



**IMPACT OF SELECTED AGRICULTURAL EXTENSION PROGRAMMES ON  
VULNERABILITY TO POVERTY AMONG RURAL FARMING HOUSEHOLDS IN  
SOUTHWEST, NIGERIA**

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**ABSTRACT**

The study examines the impact of selected agricultural extension programmes on vulnerability to poverty among rural farming households in Southwest Nigeria. Using cross-sectional primary data from 673 farm households collected between 2025 and 2026 in Oyo and Osun States, the study applies probit regression to model the probability of extension programme participation and employs Propensity Score Matching (PSM) to estimate causal impacts. The result shows Vulnerability as Expected Poverty (VEP) framework identifies 36.4 percent of households as vulnerable, with 225 households simultaneously poor and vulnerable. Socio-economic characteristics significantly correlated with vulnerability include age, farm size, farming experience, household size, and credit access. Agricultural extension participation, particularly through farmer empowerment and new agricultural technology programmes, significantly attenuates vulnerability. The study advocates for disaggregated, vulnerability-targeted extension policies that prioritise currently non-poor but at-risk households, alongside broader structural reforms addressing credit access, infrastructure, and gender inclusion in agricultural advisory services.

**Keywords:** Agricultural, Extension, Participation, PSM, Rural, Households.

**INTRODUCTION**

Poverty in rural Nigeria is extremely slippery. A household may be non-poor today but slide into poverty tomorrow, a thin gap, driven by a weather shock, illness, crop failure, market price collapse, or the loss of a key livelihood asset. This forward-looking dimension of welfare commonly referred to as vulnerability to poverty has received growing attention in development economics as a foundational complement to traditional headcount-based poverty measurement (Alkire and Foster, 2011; Chaudhuri, 2000, 2001). Understanding vulnerability is particularly important in agricultural economies, where income variability is structurally high and social protection systems remain nascent (Nyamamu *et al.*, 2025; Sileshi *et al.*, 2019).

Moreover, Nigeria's rural poverty landscape presents a compelling case for vulnerability analysis. The UNDP Nigeria Multidimensional Poverty Index (MPI) survey, conducted across all 36 states and the FCT between November 2021 and February 2022, found that 33 percent of the population approximately 70.5 million people are multidimensionally poor, with an additional 16.6 percent at risk of poverty (UNDP, 2022; NBS, 2023). More alarmingly, ActionAid Nigeria (2024) estimates that 152 million Nigerians (68 percent of the population) live in highly vulnerable conditions, encompassing physical, social, economic, and environmental dimensions. The food insecurity crisis has deepened further with over 26.5 million Nigerians faced food shortages in 2024, driven by subsidy removal, food price inflation exceeding spike over 34 percent, and ongoing agro-pastoral conflicts (AFRIPOLI, 2025; NBS, 2024).

Agricultural extension services constitute one of the most direct instruments available to locals for reducing both current poverty and future vulnerability. Extension provision increases productivity, diversifies income sources, strengthens social capital, and improves access to credit and markets, and indeed these are all channels that buffer households against poverty shocks (Aremu and Reynolds, 2024; Pan *et al.*, 2018). However, the distributional incidence of extension benefits and the specific question of whether extension reduces vulnerability for the most at-risk households remains empirically underspecified in the Nigerian context.



This paper addresses this gap through a dedicated analysis of the socio-economic determinants of vulnerability to poverty, and the disaggregated impact of five agricultural extension programme types on vulnerability among rural farm households in Southwest Nigeria. The research uses primary data from a 2026 field survey of 673 households in Oyo and Osun States. The Probit model identifies the correlates of extension programme participation, Propensity Score Matching estimates the causal impact on vulnerability, and the Vulnerability as Expected Poverty (VEP) framework classifies household vulnerability status. The contribution of this paper is in threefold: it provides an updated vulnerability profile for Southwest Nigeria; it identifies the household-level covariates that shape extension participation and vulnerability; and it estimates programme-disaggregated extension impact estimates, enabling evidence-based prioritisation of extension investments.

Vulnerability to poverty can be conceptualised as either vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), or vulnerability as uninsured exposure to risk (VER) (Chaudhuri, 2000, 2001; Sileshi *et al.*, 2019). The VEP framework adopted in this study defines a household as vulnerable if the expected probability of falling below the poverty line exceeds a critical threshold, typically set at 0.50 (Shafiul and Katsushi, 2009). Chaudhuri's (2001) three-step feasible generalised least squares (3FGLS) procedure provides the practical methodology for computing VEP from cross-sectional data, acknowledging that expected poverty is unobserved and must be estimated from observed income volatility and its determinants.

Pignataro and Costa (2023) provide a methodological advance by showing how the FGT poverty indices when decomposed through the Gini framework reveal the inequality-within-poverty component that standard headcount measures obscure. Their analysis underscores that poverty severity (FGT  $P_2$ ) captures distributional inequality among the poor, providing a bridge between static poverty and dynamic vulnerability assessment. This insight is especially relevant for policy: a household with severe poverty (high  $P_2$ ) is more likely to remain vulnerable even after temporal improvements in average household income.

In sub-Saharan Africa, empirical evidence consistently demonstrates that vulnerability is more prevalent than current poverty, and that the two populations are only partially overlapping (Sileshi *et al.*, 2019; Teklu *et al.*, 2024). Nyamamu *et al.* (2025) identify key structural drivers of rural vulnerability in SSA which include dependence on rainfed agriculture, limited financial inclusion, poor infrastructure, land tenure insecurity, and restricted access to markets and information. Each of these drivers is directly or indirectly addressable through well-designed agricultural extension interventions.

The theoretical channels through which agricultural extension reduces household vulnerability to poverty are multi-faceted. First, technology dissemination including improved seed varieties, fertiliser application protocols, and integrated pest management increases yield stability and directly reduces income volatility. Second, training programmes and farmer field schools build human capital, enabling farmers to respond adaptively to shocks. Third, empowerment programmes strengthen farmers' access to credit, cooperative membership, and information thereby reducing the probability of distressed asset sales during adverse periods. Fourth, market-oriented extension services reduce transaction costs and price risks, while also stabilising income streams (Fabregas *et al.*, 2022; Amoussouhoui and Arouna, 2023; Onyeneke *et al.*, 2023).

Aremu and Reynolds (2024), using three waves of the Nigerian General Household Survey, stated that extension access increases household welfare, with income gains particularly pronounced for households in the lower wealth quintiles. Pan, Smith and Sulaiman (2018) confirm from Uganda that extension participation enhances food security and reduces income poverty, with the impact mediated through technology adoption. Muluken *et al.* (2025) demonstrate, through PSM and endogenous switching regression, that agricultural machinery adoption in Ethiopia increased farm income by 70 percent and reduced food insecurity by 51 percent, a closely analogous causal pathway to extension-induced income gains. These findings collectively support a vulnerability-reduction model of extension, where the primary mechanism is income stabilisation rather than a one-time income shock.

The decision to participate in agricultural extension programmes is a function of household-level characteristics that simultaneously determine vulnerability status. This simultaneity creates selection bias that must be addressed in impact estimation. Also, key correlates of extension



participation documented in the literature include: age and farming experience (positively associated with participation in older-generation programmes, negatively with digital platforms); farm size (larger farms are more likely to attract extension visits); gender (male-headed households have historically higher participation rates); household size (larger households have more labour and social capital for information sharing); and credit access (credit-constrained households are less likely to adopt extension recommendations even if informed) (Aremu and Reynolds, 2024; Faruq *et al.*, 2013; Waddington *et al.*, 2010).

In Nigeria, Adepoju and Yusuff (2015) found that gender, farm size, and household income significantly determined vulnerability levels in rural Southwest Nigeria. The UNDP Nigeria MPI (2022) also listed education, employment type, and access to infrastructure as key vulnerability dimensions. These multi-dimensional correlates necessitate a probit-PSM approach that jointly models the selection into extension and the impact on vulnerability, controlling for the full vector of observed household characteristics.

## METHODOLOGY

### Study Area and Sampling

The study was conducted in Southwest Nigeria, with primary fieldwork in Oyo and Osun States during October, 2025 – March 2026. The study area characterizes a tropical rainforest climate, with mixed crop-livestock farming systems by predominantly smallholder land tenure via inheritance, and ADP-based extension infrastructure which represent conditions typical of the broader Southwest zone and provide external validity for zone-level policy inferences. A multi-stage sampling method were used in selecting the respondents in the study area. The first stage employed random selection of 2 states out of the 6 states in south west geo-political zone. The second stage involved random selection of three ADP zones (one in Osun and two in Oyo state). Third stage involved selection of three Local Government Areas (LGAs) in each of the ADP zones selected making a total of 9 LGAs. Fourth stage involved selection of 8 villages from each of the selected LGA giving a total of 72 villages. Finally, a proportionate random sampling approach was used to select respondents from each village as obtained from the ADP extension register to arrive a total of 720 respondents. However, only 673 observations (93.5% completion rate) from 720 initially targeted households were used for analysis due to incomplete responses, and inconsistent information from 47 respondents on key variables required for analysis.

### Operationalisation of Vulnerability

Vulnerability to poverty was operationalised using the VEP framework. A household was classified as vulnerable if the predicted probability of future poverty estimated from a three-step feasible generalised least squares regression of per-capita household expenditure on household characteristics, correcting for heteroscedasticity exceeded the threshold of 0.50 (Chaudhuri, 2001; Shafiul and Katsushi, 2009). The poverty line was established at two-thirds of mean per-capita household expenditure for the study area, consistent with relative poverty line conventions for rural Nigeria (Nwaka *et al.*, 2022). In parallel, the Foster-Greer-Thorbecke (FGT) indices ( $P_0, P_1, P_2$ ) were estimated for both the previous season (2025) and the current season (2026) to establish the static poverty profile.

### Probit Model for Extension Participation

Probit regression was estimated separately for each of the five extension programme typologies to identify the socio-economic covariates that determine participation. The binary dependent variable equals one (1) if the household benefited from the programme and zero (0) otherwise. The model is specified as follows:

$$P(Y_i=1|X_i) = \Phi(\beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Age}_i^2 + \beta_3 \text{Sex}_i + \beta_4 \text{Married}_i + \beta_5 \text{FarmSize}_i^2 + \beta_6 \text{HouseholdSize}_i + \beta_7 \text{FarmingExp}_i + \beta_8 \text{CreditAccess}_i + \epsilon_i)$$

Where Explained Variable:  $Y_i=1$ , if the household benefited from a specific extension programme or 0 if otherwise;  $\Phi(\cdot)$  is the cumulative standard normal distribution function;  $\beta_0$  is the intercept;  $\beta_1 \dots \beta_8$  are parameters to be estimated. Similarly, the explanatory variables include Age (years);  $\text{Age}^2$  (years<sup>2</sup>); Sex (Male = 1, Female = 2); Married (Married = 1, No = 0); Squared Farm Size (acre<sup>2</sup>); Household Size (members of the same household); Farming experience (years); Credit access (Yes = 1, No = 0) and  $\epsilon_i$  is the random error term.



Maximum likelihood estimation was applied with robust standard errors. Predictive performance was assessed using the overall correct classification rate, and the non-treatment and treatment classification rates.

**Propensity Score Matching**

PSM was implemented in four stages: (1) probit-based propensity score estimation; (2) common support condition verification; (3) balancing property testing within propensity score blocks; and (4) ATT estimation using nearest neighbour, radius, kernel, and stratification matching algorithms. Bootstrapped standard errors (200 replications) were computed to ensure robustness. The ATT for vulnerability was specified as the difference in the mean probability of future poverty between matched treated and control households. Sensitivity analysis following Rosenbaum (2002) was conducted to test the robustness of ATT estimates to potential unobserved confounders.

**RESULTS AND DISCUSSION**

**Socio-economic Characteristics**

The sample comprised 673 farm households with a mean age of 47.2 years, predominantly male (66.3 percent), and mostly married (86.8 percent). The mean household size was 6.4 members, with 46.1 percent of households having five members or fewer. Education levels were modest, 42.8 percent had primary schooling as their highest qualification, and only 12.9 percent had tertiary education. Farming was the primary occupation for 72.4 percent of respondents. Land was predominantly inherited (61.4 percent), and the mean farm size was 7.8 acres. Extension contact was predominantly monthly (33.9 percent), while 27.0 percent reported no contact with extension agents. These characteristics shows the socio-economic profile of a rural farming population with moderate asset bases, constrained educational capital, and limited formal extension reach, conditions identified in the vulnerability literature by (Nyamamu *et al.*, 2025; Chaudhuri, 2001) as structurally predisposing households to income shocks.

**Table 1: Socio-economic Profile of Respondents**

<b>Variable / Category</b>	<b>Frequency</b>	<b>Percentage (%)</b>
<b>Age Group</b>		
≤30 years	84	12.5
31–40 years	143	21.3
41–50 years	167	24.8
51–60 years	182	27.0
Above 60 years	97	14.4
Mean Age = 47.2 years		
<b>Gender</b>		
Male	446	66.3
Female	227	33.7
<b>Educational Level</b>		
No formal education	111	16.5
Primary school	288	42.8
Secondary school	187	27.8
Tertiary	87	12.9
<b>Primary Occupation</b>		
Farming	487	72.4
Civil Service	87	12.9
Trading	49	7.3
Others	50	7.4
<b>Extension Contact Frequency</b>		
Weekly	17	2.5
Monthly	228	33.9
Fortnightly	200	29.7
Occasionally	46	6.8
None	182	27.0
<b>Total</b>	<b>673</b>	<b>100.0</b>

**Source:** Field Survey, 2026



**Poverty and Vulnerability Profile**

The FGT poverty headcount was 36.4 percent in 2026, a marginal improvement from 38.0 percent in 2025. Poverty depth fell from 11.0 percent to 10.5 percent, and poverty severity from 4.5 to 4.3 percent (see Table 1). The mild downward trend in all three FGT measures is consistent with the observed slight improvement in farming household incomes documented by Thomas and Turk (2023) for Southwest Nigeria in the context of post-COVID agricultural recovery and improving fertiliser subsidy delivery under the NATIP 2021–2025 framework (Ikehi *et al.*, 2024).

**Table 2:** FGT Poverty Measures (2025 and 2026)

FGT Poverty Measure	2025 (Previous Season)	2026 (Current Season)
Headcount Ratio (P <sub>0</sub> )	0.380	0.364
Poverty Gap / Depth (P <sub>1</sub> )	0.110	0.105
Poverty Severity (P <sub>2</sub> )	0.045	0.043

**Source:** Field Survey, 2026

Among the 673 households, 245 (36.4%) were classified as vulnerable to future poverty. The cross-tabulation of current poverty and vulnerability status (Table 3) reveals a nuanced picture: 225 households were simultaneously poor and vulnerable; 31 were non-poor but vulnerable; 397 were non-poor and non-vulnerable; and 20 were poor but not vulnerable. The existence of 31 non-poor but vulnerable households is particularly policy-relevant, these households have escaped poverty but remain at high risk of reverting, and are typically invisible to poverty-targeting instruments that focus exclusively on the currently poor (Chaudhuri, 2000; UNDP, 2022).

**Table 3:** Cross-tabulation of Poverty Status and Vulnerability (Field Survey, 2026)

Vulnerability Status	Currently Poor	Currently Non-Poor
Vulnerable	225 (33.4%)	31 (4.6%)
Non-Vulnerable	20 (3.0%)	397 (59.0%)
Total	245 (36.4%)	428 (63.6%)

**Source:** Field Survey, 2026

**Determinants of Extension Programme Participation**

Table 4 presents the probit estimation results for all five extension programmes. The squared farm size was consistently significant ( $p < 0.05$ ) across all five models, indicating that households with larger farms are significantly more likely to participate in extension programmes, a structural advantage that disadvantages smallholders with less-5-acre farms, who constitute 54.7 percent of the sample. Age and Age<sup>2</sup> were jointly significant at  $p < 0.05$  for training programmes (Age:  $\beta = -0.062^{**}$ ; Age<sup>2</sup>:  $\beta = 0.0006^{**}$ ) and at  $p < 0.10$  for market-oriented (Age:  $\beta = -0.051^*$ ; Age<sup>2</sup>:  $\beta = 0.0006^{**}$ ) and farmer field school programmes (Age:  $\beta = -0.048^*$ ; Age<sup>2</sup>:  $\beta = 0.0005^*$ ) with participation peaking at middle age. This shows a non-linear inverted-U relationship between age and participation in extension programmes. In other words, this implies that respondent’s probability of participation in extension programme(s) initially declines with age, then rises with upward farming experience (squared age) thereby re-engaging with formal extension after accumulating the social capital and credibility to access group-based programmes. This is consistent with an inverted-U relationship between age and extension engagement found by Aremu and Reynolds (2024). Also, farming experience was significant at  $p < 0.05$  for empowerment ( $\beta = -0.022^{**}$ ) and training ( $\beta = 0.013^{**}$ ) programmes, and at  $p < 0.05$  for farmer field schools ( $\beta = 0.020^{**}$ ). The negative coefficient of empowerment programmes implies that less experienced farmers (particularly newer entrants) with limited capital are more likely to self-select into empowerment initiatives, presumably because of their greater need for foundational credit support. Conversely, the positive coefficients for training and farmer field school programmes indicate that more experienced farmers are more likely to participate in knowledge-intensive programmes. This is consistent with the findings of Waddington *et al.* (2010) who documented that human capital accumulated through farming experience raises the returns to further knowledge acquisition.

Likewise, Sex (Male = 1) was significant at  $p < 0.10$  for farmer empowerment programmes ( $\beta = -0.195^*$ ). The negative sign indicates that female-headed households are significantly more likely to participate in farmer empowerment programmes compared to their male counterparts, when controlling for other household characteristics. This reinforces gender-differentiated vulnerability exposure also documented by (Doss, 2018). Lastly, Household Size was significant at  $p < 0.10$  for market-oriented programmes ( $\beta = -0.036^*$ ). This indicate that farmers with larger households are less likely to participate in market-oriented extension, possibly due to the labour demands of managing larger households compete with the time required to engage with market-oriented training and advisory activities. This finding underscores the need for flexible scheduling of market-oriented extension activities that accommodate the time constraints of larger households.

**Table 4:** Probit Estimates for Extension Programme Participation

Variable	New Agric Tech	Market Oriented	Empowerment	Training	Field School
Constant	0.357	0.199	-0.231	0.588	-0.130
Age	-0.035	-0.051*	-0.014	-0.062**	-0.048*
Age <sup>2</sup>	0.0004	0.0006**	0.00009	0.0006**	0.0005*
Sex (Male=1)	-0.078	0.170	-0.195*	-0.060	0.078
Married	-0.146	-0.121	-0.208	-0.172	-0.104
Farm Size <sup>2</sup>	0.0004**	0.0005**	0.0006**	0.0004*	0.0005**
Household Size	-0.012	-0.036*	-0.022	-0.020	-0.009
Farming Exp.	0.003	0.004	-0.022**	0.013**	0.020**
Credit Access	-0.117	-0.105	-0.083	0.044	-0.008
Pseudo R <sup>2</sup>	0.018	0.032	0.071	0.041	0.067
Prob > Chi <sup>2</sup>	0.061	0.012	0.000	0.000	0.000
N	673	673	673	673	673

\*\*  $p < 0.05$ ; \*  $p < 0.10$

Source: Field Survey, 2026

### Programme Participation Distribution

Table 5 shows the distribution of treated and control respondents across the five extension programmes. Non-beneficiaries constituted the majority in all five programmes: new agricultural technology (69.8 percent control), market-oriented programming (82.9 percent control), farmer empowerment (72.7 percent control), training (75.8 percent control), and farmer field schools (79.6 percent control). This persistent majority of non-beneficiaries reflects the structural under-provision of extension services in Nigeria, a challenge acknowledged by Aremu and Reynolds (2024) and corroborated by the finding that 27.0 percent of respondents had no extension contact at all.

**Table 5:** Distribution of Programme Participation by the Respondents

Extension Programme	Beneficiaries (Treated)	%	Non-Beneficiaries (Control)	%
New Agricultural Technology	203	30.2	470	69.8
Market-Oriented Programme	115	17.1	558	82.9
Farmer Empowerment Programme	184	27.3	489	72.7
Training Programme	163	24.2	510	75.8
Farmer Field School	137	20.4	536	79.6

Source: Field Survey, 2026

### PSM Impact on Vulnerability: Bootstrapped Estimates

Table 6 presents the bootstrapped standard error ATT estimates for vulnerability to poverty across the five extension programmes. All four matching estimators produced negative and statistically significant vulnerability ATT values for new agricultural technology, farmer empowerment, training,



and farmer field school programmes ( $p < 0.05$ ). The market-oriented programme showed non-significant vulnerability impact under nearest neighbour matching but became significant under radius, kernel, and stratification matching algorithms.

The highest vulnerability reduction was achieved by the farmer empowerment programme under radius matching ( $ATT = -0.221$ ,  $p < 0.05$ ), followed by new agricultural technology ( $ATT = -0.197$  under nearest neighbour;  $-0.187$  under radius). These results are consistent across matching algorithms, and the bootstrapped standard errors confirm the robustness of findings to sampling uncertainty.

**Table 6:** Bootstrapped ATT Estimates for Vulnerability

Estimator	New Agric Tech	Market Oriented	Empowerment	Training	Field School
Nearest Neighbour MM	-0.197**	-0.087	-0.120**	-0.129**	-0.073
Radius Matching	-0.187**	-0.132**	-0.221**	-0.145**	-0.181**
Kernel Matching	-0.193**	-0.144**	-0.165**	-0.151**	-0.178**
Stratification	-0.190**	-0.142**	-0.158**	-0.144**	-0.183**

\*\*  $p < 0.05$ . Standard errors bootstrapped with 200 replications.

**Source:** Field Survey, 2026

The vulnerability profile of Southwest Nigerian rural farming households revealed by this study is both noteworthy and worrisome. The majority of households (63.6 percent) are currently non-poor and non-vulnerable implying that the region's relatively favourable agro-climatic conditions, diversified livelihood systems, and longer-standing extension infrastructure (relative to the north) provide a degree of resilience. However, the 36.4 percent vulnerability rate, the largest vulnerability concern demands sustained policy attention, particularly because thirty-one (31) of these households are currently non-poor, that is, they are invisible to standard poverty targeting instruments yet at high risk of descent into poverty.

The probit results reveal that farm size is the most consistently significant correlate of extension programme participation, with smaller farmers who constitute the majority systematically underserved. This finding echoes Aremu and Reynolds (2024) whose study reveals a positive association between farm size and extension access in the Nigerian General Household Survey, and Waddington *et al.* (2010) who identified farm size as one of the strongest predictors of extension programme participation globally. It also raises a critical equity concern: the households most vulnerable to poverty (those with smaller farms, less farming experience, and limited credit access) are precisely those least likely to access extension, this could create a paradox where even though extension improves aggregate welfare but may also deepen distributional inequalities in vulnerability.

The PSM vulnerability ATTs confirm that extension participation regardless of the specific programme type significantly reduces the probability of future poverty. The farmer empowerment programme, which combines financial literacy, group-based savings mechanisms, and market linkage facilitation, generates the largest vulnerability reduction ( $ATT = -0.221$  under radius matching). This is consistent with the broader social protection literature that emphasises asset accumulation and consumption smoothing as primary vulnerability-reduction mechanisms (Teklu *et al.*, 2024; Sileshi *et al.*, 2019). The new agricultural technology programme generates the largest vulnerability reduction under nearest neighbour matching ( $-0.197$ ), reflecting the direct income-stabilisation effect of improved production technologies.

The modest but consistent impacts of farmer field school and training programmes on vulnerability underscore the importance of participatory, knowledge-intensive extension modalities. Onyeneke *et al.* (2023) confirm that farmer field schools in Nigeria are particularly effective at building climate change adaptation capacities, an increasingly important dimension of vulnerability in the context of Nigeria's deepening climate crisis, where 26.5 million people faced food insecurity in 2024 (AFRIPOLI, 2025).



## CONCLUSIONS AND RECOMMENDATIONS

This study examines whether agricultural extension programme participation causally reduces household vulnerability to poverty in rural Southwest Nigeria, a question of considerable policy urgency particularly given that (36.4%) of sampled households were found to be vulnerable to future poverty in 2026, a rate that mirrors the current poverty headcount and confirms the pervasive but overlooked nature of the vulnerability risk. The combined application of the VEP framework, probit regression, and Propensity Score Matching with bootstrapped standard errors yields three substantive conclusions.

First, vulnerability to poverty is not coterminous with current poverty. The cross-tabulation of vulnerability and poverty status reveals that 31 households (4.6% of the sample) are currently non-poor but rather highly vulnerable households that will remain invisible to conventional poverty-targeting systems unless vulnerability-specific screening criteria are introduced. Similarly, the coexistence of the poor-and-vulnerable (225 households) and the non-poor-but-vulnerable (31 households) categories underscores that any policy framework relying solely on headcount poverty as the entry criterion for support will systematically fail a meaningful fraction of at-risk rural households.

Second, farm size is the dominant structural barrier to extension access: its consistent significance at  $p < 0.05$  across all five extension programmes reveals that the extension system in its current form is structurally biased towards farmers with larger holdings, leaving the most vulnerability-exposed smallholder majority least served. This structural inequity must be directly challenged through redesigned targeting criteria.

Third, agricultural extension participation across all five programme typologies and all four PSM matching algorithms significantly and robustly reduces household vulnerability to future poverty. Farmer empowerment programmes (ATT =  $-0.221$ ) and new agricultural technology programmes (ATT =  $-0.197$ ) generate the largest vulnerability reductions, while training and farmer field school programmes deliver consistent and statistically robust impacts. This reinforces agricultural extension as a frontline vulnerability prevention instrument, and not as a mere productivity-enhancement tool.

Based on these conclusions, the following recommendations are provided. Extension programmes should be explicitly redesigned with vulnerability-targeting criteria that enrol not only the currently poor but also non-poor at-risk households. Affirmative extension outreach policies targeting smallholder farmers with less than five acres (who were the majority of the sample and the most vulnerable segment) are urgently required; participatory modalities such as farmer field schools and community advisory groups are particularly well-suited to this population. The low credit access rates documented across all treatment groups constitute a binding constraint on the conversion of extension knowledge into income gains; bundling extension with rural finance products through cooperative savings clubs, mobile banking, and government credit schemes would amplify impact. Digital extension modalities must be urgently scaled to overcome the physical and logistical limitations that restrict extension contact for (72% of farmers) to monthly intervals or below. Finally, future research should deploy panel data methods to separate transient from chronic vulnerability, and longitudinal vulnerability tracking aligned with Nigeria's biennial MPI cycles would provide a robust monitoring framework for extension impact at scale.

## REFERENCES

- Abebe, M. B., and Endale, K. (2023). The impact of improved seed adoption on nutrition outcome: A panel endogenous switching regression analysis. *Environment for Development Discussion Paper 23-1*, University of Gothenburg.
- ActionAid Nigeria (2024). ActionAid Nigeria calls for urgent public investments in agriculture. World Food Day Statement, October 16. Abuja: ActionAid Nigeria.
- Adepoju, A. O., and Yusuff, S. A. (2015). Poverty and vulnerability in rural South West Nigeria. *Journal of Biomedicine and Nursing*, **1**(1): 58–64.
- AFRIPOLI (2025). Mainstreaming climate action into agriculture and food security in Nigeria. African Policy Institute. Retrieved from <https://afripoli.org>
- Alkire, S., and Foster, J. (2011). Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality*, **9**(2): 289–314.



- Amoussouhoui, R., and Arouna, A. (2023). Analysis of factors influencing the adoption of digital extension services: Evidence from the RiceAdvice application in Nigeria. *The Journal of Agricultural Education and Extension*, **29**(4): 387–416.
- Aremu, T., and Reynolds, T. W. (2024). Welfare benefits associated with access to agricultural extension services in Nigeria. *Food Security*, **16**(2): 295–320.
- Chaudhuri, S. (2000). Empirical methods for assessing household vulnerability to poverty. Mimeo, School of International and Public Affairs, Columbia University.
- Chaudhuri, S. (2001). Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia. Columbia University, New York.
- Doss, C. (2018). Women and agricultural productivity: Reframing the issues. *Development Policy Review*, **36**(1): 35–50.
- Fabregas, R., Harigaya, T., Kremer, M., and Ramrattan, R. (2022). Digital agricultural extension for development. In *Introduction to Development Engineering* (pp. 187–219). Springer International Publishing.
- Faruq, H., Katsushi, S., Imai, and Shonchoy, T. (2013). Impacts of agricultural extension service on crop productivity, poverty and vulnerability: Evidence from Uganda. *Community Journal of Environmental Issues and Agriculture in Developing Countries*, **2**(2–3): 234–242.
- Foster, J., Greer, J., and Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, **52**(5): 761–766.
- Ikehi, M. E., Ejiofor, T. E., and Ifeanyieze, F. O. (2024). Successive national agricultural policies/programmes, growth of GDP and expansion of agribusinesses in Nigeria. *PLoS One*, **19**(2): 291–299.
- Izuogu, C. U., Oparaojiaku, J. O., Njoku, L. C., and Okorie, D. A. (2024). Utilization of agricultural extension services among farmers in South Eastern, Nigeria. *Journal of Agriculture, Food, Environment and Animal Sciences*, **5**(2): 299–309.
- Muluken, A., et al. (2025). Does the adoption of agricultural machinery improve smallholder farmers' food security? Evidence from Arsi Zone, Ethiopia. *Discover Sustainability*. <https://doi.org/10.1007/s43621-025-01140-w>
- NBS (2023). Nigeria Multidimensional Poverty Index Survey Results 2022. Abuja: National Bureau of Statistics.
- NBS (2024). Consumer Price Index and Food Inflation Report. Abuja: National Bureau of Statistics.
- NPC (2006). National Population and Housing Census. Abuja: National Population Commission.
- Nwaka, P. C., et al. (2022). Improved generalised Foster-Greer-Thorbecke index in one-dimensional poverty. *International Innovations in Mathematics, Statistics and Energy Policies*, **10**(2): 10–24.
- Nyamamu, E. J., Nchimbi, C. S., Mteti, S. H., and Ndimbo, G. K. (2025). Potentials and challenges for rural livelihood diversification and poverty alleviation in sub-Saharan Africa: A systematic review. *SAGE Open*, **15**(1).
- Okafor, C., Ike, C., and Egwu, O. (2022). Inequality and regional poverty in Nigeria: A decomposition analysis from Foster-Greer-Thorbecke index. *ResearchGate*.
- Onyeneke, R. U., Izuogu, C. U., Njoku, L. C., Azuamairo, G. C., and Atasié, M. C. (2023). Repositioning Nigeria's agricultural extension system towards building climate change resilience. *Sarhad Journal of Agriculture*, **37**(1): 180–189.
- Pan, Y., Smith, S. C., and Sulaiman, M. (2018). Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics*, **100**(4): 1012–1031.
- Pignataro, G., and Costa, M. (2023). The Foster-Greer-Thorbecke index and the inequality factors: An analysis through the Gini index decomposition. *Journal of Economic Inequality*, **21**(3): 483–497.
- Rosenbaum, P. R. (2002). *Observational studies* (2nd ed.). New York: Springer.
- Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, **70**(1): 41–55.



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- Shafiul, M. A., and Katsushi, S. I. (2009). Vulnerability and poverty in Bangladesh. ASARC Working Paper 2009/02. Australian National University.
- Sileshi, M., Kadigi, R., Mutabazi, K. (2019). Impact of soil and water conservation practices on household vulnerability to food insecurity in eastern Ethiopia. *Food Security*, **11**(4): 797–815.
- Takahashi, K., Muraoka, R., and Otsuka, K. (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, **51**(1): 31–45.
- Teklu, A., Simane, B., and Bezabih, M. (2024). Climate smart agriculture impact on food and nutrition security in Ethiopia. *Frontiers in Sustainable Food Systems*, **7**: 107-119.
- Thomas, A. H., and Turk, R. A. (2023). Food insecurity in Nigeria: Food supply matters. International Monetary Fund Working Paper 2023/018.
- UNDP (2022). Nigeria Multidimensional Poverty Index 2022. New York: UNDP.
- Waddington, H., Snilstveit, B., White, H., and Anderson, J. (2010). The impact of agricultural extension services. International Initiative for Impact Evaluation (3ie) Synthetic Review SR009.