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**Financial Inclusion, Agricultural Inputs Use, and
Household Food Security**

Evidence from Nigeria

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Abstract

This paper examines the effects of financial inclusion on adoption and intensity of use of agricultural inputs and household welfare indicators using data from the nationally representative Nigerian LSMS wave-3 (2015/2016) survey. For this, we constructed a financial inclusion index from four formal financial services access indicators (bank account, access to credit, insurance coverage, and digital transaction) using multiple correspondence analysis (MCA). We used Cragg's two-step hurdle, instrumental variables for binary response variables, and a Generalized Method of Moments (GMM) models in the econometric analysis. Results show that households with access to formal financial services are more likely to adopt agricultural inputs and to apply these more intensively. These same households are less likely to experience severe food insecurity and are more likely to consume diverse food items. We also find that these effects are less for female farmers regardless of formal financial inclusion, suggesting that they may bear more non-financial constraints than their male counterparts. The results suggest a need for targeted interventions to increase access to formal financial services of farm households and gender-responsive interventions to address the differential constraints women farmers face.

Key words: Financial inclusion, Inorganic fertilizer, Improved seeds, Food security, Nigeria

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1. INTRODUCTION

Over the past decade or two, many low- and middle-income countries have been attempting to develop inclusive financial systems and policies that benefit poor and marginalized members of society. This is because existing evidence shows that access to financial services plays a crucial role in boosting employment, lowering inequality, and accelerating household welfare improvement (OECD, 2017; OECD, 2019; Owen and Pereira 2018; Asante et al. 2023). An inclusive financial system facilitates the provision of financial services to the unbanked segments of society and benefits lower income households (Beck et al. 2007; Mehrotra and Yetman 2015; Owen and Pereira 2018; Asante et al. 2023), as it allows them to invest in welfare improving outcomes such as education, health and livelihood opportunities and as a result help them manage income shocks, while also facilitating their escape from poverty (Clarke, Xu & Zou, 2006; Jahan & McDonald, 2011).

According to the World Bank, financial inclusion is defined by access to and use of formal¹ financial services—savings, payments, credit, and insurance—by individuals, households, and businesses, and which meet their needs. The African Development Bank (AfDB, 2013) defines it as any measure that brings formal financial services to all sectors of the population, making them available, inexpensive, and accessible. Financial inclusion starts with having a deposit or transaction account at a bank or other financial institution or through a mobile money service provider, which can be used to make and receive payments and to store or save money. In addition to having accounts, financial inclusion also includes access to credit from formal financial institutions that allow adults to invest in educational and business opportunities, as well as the use of formal insurance products that allow people to better manage financial risks. In short, financial inclusion is the availability and accessibility of formal financial services and products to individuals and businesses regardless of their income level, social status, and geographical location.

Globally, financial inclusion improved by 18 percentage points between 2011 and 2017, but in sub-Saharan Africa (SSA) only 43 percent of adults have a bank account (Global Findex 2017), suggesting that there are regional disparities in financial inclusion. The SSA region is still known for having low levels of financial inclusion, indicating that many adults in SSA are financially excluded (Demirgüç-Kunt et al., 2018). Despite some gains in improving financial inclusion over the past decade (CBN, 2018), Nigeria’s rural population

¹ Formal financial services are financial services provided by institutions that are subject to laws, regulations, and supervision such as banks and insurance companies. Informal finance takes the form of loans from moneylenders, landlords, and family who base the financial transaction on business/personal relationships.

remain largely financially excluded. For instance, studies show that of the 38 million Nigerian adults that are financially excluded, 81 percent are from rural areas (EFInA, 2020). Similarly, only 38 percent of adults living in Nigeria's rural areas are close to financial access points or service providers, and 84 percent of these are run by financial service agents which further highlights rural-urban disparities in financial inclusion (Swamy, 2014).

Within the rural settings, smallholder farmers are particularly constrained by a lack of access to financial services (Benami and Carter, 2021; Ouma et al., 2017). Mitigating these challenges and ensuring access to financial products reduces farmers' financial constraints and makes it easier for them to obtain productive technological inputs (Levine et al., 2000; Ogouvide et al., 2020). For instance, access to digital financial services can enhance financial inclusion by enabling quicker payment channels at reduced transaction costs, increasing savings, and simplifying credit access (Demirgüç-Kunt et al., 2018; Koomson et al., 2020; Koomson, et al., 2021). Similarly, having accounts in formal financial institutions and insurance products are key for financial inclusion because accountholders are more likely to use other financial services to also save money, send and receive payments, and access credit. Access to insurance products can also help individuals and businesses invest in more profitable activities and manage risks such as weather shocks.

The objective of this study is to assess the effects of financial inclusion on farmers' access/use of yield enhancing agricultural technologies and household food and nutrition security indicators. To examine the effects empirically, we constructed a financial inclusion index from the Nigerian Living Standards Measurements Study (LSMS) wave-3 (2015/2016) data on binary responses to access to formal financial services (bank accounts, access to formal credit, insurance coverage, and digital transaction) using multiple correspondence analysis. Cragg's two-step hurdle, instrumental variables for binary response variables (IV probit), and a generalized methods of moments (GMM) for count data models were used in the econometric estimations. The remainder of the paper is organized as follows. Section 2 reviews existing literature to build a conceptual framework to guide empirical analysis. Section 3 presents descriptions of the data and empirical models. Sections 4 and 5 respectively present descriptive summaries and econometric findings. Conclusions and policy implications are summarized in section 6.

2. CONCEPTUAL FRAMEWORK

Several studies show that having access to finance helps rural households increase their productivity, market orientation, input use intensity, and incomes (Kikulwe et al., 2014; Sekabira and Qaim, 2017; Aggarwal et al., 2020; Batista and Vicente, 2020; Gopane, 2020). For example, Kikulwe et al. (2014) show that rural farmers who use mobile money are more likely to use fertilizers and pesticides, hire labor, and market a larger proportion of their output. Similarly, Cole et al. (2013) and Karlan et al. (2014) found that weather-based index insurance significantly benefits farmers, as it entices them to move from subsistence to riskier cash crops, purchase more fertilizer, plant a larger area of land, and use more farm labor, consequently resulting in higher yields. It follows that streamlining investments and consumption patterns through access to a range of financial services (banking, digital financial services, insurance, and credits) may further improve household food security through agricultural production (Gregory and Coleman-Jensen 2013).

Lack of financial inclusion could affect all the four dimensions of household food security through direct or indirect pathways (Birkenmaier et al., 2016; Fitzpatrick, 2017; Koomson et al., 2020). Without access to finance, households would not be able to purchase enough food to feed their families (*access*); farmers would not be able to raise livestock or increase crop productivity (*availability*); households would find it difficult to choose and use healthy and nutritious diets (*utilization*); and households would not be able to cope with political unrest, natural disasters, or seasonal food shortages (*stability*) (Ayantoke et al., 2011; Mora-Rivera & van Gameren, 2021; Smith & Floro, 2021; Mârza et al., 2015). For instance, using survey data from rural Zimbabwe, Murendo et al. (2020) found that financial inclusion increased food consumption and dietary diversity. Similarly, Twumasi et al. (2024) found a positive relationship between financial inclusion and nutritional intake among Ghanaian households, and this was mediated via adoption of farm technologies.

In terms of the effects of financial inclusion on long-term economic wellbeing of poor households, some studies put forward contrary arguments to commonly established ones. These studies argue that because food spending is such a regular and relatively large proportion of a poor household's expenditures (*'Engel's law'*), easy access to finance by poor households may encourage them to spend a substantial proportion of their economic resources on food (food security in the short-run) instead of on profitable investments, invest in health for increased productivity, or use these funds as a buffer against livelihood

threatening shocks (Demirguc-Kunt et al., 2017; Peprah et al., 2020; Koomson, Villano, and Hadley, 2022).

However, these studies have encountered several shortcomings and gaps. First, most of these studies (with the exception of few, for instance Demirgüç-Kunt et al., 2018; Koomson et al., 2020; Koomson & Danquah, 2021) have considered some specific dimensions of financial inclusion, such as credit access (Ayantoke et al., 2011), remittance (Mora-Rivera & van Gameren, 2021; Smith & Floro, 2021) and agricultural insurance (Mârza et al., 2015), but have not employed a financial inclusion index constructed from a range of formal financial access indicators. Second, many of these studies rely on anthropogenic proxy measures of food security such as calorie intake and food expenditure. Third, most of the studies only look at specific members of the household like children (Fitzpatrick, 2017) instead of the entire household as a unit partly due to data unavailability. Finally, even though there is growing evidence regarding the interaction between household consumption and investment decisions (Kikulwe et al.), it is possible that investments in farm inputs and technologies could potentially serve as mechanism for household food security, and therefore requires thorough empirical investigation.

This paper attempts to address these shortcomings. We address the first gap by using a multiple correspondence analysis (MCA) model to construct a financial inclusion index from a set of categorical (0/1) financial access indicators: whether a household has bank accounts; whether a household utilizes digital financial services; whether a household has access to formal credits; and whether a household has insurance coverage; and whether a household uses any other types of formal financial services. Because MCA is a multivariate dimensionality reduction technique for categorical data, we use this model to identify and depict the underlying structures in a data set (Aslan et al. 2017).

To address the second gap, we employ a set of experience-based and dietary choice food security metrics and indicators, including the Food Insecurity Experience Scale (FIES) and Household Dietary Diversity Score (HDDS). A combination of these measures is more likely to capture the actual food security situation of households. For instance, Webb et al. (2006) and Pérez-Escamilla and Segall-Corrêa (2008) argue that personal experience of food deprivation measured using FIES reflects the real condition of food insecurity more accurately than other measures. Furthermore, in addition to the FIES, using the HDDS (Swindale and Bilinsky, 2006) ensures adequate examination of the association of financial inclusions and food (in)security measures. We also separately explore the implications of our variable of interests (financial inclusion) on the different food security measures computed for different farming seasons (i.e., post-planting and post-harvest seasons).

Finally, to address data gaps and limitations, we use the Nigeria 2015/16 Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) data, a nationally representative dataset that contains rich socioeconomic, demographic, agricultural production, financial access, and food security indicators.

3. MATERIALS AND METHODS

3.1 Data

We used the 2015/16² LSMS-ISA data, which is the third wave of the LSMS-ISA panel dataset for Nigeria, because the earlier waves do not have adequate information on financial services, particularly digital finance. This wave consisted of a nationally representative sample of about 5,000 households sampled across 519 enumeration areas (EAs). Households were visited twice, post-planting and post-harvest visits between July and September 2015 and January and February 2016, respectively. The survey consisted of four modules (two household modules and two agriculture modules), administered in two seasons (post-planting and post-harvest). Beyond the standard agricultural household survey questions such as demographic and assets, the four modules contain a rich set of financial, food security, and agriculture data relevant to this study—this includes questions on household food (in)security indicators and households' coping strategies to food insecurity; financial access indicators (saving, insurance, ICT/digital banking including mobile money and credit); and agriculture-related questions such as use and costs of inputs, extension services, and agriculture capital.

3.2 Construction of financial inclusion index and outcome variables

We constructed a *financial inclusion (FI) index* using a Multiple Correspondence Analysis (MCA)³ model (Abdi and Valentin 2007; Aslan et al. 2017) using categorical (yes/no) financial access variables including household use of bank accounts, digital financial services, credits, insurance, and other types of financial services. These variables take the value 1 if household uses/accesses each of them or 0 otherwise. The MCA is non-parametric and does not require multivariate normality or linearity as preconditions, in contrast to principal and factor analyses (Aslan et al. 2017). Following the procedures outlined by Aslan

² We used the 2015/2016 LSMS-ISA Data because it has variables on digital financial services. This is because the measure of financial inclusion (FI) now transcends beyond conventional measures, and according to the World Bank, includes a wide range suite of financial services, particularly, access to digital financial services such as Mobile Money.

³ MCA can be seen as a generalization of principal component analysis for categorical variables.

et al. (2017), all the financial indicators utilized in the construction of the FI index are associated with financial inclusion.

We use the two measures of food (in)security indicators: (i) food insecurity experience scale (FIES) and (ii) household dietary diversity scores (HDDS).

FIES was obtained by taking responses to the last three questions out of the eight established standard FIES questions (FAO, 2016). As established in literature (FAO, 2016), the eight binary (yes/no) FIES questions sequenced from the least severe food insecurity experience (question 1) to the most severe experience (question 8). The last three FIES questions are the most severe ones. These include whether the household experienced *'running out of food'* (question 6); *'were hungry but did not eat'* (question 7), and *'went without eating for a whole day'* (question 8) because of a lack of money or other resources in a given reference time (usually 7 days) prior to the survey. So, we examined the effect of financial inclusion on the likelihood that a household would be exposed to the three severe food insecurity experiences.

HDDS (Household Dietary Diversity Scores (HDDS)) was constructed following Swindale et al (2006) by using the "yes/no" responses to the 12 food groups that a household consumed over a certain reference period as the dietary diversity indicator. A binary response was summed horizontally to form the HDDS which ranges from zero at the minimum to twelve at the maximum.

Agriculture input uses (inorganic fertilizer and improved seeds) were first defined based on whether the household used any of these inputs and were constructed from binary 'yes/no' questions. We then measured the intensity of input use by taking the sum of the quantities used of a given input on all plots of a household cultivated. We also obtained the values of these inputs using the input prices recorded in the survey.

3.4 Econometric models

Financial inclusion, our main variable of interest, is not randomly assigned to individual households, which leads to a potential endogeneity problem, in other words, the financial inclusion variable may be correlated with the error term as due to unobserved factors that affect the outcome variables might also affect the financial inclusion status of households. For instance, people with specific cultural or belief systems or risk averse behavior do not prefer to engage in borrowing (financial access) and do not invest in yield-enhancing modern agricultural inputs. Such people self-select themselves from financial access as well as use agricultural inputs with negative effects on household food security.

Thus, to account for such potential endogeneity, we used an instrument variable (IV) or exclusion restriction variables approach in our econometric estimation.

Endogeneity associated with financial inclusion is resolved using *mobile phone ownership, internet access, use of e-wallet and distance to nearest population center with over 20,000 people* as instruments (exclusion restriction) in the double-hurdle, IV probit, and IV Poisson models. These variables satisfy the three main requirements for instrumental variables: (i) it must have a significant correlation with the endogenous explanatory variables (relevance); (ii) it must have no direct effect on the outcome variable except through the endogenous variable (exclusion); and (iii) it must be uncorrelated with the error term (independence).

Three sets of economic models were used to model the three outcome areas considered in this study: the *Cragg’s double hurdle model* for adoption and intensity of use of agriculture inputs, the *instrumental variable probit (IV Probit) model* for household food security measured via experience-based food insecurity indicators, and the *instrument variable model for count data (IV Poisson)* for modelling the household dietary diversity.

3.4.1. Double-hurdle model

We apply a two-step (double hurdle) model (Cragg, 1971) to estimate the adoption decision and intensity of use for two agricultural inputs (inorganic fertilizer and improved seeds). The double hurdle model combines a selection model that determines the boundary points of the dependent variable with an outcome model that determines its unbounded values. In double hurdle models zero observations can be generated by more than one process. They may reflect an unconstrained farmer’s optimal choice (a corner solution) or a farmer’s inability to acquire the technology due to constraints despite a positive desired demand for the technology. The double hurdle model simultaneously estimates the parameters of the factors influencing access to (participation probability) and intensity of use or demand for the technology (Croppenstedt et al., 2003).

We model a farmer’s adoption decision using an indicator function, based on net returns where the farmer chooses to use the input if the expected net returns are higher when using the input than if the input is not used. Let π_{im} be the net return for the i^{th} farmer if he/she uses the input m and π_{im0} if the input is not used (equation 1).

$$I_{im}^* = \Psi(\pi_{im} - \pi_{im0}), \text{ with } I_{im} = \begin{cases} 1 & \text{if } I_{im}^* > 0 \\ 0 & \text{otherwise} \end{cases} \dots\dots\dots(1)$$

where the Ψ is a parameter and I_{im}^* is the unobservable latent variable that determines whether the i^{th} individual chooses to use input m ($I_{im} = 1$) or not to use m ($I_{im} = 0$). Following Cragg (1971), Coady (1995), and Croppenstedt et al. (2003), the desired demand for the input m by the i^{th} farmer is represented by equation (2) and access to the input given by equation (3).

$$Dm_i^* = \beta FI_i + \gamma x_i + u_i \dots\dots\dots(2)$$

$$Am_i^* = \alpha FI_i + \theta z_i + e_i \dots\dots\dots(3)$$

where Dm_i^* and Am_i^* (both unobservable) denote the farmer's desired demand for input m and the probabilities of access to m , respectively; FI_i is the financial inclusion index; x_i represents exogenous covariates that determine demand for input m ; and z_i represents variables that determine access. Note that certain x variables can appear in z , for instance demographic characteristics such as education and sex which can affect both participation (access) and intensity of use (demand), but z can contain some specific sets of variables such as mobile phone ownership or access to internet which can affect participation (access) but not input use intensity. The γ , α , β , and θ are parameters and u_i and e_i are error terms both normally distributed and with 0 means but u_i with constant variance σ_u^2 , and e_i with variance of 1 for identification.

The observed model of demand for input (Dm_i) implied by the interactions of the latent models (2) and (3) can be expressed by equation 3(a) through 3(c), which is a composite model of three groups of farmers. Farmers in group 1 (G1) have access to m and passed the positive demand threshold for m (equation 3a); farmers in group 2 (G2) do not want m irrespective of access status because m may be too expensive and not profitable (equation 3b); and farmers in group 3 (G3) want input m but cannot get it because they cannot access it (equation 3c).

$$G1: Dm_i = \beta FI_i + \gamma x_i + u_i , \text{ iff. } (Dm_i^* > 0 \text{ and } Am_i^* > 0) \dots\dots\dots 3(a)$$

$$G2: Dm_i = 0 , \text{ if } (Dm_i^* \leq 0 \text{ and } (Am_i^* > 0 \text{ or } Am_i^* \leq 0)) \dots\dots\dots 3(b)$$

$$G3: Dm_i = 0 , \text{ if } (Dm_i^* > 0 \text{ and } Am_i^* \leq 0) \dots\dots\dots 3(c)$$

Assuming that participation and access are independent, the log-likelihood function for the double hurdle model for equation 3(a) through 3(c) as in (Croppenstedt et al., 2003) is estimated using the *churdle* command⁴ in the Stata software package.

3.4.2 IV Probit model

The three experience-based food insecurity indicators (FIES) used as dependent variables are binary (yes/no) variables. As described above, our main variable of interest, financial inclusion, may be endogenous. Thus, we used an instrumental variable probit (IV probit) to model the food insecurity indicators. IV probit are best suited to models for binary dependent variables where one or more of the covariates are endogenous and errors are normally distributed (Cameron and Trivedi, 2010). The maximum likelihood estimator is used to estimate the model. The IV probit model is specified as in equations 4(a) and 4(b):

$$y_{1i} = \beta FI_i + \gamma x_{1i} + u_i \quad \dots\dots\dots 4(a)$$

$$FI_i = \lambda x_{1i} + \psi x_{2i} + v_i \quad \dots\dots\dots 4(b)$$

where y_{1i} is the binary FIES variable; FI_i is the financial inclusion index; x_{1i} is a vector of exogenous variables, x_{2i} is a vector of instrumental variables (*mobile phone ownership, internet access, use of e-wallet, and distance to nearest population center*); β and γ are structural parameters; and λ and ψ are reduced form parameters. The $(u_i; v_i)$ is assumed to be independent and identically distributed multivariate normal, i.e., $(u_i; v_i) \sim N(0, \Sigma)$ where Σ is the variance-covariance matrix of the errors in the two equations and the variance of u_i , i.e., σ_{11} is normalized to one to identify the parameters. The maximum likelihood estimator is used to estimate the IV probit model.

3.4.3 Non-linear IV Poisson model

The HDDS, as constructed in section 3.2, exhibits the features of count data. But because financial inclusion exhibits endogeneity, an instrumental variable Poisson regression (IV Poisson) was used. However, the two-stage least squares linear instrumental variable (IV) models do not extend to nonlinear models such as the Poisson model with endogenous regressors (Cameron and Trivedi, 2010, p.392). One of the possible methods to control endogeneity in nonlinear models such as the Poisson model is use of the nonlinear instrumental variable (NLIV) or the generalized method of moments (GMM) estimator. The

⁴ *churdle* command fits a linear or exponential hurdle model for a bounded dependent variable. We fit a linear hurdle model. It combines a selection model that determines the boundary points of the dependent variable with an outcome model that determines its nonbounded values. Separate independent covariates are permitted for each model.

model may be specified using either additive or multiplicative error terms (u_i) (equations 5(a) and 5(b)).

$$y_i = \exp(\beta_1 FI_i + \beta_2 x_i) + u_i \dots\dots\dots 5(a) \quad (\text{additive error})$$

$$y_i = \exp(\beta_1 FI_i + \beta_2 x_i) u_i \dots\dots\dots 5(b) \quad (\text{multiplicative error})$$

where the dependent variable $y_i = 1, 2, 3 \dots, 12$) represents the HDDS as constructed in section 3.2; the FI_i and x_i are as defined above; and u_i an error term; the covariates x_i are independent of u_i ; while FI_i is not. A maximum likelihood estimation method using the ‘*ivpoisson gmm*’ Stata command estimates model parameters.

4. DESCRIPTIVE RESULTS

Table 1 presents the summary statistics of the variables used in this paper. Results show that about 40 percent of households surveyed used at least one financial service, with 38 percent owning and using a bank account. However, access to credit and insurance is highly limited with only 3 percent of households having access to these services⁵. Additionally, about 11 percent of households have access to digital financial services. These results align with EFINA (2016) findings which reported that only 3 percent of Nigerian adults enjoy credit access and 2 percent have insurance policies. Similarly, EFINA (2016) reported that 38 percent of adults use formal payment systems, consistent with our estimates.

Results further show that the percentage of respondents experiencing the three severe food insecurity indicators were significantly lower in the post-harvest survey than the post-planting survey: ‘*Run out of food*’ (6.1 percent compared to 26.5 percent); ‘*Hungry but did not eat*’ (5.6 percent compared to 19.8 percent); and ‘*Without eating whole day*’ (2 percent compared to 7 percent). This temporal variation in food insecurity indicators likely reflects the seasonality and transitory nature of food (in)security in Nigeria. Edeh and Gyimah-Brempong (2015) similarly reveal notable seasonal shifts in household food security. Their findings indicate that households typically experience heightened food insecurity during the post-planting phase compared to the post-harvest period.

As expected, mobile phone use among the sample is higher than internet access. Approximately 78 percent of households used mobile phones, while only 24 percent had

⁵Of the four formal financial services access indicators (bank account, access to credit, insurance coverage, and digital transaction); use of ‘bank account’ appears to be more prevalent than other services by the respondents. Thus ‘bank account’ may potentially dominate the explanatory power of the financial inclusion index (FII) compared to the other indicators used in the construction of the FII. Yet, we still argue that an index constructed from multiple indicators is a better instrument to gauge formal financial services access than using only one indicator.

internet access. Use of e-wallet use was even lower, at about 3 percent. Mobile phones and internet penetration can promote financial inclusion through the adoption of digital financial services such as mobile banking, which can significantly improve household welfare (Peprah et al., 2020; Kikulwe et al., 2014). According to Markovich and Snyder (2017), these digital services can gradually become the most convenient means of conducting financial transactions, especially for the unbanked and underserved populations in developing countries.

The household socioeconomic variables reveal that 41 percent own livestock while 69 percent are involved in non-farm businesses. The average household size is about 7 people. Atta-Ankomah et al. (2024) suggest that financial service tools such as digital financial services are associated with diversification into non-crop production, potentially providing access to credit and spreading risk. This diversification is particularly significant given that over 37 percent of farmers are financially excluded (EFINA, 2017), leaving agriculture largely outside formal finance in Nigeria. Consequently, livelihood diversification may play a crucial role in improving both financial inclusion and household welfare.

The average distance from households to main roads and from households to market centers is approximately 6 km and 68 km, respectively. Understanding socio-demographic variables that influence access to financial services is crucial in our study. The distance to key infrastructure is particularly important because inadequate financial services in the community, combined with poor overall physical infrastructure, can exacerbate the difficulties faced by rural residents in accessing financial services. This barrier often forces citizens to travel to cities for various financial transactions (Beck et al., 2008).

Table 1: Variables explanation and descriptive statistics

Variable	Descriptions	Mean	Std.
Financial inclusion indicators			
Use financial services all	Household uses at least any of the financial services (yes/no=1/0)	0.40	0.49
Use financial services Bank	Household uses Bank account (yes/no=1/0)	0.38	0.49
Use financial services credit	Household accesses credit (yes/no=1/0)	0.03	0.18
Use financial services Insurance	Household uses insurance (yes/no=1/0)	0.03	0.17
Use financial services digital	Household uses digital financial services (yes/no=1/0)	0.11	0.31
Use financial services others	Household uses other financial services (yes/no=1/0)	0.02	0.14
Agriculture input uses			
log Inorganic fertilizer quantity	Natural log quantity of inorganic fertilizer used (kg)	1.16	2.23

Variable	Descriptions	Mean	Std.
log Inorganic fertilizer value	Natural log monetary value of fertilizer used (<i>Naira</i>)	2.16	3.96
log Improved seed quantity	Natural log quantity of improved seeds used (<i>kg</i>)	0.33	1.13
log purchased seeds value	Natural log value of improved seeds used (<i>Naira</i>)	1.55	3.23
Food (in)security indicators			
HDDS	Household Dietary Diversity Score (0-12)	8.79	1.85
'Runout of Food' (PH)	Was there a time when your household ran out of food because of a lack of money or resources? (<i>yes/no=1/0</i>)	0.061	0.249
'Hungry but did not eat' (PH)	Was there a time when your household were hungry but did not eat because of a lack of money or other resources? (<i>yes/no=1/0</i>)	0.056	0.232
'Without eating whole day' (PH)	Was there a time when your household went without eating for a whole day because of a lack of money or other resources? (<i>yes/no=1/0</i>)	0.019	0.137
'Runout of Food' (PP)	Was there a time when your household ran out of food because of a lack of money or resources? (<i>yes/no=1/0</i>)	0.265	0.441
'Hungry but did not eat' (PP)	Was there a time when your household were hungry but did not eat because of a lack of money or other resources? (<i>yes/no=1/0</i>)	0.198	0.398
'Without eating whole day' (PP)	Was there a time when your household went without eating for a whole day because of a lack of money or other resources? (<i>yes/no=1/0</i>)	0.069	0.254
Household demography variables			
log household head age	Log of household head age (<i>years</i>)	3.82	0.46
Head of Household	Headed of household (<i>Female=1</i>)	0.20	0.40
Household Size	Number of household member (#)	6.98	3.67
Non-farm business	Household engage in non-farm business (<i>yes/no=1/0</i>)	0.69	0.46
Area of cultivated farm size	Household farm size under cultivation (<i>ha</i>)	0.68	2.09
Extension services access	Access to extension services (<i>yes/no=1/0</i>)	0.05	0.21
Distance to Road (Km)	Distance to nearest main road (<i>Km</i>)	5.84	7.88
Distance to Market (Km)	Distance to nearest market (<i>km</i>)	67.71	43.61
HH own livestock	Household owns livestock (<i>Yes/no=1/0</i>)	0.41	0.49
log Assets value	Log of Household assets value (<i>Naria</i>)	9.71	3.25
livelihood diversification status	Household diversify livelihood (<i>yes/no=1/0</i>)	0.41	0.49
ln total income (Naira)	Log of house total income (<i>Naira</i>)	10.84	4.21
Instruments			
Use mobile Phone	Household uses mobile phone (<i>yes/no=1/0</i>)	0.87	0.34
Use Internet access	Household have internet access (<i>yes/no=1/0</i>)	0.24	0.42
Use E-wallet	Household uses E-wallet (<i>yes/no=1/0</i>)	0.03	0.16
Distance to Population Center	Distance to population center with 20,000 people (<i>km</i>)	23.85	20.19

Source: Authors' computation, LSMS-ISA 2015/2016

Note: PH= post-harvest survey; PP= post-planting survey; Naira= Nigerian currency.

4. ECONOMETRIC RESULTS

We first present the econometric results from the double hurdle model on the adoption and intensity of use of two agricultural inputs—inorganic fertilizer and improved seeds—in Table 2. The decision to adopt and the intensity of use of inorganic fertilizer and improved seeds were considered as a two-step decision: whether to use these inputs (first step) and the quantity or rate of use (i.e., the intensity of use) of the inputs conditional on a positive value of their use (second step). Our focus in this paper is to demonstrate empirically whether financial inclusion affects adoption and intensity of the use of these inputs among smallholders in Nigeria. In addition to assessing the role of financial inclusion, we also examine the effects of other covariates such as extension services, off-farm activities, and demographic factors on the adoption and intensity of these agricultural technologies. The results in Table 2 show that financial inclusion has positive and statistically significant effects (at the 1-percent level) on both the adoption and intensity of use of inorganic fertilizer and improved seeds. The positive effect appears to be stronger for fertilizer adoption than improved seeds. Similarly, the effect is stronger for the adoption decision than intensity of use; in other words, lack of financial inclusion is a binding constraint among non-adopters of these agricultural technologies. Our findings are consistent with existing literature. For instance, Levine et al. (2000) and Ogouvide et al. (2020) demonstrated that expanding access to financial services enables farmers to acquire essential technological inputs and ultimately boosts their productivity and economic resilience. Similarly, Abate et al. (2017) observed that access to institutional finance has a significant positive effect on both the adoption and the extent of agricultural technology use.

Examining the effects of demographic and gender factors, we find that women-headed households are significantly disadvantaged (at the 1-percent level) in the use of inorganic fertilizer. As demonstrated in similar studies (e.g., Shiferaw et al., 2008), our empirical results reveal the challenges women farmers face in SSA. Women's inability to access yield-enhancing agricultural inputs or inadequate application of these inputs leads to lower output and lower associated incomes that reduce women's economic wellbeing for most women-headed households in SSA (Balana et al., 2021). We also see that the effects of household size are positive and statistically significant (at the 1-percent level) for adoption and intensity of use of these technologies.

We find that while access to extension services and farm size positively influence the adoption and intensity of technology, distance to market has a negative effect. Our findings align with Wainaina et al. (2016), who demonstrated an inverse relationship between market

distance and the adoption of agricultural innovations such as improved seeds and mineral fertilizers. This relationship is plausible, as greater market distance inherently increases both transportation and transaction costs. Consequently, farmers in more remote areas are less likely to utilize purchased inputs, highlighting the spatial dimension of agricultural technology adoption.

In contrast to our *a priori* expectation, having an off-farm business has a negative and significant effect on adoption and intensity models. A possible explanation could be that the negative coefficients for off-farm business—farmers may intend to expand their off-farm business in lieu of investing in agricultural technologies. Wambugu et al. (2018) established that non-farm income has an insignificant effect on adoption and intensity of improved seeds and inorganic fertilizers, further underscoring the trade-offs between households' investments in agricultural technologies and non-farm related investments when they participate in non-farm livelihood activities. Our findings, however, broadly imply that improving access to financial services may particularly spur the intensity of use of agricultural technologies (chemical fertilizers and improved seeds) in Nigeria. As farmers' financial inclusion increases, the probability and intensity of adopting modern agricultural technology also increases.

Table 3 reports the IV probit regression results for indicators of household food security measured in the experience-based food insecurity indicators (FIES). As discussed in the 'methods' section, we focused on the last three FIES questions which indicate the more severe food insecurity experience households encountered prior to the survey. These include: (i) '*Was there a time when your household **ran out of food** because of a lack of money or resources?*' (yes=1/no=0); (ii) '*Was there a time when your household **were hungry but did not eat** because of a lack of money or other resources?*' (yes=1/no=0); and (iii) '*Was there a time when your household **went without eating for a whole day** because of a lack of money or other resources?*' (yes=1/no=0). These questions were administered in both the post-planting and post-harvest surveys of the Nigerian LSMS wave-3 (2015/16). As reported in the descriptive statistics (Table 1), the FIES data for post-harvest survey did not have sufficient observations in the three FIES indicators considered, thus we used the post-planting data in the econometric analysis.

The Wald tests of exogeneity reported at the bottom Table 2 indicate the financial inclusion variable is endogenous (i.e., rejection of the null of no correlation between the financial inclusion and the model error). Thus, the use of instrumental variable (IV) probit regression is justified. Regression results show that the coefficient of financial inclusion

variable is negative and statistically significant (at 1 percent level) for all the three FIES indicators. For instance, at the margin, financially included households are over 25 percent less likely to experience '*running out of food*' and over 11 percent less likely to experience '*getting hungry but did not eat*'.

Table 2. Estimation results of the two-step hurdle model—adoption and use intensity of inorganic fertilizer and improved seeds

Independent variables	Inorganic fertilizer				Improved seeds			
	Adoption (selection) decision		Intensity of use		Adoption (selection) decision		Intensity of use	
	Coeff. (std. err)	Marginal Effects (dy/dx)	Coeff. (std. err)	Marginal Effects (dy/dx)	Coeff. (std. err)	Marginal effects (dy/dx)	Coeff. (std. err)	Marginal Effects (dy/dx)
Financial inclusion index	1.254*** (0.131)	0.851*** (0.185)	0.722*** (0.267)	0.851*** (0.185)	0.599*** (0.122)	0.072*** (0.020)	0.346*** (0.095)	0.072*** (0.020)
Access to extension (<i>yes=1</i>)	0.676*** (0.888)	1.016*** (0.156)	-0.027 (0.137)	1.016*** (0.156)	0.772*** (0.087)	1.661*** (0.188)	-0.187 (0.137)	1.661*** (0.188)
Log household head age (<i>years</i>)	-0.014 (0.045)	-0.043 (0.065)	-0.096 (0.097)	-0.043 (0.065)	0.040 (0.046)	0.099 (0.102)	0.051 (0.089)	0.099 (0.102)
Household size (<i>head count</i>)	0.057*** (0.006)	0.084*** (0.008)	0.034*** (0.013)	0.084*** (0.008)	0.032*** (0.006)	0.073** (0.014)	0.016 (0.013)	0.073** (0.014)
Sex household head(<i>female=1</i>)	-0.439*** (0.061)	-0.629*** (0.070)	-0.481*** (0.146)	-0.629*** (0.070)	-0.042 (0.056)	-0.141 (0.127)	-0.237** (0.120)	-0.141 (0.127)
Cultivated farm size (<i>ha</i>)	0.028*** (0.009)	0.084*** (0.014)	0.188*** (0.029)	0.084*** (0.014)	0.025** (0.010)	0.055** (0.023)	-0.007 (0.013)	0.055** (0.023)
Off-farm business (<i>yes=1</i>)	-0.173*** (0.049)	-0.099 (0.070)	0.503*** (0.095)	-0.099 (0.070)	-0.268*** (0.050)	-0.630*** (0.111)	-0.195** (0.098)	-0.630*** (0.111)
Distance to nearest road (km)	0.001 (0.003)	0.004 (0.004)	0.014** (0.005)	0.004 (0.004)	0.001 (0.003)	0.004 (0.004)	0.014** (0.005)	0.004 (0.004)
Distance to nearest market (km)	-0.006*** (0.001)	-0.006*** (0.001)	0.004*** (0.001)	-0.006*** (0.001)	-0.002*** (0.001)	-0.004*** (0.001)	0.003** (0.001)	-0.004*** (0.001)
HH uses mobile phone (<i>yes=1</i>)	0.231** (0.095)	0.289** (0.111)	-	-	0.412*** (0.106)	0.908*** (0.232)	-	-
HH use e-wallet (<i>yes=1</i>)	0.605*** (0.121)	0.912*** (0.197)	-	-	0.123 (0.125)	0.271 (0.274)	-	-
Distance nearest pop Center (km)	0.013*** (0.001)	0.017*** (0.002)	-	-	0.000 (0.001)	0.001 (0.003)	-	-
Constant	-1.113***	-	4.106***	-	-1.331***	-	7.701***	-
Ln sigma	0.348***				0.2895***			
/sigma	1.416				1.3358			
	Log likelihood: -4297.15				Log likelihood: -3873.756			
	LR Chi2(9): 897.48				LR Chi2(13): 247.15			
	Prob > chi2 : 0.000				Prob > chi2: 000			
	Pseudo R ² :0.095				Pseudo R ² : 0.0309			

Source: Authors' estimation.

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

Table 3. Results from instrumental variable probit (IV probit) model—effects of financial inclusion and other covariates on FIES

Dependent variable: Food Insecurity Experience Scale (FIES)

<i>Independent variables</i>	FIES – (Have No Food)			FIES- (Sleep Hungry Night)			FIES- (Whole Day No Food)		
	Coef. (No food)	Marginal effects (dy/dx)	Coef. (FII) (endogenous regressor) †	Coef. (Hungry)	Marginal effects (dy/dx)	Coef. (FII) (endogenous regressor) ‡	Coef. (Whole)	Marginal effects (dy/dx)	Coef. (FII) (endogenous regressor) §
Financial inclusion index	-0.425*** (0.773)	-0.425*** (0.773)	-	-0.113*** (0.615)	-0.113*** (0.615)	-	-0.309** (1.036)	-0.309** (1.036)	-
Age household head (<i>years</i>)	0.064 (0.066)	0.064 (0.066)	-0.002 (0.006)	0.039 (0.062)	0.039 (0.062)	-0.002 (0.006)	-0.023 (0.063)	-0.023 (0.063)	-0.002 (0.006)
Household size (#)	0.000 (0.009)	0.000 (0.009)	0.002*** (0.001)	0.001 (0.009)	0.001 (0.009)	0.002*** (0.001)	0.011 (0.009)	0.011 (0.009)	0.002** (0.001)
Sex household head (<i>F=1</i>)	0.135** (0.067)	0.135** (0.067)	0.009 (0.007)	0.101 (0.066)	0.101 (0.066)	0.009 (0.007)	0.096 (0.072)	0.096 (0.072)	0.010 (0.007)
Cultivated farm size (<i>ha</i>)	-0.108** (0.054)	-0.108** (0.054)	0.005*** (0.001)	-0.093* (0.049)	-0.093* (0.049)	0.005*** (0.001)	-0.010 (0.028)	-0.010 (0.028)	0.005*** (0.001)
Non-farm business (<i>yes=1</i>)	-0.097 (0.090)	-0.097 (0.090)	-0.034*** (0.008)	-0.477*** (0.073)	-0.477*** (0.073)	-0.034*** (0.008)	-0.029 (0.096)	-0.029 (0.096)	-0.034*** (0.008)
Log-durable asset values (<i>Naira</i>)	-0.231*** (0.032)	-0.231*** (0.032)	-0.046*** (0.002)	-0.255*** (0.026)	-0.255*** (0.026)	0.002 (0.026)	-0.210*** (0.046)	-0.210*** (0.046)	-0.047*** (0.002)
Log-total income (<i>Naira</i>)	-0.045*** (0.011)	-0.045*** (0.011)	-0.005 (0.001)	-0.018 (0.011)	-0.018 (0.011)	-0.005*** (0.001)	-0.042*** (0.011)	-0.042*** (0.011)	-0.003*** (0.001)
Distance to nearest market (<i>km</i>)	-0.004*** (0.001)	-0.004*** (0.001)	0.000 (0.000)	-0.002* (0.001)	-0.002* (0.001)	0.000 (0.000)	-0.003*** (0.001)	-0.003*** (0.001)	0.000 (0.000)
<i>Instruments for financial inclusion indicator (FII) endogenous regressor</i>									
HH uses mobile phone (<i>yes=1</i>)	-	-	0.004 (0.012)	-	-	0.011 (0.016)	-	-	0.005 (0.012)
HH use e-wallet (<i>yes=1</i>)	-	-	-0.016*** (0.016)	-	-	-0.003 (0.016)	-	-	-0.007 (0.017)
Distance nearest pop Center (<i>km</i>)	-	-	0.002*** (0.000)	-	-	0.002*** (0.000)	-	-	0.002*** (0.000)
Constant	1.714*** (0.547)		0.508*** (0.031)	1.958*** (0.485)		0.513*** (0.031)	1.475** (0.634)		0.497*** (0.031)
athrho2_1	0.698***	-	-	0.797***	-	-	0.377*	-	-
lnsigma2	-1.748***	-	-	-1.748***	-	-	-1.746***	-	-

Source: Authors' estimation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; FII = Financial inclusion index

†Wald test of exogeneity (corr = 0): $\chi^2(1) = 10.95$ Prob > $\chi^2 = 0.0009$.

‡Wald test of exogeneity (corr = 0): $\chi^2(1) = 15.26$ Prob > $\chi^2 = 0.0001$.

§Wald test of exogeneity (corr = 0): $\chi^2(1) = 3.10$ Prob > $\chi^2 = 0.0785$

Three of the covariates of significant interest in the regression model are the sex of the household head, land area cultivated, and household wealth status. Consistent with the preceding findings on challenges women face in accessing agricultural inputs, women-headed households are more likely to experience food insecurity than their male counterparts. For instance, results in Table 3 show that women-headed households are about 13.5 percent more likely to experience *'running out of food'* than male-headed households. Our findings are consistent with the disproportionate food insecurity burden women shoulder globally. For instance, according to WFP (2023), food insecurity disproportionately affects women globally, and women have nearly a 27 percent higher chance of being severely food insecure compared to men (WFP, 2022).

Regarding the association between cultivated land size and food security, households with larger areas of cultivated land are more likely to be food secure. This finding is consistent with Kadir and Rizky (2023) who also found that increasing household farm size could improve agricultural households' food security. This may indicate the importance of production pathways through which smallholders achieve food security in rural Africa. We used 'ownership of household durable assets' as a proxy indicator for household wealth status. Based on this metric, wealthier households are less likely to experience severe food insecurity. Overall, using a financial inclusion index, our findings provide a comprehensive measure of financial inclusion and show that financial inclusion reduces food insecurity, similar to Mora-Rivera & van Gasteren (2021) and Smith & Floro, (2021). According to Fitzpatrick (2017), unbanked households or those relying on alternative informal financial services for transactions face a higher likelihood of experiencing severe food insecurity compared to their counterparts with access to formal financial services.

Table 4. Results from Poisson model with endogenous regressors (nonlinear instrumental variable Poisson NLIV GMM model) (effects of financial inclusion and other covariates on HDDS)

<i>Independent variables</i>	<i>Dependent variable: Household Dietary Diversity Score (HDDS)</i>					
	IV Poisson GMM with additive error			IV Poisson GMM with multiplicative errors		
	Coef.	Std. Err	Coef.	Std. Err	IRR ¹	Std. Err.
Financial inclusion index	0.585***	0.052	0.621***	0.079	1.860	0.146
Age household head (<i>years</i>)	0.001	0.009	0.001	0.001	1.001	0.010
Household size (#)	0.003**	0.001	0.003**	0.002	1.003	0.002
Sex household head (<i>F=1</i>)	0.062***	0.011	0.066***	0.012	1.068	0.012
Cultivated farm size (<i>ha</i>)	0.003**	0.002	0.004**	0.002	1.004	0.002
Non-farm business (<i>yes=1</i>)	-0.031**	0.015	-0.012	0.013	0.988	0.013
Log-durable asset values (<i>Naira</i>)	-0.026***	0.007	-0.027***	0.001	0.974	0.001
Log-total income (<i>Naira</i>)	0.003	0.002	0.002	0.002	1.002	0.002
Distance to all-weather road (<i>km</i>)	0.002***	0.001	0.002**	0.001	1.002	0.001
Distance to nearest market (<i>km</i>)	0.000	0.000	0.000	0.000	1.000	0.000
Const.	2.123***	0.068	2.168***	0.101	8.737	0.878

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

¹Note: The incidence-rate ratio (IRR) is the ratio of the partial effects of a change in an independent variable (new value) to the old value after a discrete change in the in an independent variable. This makes the interpretation of the partial effects of the independent variables easier, because under the multiplicative error model IRR is constant over the data.

Table 4 reports regression results on household dietary diversity explained by household financial inclusion status and a range of other covariates. The table reports parameters estimated using a two-step GMM⁶ estimation of the Poisson regression model in which the financial inclusion variable is considered endogenous. We estimated the model with two specifications of the error terms—additive or multiplicative error terms. For the model with multiplicative errors, we report both the coefficients and incidence-rate ratios (IRR). We find that the coefficient of the financial inclusion index is positive and statistically significant (at the 1-percent level) in both the additive and multiplicative specifications. Based on IRR figures, holding other covariates constant, the expected HDDS score for financially included households is nearly twice that of households lacking access to formal financial services. Other significant covariates that affect the HDDS score positively include sex of household head and size of farm area cultivated. Other things held constant, the expected HDDS score is close to 7 percent higher for women-headed households than that

⁶ The GMM estimator uses instrumental variables to specify moment conditions that hold in the population. The GMM parameter estimates make the sample versions of these population-moment conditions as close to true as possible. The instrumental variables are assumed to be correlated with the endogenous covariates but independent of the errors. The ‘*ivpoisson gmm*’ stata command allows for heteroskedasticity of the errors, because the robust standard error is the default in Stata’s *ivpoisson gmm* command.

of male-headed households. This is an interesting empirical testimony that corroborates anecdotal observations in rural Africa on the larger roles women play in household dietary diversity than men.

5. CONCLUSIONS AND RECOMMENDATIONS

This paper explores the effects of financial inclusion on the adoption and use intensity of yield-enhancing agricultural inputs (inorganic fertilizer and improved seeds) and household welfare indicators measured in food security and dietary diversity among smallholder farmers in Nigeria. The data used in the study come from the Nigerian LSMS survey wave-3 (2015/2016). The key variable of interest, the financial inclusion index, was constructed from the binary responses of four financial access indicators (whether the household has bank account, access to credit, insurance coverage, and digital transaction). The outcome or dependent variables include adoption and intensity of use of agricultural inputs, experience-based food insecurity indicators, and household dietary diversity scores. Cragg's two-step hurdle model and instrument variables binary (IV probit) and count data (IV Poisson) models were used in the econometric estimations.

Results show that access to formal financial services (i.e., financial inclusion) positively and statistically significantly affects all the outcome areas considered in the study. Households with better financial access from formal sources are more likely to adopt and intensively use modern agricultural inputs; less likely to experience severe food insecurity; and more likely to consume diverse food items. However, a thorough examination of the results from a gender lens on the key outcome areas indicate that being a woman farmer reduces adoption and use intensity of modern inputs on the one hand and more exposed to severe food insecurity on the other. Based on the findings we offer the following policy recommendations: (1) targeted interventions on promoting access to formal financial services, especially among smallholders in rural areas, and (2) affirmative gender-differentiated policy interventions to address the relatively high constraints women farmers bear compared to their counterparts.

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