values for all the specifications (bottom of Table 3). The F-statistic on the null hypothesis that the excluded instrument is jointly nonsignificant in the first-stage equation is greater than 10, thus passing the rule-of-thumb minimum threshold for weak instruments. We use the Sargan–Hansen test of over-identifying restrictions and fail to reject the joint null hypothesis that our instrument is a valid instrument. We also apply the Hansen specification test for the endogeneity of agricultural productivity and reject the null hypothesis that agricultural productivity can be treated as exogenous.

385 **Table 3:** Climate-induced agricultural productivity change and child nutritional outcomes

	(1) Height-for-Age z-score	(2) Weight-for-Height z-score	(3) Weight-for-Age z-score	(4) Stunting prevalence	(5) Wasting prevalence	(6) Underweight prevalence
Agricultural productivity change	-0.202***	-0.082**	-0.041	0.561***	0.008	0.010
	(0.078)	(0.040)	(0.072)	(0.015)	(0.007)	(0.012)
Male child, 0/1	-0.211***	-0.138**	-0.050	0.048***	0.022**	0.044***
	(0.075)	(0.057)	(0.074)	(0.015)	(0.011)	(0.012)
Age of child	-0.429***	-0.152***	0.052	0.030***	-0.054***	-0.016**
	(0.066)	(0.039)	(0.055)	(0.010)	(0.007)	(0.007)
Education of head	0.070*	-0.010	0.013	-0.012	-0.001	-0.008
	(0.058)	(0.036)	(0.050)	(0.009)	(0.006)	(0.007)
Age of head	-0.048	-0.030	-0.004	0.025	0.010	0.021
	(0.120)	(0.119)	(0.164)	(0.026)	(0.022)	(0.022)
Value of assets	0.087**	0.072**	0.030	-0.024***	-0.002	-0.011*
	(0.042)	(0.029)	(0.035)	(0.008)	(0.005)	(0.006)
Farm size	0.196*	-0.054	0.059	0.031	-0.004	0.003
	(0.116)	(0.090)	(0.119)	(0.027)	(0.015)	(0.022)
Livestock unit	-0.040	0.007	0.063	0.033*	0.012	0.011
	(0.107)	(0.082)	(0.115)	(0.019)	(0.015)	(0.015)
Crop income	0.010	0.048**	0.061***	-0.014	-0.000	0.006**
	(0.033)	(0.020)	(0.023)	(0.010)	(0.003)	(0.003)
Non-agricultural wage income	0.597***	0.379***	0.039	-0.128**	-0.015	-0.044
	(0.177)	(0.111)	(0.145)	(0.057)	(0.020)	(0.028)
Agricultural wage income	-0.507	0.362	0.906	0.069	0.102	0.233*
	(0.616)	(0.545)	(0.596)	(0.111)	(0.123)	(0.135)
Self-employment income	0.055	0.116	0.109	-0.031	0.006	-0.001
	(0.106)	(0.076)	(0.095)	(0.022)	(0.022)	(0.016)
Transfers income	0.375	0.235	0.109	-0.245	-0.156	0.107
	(2.167)	(2.100)	(1.407)	(0.249)	(0.323)	(0.328)
Credit use	0.533	0.198	-0.096	-0.004	-0.012	-0.031
	(0.416)	(0.256)	(0.186)	(0.057)	(0.034)	(0.047)
Extension	-0.152	-0.027	0.172	0.028	0.024	0.016
	(0.202)	(0.120)	(0.184)	(0.043)	(0.022)	(0.028)
Distance to market	-0.447**	-0.218	-0.381*	-0.042	-0.026	-0.053
	(0.221)	(0.211)	(0.204)	(0.044)	(0.025)	(0.034)
Year	-0.534*	-0.085	0.232**	0.127***	0.022*	0.083***
	(0.126)	(0.076)	(0.090)	(0.021)	(0.012)	(0.015)
Constant	-0.097	-1.537*	-1.824*	0.516**	0.297**	0.381**
	(1.102)	(0.915)	(1.072)	(0.223)	(0.130)	(0.153)
Over identification test of all instruments (Hansen J statistics): $\chi 2$	43.614***	21.359***	15.613***	19.487***	13.342***	10.487***
Endogeneity test	49.577***	13.081***	13.062***	5.151***	6.232***	4.213***
Observations	7,180	7,171	7,180	7,180	7,180	7,180

386 Source: Based on LSMS–ISA W2-2012 and W3-2016 survey in Nigeria.
387 Note: All continuous variables are in log form. Enumeration area clustered standard errors in parentheses.
388 * p < 0.10, ** p < 0.05, *** p < 0.01.

389 Table 3 reports the results of the IV-FE estimation examining the implication of climate-
390 induced agricultural productivity change on child nutritional outcomes. The z-score results
391 (columns (1), (2), and (3)) reveal that climate-induced agricultural productivity change decreases
392 child height-for-age (HAZ) and weight-for-age (WAZ). A 10 percent increase in climate-induced

agricultural productivity change results in a decrease in child HAZ and WAZ by about 0.02 and 0.01, respectively. Our results suggest that weather change could affect agricultural production, and this could lead a decrease in household's food consumption for own production which can in turn lead to deficits in micronutrients or calories (Potts and Nagujja, 2007; Masset, et al., 2011; Zeng, et al., 2017; Kassie, et al., 2015; Tomich, et al., 2019). Kumar, et al. (2015) also found strong significant positive associations between increase agricultural production (through production diversity) and height for age Z-scores and a reduction in stunting prevalence among children in Zambia.

Looking at child and household characteristics, we find that girls have generally a higher HAZ than boys, which is a common finding in the research literature (e.g., Black, et al., 2013, Alderman and Headey, 2017a; Amare, et al., 2018b). Consistent with the existing literature on child nutrition in developing countries, older children are more likely to have lower nutritional outcomes (e.g., Behrman and Taubman, 1986). Education may, among other contributions, enable household to provide appropriate care for their children (Alderman and Headey, 2017). We also find education of the household head is strongly and positively associated with improved nutritional outcomes. Wealth indicators, such as land size, value of asset holding, and non-agricultural wage income, play a significant role in explaining changes in child nutritional outcomes.

The results on the prevalence of undernourished children in Table 3 (columns (4), (5), and (6)) reveal that climate-induced agricultural productivity increases child stunting. A 10 percent increase in climate-induced agricultural productivity change increases child stunting by 0.10 percent. The results also show girls are generally less stunted than boys and older children are more likely to be stunted and wasted, similar to evidence seen in other studies (Behrman and Taubman, 1986; Black, et al., 2013, Alderman and Headey, 2017a). Value of asset holding, livestock holding, and non-agricultural wage income play a positive role in reducing the prevalence of child stunting (Christian, et al., 2019; Hatab, et al., 2019).

5.3. Heterogeneous impacts

We also estimate the impact of climate-induced agricultural productivity change on child nutritional outcomes separately using access to market and education level of the household. We hypothesize that farmers' wealth differential has led to heterogeneous effects of weather changes on the outcome variables considered in the study. This was motivated by the premise that pathways for linking climate-induced agricultural productivity change to nutrition may have some heterogeneity which we can test through market access and education. Those households with

limited market access and low level of education are more likely to experience lower nutritional outcomes compared to those households having good market access and better educated. Climate-induced agricultural productivity change with limited market access will lead to decrease in income, which negatively affect dietary diversification and non-food expenditure, which may be linked, directly or indirectly, to nutritional outcomes for children within the household.

First, we estimate child nutritional outcomes by access to market. A dummy variable for households who have better access to market is defined. A household is designated as to have better access to market if the distance to the nearest market center is below the median distance to market for the households in our sample, i.e., the nearest market center is within 65 km. Households with their nearest market center being beyond 65 km distance radius are classified as having constrained access to market.

The results (Table 4) indicate that climate-induced agricultural productivity change has a negative significant impact on child HAZ and increases child stunting for households who have limited access to market compared to for households who have better access to market. Controlling for other factors, a 10 percent increase in climate-induced agricultural productivity change decreases child HAZ by 0.03 for households who have limited access to market, but it has no significant effect for household who have better access to market. Our finding is consistent with previous studies that found that agricultural productivity will have an impactful effect on nutrition outcomes if the households have limited access to market (Stifel and Minten, 2017; Hirvonen, et al., 2017; Headey, et al., 2019).

Table 4: Impact of climate-induced agricultural productivity change by household access to market

	(1)	(2)	(3)	(4)	(5)	(6)
	Child HAZ		**Child WHZ**			**Child WAZ**
	More market access	**Less market access**	**More market access**	**Less market access**	**More market access**	**Less market access**
Agricultural productivity change	-0.124	-0.310***	-0.013	-0.108	-0.084	-0.179**
	(0.201)	(0.063)	(0.161)	(0.136)	(0.147)	(0.082)
Child characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.070	5.358	-2.076*	-1.518	-1.594	-0.084
	(1.216)	(5.695)	(1.106)	(4.962)	(1.061)	(2.688)
	Child stunting		**Child wasting**		**Child underweight**	
	More market access	**Less market access**	**More market access**	**Less market access**	**More market access**	**Less market access**
Agricultural productivity change	0.145**	0.682**	0.001	0.026	0.024	0.009
	(0.038)	(0.039)	(0.024)	(0.019)	(0.027)	(0.024)
Child characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.436*	-1.076	0.402**	0.817	0.509**	0.155
	(0.233)	(1.296)	(0.175)	(0.787)	(0.199)	(0.601)
Observations	3,447	3,475	3,447	3,475	3,447	3,475

Source: Based on LSMS–ISA W2-2012 and W3-2016 survey in Nigeria.
Note: All continuous variables are in log form. Enumeration area clustered standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

We further allow for heterogeneity in the impact of climate-induced agricultural productivity change by education of the household head. A dummy variable for a more educated household head is defined as the household head having attained an educational level above the median year of schooling in our sample, i.e., having 7 years of schooling or above. The results (Table 5) indicate that climate-induced agricultural productivity change has a negative significant impact on child HAZ for households who have less level of education. Controlling for other factors, we find that a 10 percent increase in climate-induced agricultural productivity change decrease child HAZ by 0.04 and increase stunting by 0.10 percent. However, it has no significant impact on child HAZ for households with more educated household heads. Similar results were obtained by Abuya, et al. (2012) in Kenya, Stamenkovic, et al. (2016) in Serbia, and Fadare, et al. (2019) in Nigeria – households with higher educational attainment will be more nutrition sensitive and have improved dietary habits and food choices, since poor dietary habits contributes to the poor nutritional status of under-fives.

Table 5: Impact of climate-induced agricultural productivity change by educational status of household head

	(1)	(2)	(3)	(4)	(5)	(6)
	Child HAZ		**Child WHZ**		**Child WAZ**	
	More educated	**Less educated**	**More educated**	**Less educated**	**More educated**	**Less educated**
Agricultural productivity change	-0.049	-0.382**	-0.060	-0.173	-0.024	-0.144
	(0.103)	(0.159)	(0.103)	(0.144)	(0.070)	(0.115)
Child characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.230	-0.478	-1.523	-0.030	-0.817	-0.751
	(1.953)	(1.797)	(1.498)	(1.578)	(1.181)	(1.463)
	Child stunting		**Child wasting**		**Child underweight**	
	More educated	**Less educated**	**More educated**	**Less educated**	**More educated**	**Less educated**
Agricultural productivity change	0.011	0.667**	0.010	0.024	0.015	0.002
	(0.017)	(0.030)	(0.012)	(0.024)	(0.016)	(0.030)
Child characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.052	0.834**	0.303	0.081	0.054	0.113
	(0.327)	(0.347)	(0.229)	(0.260)	(0.156)	(0.350)
Observations	3,826	3,096	3,826	3,096	3,823	3,090

Source: Based on LSMS–ISA W2-2012 and W3-2016 survey in Nigeria.
Note: All continuous variables are in log form. Enumeration area clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4. Pathways from climate-induced agricultural productivity change to child nutritional outcomes

In this section, we identify the pathways on how climate-induced agricultural productivity can affect child nutritional outcomes. The results (Table 6) indicate that climate-induced agricultural productivity change has a negative significant impact on total income and household months food insecure status, although not significant, impact on improving the food security of the household. This suggests that the income effects of climate-induced agricultural productivity can negatively influence nutritional outcomes indirectly through own-consumption routes. Our findings support those of Du et al. (2015), Sheahan and Barrett (2017), and Tomich, et al. (2019) that climate resilient agriculture policies which affect supply and demand can provide increase agricultural production, which leads to enhanced own consumption, and which can foster dietary diversification and reduced undernutrition.

Table 6: Impact of climate-induced agricultural productivity change on total income and household food insecurity status

	(1) Own consumption	(2) Household months food insecure
Agricultural productivity change	-0.375***	-0.017
	(0.117)	(0.014)
Child characteristics	Yes	Yes
Household characteristics	Yes	Yes
Time dummies	Yes	Yes
Constant	2.686	0.547***
	(2.133)	(0.178)
Observations	7,180	7,180

Source: Based on LSMS–ISA W2-2012 and W3-2016 survey in Nigeria.
Note: All continuous variables are in log form. Enumeration area clustered standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

6. Conclusions and Policy Implications

This study examines the effect of climate-induced agricultural productivity change on child nutritional outcomes in Nigeria. Using micro level multiple waves of panel data from Nigeria, we specified and estimated two-stage fixed effects models– a first stage modeling changes in climate-induced agricultural productivity and a second stage fixed effects instrumental variable (FE-IV) model linking the estimated climate-induced agricultural productivity changes and child nutritional outcomes. Results from the first stage model show that high temperature (heat stress) reduces agricultural productivity. A one percent increase in harmful degree days (heat stress) result in 4 percent decrease in agricultural productivity. The estimated results from the second stage FE-IV models show that climate-induced agricultural productivity change has a negative effect on child nutritional outcomes. With a 10 percent downward change in agricultural productivity, child HAZ and WAZ decrease by about 0.02 and 0.01, respectively. The results further reveal that a downward change in climate-induced agricultural productivity increases the prevalence of child stunting. An aggregate 10 percent negative agricultural productivity change increases child stunting by 0.10 percent. We also examine heterogeneity in the impact of climate-induced agricultural productivity changes on child nutritional outcomes through market access and education. The results show that the impacts are higher for households that have limited access to market and with household heads having lower level of education.

Based on our empirical findings, we suggest three key policy recommendations. First, our results show that low precipitation and high temperature (heat stress) reduces agricultural productivity. Given the dominance of rainfed agricultural production system and high vulnerability of agriculture to climatic factors in sub-Sharan African countries like Nigeria, key

interventions for improving agricultural productivity should consider spatial and temporal variability of climatic factors for better targeting of agricultural innovations to respond to climatic risk exposure and sensitivity which could result in major improvements in food and nutrition security. Second, our analysis provides several important insights on the implications of climate-induced agricultural productivity change on child nutritional outcomes. We find climate change reduces child nutritional outcomes through its heterogenous effect on climate-induced agricultural productivity. This suggests that climate change undermine the ability of smallholder farmers to benefit from agricultural productivity changes. Thus, investment in climate smart agricultural practices such as farmer-managed small-scale irrigation systems; *ex ante* policies aimed at building smallholders' resilience to climate risk such as targeted subsidies for risk reducing inputs (e.g., drought tolerant improved seeds) and *ex post* interventions in food insecurity mitigation strategies such as social safety net programs need to be instituted to help improve child nutritional outcomes. Thirdly, our results also indicate heterogenous impacts of agricultural productivity change on nutritional outcomes for households' differential access to markets and education level. Thus, incorporating complementary interventions on market infrastructure, education and information dissemination about food choices, appropriate childcare, food preparation, sanitation, and food safety issues should be considered to reduce the impact of agricultural productivity change on nutritional outcomes.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Declarations.pdf
- References.pdf