

Heterogeneous Impact of NG CARES Program Participation on Productivity and Food Security of Rural Farming Households in Northwestern Nigeria

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Abstract

The Nigeria Community Action for Resilience and Economic Stimulus (NG CARES) Program was designed to support vulnerable populations, particularly smallholder farmers, in response to external shocks such as the COVID-19 pandemic. This study examines the *heterogeneous impact* of participation in the NG CARES Program on crop yield and food security among rural farming households in northwestern Nigeria. We collected data from 723 farming households, consisting of 361 program participants and 362 non-participants, using a multi-stage sampling approach. A logit model was employed to analyze the determinants of program participation, while the Household Food Insecurity Access Scale (HFIAS) assessed food security levels. We used Data Envelopment Analysis (DEA) to estimate technical efficiency, a proxy for crop yield. We also applied the Endogenous Treatment Effect Model (ETEM) to assess the heterogeneous impact of program participation. The results indicate that program participation significantly improved crop yield, with participants demonstrating higher technical efficiency than non-participants. However, the impact varied across demographic groups, with older farmers benefiting the most, while middle-aged and young farmers experienced mixed effects. Farmers with only a primary education also experienced notable increases in yield, while those with secondary or university education did not. Food security outcomes also varied, with the most substantial improvements observed among young farmers. Regional disparities further highlighted the need for localized policy interventions. The study concludes that while NG CARES has enhanced agricultural productivity and food security, *targeted modifications* are necessary to ensure equitable benefits across different farmer categories and regions.

Keywords: NG CARES, Program Participation, Productivity, Food Security, Rural Farming Households, Northwestern Nigeria.

Introduction

The COVID-19 pandemic led to widespread disruptions in Nigeria's food systems, supply chains, and rural livelihoods. In response, the Nigerian government launched the *NG CARES Program* to cushion the impact, particularly for vulnerable populations such as smallholder farmers (World Bank, 2020). Despite the introduction of several agricultural interventions in the past, food insecurity and productivity gaps persist, especially in Northwestern

Nigeria, due to region-specific shocks, climate variability, and weak institutional capacity. The NG CARES Program aims to address these challenges by enhancing access to inputs, services, and markets.

One of its primary goals is to enhance food security by increasing access to agricultural inputs and improving productivity. Leveraging structures from earlier programs such as NFDP and CSDP, NG CARES focused on Result Area 2, which aims to boost food production, reduce post-harvest losses, and promote safe market access (Okunmadewa, 2020).

This study evaluates the differentiated impacts of NG CARES participation on crop productivity and household food security. It fills a significant gap in existing literature by analyzing how demographic (age, education) and geographic (agricultural zones) factors influence outcomes.

Problem Statement

Despite the commendable achievements of NG CARES, limited empirical evidence exists on how participation impacts yield and food security among diverse farming populations in Nigeria's northwestern region. Past studies have mainly focused on average effects, neglecting variations across age, education, and regions. Additionally, existing analyses often fail to control for selection bias, resulting in inconclusive policy guidance. This research aims to identify these heterogeneous effects and inform more inclusive agricultural policy.

Theoretical Background

This study uses the Theory of Planned Behavior (TPB) as its main method, which suggests that people's choices are shaped by their attitudes, social pressures, and their ability to act (Ajzen, 1991). Within the context of agricultural interventions, TPB provides a lens to understand farmers' decisions to participate in the NG CARES Program based on perceived program benefits, social influences, and access to resources. However, we also integrate the Theory of Change (ToC) to enhance the robustness of analysis. ToC focuses on how different factors lead to results and highlights the specific challenges and supportive conditions in each situation (Weiss, 1997). Together, these frameworks justify examining farmers' choices to participate and how program design influences observed outcomes. Guided by this framework, the study employed a logit model to identify the socio-economic and institutional factors influencing program participation. We estimated technical efficiency, a proxy for crop yield, using Data Envelopment Analysis (DEA) to measure agricultural productivity. The causal and heterogeneous impacts of program participation on productivity and food security were analyzed using the Endogenous Treatment Effect Model (ETEM), which addressed potential selection bias and unobserved heterogeneity. This combined approach helps to thoroughly assess how being part of NG CARES influences productivity and food security for different types of farming households.

Materials and Methods

Study Area

The study was conducted in northwestern Nigeria, which has approximately 39,762 square kilometers and a diverse population estimated at 5.8 million, predominantly comprising Hausa, Fulani, and other ethnic groups (Zamfara State Government, n.d.). Geographically, it falls within the Sudan Savannah Agro-Ecological Zone, experiencing distinct wet and dry seasons, with annual rainfall between 675mm and 1000mm and average temperatures ranging from 26°C to 30°C (Tasie et al., 2011). Agriculture is the primary economic activity, engaging over 80% of the population in the cultivation of rainfed and irrigated crops, including millet, sorghum, rice, and vegetables, alongside extensive livestock farming.

Sampling procedures and Data Collection

The study employed a multi-stage sampling approach across two agricultural zones in northwestern Nigeria. In the first stage, four Local Government Areas (LGAs)—Bungudu, Gusau, Bakura, and Talata-Mafara—were purposively selected based on the number of supported Farmers Community Associations (FCAs) and security considerations. In the second stage, following standard research methods, 30% of the 270 participating and 218 non-participating FCAs were chosen randomly, resulting in 81 benefiting and 65 non-benefiting FCAs, which included 5,756 and 6,250 farming households, respectively. We applied a sample size of 30%. In the third stage, Raosoft's sample size calculator was used to determine a final sample of 361 participants and 362 non-participants and a total of 723 respondents for the study.

Analytical Techniques

Both the Theory of Planned Behavior (TPB) and the Theory of Change (ToC) guided the analytical approach. TPB helped choose the social and economic factors that affect participation decisions, like being part of a cooperative (social norms), level of education (attitudes), and how far away the market is (perceived behavioral control). ToC helped create a model that shows how program activities lead to results, supporting the use of Endogenous Treatment Effect Models to separate both direct and indirect impacts.

We used robust standard errors to correct for heteroscedasticity due to outliers and ensure our statistical conclusions were still valid.

The logit model was used to identify the determinants of participation in the NG CARES Program, while the Household Food Insecurity Access Scale (HFIAS) was used to determine the food security status among participating and non-participating respondents. We used Data Envelopment Analysis (DEA) to estimate technical efficiency, a proxy for crop yield. We assessed the program's heterogeneous impact using the Endogenous Treatment Effect (ETEM) model.

Logit Model Specification

Agresti (2015) states that we can represent the logit model in its general form. The logit function is the natural log of the odds ratio, which is the sum of the product of the regression coefficients and the predictor variables, plus an error term.

$$\text{The equation } \text{logit}(p) = \ln(1-p/p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$$

The variable p represents the likelihood of the outcome being 1; this corresponds to participation; otherwise, otherwise = 0.

$X_1, X_2, \dots, X_n$ are the independent variables.

The coefficients to be estimated are denoted as $\beta_0, \beta_1, \dots, \beta_n$. The symbol ϵ is used to denote the error term. The independent variables hypothesised to determine participation in the Program are presented in Table 1.

Table 1: Variables used in the Logit model and their hypothesized effects

Variable Name	Description of the Variable	Unit of Measure	Apriori Expectation
Y	Participation in NG CARES Program	participants = 1, otherwise 0	N/A
Age	Age of the household head	years	±
Gender	Gender of the household head	Categorical (1 = male, 0 = female)	±
Household size	Household size	number	+
Education status	Educational status of household head	years	+
Land size cultivated	Land size cultivated	ha	+
Dependency ratio	Dependency ratio (Ratio of dependents to working-age population)	ratio	-
Total inputs cost	Total inputs cost	(₦)	±
Agric zone	Agricultural Zone	Number	±
Distance to nearest market	Distance to market	Km	-
No of previous agric projects	Number of previous participations in agricultural projects/Programs	number	+
Years of membership of Group/Cooperative	Number of years as a cooperative/group member	years	+

Source: Author's computation from Field Survey, 2024

Technical efficiency was used instead of yield, and it was calculated using a Variable Returns to Scale Data Envelopment Analysis (DEA) model, as recommended by Banker (1984). The DEA model measures technical efficiency by looking at how decision-making units (DMUs), like farmers, use their resources compared to others in the same group. The model lowers the output expansion factor (Z) while ensuring that the total weighted outputs of all DMUs

are at least equal to the actual outputs of the DMU being evaluated and that the total inputs remain within the observed limits. We express the model specification for technical efficiency (TE) as follows:

Minimize: $Z=1-\lambda$

Subject to: $\sum \lambda_j y_{jkr} \geq y_{kr}, \sum \lambda_j x_{ij} \leq x_{ir}, \lambda_j \geq 0$

Where Z represents the output expansion factor, λ_j are non-negative weights, y_{jkr} and y_{kr} denote crop yields, and x_{ij} and x_{ir} represent input levels. Furthermore, the relationship between technical efficiency, farmers' characteristics (X_i), and NG-CARES participation (A_i) was modeled as

$$TE_i = \beta_i X_i + \delta_k A_i + \beta_j \lambda_j + \eta_i$$

where TE_i represents technical efficiency as a proxy for yield, X_i includes household characteristics such as age, gender, education, farm size, and access to credit, A_i denotes NG-CARES participation, λ_j is the Inverse Mills Ratio (IMR), and η_i is the error term. This model captures how participation in NG-CARES and socio-economic factors influence farmers' yield and crop agricultural productivity.

Measurement of Food Insecurity

The Household Food Insecurity Access Scale (HFIAS), created by the Food and Nutrition Technical Assistance Project (FANTA), was used to evaluate food insecurity in farming households, classifying them by how serious their food insecurity was (Knueppel et al., 2009). The assessment involved a 30-day recall period, asking respondents whether they had faced food insecurity situations and how frequently they occurred, ensuring strict adherence to "skip rules" for accuracy. A main measure from this system, the Household Food Insecurity Access Prevalence (HFIAP), was used to sort households into four groups: food secure, mildly food insecure, moderately food insecure, and severely food insecure (Otekunrin et al., 2021). We classified households experiencing extreme situations, such as skipping meals or going a whole day without food, as severely food insecure. The methodology ensured a comprehensive measurement of food insecurity, capturing both the incidence and frequency of food-related hardships. To standardize classification, the study also referenced cut-off points recommended by the United States Department of Agriculture (USDA) (2021), distinguishing between high, marginal, low, and very low food security. This approach provided a robust framework for understanding food insecurity trends and evaluating the effectiveness of food security interventions.

Endogenous Treatment Effect Model Specification

The endogenous treatment effect model with a control function is commonly described by two equations: the result equation and the treatment equation (Heckman, 1979). The result equation comprises the endogenous treatment variable, exogenous variables, and the control function, which is used to assess the treatment impact on the outcome variable. The treatment equation, commonly known as the first-stage equation, represents the endogenous treatment variable as a function of external variables and instruments (Angrist

& Pischke, 2008). The treatment model, also known as the first-stage equation in the Endogenous Treatment Effect Model (ETEM) with a control function, can be represented as

$$D_i = (Z_i) + \eta_i \quad D_i = f(Z_i, W_i) + \eta_i$$

Where:

D_i is the binary treatment variable that equals 1 if unit i receives the treatment (participates in the NG CAREs Program) and 0 otherwise. (Z_i) is the function that relates the endogenous treatment variable to the exogenous variables (Z_i) and instruments (W_i) . W_i is a set of extra variables or tools used to fix endogeneity, like how many past agricultural projects someone has been involved in, how long they've been part of a group or cooperative, and whether they have access to advisory services. η_i is the error term in the treatment equation, capturing unobserved factors affecting the endogenous treatment variable. The treatment equation demonstrates the mathematical relationship between the endogenous treatment variable and external factors and tools (Angrist & Pischke, 2008). This equation estimates the propensity for receiving treatment based on observed characteristics and instruments. By estimating this equation, researchers can obtain consistent and efficient estimates of the treatment assignment process while addressing endogeneity concerns.

Specifically, the result equation can be specified as

$$Y_i = \alpha + \tau D_i + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots + \beta_n X_n + g(Z_i, W_i) + U_i$$

Where:

Y_i represents the dependent variable, which in this case is the food security status measured using the HFIAS. D_i is a binary treatment variable that equals 1 if unit i participates in the Ng CAREs Program and 0 otherwise. α is the intercept term.

$X_1, X_2, \dots, X_n$ are the independent variables.

τ is the coefficient of the treatment variable, representing the treatment effect.

$\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the independent variables.

(Z_i, W_i) is the control function, which depends on outside factors Z_i (like years of farming experience, gender, age, and access to services) and tools W_i (like the number of past projects, years in a group or cooperative, and access to advice) used to fix endogeneity. U_i represents the error term, which captures unobserved factors influencing the outcome.

X_1 = Total cost per hectare (₦), X_2 = Household size (No.), X_3 = Educational status of household head (number), X_4 = Age of respondent (No.), X_5 = Gender of the household head (1 = male; 0 = otherwise), X_6 = Distance to the nearest market (km), U = error term. The terms b_0 to b_n = coefficients of parameters estimated, $X_1, \dots, X_n$. The variables featured in the food security status model are described in Table 2.

Table 2: Variables used in the ETE food security model and their hypothesized effects

Variable Name	Description of the Variable	Unit of Measure	Apriori Expectation
Y	HFAIS (Food security score)	Food security score	N/A
Cost per Hectare	Cost per ha of production	₦	±
Household size	Household Size	No	±
Education level	Educational status of household head	years	+
Gender	Gender of the household head	Male = 1, Female = 2	±
Distance to nearest Market	Distance to market	Km	-
Resid_participation	Control function		±

Source: Author's computation from Field Survey, 2024

Results

Factors Influencing Participation in NG CARES

As presented in Table 3, the results reveal that education level, land cultivated, and years of cooperative membership are significant determinants of participation in the NG CARES Program. Specifically, education level was found to negatively influence participation, with an odds ratio (OR) of 0.4015 and statistical significance at the 1% level ($p < 0.01$). This evidence suggests that farmers with higher levels of education were less likely to participate in the program. Similarly, landholding size had a strong negative association with participation ($OR = 3.07e-07$, $p < 0.01$), implying that the program effectively targets smallholder farmers as intended. On the other hand, the number of years a farmer had been a member of a cooperative or farmer group had a significant and positive effect on participation ($OR = 1.4171$, $p < 0.01$), indicating the critical role of social capital in facilitating access to development programs. Additionally, variables such as dependency ratio ($p < 0.10$), total input cost ($p < 0.10$), and agricultural zone ($p < 0.10$) were found to be weakly significant. However, age, gender, household size, distance to market, and number of previously accessed projects were not statistically significant predictors of program participation. These findings underscore the importance of educational, economic, and institutional factors in shaping farmers' access to and involvement in publicly funded agricultural support programs.

Table 3: Determinants of participation in NG CARES

Variable	Odds Ratio	Std. Error	z-Statistic	P-value
Age	0.9697	0.0305	-1.01	0.312
Gender	0.0023	4.3531	-1.4	0.162
Education level	0.4015*	0.2074	-4.4	0.000***
Household size	1.0318	0.0588	0.53	0.595
Dependency Ratio	1.0048*	0.0028	1.71	0.088*
Land cultivated in ha	3.07e-07*	1.9207	-7.81	0.000***
Total inputs Cost	1.00001	6.9e-06	1.91	0.056*
Agricultural zone	3.7966	0.7043	1.89	0.058*
Distance to nearest market	0.9883	0.0088	-1.34	0.18
Number of previous projects	1.6772	0.3636	1.42	0.155
Years of membership of group/cooperative	1.4171*	0.0828	4.21	0.000***

Source: Field Survey, 2024. *** p < 0.01, ** p < 0.05 and * p < 0.10

Technical Efficiency Distribution amongst participants and non-participants of the NG CARES Program

Table 4 presents the summary statistics for technical efficiency among participants and non-participants of the NG CARES Program. The mean technical efficiency for program participants was 0.9980, which is significantly higher than the 0.6311 reported for non-participants (p < 0.01). Although both groups had a maximum technical efficiency of 1.0000, participants showed a steadier level of efficiency, shown by their lower standard deviation of 0.0386, while non-participants had more variation with a standard deviation of 0.2290. The overall sample recorded a mean technical efficiency of 0.8148. These results suggest that program participants achieved near-optimal efficiency levels, potentially because of the support provided under NG CARES.

Table 4: Summary statistics for Technical Efficiency estimates

Participation Status	Mean	Std. Dev.	Min	Max
Non-Participants	0.6311	0.2290	0.1026	1.0000
Participants	0.9980***	0.0386	0.2665	1.0000
All	0.8148	0.2461	0.1026	1.0000

Source: Field Survey, 2024. *** p < 0.01, ** p < 0.05, * p < 0.10

Heterogeneous Impact on Yield (Technical Efficiency) Disaggregated by Age

Table 5 shows how participating in the NG CARES Program affects crop yield (measured by technical efficiency) differently based on age, education level, and agricultural zone. Among age groups, elderly farmers experienced the highest yield improvement, with an

average treatment effect (ATE) of 0.3502, significant at the 1% level ($p = 0.000$). Middle-aged and youth groups recorded lower ATEs (0.0919 and 0.231, respectively), but these were not statistically significant. In terms of educational attainment, the program had the greatest impact on farmers with no formal education (ATE = 0.4686, $p < 0.01$) and those with only primary education (ATE = 0.3774, $p < 0.01$). Farmers with secondary or tertiary education did not show any significant effects. When looking at different agricultural areas, both Zone I and Zone II showed meaningful increases in yield, with Zone I, having a slightly larger improvement.

Table 5: Results for Heterogeneous Impacts on Yield

Variable	Coefficient (ATE)	Std. Error	z-Statistic	P-value
Elderly	0.3502	0.0312	11.24	0.000***
Middle-aged	0.0919	0.1686	0.55	0.586
Youth	0.231	1.1569	0.20	0.842
Primary	0.3774	0.0481	7.84	0.000***
Secondary	0.0416	0.5717	0.07	0.942
Tertiary	1.1836	0.9336	1.27	0.205
No Formal	0.4686	0.0719	6.52	0.000***
Zone II	0.3184	0.0545	5.85	0.000***
Zone I	0.3947	0.0501	7.89	0.000***

Source: Field Survey, 2024. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Food Security amongst participants and non-participants of NG CARES Program

Table 6 presents the distribution of food security status among participants and non-participants in the NG CARES Program, using the Household Food Insecurity Access Scale (HFIAS). The results indicate that a large proportion of respondents (49.65%) fall under the Low Food Secure (LFS) category, with more non-participants (236) than participants (124) in this group. The Marginally Food Secure (MFS) category, which comprises 43.27% of the sample, includes more participants (212) compared to non-participants (100), suggesting a potential positive influence of program participation on food security. Highly Food Secure (HFS) households account for only 6.38% of the total, with an equal split between participants and non-participants (23 each). The Very Low Food Secure (VLFS) category, representing the most severe food insecurity, includes just 0.69% of the sample (5 households). These findings suggest that while NG CARES has made progress in improving household food security among participants, a significant share of them remain in the marginal and low food security categories, indicating the need for enhanced and complementary interventions.

Table 6: Food Security Distribution amongst participants and non-participants of NG CARES Program

HFIAS Category	Total (%)	Non-Participants	Participants	Mean HFIAS	Std. Dev.
High Food Secure (HFS)	6.38%	23	23	3.09	1.21
Marginal Food Secure (MFS)	43.27%	100	212	7.10	1.35
Low Food Secure (LFS)	49.65%	236	124	10.54	0.94
Very Low Food Secure (VLFS)	0.69%	3	2	15.20	0.45

Source: Field Survey, 2024

Heterogeneous impact of NG CARES on Food Security

Table 7 summarizes the heterogeneous impact of the NGCARES Program on household food security, disaggregated by age, education level, and agricultural zone. Among age groups, the program had a significant positive impact on youth (ATE = 0.8316, $p < 0.01$), a marginally significant effect for middle-aged participants (ATE = 0.6544, $p = 0.074$), and no statistically significant effect for elderly participants (ATE = -0.5809, $p = 0.145$). In terms of education, a significant reduction in food insecurity was observed among those with primary education (ATE = -0.2501, $p < 0.01$), while the effects for secondary and tertiary education were not significant. For geographic zones, no statistically significant effects on food security were found in either Zone I (ATE = -0.0062, $p = 0.965$) or Zone II (ATE = -0.4013, $p = 0.139$), although Zone II showed a relatively stronger but still non-significant trend.

Table 7: Results for Heterogeneous Impacts on Food Security

Variable	Coefficient (ATE)	Std. Error	z-Statistic	P-value
Elderly	-0.5809	0.3984	-1.46	0.145
Middle-aged	0.6544	0.3666	1.78	0.074*
Youth	0.8316	0.2921	2.85	0.004***
Primary	-0.2501	0.0621	-4.03	0.000***
Secondary	-2.4729	2.9966	-0.83	0.409
Tertiary	9.3928	11.5085	0.82	0.416
No Formal	0.4686	0.0719	6.52	0.000***
Zone II	-0.4013	0.2714	-1.48	0.139
Zone I	-0.0062	0.1431	-0.04	0.965

Source: Field Survey, 2024. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Discussion

Factors Influencing Participation in NG CARES

Joining agricultural programs like NG CARES is affected by people's behavior, their economic situation, and the organizations around them, which aligns with the Theory of Planned Behavior (TPB). This theory emphasizes how attitudes, the ability to act, and social expectations influence choices (Abebe et al., 2021; Gatiso et al., 2022). As shown in Table 3, the logit regression revealed that educational level, land cultivated, and cooperative membership were significant determinants.

The negative relationship between education level and participation matches recent research by Ndjeunga et al. (2023), indicating that more educated farmers might find other ways to get inputs and services, like using private extension providers, commercial markets, or digital platforms. According to TPB, the findings could reflect a reduced sense of perceived behavioral control or differing subjective norms surrounding participation in public programs.

In the same way, the negative connection between how much land people own and their involvement supports the idea behind NG CARES, which focuses on helping poor and vulnerable farmers (Babatunde et al., 2020). This highlights the effectiveness of NG CARES in reaching its intended beneficiaries.

Being part of a group helps show how social capital and working together can improve access to programs (Tambo & Wünscher, 2017; Ayedun et al., 2022), which matches the Theory of Planned Behavior's idea that peer networks and established institutions have a strong influence. This conclusion affirms the value of farmer-based organizations as platforms for amplifying awareness, disseminating information, and building trust in intervention processes.

The less strong but still important role of factors like dependency ratio, total input cost, and agricultural zone indicates that things like population pressure, access to resources, and changes in the environment influence participation. Overall, these results highlight the importance of creating policies that not only support small farmers but also improve things like forming farmer groups, adapting to local needs, and ensuring everyone can communicate effectively. Tailoring program design to better engage youth, educated farmers, and emerging medium-scale producers, while ensuring equitable inclusion, could significantly enhance the overall impact and long-term sustainability of interventions like NG CARES.

Technical Efficiency Distribution among Participants and Non-Participants of the NG CARES Program

The results show a big difference in technical efficiency between NG CARES participants and those who did not participate, highlighting how agricultural support programs can improve farm productivity. The high mean efficiency score among participants (0.9980) implies that farmers who benefitted from the program were operating very close to optimal

efficiency levels—likely due to timely access to inputs, advisory support, and monitoring mechanisms.

This finding matches recent evidence that focused agricultural efforts improve efficiency by easing problems with inputs and helping farmers make better production choices (Effiong et al., 2021; Adedeji et al., 2023). These interventions help overcome problems like the cost of inputs, lack of labor, and access to farming information, especially when done through cooperatives or organized delivery systems.

In contrast, the considerable variability in efficiency observed among non-participants reflects underlying disparities in access to institutional support. These ongoing issues—like not having enough access to extension services, credit, and dependable input markets—are typical problems in rural areas that don't get enough support.

From a policy perspective, these findings reinforce the need to scale up input support programs, strengthen public extension services, and improve the reliability of last-mile delivery systems. Programmatic expansion to cover currently excluded farmers and geographies would help bridge productivity gaps and foster a more inclusive and efficient agricultural transformation.

The heterogeneous impact of NG CARES on crop yield (technical efficiency)

The findings underscore the heterogeneous nature of the impact of the NG CARES Program on crop yield. The noticeable increase in crop yields for older farmers shows that they might benefit more from agricultural support programs, probably because they have more farming experience, feel a stronger connection to the program, and are more likely to use the resources offered through organized efforts (Yameogo et al., 2021; Bahta et al., 2022). On the other hand, the lack of major improvements for middle-aged and young farmers might be due to a few obstacles, such as not being very involved with the program, a mismatch between the help they receive and their farming goals or having trouble dealing with institutional processes (Ayanlade & Radeny, 2020; Suleiman et al., 2023).

In the same way, the better results seen in participants with no formal education or just primary education suggest that farmers with less education gain more from direct help with inputs and basic advice. These results align with findings from Adeyemo et al. (2021), which suggest that simplified delivery models have greater impact among farmers with limited formal training. Conversely, farmers with secondary or tertiary education may require more tailored or market-oriented packages to unlock similar gains (Umeh et al., 2020; Ojo et al., 2023).

The important effects seen in both Zone I and Zone II show that NG CARES can improve productivity in different farming environments, but the slightly stronger impact in Zone I might be because of better infrastructure, more cooperation, or better farming conditions. Overall, these results highlight how important it is to use different program strategies that consider age, education, and local factors to make interventions like NG CARES more inclusive and effective.

Subgroup analyses revealed meaningful heterogeneity. For instance, technical efficiency gains were significantly higher among elderly farmers—a reflection of their receptiveness

to input use and advisory services, consistent with TPB's view on behavioral control and experience. Yield improvements among less educated farmers support ToC's proposition that simpler interventions produce more visible effects in underserved groups. In contrast, the non-significant impact among educated or middle-aged participants may reflect mismatches between program design and beneficiary expectations.

Heterogeneous impact of NG CARES on food security

The HFIAS-based results demonstrate clear distinctions in food security outcomes between NG CARES participants and non-participants. The fact that more participants are in the Marginal Food Secure category and fewer are in the Low Food Secure group compared to non-participants shows that the program has a positive effect on how well households can access food and handle difficulties. These findings match recent research that shows focused farming programs help people have more stable diets and better handle difficult situations (Otekunrin et al., 2021; Alemayehu et al., 2022).

However, a large share of both groups persists in the marginal and low food secure categories, pointing to unresolved vulnerabilities and limited program coverage. The fact that only 6.38% of households are classified as highly food secure, while a small number still fall into the very low food secure group, underscores the importance of scaling complementary strategies—such as nutrition education, climate-smart agriculture, and access to inclusive food markets. These approaches have been shown to yield significant improvements in household food security when layered onto direct support schemes (Onyeneke et al., 2020; Ojo et al., 2023).

As shown in Table 7, the impact of NG CARES on household food security varied significantly across age and education groups. The Theory of Planned Behavior (TPB) explains these variations, emphasizing how age and education influence perceived behavioral control, normative expectations, and access behavior. Youth showed a statistically significant reduction in food insecurity, likely due to their responsiveness to short-term support and higher adaptability to intervention mechanisms (Adepoju et al., 2023).

Middle-aged participants recorded modest, marginally significant improvements, while elderly participants experienced no statistically significant change. Mobility constraints, age-related fatigue, or reduced engagement with market-based interventions may be the cause of this (Suleiman et al., 2023).

Looking at it through a Theory of Change (ToC) perspective, the differences in food security results show that there are mismatches between what programs provide and important factors like how families work, farming challenges, and how food is shared within households. Better results for farmers with primary education support the idea that simpler programs work better when they match the knowledge and resources of the people they are meant to help (Ayanlade et al., 2020).

These findings emphasize the importance of age- and education-sensitive programming under NG CARES and similar initiatives. The observed differential impacts

affirm the importance of combining behavioral and structural lenses in understanding program outcomes. TPB explains how educational status and group affiliation shaped participation and engagement, while ToC highlights how tailored inputs lead to differentiated household effects based on context.

Finally, the robustness diagnostics conducted reinforce the reliability of these conclusions. We detected no significant bias from outliers or heteroscedasticity after applying the appropriate estimation corrections.

Conclusion

This study provides strong empirical evidence that participation in the NG CARES Program significantly improves agricultural productivity and enhances food security among rural farming households in northwestern Nigeria. Participants exhibited higher technical efficiency, a proxy for yield, compared to non-participants. Moreover, food security improvements were most evident among younger farmers and those with primary or no formal education.

However, the study also finds that the impacts of the program are not uniform across all groups. Differences based on age, education, and geographic zones underscore the necessity for more tailored and inclusive intervention designs. For instance, while elderly farmers experienced the greatest productivity gains, youth showed the most improvement in food security. The evidence suggests that demographic-specific constraints and capacities influence the effectiveness of agricultural interventions.

The novelty of this research lies in its identification of heterogeneous impacts using a combination of Logit, DEA, and ETEM models. This approach allowed for nuanced analysis that goes beyond average treatment effects, offering insights that can inform more targeted policy responses.

Ultimately, the study calls for a recalibration of agricultural support programs like NG CARES. By including different types of people, strengthening organizations like farmer groups, and tackling differences in access and results across regions, policymakers can improve fairness and success in these programs.

Policy Recommendations

- Strengthen farmer education and awareness campaigns targeting educated but disengaged farmers.
- Scale up cooperative membership support and peer-learning platforms to improve program outreach.
- Tailor extension delivery by age and educational category, offering differentiated packages for youth and elderly.
- Expand regional adaptation strategies to address agro-ecological variability and market constraints.
- Improve data and feedback systems to monitor subgroup responses and iterate policy.

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Conflict of Interest

The authors declare no conflicts of interest related to this research.

Ethical Compliance

This study adhered to ethical research standards, including obtaining informed consent from all participants.

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