Food and Agriculture Organization of the United Nations

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Abstract

Food insecurity is one of the world's greatest challenges and there is still a strong debate on which structural strategies should be adopted to cope with it. In sub-Saharan Africa food insecurity is accompanied by very poor technical efficiency of farmers, particularly smallholders, resulting in below potential agricultural profits. The food security and technical efficiency challenges can be tackled with some common solutions: this paper studies the relation between agricultural technical efficiency and food insecurity in Nigeria using a two-step approach. It first estimates farmers' technical efficiency, employing a profit stochastic frontier framework on three waves of Nigeria's General Household Survey between 2010 and 2016. Then, it assesses the impact of these estimates on both moderate and severe measures of food insecurity at the province level, thanks to both probit and biprobit models with a rich set of covariates, including demographic, economic, agricultural and geographic characteristics. The results suggest that technical efficiency improvements are particularly effective in reducing the more severe types of food insecurity: an increase by 1 percent in technical efficiency reduces moderate (severe) food insecurity by 0.40 (0.45) percent. Therefore, policies aimed at improving farmers' technical efficiency can also have a strong impact on reducing food insecurity.

Keywords: food security, technical efficiency, stochastic frontier, Nigeria.

JEL codes: D24, D61, Q12, Q18.

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1 Introduction

Food insecurity and the associated coping strategies of policymakers are increasingly being analysed. One of the key regions in this respect is sub-Saharan Africa, where most food insecure countries are. Despite the urgency and magnitude of the issue, until recently there was a lack of common understanding of the phenomenon. This has led to the development of a standard definition and measurement methodology, i.e. the Food Insecurity Experience Scale (FIES) questionnaire, as detailed in Section 4. However, while in the last few decades the focus of several policies in developing countries has been re-oriented towards agriculture, a consensus has not been reached in relation to the most appropriate strategies that countries should adopt to cope with food insecurity (Giller, 2020; Mogues *et al*., 2012; Saint Ville *et al*., 2019). This clearly relates to the fact that all countries have very different and peculiar contexts, but there exist pathways that seem to be effective across time and continents.

Agricultural productivity growth has in fact been commonly reported as a key strategy to reduce food insecurity and poverty and increase rural incomes, from the seminal work of Byerlee, De Janvry and Sadoulet (2009) to recent papers such as Chavas *et al.* (2022) and Gollin, Hansen and Wingender (2021). A large literature has thus developed on the estimation and determinants of farmers' agricultural technical efficiency, a major contributor to the growth in agricultural productivity (Adom and Adams, 2020). The most common methodology employed in this field is the stochastic frontier analysis, originally devised by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), and further improved in subsequent decades (e.g. Battese and Coelli, 1995; Kumbhakar and Lovell, 2000; Huang, Huang and Liu, 2014; Maruyama *et al*., 2018). This method is able to model the deterministic part of a productivity or profitability frontier (including its inefficiency component) as well as the part influenced by random noises, and it has been largely applied in the literature (see Section 3).

However, while both food security and agricultural technical efficiency have been separately studied in detail, the link between the two has not been widely explored yet: Liverpool-Tasie, Kuku and Ajibola (2011) specifically call for future research to investigate how agricultural productivity in Nigeria can contribute to household food security. The only recent studies on the topic report (i) that technical efficiency and food insecurity have common determinants – using separate regressions – and (ii) that there exist either a negative correlation between the two or no significant relationship at all (Ajayi and Oluntumise, 2018; Hakim, Haryanto and Sari, 2021; Oyetunde-Usman and Olagunju, 2019). Moreover, none of these studies exploit a multi-year nationally representative dataset and may not claim causal statements given the descriptive methods employed (e.g. OLS, Probit or Logit multivariate regressions).

This paper fills these gaps in the literature by studying the agricultural technical efficiency-food insecurity nexus in Nigeria. It uses the nationally representative General Household Survey (GHS) data over three waves between 2010 and 2016 (Nigeria National Bureau of Statistics, 2010–2016) and constructs two complementary measures of food insecurity. Then, a two-step methodology is employed to estimate the relationship under study. First, a profit stochastic frontier analysis produces an estimate of farmers' technical efficiency, and these measures are then aggregated at the level of provinces (local government authorities). Second, the relationship between food insecurity and technical efficiency is estimated controlling for a large set of covariates. The model estimates the systemic impact on overall food insecurity of improvements in farmers' technical efficiency, i.e. including all potential spill overs and general equilibrium effects. To tackle potential endogeneity issues, after using a simple probit model, an instrumental variable (IV) strategy for technical efficiency is also employed using a biprobit framework.

The results suggest that food insecurity is widely diffused in Nigeria, with particularly high rates for moderate and severe food insecurity, in concordance with the estimates from FAO (2021). Moreover, Nigerian farmers are on average characterized by very low technical efficiency figures, in line with the previous results of the literature (Amos, 2007; Fasasi, 2007; Ogunniyi and Oladejo, 2011; Oyetunde-Usman and Olagunju, 2019). The association between technical efficiency and food insecurity is a strongly negative one. Moreover, this is consistently confirmed by the biprobit results, whose instrument validity is reinforced by the robustness checks in Section 5.2.3. Using the full specification, the estimated impact of a 1 percentage point increase in agricultural technical efficiency is a 0.37 (0.46) percentage point decrease in moderate (severe) food insecurity.

The remainder of the paper is organized as follows. Section 2 describes the Nigerian context with respect to food insecurity and the policy measures taken to cope with it. Section 3 outlines the methodology employed in the first and the second steps of the empirical strategy. Section 4 presents the data and some descriptive statistics. Section 5 discusses the results and Section 6 concludes.

2 The Nigerian context

Nigeria accounts for about half of West Africa's population with approximately 212 million people and is one of the youngest populations in the world. As of 2022, the country is Africa's largest economy, but its gross domestic product (GDP) per capita places Nigeria only twenty-second among African countries, according to IMF estimates (IMF, 2022). Despite high growth rates, as its benefits do not accrue evenly to all income groups, progress in poverty reduction is still weak. 39.1 percent of the population still live under the USD 1.90 per day poverty line, with a further 31.9 percent between the USD 1.90 and USD 3.20 per day thresholds, mostly in rural areas (World Bank, 2022). Poverty, as a multidimensional phenomenon, is generally intertwined with other plagues, among which the most prominent are hunger and malnutrition (Omotayo *et al*., 2018).

As of 2021, according to the most recent FAO estimates, the prevalence of undernourishment in Nigerian population was 12.7 percent and severe food insecurity was as high as 31.7 percent of the population. These figures have been worsening for the last 15 years, particularly between 2018 and 2019 and with the COVID-19 pandemic (FAO *et al*., 2021, 2022). Malnutrition, as with several other poverty indicators, typically has strong territorial and ethnic components. In general, these indicators present worse rates in rural areas, but the food security situation has particularly deteriorated over the last two decades in Nigeria's North-East area, due to the renewed conflict between the government and Non-State Armed Groups (NSAGs) (WFP, 2021).

One of the most effective pathways through which agricultural research and technology adoption can increase rural incomes, reduce poverty and food insecurity is agricultural productivity growth, as highlighted by Gollin, Hansen and Wingender (2021) and Byerlee, De Janvry and Sadoulet (2009). In its *World Development Report 2008*, the World Bank argued that development of the agricultural sector has led to greater economic development, higher incomes and improved food security, nutrition and health in many countries. It also estimates that GDP growth originating in agriculture is at least twice as effective in reducing poverty compared to the same magnitude of growth in other sectors of the economy (World Bank, 2007).

Several studies support this argument, by showing that the adoption of improved agricultural technologies is important in reducing poverty and food insecurity in developing countries, including in sub-Saharan Africa (e.g. Ali and Abdulai, 2010; Becerril and Abdulai, 2010; Kassie *et al*., 2018; Kassie, Shiferaw and Muricho, 2011; Mendola, 2007; Renkow and Byerlee, 2010; Warr and Suphannachart, 2021; Wossen *et al*., 2019). Over the last couple of decades, in fact, several sub-Saharan African countries have enjoyed some improvements in the food security situation, except the recent period since 2018, during which most developing countries have witnessed an increase in the prevalence of undernourishment (FAO *et al*., 2022; Masanjala, 2006).

Hunger and malnutrition have historically been crucial challenges in Nigeria, despite being characterized by a diverse agro-ecosystem, with a variety of annual and perennial crops. In fact, Nigeria's agricultural growth is well below potential and the sector has been unable to provide growth prospective for the poor, in particular rural ones, while high food prices inflation having a negative impact especially on the urban poor (Liverpool-Tasie, Kuku and Ajibola, 2011; Shimeles, Verdier-Chouchane and Boly, 2018). To explain this situation, there are some idiosyncratic factors that affect agriculture as well as several other sectors of the economy, such as the continued insurgency in the Northeast and the resource curse associated with the dependency on oil production. One of the characteristics of the agriculture sector in Nigeria is that it consists of small-scale subsistence farmers, employing low yielding technologies and practices and using low rates of synthetic inputs. Moreover, during the past few decades, the country has been mostly pursuing policies aimed at industrialization while agriculture has been transitioning too, albeit at a slow pace.

Several reforms and efforts were made in Nigeria to revive the agricultural sector and to boost the economy over the past few decades. Those promoted from the 1970s until 2010 have largely failed, resulting in an agricultural sector with most smallholder farmers trapped in poverty, very low rate of structural transformation and in a nation suffering from chronic food deficit and increasing dependence on food imports (Naiya and Manap, 2013). The government of Nigeria embarked on a new journey of reforming the agricultural sector in 2010 with the implementation of the new strategy named Agricultural Transformation Agenda (ATA) (see AfDB, 2013). The key principle was to view the agriculture as a business and to drive the economy through a sustainable agricultural sector having a business-like attitude.

After the lessons taken from the ATA, a new policy, the Agricultural Promotion Policy 2016–2020 (APP), was developed in 2016 as the outcome of an intensive consultative process (FMARD, 2016). The APP guiding principles were all aimed at improving productivity, upgrading value chain, motivating private sector participation, improving infrastructures, improving access to finances, and promoting innovation and exploiting demand locally and internationally. The overall aim of the policy was to build an agribusiness economy capable of delivering sustained prosperity by meeting domestic food security goals, generating exports, and supporting sustainable income and job growth.

As for many other developing countries, agriculture–based rural transformation is thus crucial for achieving food security in Nigeria, given that agriculture is the main source of livelihoods for most poor rural households (Alene, 2010; Allen, Heinrigs and Heo, 2018). While some agricultural investments have in part contributed to pulling farmers out of extreme poverty and severe food insecurity, the growth so far has not been sufficient in this respect to affect the largest part of the farming population. Moreover, current sub-Saharan African crop production trends are projected to be insufficient to meet future food demand, with poverty persistently remaining at significant levels (Onyutha, 2018). This paper aims thus at identifying which investments and other factors related to farmer's and land's characteristics would improve technical efficiency and agricultural profitability, and whether and to what extent technical efficiency improvements would lead to reductions in food insecurity.

3 Methodology

3.1 Modelling farmers' efficiency: the basics

In order to evaluate whether farmers in Nigeria are technically efficient in their production process and market participation, the paper uses a stochastic frontier (SF) approach. In this framework, agricultural potential and efficiency are measured in terms of profits. In other words, areas are considered to be of high potential if under the existing technology, prices and agroecological conditions, the expected profits are high in that area. Inefficiency is measured as the distance between the observed profits in a given province from their maximum potential profits. Therefore, productive units are 100 percent efficient if their observed profits coincide with the agricultural potential in the province. This agricultural potential is not observed and needs to be estimated econometrically. To do so, the standard approach followed is to rely on SF models, which are the focus of this section.

The two most commonly used methods to estimate the efficiency of production units are data envelopment analysis (DEA) (Charnes, Cooper and Rhodes, 1978, 1981) and SF analysis (Aigner, Lovell and Schmidt, 1977; Khumbakar and Lovell, 2000; Meeusen and van den Broeck, 1977). DEA is a non-parametric approach that uses linear programming to identify the efficient frontier, while SF analysis is a parametric approach that hypothesizes a functional form and uses the data to econometrically estimate the parameters of that function. Both methods measure efficiency as the distance between observed and maximum possible (frontier) outcomes, but the key advantage of SF analysis for our purposes is that it allows to separate random noise in the error term from the actual efficiency score. This is an important feature when analysing agricultural activities, which are constantly exposed and extremely sensitive to (negative and positive) random shocks, including but not limited to droughts and variation in prices.

In the SF approach, inefficiency is defined as the loss incurred by operating away from the frontier given the current prices and fixed factors faced by a farmer. By estimating where the frontier lies, and how far each producer is from it, the stochastic frontier approach helps to identify the local potential and efficiency of each household. Using the basic model proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), the single output stochastic frontier production function is defined as:

$$y_i = f(\boldsymbol{x}_i, \boldsymbol{\beta})exp(v_i - u_i) \quad (1)$$

Where y_i is the output for farmer *i*, $\boldsymbol{x}_i$ is a vector of inputs for farmer *i*, such as land, labour, etc., $\boldsymbol{\beta}$ is the vector of technology parameters associated to the inputs of production, v_i is an i.i.d. random error distributed as a $N(0, \sigma^2)$, representing random factors that are not under the farmer's control, and u_i is a non-negative random variable associated with factors that prevent farmer i from being efficient. Aigner, Lovell and Schmidt (1977) assumed a half-normal distribution, that is, $u_i \sim N^+(0, \sigma_u^2)$, while Meeusen and van den Broeck (1977) opted for an exponential one, $u_i \sim Exp(\sigma_u)$. Other commonly adopted distributions are the truncated normal (Stevenson, 1980) and the gamma distributions (Greene, 1980a, 1980b, 2003).

Given that the production frontier of farmer i is $y_i^* = f(\boldsymbol{x}_i, \boldsymbol{\beta})exp(v_i)$, which implies that $u_i = 0$, the technical efficiency can be defined as:

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(\boldsymbol{x}_i, \boldsymbol{\beta})exp(v_i - u_i)}{f(\boldsymbol{x}_i, \boldsymbol{\beta})exp(v_i)} = exp(u_i) \quad (2)$$

A very important issue in SF analysis is the inclusion in the model of exogenous variables that are supposed to affect the distribution of inefficiency. These variables, which usually are neither the inputs nor the outputs of the production process but nonetheless affect the productive unit performance, could be incorporated in a variety of ways: i) they may shift the frontier function or the inefficiency distribution; ii) they may scale the frontier function or the inefficiency distribution; and iii) they may shift and scale the frontier function or the inefficiency distribution. Kumbhakar and Lovell (2000) stress that the presence of unobservable heterogeneity in u_i and v_i may affect the inference in SF models. Indeed, while neglected heteroskedasticity in v_i does not produce any bias for the frontier's parameter estimates, it leads to biased inefficiency estimates.

A natural starting point for introducing exogenous variables in the model is in the location of the inefficiency distribution. The most well-known approaches are those suggested by Kumbhakar, Ghosh, and McGuckin (1991) and Huang and Liu (1994). They proposed to parametrize the mean of the pre-truncated inefficiency distribution:

$$u_i \sim N^+(\mu_i, \sigma_u^2) \quad (3)$$

$$\mu_i = \boldsymbol{z_i}\varphi \quad (4)$$

Where $\boldsymbol{z_i}$ is a vector of farmer-specific factors affecting their performance.

Similarly, Caudill and Ford (1993) and Caudill, Ford and Gropper (1995) showed that in presence of heteroskedasticity in u_i, its distribution will not be the same for all the observations in the sample and a correction for heteroskedasticity needs to be made by parameterizing the variance of the pre-truncated inefficiency distribution in the following way:

$$u_i \sim N^+\left(0, \sigma_{u_i}^2\right) \quad (5)$$

$$\sigma_{u_i}^2 = exp(\boldsymbol{z_i}\varphi) \quad (6)$$

3.2 Estimating a stochastic frontier

To estimate the model expressed by equations (1)-(6), the methodology applied follows Maruyama *et al.* (2018) with some adaptation to our specific context. The SF profit[1] function can thus be expressed as:

$$\pi_i = f(\boldsymbol{p}_i, \boldsymbol{w_i}, X_i; \boldsymbol{\beta})exp(v_i - u_i) \quad (7)$$

where p_i and w_i are the output and input prices, respectively, and X_i are the variables modelling the stochastic frontier. In fact, in the agricultural context, it is also necessary to consider other production factors, such as climate and soil quality, that affect the farm's potential, but cannot be easily modified in the short or medium term. For this reason, the farm's frontier is adjusted

[1] Total profits are considered instead of revenues as the output measure, since profits are more likely than revenues to capture total value added and surplus generated. Moreover, compared to most household surveys, the available data in Nigeria's GHS are relatively well suited to estimate a profit stochastic frontier.

using GIS data on agroecological zones (land use types or crop suitability) and weather conditions. These variables are introduced as shifters of the deterministic portion of the frontier.

Equation (7), which maintained a generic functional form, is then estimated as a linear equation at the household level. Specifically, the following equation is estimated:

$$\pi_i = \alpha_o + \sum_m \beta_m p_m + \sum_n \gamma_n w_n + \sum_q \delta_q x_q - u_i + v_i \tag{8}$$

where *i* is the farmer unit. The dependent variable and most independent variables are transformed using the Inverse Hyperbolic Sine (IHS) transformation.[2] Compared to the log transformation, the IHS transformation allows to keep more observations, since it can handle negative values, while keeping the interpretation of the coefficients very similar to the log-transformation (see Bellemare Wichman 2020). Equation (8) above is broken down in different components, namely:

1. Dependent variable (π_i) is the ihs transformation of farmer *i*'s total profits.
2. Determinants of the frontier (or agricultural potential):
    a. A constant term α_o.
    b. Prices of outputs *m* (p_m) and costs of inputs *n* (w_n) in their ihs transformation: in principle, higher output prices and lower input costs will lead to higher profits.
    c. Variables x_q that are expected to affect the frontier, i.e. what may determine the potential maximum profits a farmer can reach on average. These typically include the proportion of land in a province covered by a given land use suitable for cultivating a specific crop (e.g. crop land, forest, barren land, water bodies, shrublands and savannah) and variables that capture the long-term climatic conditions as these are likely to be key determinants of long-term potential (e.g. the long-run mean of NDVI, the Normalized Difference Vegetation Index).
3. Inefficiency term u_i that includes the determinants of inefficiency which are expected to affect how distant from their frontier a given farmer will be. These include market accessibility, number of hectares of cultivated land, income from social assistance programs, household size and wealth, average household education, gender and age, as well as deviations from the long-term mean of rainfall, to capture weather shocks.
4. The random error term v_i whose heteroscedasticity is modelled by variables accounting for total farm size, such as the area of cultivated land or the number of livestock units owned by the farmer.

Once equation 8 is estimated, the estimated coefficients at the household-level are used to predict the potential and efficiency levels of a given province (Nigeria's administrative level below the state), by averaging individual-level observations. As explained above, the potential is represented by the frontier, i.e. the maximum achievable profits for a farmer within a province and given existing technology, prices and agroecological conditions. The efficiency is instead the ratio between observed and potential profits, as modelled in Equation (2).

[2] The Inverse Hyperbolic Sine (IHS) or arcsinh transformation is defined as: $\log(x_i + \sqrt{x_i^2 + 1})$.

3.3 Food insecurity specification

The second step consists of estimating a reduced form equation of measures of food insecurity on the technical efficiency estimate and a set of covariates at the province level. Notice that the food insecurity measures are obtained using a nationally representative sample of households, while the technical efficiency estimates are obtained from farmers pursuing agricultural activities. Therefore, this model estimates the systemic impact on overall food insecurity of improvements in farmers' technical efficiency, i.e. including all potential spillovers and general equilibrium effects. Specifically, the baseline equation is:

$$FI_p = \alpha_o + \beta TE_p + \sum_q \gamma_q x_q + u_p \tag{9}$$

where FI_p is a proportion of households within province p that are food insecure to a certain extent (see Section 4) and is thus bounded between 0 and 1. α_o is the constant term, TE_p is the estimated technical efficiency from the first step, and x_q includes the set of covariates which depends on each model. As shown in Table 1, several covariates are in fact added to the model in subsequent blocks: demographic and socioeconomic covariates, geographical covariates, transfers and wages, input costs, output prices, agricultural and input variables. Model x1 only includes the main independent variable of interest (technical efficiency) and year fixed effects. This equation is estimated through a Probit model, with standard errors clustered at the province level.

These specifications may still suffer from endogeneity bias, in particular reverse causality, measurement error and omitted variable bias. Suppose that provinces with more food secure households also tend to become more technically efficient. This would inflate the estimation of the main coefficients. Clearly, since the technical efficiency variable is obtained from a previous estimation, it could also be measured with error, resulting in the classical errors-in-variables which biases estimates towards zero. In addition, despite the richness of the full specification, the model cannot control for farmers' intrinsic ability, which may be unrelated to their level of education or experience but correlated with the food insecurity outcomes. These cases would bias the simple probit estimates and call for another identification strategy. For this reason, an instrumental variable strategy, through the biprobit model, is employed using the rainfall long-term mean and its short-term deviations as instruments for technical efficiency.

Table 1. Covariates added in each specification

x2 Geographical variables	x3 Socioeconomic variables	x4 Transfers and wages	x5 Input costs	x6 Output prices	x7 Agricultural variables
Annual mean temperature	Female	Social assistance	Hired labour unit cost	Beans cowpea unit price	HH labour (person-days)
Potential wetness index	Age	Food aid	Land rent unit cost	Cassava unit price	Hired labour (person-days)
Distance to nearest road	HH size aged 15–60	Cash transfers	Herbicide unit cost	Peanuts unit price	Plot area (ha)
Distance to nearest market	Number of kids	Other in-kind transfers	Pesticide unit cost	Sorghum unit price	Has plot legal title
Distance to population centre	HH average education	Total income from assistance	Fertilizer unit cost	Maize unit price	Has source of irrigation
	Rural area	Yearly off-farm wages	Livestock labour unit cost	Millet unit price	Herbicide quantity use (lt)
	Access to electricity		Livestock vet unit cost	Rice unit price	Pesticide quantity use (lt)
	Wealth index		Livestock feed unit cost	Yamwhite unit price	Fertilizer quantity use (lt)
			Infrastructure unit cost	Wateryam unit price	Has animal traction
			Compensation unit cost	Sesame unit price	
				Okro unit price	
				Soyabeans unit price	
				Eggs unit price	
				Milk unit price	
				Cow unit price	
				Goat unit price	
				Sheep unit price	

Note: baseline model x1 only includes technical efficiency and year fixed effects, each subsequent model adds the listed covariates on the previous one.

Source: Author’s own elaboration.

These two instruments were chosen as they are expected to affect technical efficiency both on its frontier component (the long-term mean) and on its inefficiency component (the short-term deviations), and to affect food insecurity only through this channel. In fact, the first stages’ strength shows that the instruments are relevant, particularly the rainfall short-term deviations. As for the instruments’ validity, it can be argued that rainfalls are unrelated to the intrinsic ability of farmers and that, controlling for observables, they affect food insecurity only via technical efficiency. This is especially guaranteed from the presence of other geographic and meteorological covariates, in particular the annual mean temperature and the potential wetness index, from model x2 onwards. Moreover, in Section 5.2.3, robustness tests for the IV validity are presented to further reinforce the argument. The final specification thus becomes:

$$FI_p = \alpha_o + \beta\widehat{TE}_p + \sum_q \gamma_q x_q + u_p \tag{10}$$

where $\widehat{TE}_p$ is the technical efficiency measure after instrumentation. Since also technical efficiency is a variable bounded between 0 and 1 (see Section 3.1), the most appropriate model to use in this context is the pooled IV bivariate probit (or simply biprobit) model, with standard errors clustered at the province level. Being able to model between 0 and 1 both dependent variables in the first and second stage regressions, this approach is preferred to a standard 2SLS (two-stage least square) one, which may produce unreliable estimates. The latter, however, is retained to calculate some statistics as robustness tests (which are not available using the biprobit model). Specifically, Table 7 also presents the p-values of the Sargan-Hansen test of overidentifying restrictions for these regressions.

Moreover, each biprobit regression also presents the p-values of the *rho* coefficient, a Wald test of exogeneity for the correlation between the estimated residuals from the first stage and those from the second stage. If the test does not reject the null hypothesis of exogeneity (*rho = 0*), the first and second stage equations can be treated independently from each other: both probit and biprobit models yield consistent estimates, but probit is more efficient than biprobit. If instead *rho* is not statistically different from zero, the biprobit model is the only consistent one and should be preferred over the simple probit estimates.

4 Data and descriptive statistics

The main data source is the General Household Survey (GHS) run by the National Bureau of Statistics of Nigeria and implemented together with the World Bank Living Standard Measurement Study (LSMS) and a series of other agencies of the federal government of Nigeria. Since 2010 5 000 households were selected from 500 enumeration areas of the 37 Nigerian states to be included in a panel component of the GHS to be repeated every two to three years. These households were selected to be representative of all administrative zones of Nigeria and at both the rural and urban level. The data employed are the 2010–2011, 2012–2013 and 2015–2016 waves of this panel data, and each of them includes both a post-planting visit (between August–October) and a post-harvest visit (between February–April).

Of the 5 000 households initially sampled, 4 916 completed the questionnaire in the first wave. As families move to other regions and states over time, a tracking visit was conducted after both post-planting and post-harvesting visit so to identify and interview as many of the households who moved following one of the previous waves as possible. In the second wave, 4 851 households completed the questionnaires of both visits, that is a 1.3 percent attrition rate. By the third wave 4 581 households of the original households have remained in the sample, which yields a 6.8 percent attrition rate. This represents a quite high response rate, especially for a sub-Saharan African country. Moreover, as most variables used were collected in both visits of each wave, their information is combined by substituting missing values in the post-planting visit with the post-harvest data, to obtain even lower attrition.

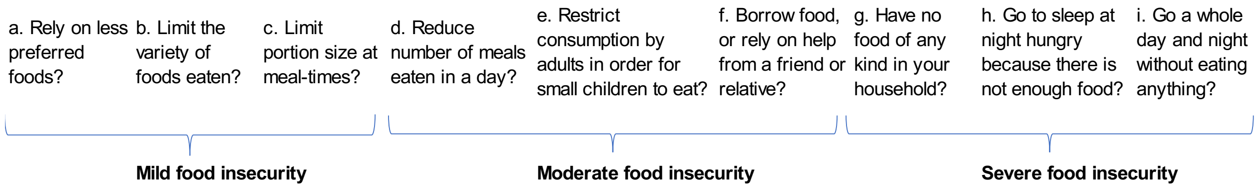
The outcome of interest in this study is food insecurity. The 1996 Rome Declaration on Food Security reached an agreement on the following definition: "food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life" (FAO, 1996). Measuring its absence, food insecurity, and the related gradient has generated a long-standing debate among both academics and policymakers. Recognising this data measurement gap, USAID developed the Household Food Insecurity Access Scale (HFIAS) for Measurement of Food Access, to monitor food security in a comparable manner (Coates, Swindale and Bilinsky, 2007). The HFIAS has been then overcome in 2013 by the Food Insecurity Experience Scale (FIES), developed by the FAO to be employed in micro-level surveys (Saint Ville *et al.*, 2019). The FIES consists of eight questions in order of severity, which have been developed following a Rasch model-based procedure (Cafiero, Viviani and Nord, 2018). Recent studies confirm its internal validity, with specific reference to the sub-Saharan African context (Wambogo *et al.*, 2018).

The GHS has a food security module, inspired by the HFIAS and the FIES, but adapted to the Nigerian context. As shown in Figure 1, the GHS module consists of nine questions that, while being similar to the FIES ones, have some notable differences which makes them not directly comparable to the FIES estimates and therefore across countries.[3] The questions are asked

[3] Specifically, GHS questions *a* (relied on less preferred food), *e* (restricted consumption by adults in order for small children to eat) and *f* (borrowed food or relied on help from a friend or relative) are not present in the FIES, while questions WORRIED (being worried you would not have enough food to eat because of a lack of money or other resources) and ATELESS (having eaten less than you thought you should because of a lack of money or other resources) from the FIES are not present in the GHS. The other questions measure similar concepts but are phrased differently, which makes not directly comparable as well.

to the household's senior female or person most knowledgeable about food consumption over the 7 days before the survey, a shorter recall period than both the HFIAS (four weeks) and the FIES (twelve months).[4] The nine questions are coded as dummy variables with reference to whether the event described happened to any person in the household. These items are then grouped into three categories of food insecurity severity, using as thresholds question *d* (reduced number of meals eaten in a day) ad *g* (have no food of any kind in the household), as commonly done in the literature (FAO, 2018). The three categories – mild, moderate and severe food security – are also dummy variables, indicating whether there is a positive answer in either of the three related questions. The analytical part of this paper considers only the moderate and severe food insecurity measures, as the probability of people falling in the mild food insecurity group being actually food secure is not negligible, making therefore its interpretation more complicated.

Figure 1. Food insecurity outcome variables



Source: Author's own elaboration based on the Nigeria General Household Survey.

Table 2 presents the descriptive statistics for the moderate and severe food insecurity measures presented above. The average moderate food insecurity across households in each survey year is higher than the average severe food insecurity. That is, the milder measures of food insecurity is more frequent than the harsher one, which affect less households. These averages are also quite high: about 30 percent of the surveyed households were moderately food insecure. Severe food insecurity, which is typically the most policy-relevant aspect, was experienced by about one household in ten across the survey waves, which is in line with the FAO estimates presented in Section 2. While moderate food insecurity has increased between the first and the third wave, severe food insecurity has slightly decreased.

Table 2. Descriptive statistics of the food insecurity outcome variables

		2010	2013	2016
Moderate food insecurity	Mean	0.307	0.286	0.322
	SD	(0.327)	(0.346)	(0.301)
Severe food insecurity	Mean	0.110	0.100	0.097
	SD	(0.191)	(0.219)	(0.161)
	N	338	342	349

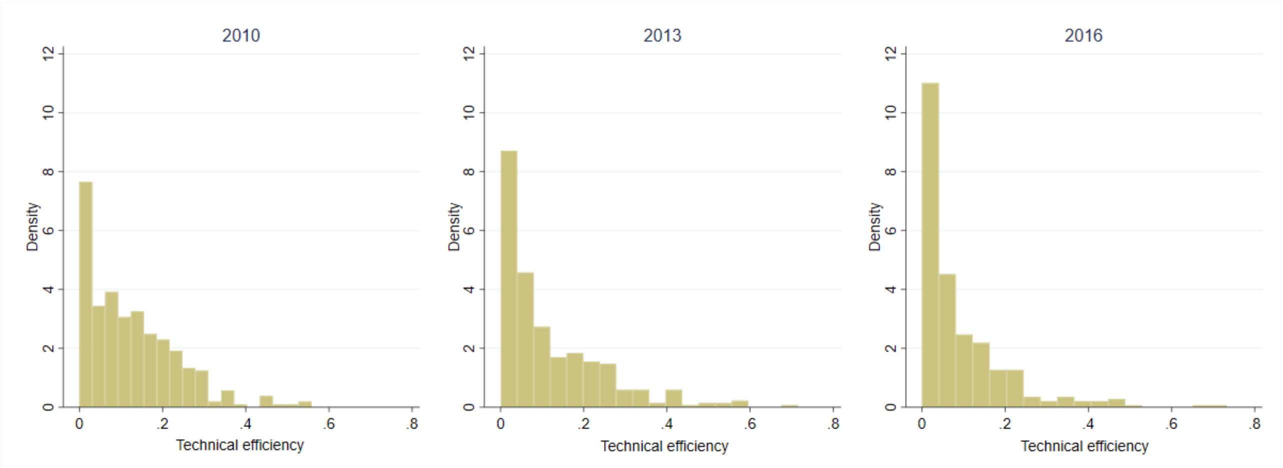
Note: N is the number of enumeration areas in each survey year.

Source: Author's own elaboration from the Nigeria General Household Survey.

[4] The shorter recall period reduces the recall bias, but also increases the likelihood of responses being affected by particular events that impacted the household in the week prior to the survey.

The main independent variable of interest is the profits technical efficiency estimate, derived following the steps outlined in Section 3.2. As shown in Figure 2, the technical efficiency estimates are bounded between 0 and 1 and it follows a skewed distribution, with higher density near zero and very few observations beyond 0.5. The average technical efficiency is 0.11 across the full sample, a figure that has been decreasing from an average of 0.125 in 2010 to an average of 0.088 in 2016. Such low efficiency of Nigerian farmers finds support in the literature (see for instance Fasasi, 2007; Ojo, 2009; Okoruwa *et al*., 2014).

Figure 2. Estimates of farmers' technical efficiency by survey year



Source: Author's own elaboration from the Nigeria General Household Survey.

As shown in Table 3, technical efficiency and food insecurity are both relatively similar across the six administrative zones of Nigeria, with two exceptions. First, technical efficiency is particularly low in the South-east zone and particularly high in the South-west zone, where Lagos is located. Second, the South-east zone, together with the South-south zone, is also very food insecure across the two levels of severity. For both the moderate and severe food insecurity, the difference between these two zones and the other four is very stark, with proportions of food insecure households being two to three times higher.

Table 3. Technical efficiency and food insecurity across geopolitical zones

Zone	Technical efficiency		Severe	Moderate	
	Mean (SD)	N	Mean (SD)	Mean (SD)	N
North-central	0.115	181	0.111	0.278	238
	(0.103)		(0.187)	(0.292)	
North-east	0.103	177	0.152	0.262	236
	(0.093)		(0.218)	(0.267)	
North-west	0.102	228	0.114	0.240	298
	(0.108)		(0.194)	(0.279)	
South-east	0.059	167	0.310	0.594	222
	(0.074)		(0.315)	(0.314)	
South-south	0.112	157	0.266	0.485	208
	(0.136)		(0.324)	(0.367)	
South-west	0.197	116	0.128	0.270	165
	(0.157)		(0.245)	(0.302)	

Note: N is the number of enumeration areas in each survey year.

Source: Author's own elaboration from the Nigeria General Household Survey, average across the 2010, 2013 and 2016 waves.

As mentioned in the introduction, the literature found a negative correlation between technical efficiency and food insecurity, indicating that higher efficiency is associated to higher food security. From a purely descriptive standpoint, this paper confirms this pattern reporting a negative correlation across provinces, ranging from -0.15 between technical efficiency and severe food insecurity to -0.20 between technical efficiency and moderate food insecurity. However, these simple correlations do not uncover the causal relationship between the two factors, which is explored in Section 5. Intuitively, the two measures of food insecurity are positively correlated, but with a correlation coefficient of 0.60, indicating that they measure different aspects of food insecurity.

With respect to the other covariates included in the specifications, they are all derived from the GHS survey data. Specifically, the wealth index was obtained through a principal component analysis (PCA) of the assets owned by the household and the characteristics of house in which it lives. In general, the richness of the covariate sets aims at capturing different aspects (geography, meteorology, demography, labour, assistance and aid, markets, productivity and technology) affecting either technical efficiency or food insecurity in the respective regressions of the two-step model.[5]

[5] Not all variables used in the second step (food insecurity specification) were also used in the first step (technical efficiency estimation), both because some variables were not relevant for the stochastic frontier analysis and because of model's convergence issues.

5 Results

5.1 A profits stochastic frontier of Nigerian farmers

The first step of the analysis consists of estimating the main independent variable of interest, the agricultural technical efficiency. All farmers reporting profits (positive or negative) in the GHS data have been used in the analysis, including both crop, livestock and mixed farmers. The profit stochastic frontier analysis has been estimated using an exponential distribution, following Meeusen and van den Broeck (1977), and with robust standard errors. The *sfcross* command in STATA has been used for the analysis. Table 4 shows the SF results divided into its frontier, inefficiency and random error components.

The first column presents the estimation for the variables affecting the efficiency frontier. Among the statistically significant variables are the long-run mean of the Normalized Difference Vegetation Index (NDVI), which captures the long-term climatic conditions, the savannah and cropland/natural vegetation land use dummy variables. In terms of input costs, hired labour and fertilizer unit costs are not significant predictors of the frontier, while livestock feed and veterinary unit costs are. Most output prices – both crops and livestock – are also significant, while the year dummy variables are not.

Among the significant variables affecting the inefficiency term, the short-term deviations from the NDVI long-term mean and household size of working age members (i.e. aged between 15 and 60) have a negative sign, thereby decreasing farmers' inefficiency. Vice versa, the share of female members of the household, the average household years of education and the total income from social assistance program negatively affect efficiency. The household wealth index and the necessary time to reach the closest city do not significantly affect the inefficiency term. Finally, being measures of size of the farmer's activity, the total area of cultivated land and the total number of livestock units positively and significantly affect the heteroscedasticity of the error term, while not impacting inefficiency.

Table 4. Profit stochastic frontier analysis

	(1) Frontier	(2) Inefficiency	(3) Random error
NDVI long-run mean (ihs)	5.460***		
	(0.845)		
Land use: savannah (ihs)	-0.0574*		
	(0.0335)		
Land use: grasslands (ihs)	0.0341		
	(0.0210)		
Land use: crop lands (ihs)	-0.00492		
	(0.0237)		
Land use: cropland/natural vegetation (ihs)	0.0577**		
	(0.0277)		
Hired labour unit cost (ihs)	-0.0800		
	(0.107)		
Fertilizer unit cost (ihs)	-0.0884		
	(0.202)		
Livestock feed unit cost (ihs)	0.472***		
	(0.156)		

	(1) Frontier	(2) Inefficiency	(3) Random error
Livestock vet unit cost (ihs)	-0.414**		
	(0.164)		
Beanscowpea unit price (ihs)	0.231		
	(0.259)		
Cassava unit price (ihs)	-0.542***		
	(0.163)		
Peanuts unit price (ihs)	0.472*		
	(0.243)		
Sorghum unit price (ihs)	0.717**		
	(0.360)		
Millet unit price (ihs)	-0.630		
	(0.598)		
Rice unit price (ihs)	-0.860***		
	(0.216)		
Cow unit price (ihs)	0.805**		
	(0.318)		
Goat unit price (ihs)	0.255**		
	(0.118)		
Sheep unit price (ihs)	0.215		
	(0.181)		
Year = 2013	0.185		
	(0.165)		
Year = 2016	-0.00553		
	(0.218)		
NDVI short-term deviation (ihs)		-1.005***	
		(0.185)	
HH size aged 15-60 (ihs)		-0.101**	
		(0.0455)	
HH share females (ihs)		0.310***	
		(0.0435)	
Time to nearest city (ihs)		0.0115	
		(0.0455)	
HH average education (ihs)		0.0888***	
		(0.0239)	
Wealth index (ihs)		0.000331	
		(0.0384)	
Total income from assistance (ihs)		0.0271*	
		(0.0150)	
Cultivated plot area (ihs)		-0.0278	0.383***
		(0.0362)	(0.125)
Total livestock units (ihs)		0.0497	0.497***
		(0.0268)	(0.0703)
Constant	-2.436	3.820***	-1.385***
	(2.353)	(0.0908)	(0.175)
Observations	5 934	5 934	5 934
Sigma u	9.125	9.125	9.125
Sigma v	0.743	0.743	0.743

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's own elaboration from the Nigeria General Household Survey.

5.2 The food insecurity-technical efficiency nexus

The second step of the analysis is to assess the relationship between the two food insecurity measures outlined in Section 3.3 and the agricultural technical efficiency estimates of the previous section. Following the literature, simple probit results are first presented. Compared to Hakim, Haryanto and Sari (2021) and Nsiah and Fayissa (2019), who use data envelopment analysis to estimate technical efficiency, this paper employs stochastic frontier analysis that, as explained in Section 3.1, allows to separate random noise in the error term from the actual efficiency score and is thus better suited than DEA. Oyetunde-Usman and Olagunju (2019) also use the SFA model with Nigeria's GHS data, but only focus on the 2015–2016 wave, while in this setting all three waves are employed in a pooled model with standard errors clustered at the province level. Moreover, this paper relies both on more encompassing measures of food insecurity compared to the previous literature and on a richer set of covariates.

Then, to tackle potential endogeneity concerns and further refine the estimation of the food insecurity-technical efficiency nexus, an instrumental variable strategy is employed using a biprobit model as outlined in Section 3.3. Two are the instruments for agricultural technical efficiency: the rainfall long-term mean and its short-term deviations. The former is more stable over time and is thus not always significant in the first stage estimates, while the latter has higher relevance to the endogenous independent variable. On the other hand, the rainfall long-term mean is more likely to satisfy exogeneity claims. The combination of the two can thus be employed to test the validity of this empirical approach thanks to the Sargan-Hansen test of overidentifying restrictions, as outlined in Section 5.2.3.

To better gauge the different influence of each covariate group, all regression tables first present the relationship between technical efficiency and food insecurity with just the addition of year fixed effects and then subsequently add all covariate groups. The last one to be added is the set of agricultural variables, since it leads to a drop in the sample of 43 observations. Results are thus not directly comparable to the other specifications. Nevertheless, the importance of this covariate group requires its inclusion to inform policy considerations. Each table reports both the probit/biprobit coefficients, which are not directly interpretable, and the corresponding marginal effects, together with the respective robust standard errors.

5.2.1 Results from Probit estimation

Tables 5a and 5b present the probit results for the effect of agricultural technical efficiency on moderate and severe food insecurity, respectively. The sign of the relationship is always negative, and the effects are significant for both the moderate and the severe food insecurity specifications. Moreover, the marginal effects are increasingly larger across the two types of food insecurity. This suggests that the effect of improved technical efficiency is particularly strong for the harsher type of food insecurity, while it is not for the more moderate version, although no causal statements can be made. Marginal effects and coefficient magnitudes are also generally stable across the various specifications, indicating that the different covariate sets do not significantly affect the estimations.

Table 5. Probit results

a. Moderate food insecurity

	x1	x2	x3	x4	x5	x6	x7
	Moderate food insecurity						
Technical efficiency	-1.234*** (0.362)	-1.091*** (0.379)	-1.051*** (0.388)	-1.060*** (0.391)	-1.066*** (0.392)	-1.067*** (0.397)	-1.028** (0.428)
Marginal effect							
Technical efficiency	-0.453*** (0.131)	-0.390*** (0.134)	-0.374*** (0.137)	-0.375*** (0.137)	-0.360*** (0.131)	-0.351*** (0.129)	-0.329** (0.136)
Year FE	YES	YES	YES	YES	YES	YES	YES
Socioeconomic variables	NO	YES	YES	YES	YES	YES	YES
Geographical variables	NO	NO	YES	YES	YES	YES	YES
Transfers and wages	NO	NO	NO	YES	YES	YES	YES
Input costs	NO	NO	NO	NO	YES	YES	YES
Output prices	NO	NO	NO	NO	NO	YES	YES
Agricultural variables	NO	NO	NO	NO	NO	NO	YES
Observations	1 026	1 026	1 024	1 024	1 024	1 024	981

b. Severe food insecurity

	x1	x2	x3	x4	x5	x6	x7
	Severe food insecurity						
Technical efficiency	-1.619*** (0.409)	-1.479*** (0.413)	-1.406*** (0.421)	-1.435*** (0.424)	-1.340*** (0.429)	-1.371*** (0.434)	-1.509*** (0.476)
Marginal effect							
Technical efficiency	-0.576*** (0.143)	-0.522*** (0.143)	-0.493*** (0.146)	-0.498*** (0.145)	-0.447*** (0.141)	-0.439*** (0.137)	-0.483*** (0.150)
Year FE	YES	YES	YES	YES	YES	YES	YES
Socioeconomic variables	NO	YES	YES	YES	YES	YES	YES
Geographical variables	NO	NO	YES	YES	YES	YES	YES
Transfers and wages	NO	NO	NO	YES	YES	YES	YES
Input costs	NO	NO	NO	NO	YES	YES	YES
Output prices	NO	NO	NO	NO	NO	YES	YES
Agricultural variables	NO	NO	NO	NO	NO	NO	YES
Observations	1 022	1 021	1 020	1 020	1 020	1 020	978

Notes: Robust standard errors clustered at the province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's own elaboration from the Nigeria General Household Survey.

5.2.2 Results from Biprobit estimation

Tables 6a and 6b present the biprobit results. The tables follow the same structure as the probit ones, with the addition of the first stage estimates of the instrumental variables. The negative impact of agricultural profit technical efficiency on food insecurity is confirmed and with slightly larger point estimates compared to the probit estimates.

As shown in Table 6a, the effect on moderate food insecurity is consistently estimated, with a 1 percent level of statistical significance in all specifications. The marginal effect fluctuates around -0.4: the elasticity is 43 percent in model x6 and it is 37 percent in model x7, which is characterized by the full set of covariates (i.e. including also agricultural variables) but also by a smaller sample size. The severe food insecurity estimates in Table 6b are slightly larger: the estimated impact of a 1 percentage point increase in technical efficiency ranges between 0.43-0.46 percentage point decrease in severe food insecurity, depending on the model and sample size considered. Also in this case, these are quite stable and precisely estimated coefficients across the range of covariate sets.[6]

The *rho=0* tests for the moderate food insecurity specifications clearly indicate the preference of the biprobit model over the basic probit one, with p-values well below the standard 0.05 threshold. However, in the case of the severe food insecurity specifications, p-values are above the standard threshold. This suggests that probit should be preferred over biprobit, but interestingly the estimates for the two models are very similar for severe food insecurity, with a marginal effect between -0.44 and -0.48 in the probit estimates with full specifications. As a results, in this case the two models point to similar conclusions also in terms of point estimates' magnitude.

Looking at the first stage estimates, it is evident how the strongest instrument for the technical efficiency variable is the rainfall deviations from the long-term mean, with a positive coefficient. Conversely, the rainfall long-term mean has a less precisely estimated negative effect on agricultural technical efficiency. However, as already mentioned, the inclusion of this second instrument is conceptually important to have the IVs affecting both the frontier and the inefficiency components of the SF, and can help to assess the robustness of the empirical strategy, which is the focus of the next subsection.[7]

[6] Full regression tables are available from the author upon request.

[7] Excluding the second IV does not significantly impact the estimates. Results available from the author upon request.

Table 6. Biprobit results

a. Moderate food insecurity

	x1		x2		x3		x4		x5		x6		x7	
	Moder FI	TE	Moder FI	TE	Moder FI	TE	Moder FI	TE	Moder FI	TE	Moder FI	TE	Moder FI	TE
Technical efficiency	-1.560***		-1.363***		-1.362***		-1.387***		-1.409***		-1.420***		-1.246***	
	(0.367)		(0.386)		(0.391)		(0.393)		(0.390)		(0.398)		(0.429)	
Marginal effect														
Technical efficiency	-0.527***		-0.450***		-0.447***		-0.452***		-0.439***		-0.431***		-0.371***	
	(0.121)		(0.125)		(0.126)		(0.126)		(0.119)		(0.119)		(0.126)	
First stage														
IV: Rainfall deviation from LR mean		5.547***		5.837***		6.069***		6.025***		5.237*		6.086*		8.191**
		(1.978)		(2.033)		(2.216)		(2.259)		(2.699)		(3.282)		(3.751)
IV: Rainfall LR mean		-0.399**		-0.372		-0.410*		-0.415*		-0.187		-0.173		-0.118
		(0.163)		(0.230)		(0.231)		(0.229)		(0.278)		(0.297)		(0.377)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Socioeconomic variables	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Geographical variables	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Transfers and wages	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Input costs	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Output prices	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
Agricultural variables	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Observations	1 026	1 026	1 026	1 026	1 024	1 024	1 024	1 024	1 024	1 024	1 024	1 024	981	981
***rho=0* (p-value)**	0.0001		0.0003		0.0005		0.0003		0.0002		0.0002		0.0014	

b. Severe food insecurity

	x1		x2		x3		x4		x5		x6		x7	
	Severe FI	TE	Severe FI	TE	Severe FI	TE	Severe FI	TE	Severe FI	TE	Severe FI	TE	Severe FI	TE
Technical efficiency	-1.731***		-1.551***		-1.504***		-1.519***		-1.441***		-1.452***		-1.542***	
	(0.424)		(0.428)		(0.435)		(0.437)		(0.443)		(0.453)		(0.488)	
Marginal effect														
Technical efficiency	-0.575***		-0.511***		-0.492***		-0.492***		-0.447***		-0.432***		-0.457***	
	(0.139)		(0.139)		(0.141)		(0.140)		(0.136)		(0.134)		(0.143)	
First stage														
IV: Rainfall deviation from LR mean		5.417***		5.616***		5.893***		5.739***		4.752*		5.015		7.498**
		(1.974)		(1.999)		(2.174)		(2.208)		(2.642)		(3.286)		(3.693)
IV: Rainfall LR mean		-0.297*		-0.242		-0.248		-0.235		-0.061		0.066		0.136
		(0.160)		(0.222)		(0.223)		(0.220)		(0.265)		(0.296)		(0.371)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Socioeconomic variables	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Geographical variables	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Transfers and wages	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Input costs	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Output prices	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
Agricultural variables	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Observations	1 022	1 022	1 021	1 021	1 020	1 020	1 020	1 020	1 020	1 020	1 020	1 020	978	978
***rho=0* (p-value)**	0.1808		0.2108		0.2467		0.3248		0.2630		0.3909		0.4989	

Notes: Robust standard errors clustered at the province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's own elaboration from the Nigeria General Household Survey.

5.2.3 Instrument validity

To give further evidence on the robustness of the empirical strategy, the Sargan-Hansen test of overidentifying restrictions is employed. When at least two instrumental variables are employed and there are doubts about the exogeneity of one of the two, this test allows to assess whether the hypothesis of joint validity of the instruments is rejected. The second IV, the rainfall long-run mean, has a very low likelihood of being endogenous given its slow movements over time. Therefore, Table 7 reports the p-values of the Sargan-Hansen test, which has a null hypothesis of joint validity of the instruments.[8] With one exception, the p-values are all above the conventional threshold of 0.05, implying that that null hypothesis is not rejected. Only the p-value for model x7 in the moderate food insecurity specification, which has a smaller sample size, is below 0.05 but well above the 0.01 threshold. For the most policy-relevant measure, severe food insecurity, the p-values of all specifications are well above any conventional threshold.

Table 7. Sargan-Hanses tests of overidentifying restrictions

	x1	x2	x3	x4	x5	x6	x7
	Moderate food insecurity						
Sargan-Hansen test (p-value)	0.149	0.369	0.289	0.183	0.347	0.258	0.041
	Severe food insecurity						
Sargan-Hansen test (p-value)	0.344	0.588	0.402	0.271	0.579	0.587	0.311

Source: Author's own elaboration from the Nigeria General Household Survey.

[8] The test was run using a linear probability model (i.e. the standard 2SLS), since it is not available for the biprobit. The actual estimation of the coefficients using this model is not relevant for this context, since the dependent variables of both first and second stages are bounded between 0 and 1, and the 2SLS would not produce consistent results.

6 Conclusions

This paper contributes to the literature on food insecurity, a very pressing issue in Nigeria, and explores one of the main mechanisms through which both farmer and policymakers can cope with it: by enhancing agricultural technical efficiency. The relation between food insecurity and technical efficiency is in fact very strong and statistically significant: Nigerian provinces with more efficient farmers can thus expect to reduce food insecurity rates. This nexus is robust to controlling for different sets of covariates, to the use of both simple probit and more sophisticated biprobit estimations, and to robustness tests to the proposed identification strategy.

Interestingly, the impact of improved technical efficiency is stronger for harsher types of food insecurity, which are also the most urgent and relevant ones for policymakers. The estimated impact of a 1 percentage point increase in agricultural technical efficiency is between 0.37–0.43 percentage point reduction in moderate food insecurity, and the equivalent effect on severe food insecurity is in the range of 0.43–0.46 percentage point decrease. This is a quite high elasticity, a promising avenue that policymakers should try to exploit, by targeting the inefficiencies that characterize Nigerian farmers. Both land use, climatic, market, socioeconomic and social protection aspects should be taken into consideration in this context.

Moreover, technical efficiency is only one of the four components of total factor productivity (TFP), together with technological progress, allocative efficiency and economies of scale (see Christensen, 1975; Plastina and Lence, 2018). This points to a limitation of the paper, but also implies that greater advancements in food security can be unlocked by tackling the other three components. Future research should address more holistically the nexus between total factor productivity and food security, by gauging the relative weight and direct impact of each of the four TFP components. Then, cost–benefit analyses can be useful to evaluate the soundness of policies and investments aimed at improving total factor productivity and, ultimately, food security.

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