Experience-based Food Insecurity and Agricultural Productivity in Nigeria

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Abstract

In this study, we use panel data, three waves (2010-2016), to investigate the impact of agricultural productivity on experience-based measures of food security among Nigerian households. Experience-based measures of food security capture the diversity of diets, food shortage, and other aspects of food security, including psychological and behavioral manifestations of insecure food access. In Nigeria, the agricultural sector contributed about 22.35% to the nation's gross domestic product during 2021. In addition, almost 70% of Nigerians engage in farming for subsistence purposes, with climate change and poor irrigation systems affecting their agricultural productivity. Consistent with previous work linking higher agricultural productivity with better welfare outcomes among Nigerian households, we find that an increase in agricultural productivity increases food security as measured by experience-based indicators. Specifically, a 10% growth in agricultural productivity decreases the likelihood of (i) relying on less preferred foods, (ii) limiting the variety of food eaten, and (iii) limiting portion size at mealtimes by 3.7%, 3.9%, and 1.9%, respectively.

Keywords: weather shocks, agricultural productivity, food insecurity, experience-based.
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1. Introduction

Many Sub-Saharan African (SSA) countries still experience extreme hunger[1] and food shortages. As of 2020, Nigeria is the most populated country in SSA, with an estimated population of 206 million people (World Bank, 2021a). It is estimated that 39% of Nigerians lived below the international poverty line of $1.90 per person per day (2011 PPP) in 2018/19; while 32% had consumption levels between $1.90 and $3.20 per person per day (World Bank, 2021b). Despite being one of the largest crude oil producers globally, oil activities have not helped combat the country's high levels of food insecurity (Amare, Abay, et al., 2021; George et al., 2020). Given that Nigerians' current consumption levels make them vulnerable to extreme poverty when weather shocks occur, other ongoing crises can push 10 million additional Nigerians into poverty by 2022, exacerbating food insecurity in the country (World Bank, 2021b).

Food security, as defined by the Food and Agriculture Organization FAO (1996), is "a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life." To classify households as food-insecure, one of the most frequently used measures is experience-based indicators[2]. These indicators capture the diversity of diets, food shortage, and other aspects of food security, including psychological and behavioral

[1] Hunger is defined as the feeling of discomfort that is the major body's signal that it is in dire need of food. By definition, hunger and food go hand in hand, but concepts such as calorie deficiencies, micronutrient deficiencies, and related health problems also guide the discussion around hunger (Gödecke et al., 2018).

[2] These indicators are popular due to their lower costs of collection (Broussard & Tandon, 2016), their easiness to conduct and analyze, and their ease of interpretation and understanding by policymakers (INDDEX International Dietary Data Expansion Project, 2022). Other less popular indicators include Nutrition-Based Measures (e.g. Food Consumption Score or Dietary Diversity Score).

manifestations of insecure food access. (Hossain et al., 2019). They help classify households as food-insecure if they undergo certain conditions or behaviors related to insufficient food.

For many rural households in Nigeria, agricultural production remains a natural means to fight food insecurity. After all, agricultural activities help create rural jobs, food supply, and higher incomes for rural families (Christiaensen et al., 2011; Collier & Dercon, 2014). Thus, the importance of agriculture suggests a strong link between farming households' agricultural yields and food security (Arimond & Ruel, 2004).

The connections between agriculture, food security, and other related issues in Nigeria, including conflict, have been investigated by various recent studies. Amare et al. (2021) explore how climate-induced variability in agricultural productivity affects household consumption, as measured by aggregate food and nonfood expenditures. George et al. (2020) does not focus on agriculture, however, they focus on analyzing how armed conflicts impact food security, as measured by experience-based indicators. Similarly, Amare et al. (2018) investigate the impact of rainfall shocks on agricultural productivity and household consumption, also measured as aggregate food and nonfood expenditures. Taken together, these studies present a wide-ranging view of food security-related issues during recent years in Nigeria. However, the relationship between households' agricultural productivity and yields, with standard measures of food security used by international development agencies, such as experience-based indicators, has received lesser attention.

This article aims to fill this gap in the literature and complement the studies mentioned above. Our approach is similar in spirit to the work of Amare et al. (2018, 2021); however, our focus is exclusively on experience-based measures of food security that assess access to adequate variety, quantity, and quality of food. To investigate the role of rural households' agricultural output value and productivity on standard measures of food security, we use data from the living standards measurement study—integrated surveys on agriculture (LSMS–ISA). This survey data provides information on various food security measures for a panel of households across three different waves from 2010–2016. Rather than using standard output or yield measurement, this study uses a monetary unit of agricultural output to better measure output and productivity (Carletto et al., 2013; Desiere & Jolliffe, 2018).

As a robustness check, and to address endogeneity concerns related to unobserved time-invariant and time-variant household characteristics, we use average daily precipitation (in mm/day) and average degree days —a novel measure of cumulative exposure to heat— as proxies for estimating the exogenous variability in agricultural output and agricultural productivity (Aragón et al., 2021). Average precipitation and average degree days serve as suitable instruments because irrigation covers only 2.5% of the land of the average farmer in our sample, highlighting the importance of weather for agricultural production in Nigeria. We link the LSMS-ISA nationally representative household surveys with weather satellite imagery at the local government area (LGA) level.

Our study finds that an increase in agricultural productivity positively affects food security circumstances for rural households in Nigeria. Specifically, a 10% increase in agricultural productivity (i) decreases the probability that households would have to rely on less preferred foods by 3.7%, (ii) decreases the probability that households would have to limit the variety of foods eaten by 3.9%, and (iii) decreases the probability that households would have to limit the portion size of meals consumed by 1.9%. Similar results were found for the impact of agricultural output value on the same measures of food security.

This study makes several contributions to our understanding of the role of agriculture on food security. First, we contribute to the literature that examines the role of agricultural productivity and proceeds to link it with experience-based food security outcomes in Sub-Saharan Africa (SSA). Previous studies focused on the impact of agricultural productivity on total consumption have not investigated if households may be increasing or decreasing the diversity of their consumption or relying on less preferred diets (see, for example, Amare et al. 2018, 2021). Thus, our results shed light on the quantity-quality dynamics between agricultural productivity and food security.

Second, our results underline the importance of increasing agricultural productivity to sustain food security throughout the country. As we estimate the positive impacts of households' agricultural productivity on food security, our results provide critical insights to development agencies working towards increasing agricultural productivity, food, and nutrition security in the region. Finally, we build the credibility of our findings by using several experience-based food security measures in conjunction with a novel instrument to mitigate endogeneity concerns. In contrast to much of the literature that uses rainfall or temperature shocks[3] as proxies for estimating the exogenous variability in agricultural productivity, we use a continuous measure of cumulative exposure to heat during the growing season.

[3] Rainfall and/or temperature shocks are typically constructed using the standardized deviation of a given year's measure from historical averages, which ultimately are used as dummy variables indicating negative or positive shocks.

The next sections of this paper are organized as follows. Section 2 presents background on agriculture and food security in Nigeria. Section 3 discusses the data sources and provides descriptive statistics of the main variables used for the empirical analysis. Section 4 presents a conceptual framework to explain how a household's agricultural output value affects food consumption, and thus its food security. Sections 5 and 6 present our empirical strategy and the discussion of the main results. Section 7 concludes, highlights our main findings, and discusses relevant policy implications.

2. Background

Despite being Africa's biggest oil exporter, Nigeria currently faces critical challenges. The size of its economy was projected to contract by over 4% in 2020, with government revenues falling by more than 15 billion dollars. Projections suggest that its deepest recession since the 1980s is around the corner, which will push up to 20 million Nigerians into poverty by 2022. This economic downturn and the decline in fiscal resources can make the country repeat the shocks experienced in the 1980s that wiped out decades of the country's development progress[4] (World Bank, 2020b).

The root of the fragile situation of Nigeria is described by the World Bank (2020a) as multidimensional. It includes poor social and economic outcomes, low levels of human security, inequality of opportunity, social exclusion, and low levels of trust in public institutions. In addition, increased exposure to climate-change risks have disrupted agriculture supply chains and threatens food security. It is estimated that annual post-harvest losses are at around 10% of

[4] Nigeria has one of the lowest human capital scores in the world. It ranks 152 out of 157 countries according to the World Bank's 2018 Human Capital Index.

value of domestic production due to the lack of adequate power supply[5], storage, transportation, and irrigation infrastructure (FAO, 2021). The situation is aggravated by current conflicts across the country, including: the Boko Haram conflict in the North East, farmer-herder clashes in the fertile Middle Belt and North West, Militancy in the Niger Delta rooted in anti-oil movements, and long-standing separatist violence in the South East

2.1 Agriculture, Food Security, and Climate Change in Nigeria.

Nigeria has four primary agro-ecological zones: tropic-warm/semiarid, tropic-warm/subhumid, tropic-warm/humid, and tropic-cool/subhumid. Southern Nigeria is predominantly classified as tropic-warm/subhumid with more favorable conditions for agriculture, having more rainfall and longer growing days than the North. Most rural farm households grow staple crops, but it is not uncommon for farmers to grow at least one cash crop. Nigeria's cash crops include groundnut, cotton, cocoa, rubber, cotton, and oil palm. Cash crop activities are much more common in the South, while livestock activities are much more common in the North, however, very few households are engaged in fishing (World Bank, 2014).

Over 80 percent of the labor force in Nigeria depends on the informal economy, mainly the agriculture sector. The agricultural sector has the highest poverty incidence in the country (Phillip et al., 2009), therefore, improving the agricultural sector in Nigeria is vital to increasing food security, especially in rural areas (World Bank, 2014). As commonly found in other low-and-middle-income countries (LMIC), the inverse-land size productivity relationship has been observed in Nigeria. That is, an increase in harvested land size likely decreases agricultural productivity, all else being equal (Amare et al., 2018; World Bank, 2014). Likewise, having larger

[5] More than 80 million Nigerians still lack access to electricity (World Bank, 2020b).

land sizes are not positively correlated with a lower likelihood of being poor in Nigeria (World Bank, 2014).

Agricultural productivity in Nigeria is significantly constrained by poor access to input and output markets, land degradation, low investment in agricultural research, and major gaps in transportation and irrigation (Ogunlela & Ogungbile, 2006; Phillip et al., 2009). Only 30 percent of roads are paved (compared with 50 percent in LMIC), and only 1 percent of croplands are irrigated (World Bank, 2020a). There are also substantial gender gaps that significantly affect women's productivity as farmers and restrict their ability to engage in agribusiness. Some of the associated issues related to gender gaps include crop choices, access to productive farm labor, access to productive non-labor inputs such as fertilizer, as well as women's lower access to capital/finance, skills, and segregation, with women operating in lower-paying sectors and segments of the agricultural value chains (World Bank, 2020a).

Climate-related shocks, including droughts, floods, heatwaves, shifts in the timing of the rainy season, and increasing rainfall intensity, are commonly increasing in Nigeria. According to Great Britain's Department for International Development (2010), Nigeria is one of the ten most vulnerable countries to the impacts of climate change and natural hazards. Still, this vulnerability is not uniform across the country and its economic sectors. The more arid northern savanna ecosystems and climate-sensitive industries—including agriculture, forestry, oil, and gas extraction— are more at risk. Implications of climate change for Nigeria's food and agricultural sector include a further reduction in productivity, a surge in crop failures, increasing conflicts between pastoralists and sedentary farmers, and increased food prices, all of which can result in increased food insecurity. Estimates suggest that climate change inaction could cost Nigeria a loss of US$100-460 billion (World Bank, 2020a).

To support small farmers improve their access to inputs and technology and increase their income, the Government of Nigeria, with the support of other international institutions, has implemented various programs during the last decade. Some examples include Fadama 3, the Commercial Agriculture Development Project, and the West Africa Agriculture Productivity Project (WAAPP), which have helped farmers receive improved agricultural technology. However, and despite these efforts, food insecurity has deteriorated rapidly over the last decades in the country. According to FAO (2020), the prevalence of undernutrition in Nigeria increased from 7.4 percent in 2004-2006 to 12.6 percent in 2017-2019. In line with vulnerability and poverty rates, food insecurity is more pronounced in the north of the country, with most parts of the North East classified as IPC 3 and IPC 4 according[6] to The Famine Early Warning Systems Network (2021).

3. Data and Descriptive Statistics

This study uses the 2010–2011, 2012–13, and 2015–16 panel household datasets from the Nigeria Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). We combine these datasets with satellite weather information to construct household-specific climatic variables for our empirical analysis. The Nigeria LSMS-ISA is nationally representative and geo-referenced. We use these LSMS-ISA to obtain information on (i) household and farm characteristics, including socioeconomic characteristics, demographic characteristics, and plot

[6] The Integrated Phase Classification (IPC) is a five-phase scale that describes the severity of food emergencies. It is intended to help governments and other humanitarian actors understand a crisis (or potential crisis) and take action. IPC 1 = minimal; IPC 2 = stressed; IPC 3 = crisis; IPC 4 = emergency; IPC 5 = famine.

ownership; (ii) agricultural operations, including irrigation, planted area, labor, and inputs use; and (iii) farm outcomes, including agricultural production and prices. From the LSMS-ISA we also obtained information on different experience-based food security measures. Specifically, households reported whether during the last 7 days they had to (a) rely on less preferred foods, (b) limit the variety of food eaten, and (c) limit the portion size at mealtimes. We use these binary responses as dependent variables in our empirical analysis. As discussed in George et al. (2020), these experience-based food security measures capture different aspects of food security, including the diversity of diets, food shortage, and other severe forms of food insecurity.

To compute a measure of real agricultural output for each household, we follow Aragón et al. (2021) and construct a Laspeyres index using the household's quantity produced of each crop and baseline local prices. As local prices, we use the median price of each crop at the six different geopolitical zones of Nigeria[7] in 2010. We measure agricultural productivity as the value of real agricultural output per hectare (ha).[8]

Weather data for the growing season—ranging from March to August when the average farmer in our sample plants about 90% of the total cultivated area—was gathered from two sources. First, the high-resolution satellite temperature measures were obtained from the MOD11C1 product by NASA (Wan et al., 2021). We use the Terra satellite's observations of morning land surface temperature with a resolution of 0.05x0.05 degrees. Second, rainfall data

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[7] North Central, North East, North West, South East, South South (also known as Niger Delta region), and South West are the current six geopolitical zones recognized in Nigeria's constitution and function as federating units.
[8] The 2010 Nigeria LSMS-ISA does not provide data on hired labor expenditures in the planting season. We estimate this values by multiplying 0.6 times this wave's hired labor expenditures in the harvesting season. The rationale behind this approximation comes from the median ratio of "planting hired labor expenditures to harvesting hired labor expenditures" in the 2012, 2015, and 2018 LSMA-ISA surveys is approximately 60%. For our analysis we do not consider data from the 2018 surveys, as this wave used a recall period of 30 days to measure experience-based food security indicators.

consist of monthly average rainfall at a resolution of 0.05x0.05 degree bins that were obtained from the Climate Hazards Group InfraRed Precipitation with Station CHIRPS (Funk et al., 2015). We drop the observations that do not report the variables required for estimating each of our empirical models.

Table 1 presents summary statistics of the key variables for household and farm characteristics in our sample. Most farmers are male with an average age of 50 years and an average farm size of around 1 hectare with low educational attainment (4 years). Most rely on domestic labor, and irrigation is practically inexistent. This signals that weather affects production and productivity for most farmers in Nigeria, and therefore, affects the country's food security.

[Insert Table 1 here]

Table 2 presents summary statistics of households' agricultural productivity and output value grouped by year and the various food insecurity outcomes we use for our study. Overall, we see food insecurity, as measured by experience-based indicators (outcomes), rising during the 2010-2016 period. For example, the proportion of households affirming they have relied on less preferred foods rose from 17% in 2010/11 to 25% in 2012/13 and 35% in 2015/16. Similarly, the proportion of households affirming they have limited the variety of food eaten and/or the portion size at mealtimes also increased through time. These results are consistent with previous studies related to food security in Nigeria (see George et al., 2020).

There is significant variability in the value of agricultural output between food secure and food insecure households in our sample. Specifically, food-insecure families had less agricultural output value than food-secure households during the first (2010–11) and third (2015–16) waves of the LSMS-ISA surveys. This may be in part due to the effect of weather on food security.

A growing number of studies have shown that climate change, including rainfall variability and extreme temperatures, affects food production (Burke & Emerick, 2016; Deschênes & Greenstone, 2007; Schlenker et al., 2006; Schlenker & Roberts, 2009; Taraz, 2018). Change in climatic conditions directly affects crop yields and indirectly through migration, labor supply, and adaptation (Alem et al., 2010; Bazzi, 2017; Dillon et al., 2011; Huang et al., 2020; Jessoe et al., 2018). The average agricultural productivity in our data set is 3,509 USD per hectare[9]. However, significant variability in agricultural productivity between food secure and food insecure households in our sample was not found. This difference could be masked by the effects of the inverse-land size productivity relationship. For reference, in table 2, we also report descriptive statistics about our main weather variables at the household level based on the growing season. The definitions of these weather variables are described in the Empirical Framework section.

[Insert Table 2 here]

4. Conceptual Framework

We follow a standard constrained utility maximization problem to explain how a Nigerian household's agricultural output value can affect its food security conditions. We assume a representative household that derives its utility from food consumption F. The household's food consumption demand F is represented by

$$F = F(p, w, Y, K, S). \qquad (1)$$

[9] This value is close to that of Amare et al., (2021) which uses the same database.

In equation (1), p represents the general price level; w is the wage rate; Y represents income; K are the inputs used in the production process; S is a productivity shifter that depicts the notion that farmers using identical inputs can have different levels of output, i.e., due to different management skills, risk preferences, weather, etc.

Following George et al. (2020) and Singh et al. (1986), we credit that agricultural output affects food consumption, via different channels, including: (a) price shock, (b) wage shock, (c) income shock, (d) input shock, and (e) productivity shocks. From equation (1), we can represent the total marginal effect of agricultural output value on food consumption as:

$$\frac{\delta F}{\delta A} = \left(\frac{\delta F}{\delta p} . \frac{\delta p}{\delta A}\right) + \left(\frac{\delta F}{\delta w} . \frac{\delta w}{\delta A}\right) + \left(\frac{\delta F}{\delta Y} . \frac{\delta Y}{\delta A}\right) + \left(\frac{\delta F}{\delta K} . \frac{\delta K}{\delta A}\right) + \left(\frac{\delta F}{\delta S} . \frac{\delta S}{\delta A}\right). \quad (2)$$

In equation (2), A represents a household's agricultural output[10]. Given our experience-based food security measures are contrariwise to food consumption demand—i.e., families with low food consumption answered (Yes=1) when asked if they had to limit the portion size at mealtimes and vice versa— it follows that the total marginal effect of agricultural output value on food insecurity is represented as:

$$\frac{\delta FI_z}{\delta A} = \eta_z \left[\left(\frac{\delta F}{\delta p} . \frac{\delta p}{\delta A}\right) + \left(\frac{\delta F}{\delta w} . \frac{\delta w}{\delta A}\right) + \left(\frac{\delta F}{\delta Y} . \frac{\delta Y}{\delta A}\right) + \left(\frac{\delta F}{\delta K} . \frac{\delta K}{\delta A}\right) + \left(\frac{\delta F}{\delta S} . \frac{\delta S}{\delta A}\right)\right]. \quad (3)$$

In equation (3), FI_z is the food insecurity measure (Yes=1, No=0) and η_z is the coefficient associated with the z[th] food insecurity measure. For the three measures of food insecurity that we analyze in this paper, we assume η_z to be negative given the inverse relationship between F

[10] $\left(\frac{\delta F}{\delta p} . \frac{\delta p}{\delta A}\right)$ represents the effect of agricultural output on food consumption via its impact on prices; $\left(\frac{\delta F}{\delta w} . \frac{\delta w}{\delta A}\right)$ represents the effect of agricultural output on food consumption via its impact on wages; $\left(\frac{\delta F}{\delta Y} . \frac{\delta Y}{\delta A}\right)$ represents the effect of agricultural output on food consumption via changes in income; $\left(\frac{\delta F}{\delta K} . \frac{\delta K}{\delta A}\right)$ represents the effect of agricultural output on food consumption via its impact on input use; $\left(\frac{\delta F}{\delta S} . \frac{\delta S}{\delta A}\right)$ represents the effect of agricultural output on food consumption via its impact on productivity.

and FI_z. This means that as η_z increases, the probability of experiencing the z^th food insecurity measure decreases, and vice versa. The analysis of the total marginal effect of agricultural productivity on food security is analogous.

5. Empirical Framework

To quantify the effects of agricultural productivity on food security, we employ two different linear probability models: (i) a simple pooled OLS regression with fixed effects and time-varying control variables that might influence food security, and (ii) an instrumental variable estimation. Following George et al. (2020), we first use pooled OLS regressions where the different binary outcomes measuring food security are regressed on our measure of agricultural productivity. The model for this pooled OLS regression with fixed effects and time-varying control variables that might influence food security is expressed as:

$$P\left(Y_{ijt} \middle| agpr_{ijt}, \boldsymbol{X}_{ijt}, \boldsymbol{W}_{ijt}, \boldsymbol{\theta}_j, \boldsymbol{\gamma}_t\right) = \alpha + \beta \ln\left(agpr_{ijt}\right) + \boldsymbol{\psi}\boldsymbol{X}_{ijt} + \boldsymbol{\lambda}\boldsymbol{W}_{ijt} + \boldsymbol{\theta}_j + \boldsymbol{\gamma}_t + \varepsilon_{ijt} \ . \tag{4}$$

In equation (4), Y_{ijt} represents binary food security indicators related to the responses to the experience-based food security questions for household *i*, in LGA *j* during time period *t*. α is the intercept term and $agpr_{ijt}$ is the agricultural productivity for household *i*, in LGA *j* during time period *t*. $\boldsymbol{X}_{ijt}$ represents a vector of personal and farm-level characteristics that includes farmer's age, years of schooling, and gender, as well as area planted, irrigation, and labor (on and off the farm). $\boldsymbol{W}_{ijt}$ represents a vector of additional controls, including agro-ecological zones, soil characteristics, and the month when the post-harvesting questionnaire was administered to the household, as this was when the food security questions were asked. $\boldsymbol{\theta}_j$ are local government area (LGA) fixed effects that capture location time-invariant characteristics. $\boldsymbol{\gamma}_t$ are survey year fixed effects that capture temporal shocks, which may have influenced household-level food security measures for each unit of time (George et al., 2020). Finally, ε_{ijt} is the idiosyncratic error term. We report clustered standard errors at the LGA level to account for intra-cluster correlation when estimating equations (4), (6), and (7) (Abadie et al., 2017).

If there were no endogeneity concerns related to reverse causality and no omitted time-variant individual-level variables, the coefficient β in equation (4) would capture the causal effect of agricultural productivity on experience-based food security. Nonetheless, if food insecurity directly affects agricultural productivity, the OLS estimation of equation (4) will produce a biased estimate for the coefficient β. In addition, agricultural productivity is also expected to be correlated with unobserved heterogeneity—i.e., variation in plot characteristics, risk preferences, aspirations, armed conflicts, etc.— which may affect a household's food security. Although the panel data we use in our analysis minimize the occurrence of these simultaneous relationships, one can argue that the nature of the data alone cannot fully control it.

To address this, we employ an instrumental variable approach that helps us identify the exogenous variation in agricultural productivity that affects our food security measures. Our identification strategy exploits exogenous household-level variation in weather to estimate the exogenous variability in agricultural productivity. The rationale behind our choice of instruments is guided by the idea of finding that part of agricultural productivity that is affected only by weather, and consequently, represents only exogenous variation in agricultural productivity, which ultimately affects food security. Empirically, we need to identify a set of legitimate IVs that are highly correlated with agricultural productivity but uncorrelated with the outcome: food security. Following Aragón et al. (2021), we compute a novel measure of cumulative exposure to heat during the growing season: Average Degree Days (ADD). ADD measures the cumulative exposure to temperatures between a lower bound, usually 8°C, up to an upper threshold, 40°C (Mayorga et al., 2022). Formally, ADD is defined as:

$$ADD = \frac{1}{n}\sum_{d=1}^{n}(\min(h_d, 40) - 8)1(h_d \geq 8)\,. \quad (5)$$

In equation (5), h_d is the average daytime temperature in day *d* and *n* is the total number of days in a growing season with valid temperature data. As noted in Aragón et al. (2021), estimating average degree days instead of total degree days help address missing observations due to satellite swath errors. Table 2 shows significant variability in the value of average degree days between food secure and food insecure households in our sample. Specifically, food-insecure families had fewer average degree days than food-secure households during the first (2010–11) and second (2012–13) waves of the LSMS-ISA surveys.

We use this novel instrument and average daily precipitation (PP) during the growing season and its square form (PP^2) as the IV set. This choice of instruments is motivated by the high dependency of households on rainfall for their agricultural activities. As mentioned before, irrigation covers only 2.5% of the land of the average farmer in our sample. Therefore, precipitation and temperatures during the growing season have essential impacts on agricultural yields, and thus, they can serve as plausible instruments for predicting agricultural productivity values[11].

The IV approach followed a two-stage estimation procedure. The first stage regression is expressed as:

[11] Previous studies relevant to this paper that have used instruments constructed from weather data as proxies of the exogenous variation in agricultural productivity include Amare et al. (2018, 2021), Aragón et al. (2021), Björkman-Nyqvist (2013), and Rocha & Soares (2015).

$$\ln\left(agpr_{ijt}\right) = \boldsymbol{\beta}_0 \boldsymbol{X}_{ijt} + \boldsymbol{\beta}_1 \boldsymbol{W}_{ijt} + \boldsymbol{\beta}_2 \boldsymbol{Z}_{ijt} + \boldsymbol{\zeta}_j + \boldsymbol{\eta}_t + \nu_{ijt} \, . \tag{6}$$

In equation (6), $\boldsymbol{Z}_{ijt}$ represents a vector of instruments for household *i*, in LGA *j* during period *t*. $\boldsymbol{\zeta}_j$ and $\boldsymbol{\eta}_t$ stands for the inclusion of LGA and survey year fixed effects in the first stage, respectively. Then, the predicted $\widehat{agpr_{ijt}}$ from the first stage was used in the second stage regression:

$$P\left(Y_{ijt} \middle| \widehat{agpr_{ijt}}, \boldsymbol{X}_{ijt}, \boldsymbol{W}_{ijt}, \boldsymbol{\theta}_j, \boldsymbol{\gamma}_t\right) = \alpha + \beta \ln\left(\widehat{agpr_{ijt}}\right) + \boldsymbol{\psi} \boldsymbol{X}_{ijt} + \boldsymbol{\lambda} \boldsymbol{W}_{ijt} + \boldsymbol{\theta}_j + \boldsymbol{\gamma}_t + \varepsilon_{ijt} \, . \tag{7}$$

$\widehat{agpr_{ijt}}$ is interpreted as the exogenous variability in agricultural productivity instrumented using our measures of cumulative exposure to heat and rainfall $\boldsymbol{Z}_{ijt}$. The rest of the notations in equation (7) are similar to those in equation (4). Estimating the effects of agricultural output value on food security followed an analogous procedure.

To examine the validity of our instruments, we tested for the relevance of the instruments and weak instruments. We assessed the relevance of the instruments by conducting an under-identification test based on the Kleibergen-Paap rank L.M. statistic. The null hypothesis of this test is that the instruments are not significantly correlated with the endogenous variable (Baum et al., 2007; Kleibergen & Paap, 2006). We also used the Stock-Yogo weak identification tests to assess the strength of the correlation between the instruments and the endogenous variables. The null hypothesis of this test is that instruments are weak and lead to an asymptotic relative bias greater than a certain threshold (Stock & Yogo, 2005).

6. Results and Discussion

In this section, we describe the results obtained from estimating equations (4), (6), and (7). Since the equations represent linear probability models, tables 3, 4 and 5 report the regression results for the estimated effects of household's agricultural output value and agricultural productivity on the probability of a household: (i) relying on less preferred foods, (ii) limiting the variety of food eaten, and (c) limiting the portion size at mealtimes. At the aggregate level, these results are equivalent to the effect of a household's agricultural output value and productivity on the prevalence of food insecurity as measured by experience-based indicators.

Tables 3, 4 and 5 also report the test results for the relevance of the instruments and the test for weak instruments. The null hypothesis in the under-identification tests (relevance of the instruments) was rejected in all models, suggesting the instruments are indeed correlated with the endogenous variable. The hypothesis for the weak instrument test was rejected in the first-stage regression based on the bias test at a cutoff of 5%-10% maximal IV relative bias level for all models. The cutoff was less than 5% maximal IV relative bias level for the model presented in column 4 of table 3. These were based on the Stock-Yogo tabulations (Stock & Yogo, 2005). This means that the relative bias of the IV estimates with respect to OLS will be no more than 5% or 10% of the bias of OLS, indicating a sufficiently strong IV in the samples. Next, we examine each table in more detail.

6.1 Effects of Agricultural Output and Agricultural Productivity on Experience-based Food Security Measures

The estimated coefficients of interest on each corresponding model specifications have a statistically significant impact on food security as measured by experience-based indicators. Their signs are in line with the conceptual framework discussed in section 4.

Table 3 shows the effects of agricultural output and agricultural productivity on the probability of a rural household limiting their intake of preferred food, that is, on food insecurity. Specifically, the table reports the estimated effects of agricultural output (columns 1 and 2) and agricultural productivity (columns 3 and 4) on the likelihood of relying on less desired foods during the last 7 days.

The OLS models (columns 1 and 3) show that a 10% increase in agricultural output value and/or agricultural productivity decreases the likelihood of a household relying on less preferred foods (during the last 7 days) by about 0.24%.[12] The IV estimates in columns 2 and 4 of Table 3 show that after controlling for endogeneity, the effects are significantly higher (in absolute terms) than those obtained by the OLS models. One reason for this type of results is the existence of an omitted variable that is negatively correlated with agricultural productivity. The omitted variable would lead to a downward bias in the OLS estimate. In our case, we do not control for armed conflicts, which negatively correlate to agricultural productivity. In the context of Nigeria, this negative correlation has been documented by George et al. (2021). Nevertheless, the IV estimates are robust to this omitted variable bias.

Specifically, IV estimates reveal that a 10% increase in agricultural output value and/or agricultural productivity decreases the probability of a household relying on less preferred foods (during the last 7 days) by about 3.7%. Indeed, our estimate reveals that after correcting for endogeneity, the magnitude of parameter estimates improves significantly. A possible explanation is that weather conditions and variability in weather conditions primarily affect agricultural output. Thus, rural households have adapted to the impact of weather variability and, as a result, changed their consumption pattern. Farmers may not know climate change, but by

[12] Given our linear probability model is a level-log model, the interpretation of our coefficient of interest is as follows: a 1% increase in X increases Y by (β/100) units of Y. If, for example, β=0.55, then a 1% increase in X, increases Y by (0.55/100=0.0055). Therefore a 10% increase in X, increases Y by 0.055. A change from 0 to 0.055 is interpreted as a 5.5% increase in the likelihood of being food insecure.

observing weather patterns can adopt climate risk management strategies (Tripathi & Mishra, 2017). In response, smallholders are also quick to adjust their consumption patterns (Khanal & Mishra, 2017). This finding is consistent with Misselhorn (2005).

[Insert Table 3 here]

Next, we examine the effect of agricultural output and agricultural productivity on the likelihood of relying on less preferred foods. The estimates of all models reported in Table 4 are close to those obtained in Table 3. We will focus on the estimates presented in columns 2 and 4 of Table 4 (IV estimates). The estimated coefficient shows that after controlling for endogeneity, a 10% increase in agricultural production (value of output) decreases the likelihood of a household limiting the variety of food they eat (during the last 7 days) by about 4.5%. Likewise, a 10% increase in agricultural productivity decreases the likelihood of a household limiting the variety of food they eat (during the last 7 days) by about 3.9%. In both cases, Table 3 and Table 4, agricultural productivity decreases the likelihood of experiencing food insecurity by about the same magnitude (between 3.7% and 3.9%). This suggest that the effect of an increase in agricultural output and/or productivity in combating food insecurity among rural Nigerian households is promising, at least when food security is measured using experience-based indicators.

[Insert Table 4 here]

Finally, Table 5 reports the effects of agricultural output and agricultural productivity on the likelihood of reducing the portion size of meals during the last seven days. Consistent with previous tables, we report estimates of all model specifications. Likewise, we focus on the estimates presented in columns 2 and 4 (IV estimates). The estimated coefficient shows that after controlling for endogeneity, a 10% increase in agricultural production (value of output) and/or agricultural productivity decreases the likelihood of a family limiting their portion size of the food they eat by about 1.9% during the last seven days. Our finding is consistent with Misselhorn (2005), who argued that a sudden drop in regional cereal productivity was one of the causes of food insecurity in Southern Africa.

In summary, agricultural productivity growth and, therefore, growth in agricultural output decreases food insecurity among rural families in Nigeria. Note that agricultural output is significantly affected by, among other factors, uncertainty in weather conditions and climate change. Thus, policies that encourage and enhance agricultural productivity are still necessary and a viable tool to fight food insecurity in Nigeria, especially in the short term.

[Insert Table 5 here]

7. Discussion and Policy Implications

The Nigerian agricultural sector plays a vital role in both the national economy and the lives of most Nigerians. Recent reports show that rural Nigerians still rely heavily on subsistence farming and agriculture accounts for most of the rural net income. However, the agricultural sector faces significant obstacles, notably lower farm productivity. Policymakers have provided incentives to increase farm output to meet domestic demand and combat rampant food insecurity, especially in rural areas. During the last decade, some of these efforts have included programs such as Fadama 3, the Commercial Agriculture Development Project, and the West Africa Agriculture Productivity Project (WAAPP), which have helped farmers receive improved agricultural technology. However, and despite these efforts, food insecurity has deteriorated rapidly over the last decades in Nigeria.

The objective of this study was to analyze the impact of agricultural productivity and agricultural output on food security in Nigeria as measured by experience-based indicators. The study contributes to our understanding of the role of agriculture on food security in various novel ways. First, we link agricultural productivity with experience-based food security indicators. These indicators are more popular among policymakers than nutrition-based measures (e.g., Food Consumption Score or Dietary Diversity Score). This is due to the ease they represent at the moment of data collection, saving time and associated costs, as well as their ease for analysis and interpretation (Broussard & Tandon, 2016; INDDEX International Dietary Data Expansion Project, 2022). Secondly, our results provide critical insights to national governments and development agencies working towards increasing agricultural productivity, food, and nutrition security in the SSA region.

Taken together, our results draw one main conclusion: "An increase in agricultural productivity and output remains an effective means to decrease food insecurity among Nigerian families." Specifically, our results show that with increased agricultural productivity and output, Nigerian farm families are able to: (1) decrease the probability of reliance on less preferred foods; (2) reduce the likelihood of limiting the variety of food consumed, and (3) reduce the probability of reducing portion size at mealtimes. The associated impacts of a 10% increase in agricultural productivity (and output) on reducing the likelihood of experiencing food insecurity range between 1.9% to 4.4% across the different food security measures examined in this paper.

These findings are consistent with previous work conducted in Nigeria, highlighting the importance of agricultural productivity. For example, Amare et al. (2021) find that a 10% increase in the levels of rainfall-induced agricultural productivity shocks tends to decrease consumption by 3.7% on average. Similarly, The World Bank (2014) finds that a 10% increase in agricultural productivity reduces the likelihood of being poor by between 2.5% and 3%. While the prevalence of food insecurity, poverty, and consumption do not always overlap (Barrett, 2010), our results suggest that changes in agricultural productivity have similar effects over these multidimensional welfare indicators for Nigerian farmers.

Although theoretically income from other nonfarm activities could have larger impacts, our results show a sizeable effect of agricultural productivity over food security. This highlights the importance of agriculture in Nigeria. It also suggests that improvements in agricultural productivity are still an effective means to reduce rural poverty and food security in the country.

Based on our results, we draw two main policy implications. First, since production agriculture in Nigeria is highly dependent on weather, mitigating the effects of extreme weather events (or weather shocks) could shore up agricultural productivity in Nigeria, contributing to fighting food insecurity in the country. To this end, irrigation infrastructure is of utmost importance. The Government of Nigeria has conducted projects to improve access of small farmers' access. However, challenges remain when it comes to providing this type of service—notably related to security issues. To minimize interruptions in the execution and provision of irrigation services, policymakers should address security issues first, especially if the targeted areas are prone to crime, which is common in the North and North-West areas of the country affected by Boko Haram. Recent experiences, such as those from the "Transforming Irrigation and Water Resources Management Project," showcase the importance of addressing violence and conflict issues during the design of policy interventions rather than reacting to incidents.

Second, although increasing access to modern inputs like fertilizer and herbicides could increase agricultural productivity and, in turn, strengthen food security, one of the main constraints that remain in the Nigerian agricultural sector is the low rates of input use. In this context, the policy design process needs to factor in that Nigeria has already experimented with various fertilizer subsidy programs in the past. These programs were targeted at increasing agricultural productivity. Nonetheless, they have proved unsuccessful. These interventions have been documented to distort input markets, be very expensive, and ultimately fail to reach the smallholder farmers who were the intended beneficiaries (Eboh et al., 2011; Phillip et al., 2009; Takeshima & Yamauchi, 2012). Recent evidence suggests that non-poor households appear to have more access to agriculture advice than poor households (World Bank, 2014). Thus, policymakers can explore alternative interventions to facilitate access to education, disseminate climate change information, and provide extension services that educate farmers on adopting agro-climatic resilience in crop production, especially in arid lands. Implementing targeted interventions could significantly reduce Nigerians' food insecurity for all rural areas. The availability of information on changes in weather patterns may be fruitful in raising awareness among smallholders in Nigeria on the threats that climate change poses on agriculture productivity and thereby improving food security. In addition, to build climate resilience the government of Nigeria could emphasize land quality, natural ecosystem, and water resources management.

Finally, although our results might not let us ascertain definitive causality between agricultural productivity and food security, through our analysis, we are able to show a strong link between increased agricultural productivity and food security in rural Nigeria—as measured by experience-based indicators. We offer this link is robust to different food security indicators, and it holds to two alternatives variables (agricultural output value and agricultural productivity). Thus, policies favorable to increasing agricultural productivity remain an effective means to reduce food insecurity in the country.

Table 1. Summary Statistics: Household and Farm Characteristics

Variable	Mean	SD
Age of household head (years)	49.56	14.43
Female headed household (female = 1)	0.06	0.24
Educational attainment of household head (years)	4.22	4.61
Area planted (hectares)	1.06	1.31
Irrigated land (% of landholding)	0.02	0.13
Number of household members working on farm	2.46	2.07
Cost of hired labor (2010 USD)	1020.19	5630.24
Observations	3658	

Table 2. Summary Statistics: Food Security and Weather

	Have Relied on Less Preferred Foods During the Last 7 Days			Have Limited the Variety of Food Eaten During the Last 7 Days			Have Limited Portion Size at Meal Times During the Last 7 Days		
	No	Yes	Diff.	No	Yes	Diff.	No	Yes	Diff.
Panel A: First Wave (2010/11)									
Agricultural output value	1921.55	1125.01	796.54*	1853.89	840.09	1013.80*	1863.86	766.28	1097.58
Ag. productivity	5347.09	2918.36	2428.73	5057.79	2969.17	2088.62	5058.11	2879.67	2178.44
Degree days	25.12	23.74	1.38***	25.22	22.84	2.38***	25.07	22.75	2.32***
Precipitation (mm/day)	4.52	5.71	-1.19***	4.41	6.22	-1.82***	4.58	6.29	-1.71***
Observations	1074	214		1112	130		1209	94	
Percentage	0.83	0.17		0.90	0.10		0.93	0.07	
Panel B: Second Wave (2012/13)									
Agricultural output value	1772.12	1438.13	333.98	1734.46	1558.55	175.91	1699.57	1668.42	31.16
Ag. productivity	2892.67	2662.07	230.61	2788.78	3066.89	-278.1	2763.25	3380.22	-616.97
Degree days	25.93	25.83	0.09	25.96	25.47	0.49***	25.96	25.35	0.60***
Precipitation (mm/day)	4.26	4.58	-0.33***	4.27	4.70	-0.44***	4.29	4.79	-0.50***
Observations	990	327		1093	219		1189	134	
Percentage	0.75	0.25		0.83	0.17		0.90	0.10	
Panel C: Thrid Wave (2015/16)									
Agricultural output value	1801.17	1273.09	528.08***	1736.92	1218.44	518.48**	1686.56	1031.05	655.52**
Ag. productivity	2664.50	2651.38	13.13	2627.42	2672.39	-44.97	2723.22	2171.89	551.34
Degree days	26.55	27.08	-0.53***	26.70	26.86	-0.16	26.72	26.63	0.08
Precipitation (mm/day)	4.01	3.78	0.23***	3.92	3.85	0.08	3.92	3.81	0.11
Observations	660	363		763	258		887	145	
Percentage	0.65	0.35		0.75	0.25		0.86	0.14	

Notes: Agricultural output value in 2010 USD. Agricultural Productivity in 2010 USD per hectare. Degree days and precipitation at the household level based on the growing season period only. No and Yes columns represent mean values of variables for households who answered No and Yes to the food security question in the first row, respectively. Column Diff. represents difference in means. Asterisks, *, **, and *** represent $p < .10$, $p < 0.5$, and $p < 0.01$, respectively, associated with the test of equality of outcomes.

Table 3. Effects of Agricultural Productivity and Output Values on the Probability of Households Relying on Less Preferred Foods

	Dependent Variable: Have Relied on Less Preferred Foods During the Last 7 Days (Yes = 1, No = 0)			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	IV	OLS	IV
Agricultural output value	-0.024***	-0.378**	-	-
	(0.008)	(0.158)	-	-
Agricultural productivity	-	-	-0.024***	-0.374***
	-	-	(0.007)	(0.121)
Age	0.000	0.006	0.000	0.003
	(0.003)	(0.005)	(0.003)	(0.005)
Female headed household	-0.006	-0.101	-0.006	-0.014
	(0.036)	(0.071)	(0.036)	(0.048)
Education	-0.005***	-0.005*	-0.005***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.003)
Demographic Characteristics Controls	Yes	Yes	Yes	Yes
Farm Characteristics and Labor Controls	Yes	Yes	Yes	Yes
AgroEcological Zones Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Interview-Month Fixed Effects	Yes	Yes	Yes	Yes
Soil Characteristics Fixed Effects	Yes	Yes	Yes	Yes
LGA Fixed Effects	Yes	Yes	Yes	Yes
Underidentification Test				
Kleibergen-Paap rk LM statistic (Chi-sq)		8.976**		13.267***
Weak Identification Test				
Cragg-Donald Wald F statistic		11.379		14.444
Relative Bias		5%-10%		<5%
Observations	3615	3615	3615	3615

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the LGA level in parenthesis. Agricultural output value and agricultural productivity calculated using Laspeyres index and given in log form. Complete regression results with all control variables, including IV First Stage regression results, are shown in Appendix. Stock–Yogo tabulations based on the Cragg–Donald statistic were used for the weak identification test.

Table 4. Effects of Agricultural Productivity and Output Values on the Probability of Households Limiting the Variety of Food Eaten

	Dependent Variable: Have Limited the Variety of Food Eaten During the Last 7 Days (Yes = 1, No = 0)			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	IV	OLS	IV
Agricultural output value	-0.023***	-0.445***	-	-
	(0.007)	(0.134)	-	-
Agricultural Productivity	-	-	-0.020***	-0.393***
	-	-	(0.006)	(0.097)
Age	0.005*	0.012**	0.005*	0.007*
	(0.002)	(0.005)	(0.003)	(0.004)
Female headed household	0.042	-0.106	0.045	0.011
	(0.036)	(0.071)	(0.036)	(0.049)
Education	-0.003	-0.002	-0.003*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Irrigation and Hired Labor Controls	Yes	Yes	Yes	Yes
Off-farm Labor Controls	Yes	Yes	Yes	Yes
AgroEcological Zones Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Interview-Month Fixed Effects	Yes	Yes	Yes	Yes
Soil Characteristics Fixed Effects	Yes	Yes	Yes	Yes
LGA Fixed Effects	Yes	Yes	Yes	Yes
Underidentification Test				
Kleibergen-Paap rk LM statistic (Chi-sq)		8.311**		13.936***
Weak Identification Test				
Cragg-Donald Wald F statistic		9.892		12.814
Relative Bias		5%-10%		5%-10%
Observations	3560	3560	3560	3560

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the LGA level in parenthesis. Agricultural output value and agricultural productivity calculated using Laspeyres index and given in log form. Complete regression results with all control variables, including IV First Stage regression results, are shown in Appendix. Stock–Yogo tabulations based on the Cragg–Donald statistic were used for the weak identification test.

Table 5. Effects of Agricultural Productivity and Output Values on the Probability of Households Limiting the Portion Size at Mealtimes

	Dependent Variable: Have Limited Portion Size at Meal Times During the Last 7 Days (Yes = 1, No = 0)			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	IV	OLS	IV
Agricultural output value	-0.020***	-0.198**	-	-
	(0.006)	(0.083)	-	-
Agricultural Productivity	-	-	-0.016***	-0.187***
	-	-	(0.005)	(0.069)
Age	0.002	0.005*	0.002	0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Female headed household	0.016	-0.043	0.020	0.004
	(0.029)	(0.043)	(0.029)	(0.031)
Education	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Irrigation and Hired Labor Controls	Yes	Yes	Yes	Yes
Off-farm Labor Controls	Yes	Yes	Yes	Yes
AgroEcological Zones Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Interview-Month Fixed Effects	Yes	Yes	Yes	Yes
Soil Characteristics Fixed Effects	Yes	Yes	Yes	Yes
LGA Fixed Effects	Yes	Yes	Yes	Yes
Underidentification Test				
Kleibergen-Paap rk LM statistic (Chi-sq)		9.055**		11.968**
Weak Identification Test				
Cragg-Donald Wald F statistic		12.530		12.987
Relative Bias		5%-10%		5%-10%
Observations	3641	3641	3641	3641

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the LGA level in parenthesis. Agricultural output value and agricultural productivity calculated using Laspeyres index and given in log form. Complete regression results with all control variables, including IV First Stage regression results, are shown in Appendix. Stock–Yogo tabulations based on the Cragg–Donald statistic were used for the weak identification test.

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Appendix

Table A1. Effects of Agricultural Output Values on the Probability of Households Relying on Less Preferred Foods- First Stage Regression & Robustness Tests

First-stage regressions

First-stage regression of lnoutput:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs = 3615
Number of clusters (lga) = 254

lnoutput	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	.024345	.0352776	0.69	0.490	-.0448212	.0935112
rfavg	.7107022	.1774839	4.00	0.000	.3627225	1.058682
rfavg2	-.063617	.0143866	-4.42	0.000	-.0918237	-.0354103
age	.016861	.0078311	2.15	0.031	.0015071	.032215
age2	-.0001642	.0000744	-2.21	0.027	-.0003101	-.0000184
female	-.2746229	.1065298	-2.58	0.010	-.4834882	-.0657577
edu	.0006778	.0045886	0.15	0.883	-.0083188	.0096744
shareirrigatedpc	.004888	.0018297	2.67	0.008	.0013008	.0084753
lnhhownfarmworknum	.0553106	.0149189	3.71	0.000	.0260603	.084561
lnhiredlaborusd	.0498031	.0068674	7.25	0.000	.0363386	.0632675
lnareaplantedha	.3603109	.0251524	14.33	0.000	.3109964	.4096254
dhhofffarmwork	-.1329817	.0800924	-1.66	0.097	-.290013	.0240496
dhhofffarmwork_ph	.0920547	.0622563	1.48	0.139	-.0300067	.2141161

F test of excluded instruments:
F(3, 253) = 6.75
Prob > F = 0.0002
Sanderson-Windmeijer multivariate F test of excluded instruments:
F(3, 253) = 6.75
Prob > F = 0.0002

Underidentification test (Kleibergen-Paap rk LM statistic): 8.976
Chi-sq(3) P-val = 0.0296

Weak identification test (Cragg-Donald Wald F statistic): 11.379

Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39

Table A2. Effects of Agricultural Output Values on the Probability of Households Limiting the Variety of Food Eaten - First Stage Regression & Robustness Tests

First-stage regressions

First-stage regression of lnoutput:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs = 3560
Number of clusters (lga) = 251

lnoutput	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	.0213969	.0351318	0.61	0.543	-.0474838	.0902777
rfavg	.6897694	.1876166	3.68	0.000	.3219211	1.057618
rfavg2	-.0620149	.0159671	-3.88	0.000	-.0933206	-.0307092
age	.0176607	.0078358	2.25	0.024	.0022975	.0330239
age2	-.0001734	.0000746	-2.32	0.020	-.0003198	-.0000271
female	-.3638883	.0998557	-3.64	0.000	-.5596692	-.1681074
edu	.0002556	.0046822	0.05	0.956	-.0089244	.0094357
shareirrigatedpc	.0041446	.0017627	2.35	0.019	.0006887	.0076006
lnhhownfarmworknum	.0536684	.0146242	3.67	0.000	.0249957	.082341
lnhiredlaborusd	.0531608	.0068585	7.75	0.000	.0397137	.0666079
lnareaplantedha	.3515	.02506	14.03	0.000	.3023664	.4006337
dhhofffarmwork	-.1430976	.083394	-1.72	0.086	-.306603	.0204077
dhhofffarmwork_ph	.106358	.0633962	1.68	0.094	-.017939	.230655

F test of excluded instruments:
F(3, 250) = 5.32
Prob > F = 0.0014
Sanderson-Windmeijer multivariate F test of excluded instruments:
F(3, 250) = 5.32
Prob > F = 0.0014

Underidentification test (Kleibergen-Paap rk LM statistic):		8.311
	Chi-sq(3) P-val =	0.0400
Weak identification test (Cragg-Donald Wald F statistic):		9.892
Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39

Table A3. Effects of Agricultural Output Values on the Probability of Households Limiting the Portion Size at Mealtimes - First Stage Regression & Robustness Tests

```
First-stage regressions
-----------------------


First-stage regression of lnoutput:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs =                  3641
Number of clusters (lga) =        252
```

lnoutput	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	.037207	.0354057	1.05	0.293	−.0322102	.1066242
rfavg	.7153311	.1750494	4.09	0.000	.3721253	1.058537
rfavg2	−.0646252	.0140768	−4.59	0.000	−.0922246	−.0370259
age	.0201391	.0075956	2.65	0.008	.0052469	.0350313
age2	−.0001947	.0000722	−2.70	0.007	−.0003363	−.0000531
female	−.3423069	.1027991	−3.33	0.001	−.5438571	−.1407567
edu	−.0005863	.0046104	−0.13	0.899	−.0096255	.0084529
shareirrigatedpc	.0049934	.0019484	2.56	0.010	.0011734	.0088135
lnhhownfarmworknum	.0485204	.0145172	3.34	0.001	.0200577	.0769831
lnhiredlaborusd	.050988	.0069098	7.38	0.000	.0374406	.0645354
lnareaplantedha	.3576282	.0253008	14.14	0.000	.3080229	.4072336
dhhofffarmwork	−.1026217	.0808206	−1.27	0.204	−.2610805	.055837
dhhofffarmwork_ph	.0917723	.0614173	1.49	0.135	−.0286438	.2121884

```
F test of excluded instruments:
  F(  3,   251) =     7.20
  Prob > F      =   0.0001
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(  3,   251) =     7.20
  Prob > F      =   0.0001
```

Underidentification test (Kleibergen-Paap rk LM statistic): 9.055
Chi-sq(3) P-val = 0.0286

Weak identification test (Cragg-Donald Wald F statistic):		12.530
Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39

Table A4. Effects of Agricultural Productivity on the Probability of Households Relying on Less Preferred Foods- First Stage Regression & Robustness Tests

First-stage regressions

First-stage regression of lnprod:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs = 3615
Number of clusters (lga) = 254

lnprod	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	-.0149379	.0421063	-0.35	0.723	-.0974926	.0676168
rfavg	.8690776	.174389	4.98	0.000	.5271658	1.210989
rfavg2	-.0771945	.0126885	-6.08	0.000	-.1020719	-.0523172
age	.0089933	.0088838	1.01	0.311	-.0084245	.0264111
age2	-.0001058	.0000837	-1.26	0.206	-.0002698	.0000582
female	-.034384	.0995943	-0.35	0.730	-.2296514	.1608834
edu	-.0014337	.005113	-0.28	0.779	-.0114583	.0085909
shareirrigatedpc	.0044836	.0022352	2.01	0.045	.0001012	.008866
lnhhownfarmworknum	.0305274	.0169801	1.80	0.072	-.0027642	.063819
lnhiredlaborusd	.0250665	.0078549	3.19	0.001	.0096659	.0404671
dhhofffarmwork	-.1077159	.0886975	-1.21	0.225	-.2816185	.0661868
dhhofffarmwork_ph	.1073622	.0649891	1.65	0.099	-.0200572	.2347817

F test of excluded instruments:
F(3, 253) = 15.03
Prob > F = 0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
F(3, 253) = 15.03
Prob > F = 0.0000

Underidentification test (Kleibergen-Paap rk LM statistic): 13.267
Chi-sq(3) P-val = 0.0041

Weak identification test (Cragg-Donald Wald F statistic):		14.444
Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39

Table A5. Effects of Agricultural Productivity on the Probability of Households Limiting the Variety of Food Eaten - First Stage Regression & Robustness Tests

```
First-stage regressions
-----------------------


First-stage regression of lnprod:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs =                   3560
Number of clusters (lga) =         251
```

lnprod	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	-.0185678	.0422585	-0.44	0.660	-.1014215	.0642858
rfavg	.8521409	.1801842	4.73	0.000	.498865	1.205417
rfavg2	-.0747143	.0140174	-5.33	0.000	-.1021974	-.0472312
age	.0074508	.0090221	0.83	0.409	-.0102382	.0251398
age2	-.0000917	.0000852	-1.08	0.282	-.0002587	.0000753
female	-.1135978	.0974836	-1.17	0.244	-.3047278	.0775323
edu	-.0028027	.005178	-0.54	0.588	-.0129548	.0073494
shareirrigatedpc	.0034051	.0021267	1.60	0.109	-.0007645	.0075748
lnhhownfarmworknum	.0295304	.0167656	1.76	0.078	-.0033409	.0624016
lnhiredlaborusd	.0299745	.0077947	3.85	0.000	.0146919	.0452571
dhhofffarmwork	-.1073694	.090331	-1.19	0.235	-.2844757	.069737
dhhofffarmwork_ph	.1157134	.065431	1.77	0.077	-.0125731	.244

```
F test of excluded instruments:
  F(  3,    250) =    11.76
  Prob > F       =   0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(  3,    250) =    11.76
  Prob > F       =   0.0000
```

Underidentification test (Kleibergen-Paap rk LM statistic): 13.936
Chi-sq(3) P-val = 0.0030

Weak identification test (Cragg-Donald Wald F statistic): 12.814
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 13.91
10% maximal IV relative bias 9.08
20% maximal IV relative bias 6.46
30% maximal IV relative bias 5.39

Table A6. Effects of Agricultural Productivity on the Probability of Households Limiting the Portion Size at Mealtimes - First Stage Regression & Robustness Tests

```
First-stage regressions
-----------------------

First-stage regression of lnprod:

Statistics robust to heteroskedasticity and clustering on lga
Number of obs =                    3641
Number of clusters (lga) =          252
```

lnprod	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
dd840	-.0086372	.0423619	-0.20	0.838	-.0916929	.0744184
rfavg	.8226011	.1776117	4.63	0.000	.4743716	1.170831
rfavg2	-.0706565	.0136372	-5.18	0.000	-.0973939	-.0439191
age	.0107569	.0086136	1.25	0.212	-.0061312	.0276451
age2	-.0001226	.000081	-1.51	0.130	-.0002815	.0000363
female	-.1096986	.096324	-1.14	0.255	-.2985537	.0791564
edu	-.0034563	.0051066	-0.68	0.499	-.0134684	.0065559
shareirrigatedpc	.0046591	.0023335	2.00	0.046	.0000839	.0092343
lnhhownfarmworknum	.0229717	.0168512	1.36	0.173	-.0100671	.0560105
lnhiredlaborusd	.0262376	.0079461	3.30	0.001	.0106583	.041817
dhhofffarmwork	-.0797826	.0906694	-0.88	0.379	-.2575511	.0979859
dhhofffarmwork_ph	.1104389	.0659044	1.68	0.094	-.0187748	.2396525

```
F test of excluded instruments:
  F(  3,   251) =     10.60
  Prob > F      =    0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(  3,   251) =     10.60
  Prob > F      =    0.0000
```

Underidentification test (Kleibergen-Paap rk LM statistic): 11.968
Chi-sq(3) P-val = 0.0075

Weak identification test (Cragg-Donald Wald F statistic): 12.987

Stock-Yogo weak ID test critical values:		
	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39