



Determinants of Non-farm Income and Their Effects on Agricultural Productivity Among Farming Households in Nigeria

Nijerya'daki Çiftçi Haneleri Arasında Tarım Dışı Gelirin Tarımsal Üretkenlik Üzerindeki Belirleyicileri

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Abstract

The agricultural sector accounts for about 23% of Nigeria's Gross Domestic Product (GDP), with over 70% of the population involved in one agricultural activity or the other. Despite this huge involvement in the agricultural sector by farming households, majority are still relatively poor. As a result of this poor narrative among these households, it is not easy for them to attain optimum agricultural productivity. This also implies that majority of these farmers are easily prone to shocks and natural hazards assailing the agricultural sector negatively. To this end, this study investigated the determinants of non-farm income and their effects on the productivity of agricultural farming households in Nigeria, as a way of mitigating shocks. The World Bank Data on Emergencies Monitoring Household Survey 2021 was used to ascertain these claims. The descriptive statistics was used to determine the socio-economic characteristics of farming households while the Probit and the linear regression models were used in estimating the determinants of non-farm income and agricultural productivity. The results obtained elucidates on what effect agricultural non-farm income has on the productivity of farming households and how policy makers can make informed decisions that would support sustainable agriculture and mitigation of shocks in the Nigerian agricultural sector.

Keywords: Agricultural Productivity, Farming households, Mitigating shocks, Non-farm income

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Özet

Tarım sektörü Nijerya'nın Gayri Safi Yurtiçi Hasılasının (GSYİH) yaklaşık %23'ünü oluşturur ve nüfusun %70'inden fazlası bir tarımsal faaliyette yer alır. Çiftçi hanelerin tarım sektöründeki bu büyük katılımına rağmen, çoğunluk hala nispeten fakirdir. Bu haneler arasındaki bu zayıf anlatının bir sonucu olarak, optimum tarımsal üretkenliğe ulaşmaları kolay değildir. Bu ayrıca, bu çiftçilerin çoğunun tarım sektörünü olumsuz yönde etkileyen şoklara ve doğal afetlere kolayca maruz kaldığı anlamına gelir. Bu amaçla, bu çalışma, şokları azaltmanın bir yolu olarak, tarım dışı gelirin belirleyicilerini ve Nijerya'daki tarımsal çiftçilik hanelerinin üretkenliği üzerindeki etkilerini araştırdı. Bu iddiaları doğrulamak için Dünya Bankası Acil Durum İzleme Hane Halkı Anketi 2021 Verileri kullanıldı. Betimleyici istatistikler, çiftçilik hanelerinin sosyo-ekonomik özelliklerini belirleyicilerini tahmin etmek için kullanıldı. Elde edilen sonuçlar, tarımsal tarım dışı gelirin çiftçilik hanelerinin üretkenliği üzerindeki şokların azaltılmasını destekleyecek bilinçli kararlar nasıl alabileceklerini açıklamaktadır.

Anahtar kelimeler: Tarımsal Üretkenlik, Çiftçi haneleri, Şokların azaltılması, Tarım dışı gelir

1. INTRODUCTION

Nigeria is the largest country in West Africa with a population of over 200 million people. The agricultural sector accounts for about 23% of Nigeria's Gross Domestic Product (GDP), with over 70% of the population involved in one agricultural activity or the other (Abiola and Adefabi, 2022; Akenbor and Esheya, 2022). Despite this huge involvement in the agricultural sector by farming households, majority are still relatively poor (Berchoux et al., 2019). As a result of this poor narrative among these households, it is not easy for them to attain optimum agricultural productivity (Amare et al., 2018). This also implies that majority of farmers are easily prone to shocks and natural hazards assailing the agricultural sector negatively. Agricultural productivity is the rise in per capita output of agricultural produce within an economy over a period of time (Muhammad et al, 2022) which could be monthly, quarterly or annually. Furthermore, agricultural productivity can also be the output produced by a given level of inputs in the agricultural sector of the economy over a given period of time (Awoyemi et al., 2017). This in a more technical terms can be referred to as the value of total farms output to the value of total farms inputs ((Muhammad Sani Burodo, et al., 2022). Non-farm income earnings or proceeds generated from non-agricultural activities, is a form of diversification from the income obtained from farming activities (Guest Editorial, 2024). In most cases it serves as a form of boost or shock absorber to farming households. Ability to diversify or engage in other activities other than farming helps them to reduce vulnerability to shocks and market fluctuations, thereby achieving sustainable agricultural practices (Mengistu and Belda, 2024). Some non-farming activities engaged by farming households includes but are not limited to trading-buying and selling, craftmanship, carpentry, commercial motorcycling, commercial bus driving, commercial gardening, artisans, part time laborers (Pappas and Papadas, 2024). Aside income generated from non-farming activities, remittances or income from migrant family

members abroad can also be tailored towards achieving successes from the agricultural sector by farming families.

In empirical studies, the primary theoretical framework explaining the linkage between nonfarm and farm sectors is articulated by Singh et al. (1986). They propose that households, considering their labor and resource endowments, make allocation decisions based on the sector offering the highest utility in returns. Consequently, households tend to allocate more labor to the sector with the most favorable returns. An important aspect of the relationship between the nonfarm sector and the farm sector is the investigation into how household engagement in non-farm activities and the sale of their agricultural products impact this connection (Nkegbe et al., 2022). This study defines nonfarm activities as all endeavors undertaken by farming households away from their primary agricultural operations to generate additional income. Focusing exclusively on agricultural households, any economic pursuits they undertake outside of agriculture are categorized as nonfarm activities. These endeavors encompass a wide range of economic activities such as handicrafts, smallscale manufacturing (both household and nonhousehold), construction, mining, quarrying, repair services, transportation, petty trading, and others.

An access to other forms of income affects agricultural sector either positively or negatively (Sun *et al* 2024). Positively, it boosts access to inputs, reduce postharvest losses because farmers will be able to improvise or provide adequate storage for their farm produce thereby reducing losses (Mengistu and Belda, 2024). Non-farm income reduces dependence on agriculture, since the income generated can be used to augment purchase of inputs and equipment, expansion of soil and or improvement of soil fertility (Pappas and Papadas, 2024). Having another source of income increases interactions with other people thereby improving social capita and people net worth.

On the negative side, farmers or farming households involved in non-farming activities in

order to generate more income have the tendency of paying more attention to these activities than farming Sun et al., (2024). Non-agricultural income can have several long-term effects on individuals, households, and economies, these includes diversification of the economy. This reduces reliance on agriculture, allowing economies to become more resilient to agricultural shocks. Improved Living Standards since households with nonagricultural income tend to have higher consumption levels and better access to goods and services. Urbanization and Migration is not inevitable. increased non-agricultural income can encourage rural-to-urban migration, shifting labor dynamics. While non-agricultural income can boost financial stability, excessive reliance on it may reduce agricultural productivity, affecting food supply security. Higher income from nonagricultural sources can lead to greater investment in agricultural technology, improving efficiency.

1.1. Problem Statement

Despite the importance of the agricultural sector to the Nigerian economy, the sector is still facing many challenges (Abubakar and Attanda, 2013), critical amongst which are: use of outdated farming equipment and methods, inadequate infrastructures, limited access to credit and inputs, lack of access to information, inconsistent policies of government in relation to the agricultural sector and many more (Korgbeelo, 2022). Modernization of the agricultural sector can never be achieved with lack of adequate funds (Fadeyi, 2021). Consequent on the problem of lack of credit and input as well as need for farmers to mitigate certain shocks associated with farming activities, most farmers therefore engage in other moneymaking ventures other than farming (Benjamin et al., 2020). Furthermore, in 2021, over 8.7 million people in Adamawa, Borno and Yobe states needed humanitarian support as a result of farmer herder clashes, insecurity and the aftermath of COVID-19 pandemic¹. These states have been declared with heightened scenarios of food insecurity and hunger because majority of the occupants and inhabitants are mostly farmers. These states were worse hit by insurgencies and farmer herder clashes. On the hand, Katsina and Zamfara States were on the fore front of struggle for natural resources control, banditry, farmer herder clashes and criminality. Because more than 70% of the inhabitants of these states are farmers, these inhumane actions had displaced more than 70,000 farmers from their original lands, there had been displaced to neighboring villages and communities and as far as Niger Republic a neighboring country². This can in no wise enhance sustainable agricultural practices nor agricultural productivity in these states, hence the need for this research to access how farming households in these five States have used non-farming income to mitigate shocks and achieve agricultural productivity.

1.2. Objectives of the Study

The main objective of this study access effects non-farm income has on Agricultural Productivity and sustainable agriculture in order to mitigate shocks among farming households in Nigeria. The specific objectives are: to profile farming households and non-farm income available to them, to estimate the effect of non-farm income on agricultural activities/productivity and to identify shocks and ways farming households mitigated them

1.3. Justification for the Study

In order to augment the meagre resources available to farmers, there is need for farming households to engage in other non-farming income generating activities in order to mitigate shocks and enhance agricultural productivity (Guest Editorial, 2024; Obed *et al.*, 2021). According to Pappas and Papadas, (2024), nonfarm income has played a crucial role in mitigating

¹ North-east Nigeria: Borno, Adamawa and Yobe states Humanitarian Dashboard (January to March 2021) -Nigeria | ReliefWeb

 ² Nigeria: Protection Monitoring Report - Katsina, Sokoto and Zamfara 3 - 15 January 2021 - Nigeria | ReliefWeb

shocks and enhancing productivity of farming households. Some of the identified ways of actualizing this are via: Diversification of income sources. These provides farmers with an additional source of income beyond agriculture. During the times of shocks or crises, such as disease outbreaks, natural disasters, market fluctuations, man-made disasters or attacks, non-farm income can serve as a buffer, helping farming households withstand the impact of these shocks. Diversified income sources reduce their vulnerability and dependence on agricultural incomes at such times (Omodero and Ehikioya, 2022). Consequently, agricultural production is often exposed to diverse risks including climate-related hazards, price volatility, environmental and man-made hazards, market uncertainties (Oberc & Arroyo Schnell, 2020). Therefore, with access to other forms of income which might otherwise be more stable and reliable, farmers are less susceptible to risks prone to the agricultural sector (Li et al., 2022). Furthermore, since households will have access to supplementary sources of income when they engage in other non-agricultural generating ventures, as a means of covering other expenses like investments, divesting in agricultural inputs and technologies and expansions. They can better build savings or have ready funds in cases of emergencies, which puts them in a better stead than when there are no other sources of income.

Non-farm income provides farmers with additional financial resources to invest in their agricultural activities (Martinson and Abbas, 2022). Farmers are able to allocate a portion of towards improving farming these income practices, thereby acquiring new technologies, access trainings and extension services, or invest in infrastructure (Ming et al., 2022). These investments can lead to increased agricultural productivity, better crop yields, enhanced livestock management, and improved overall agricultural performance (Obed et al., 2021). We can also argue that non-farm income opportunities can reduce labor fluctuations in agriculture during times of shocks (Benjamin and Kwame, 2020). When non-farm income provides alternative employment opportunities, it can help stabilize the

labor force engaged in agricultural activities. This stability ensures the availability of skilled labor for essential farming operations, which is vital for maintaining productivity, particularly during periods of shocks or increased demand. Non-farm income activities often involve engagement in non-agricultural sectors such as food processing, agro-industries, or marketing (Li *et al.*, 2022).

These activities contribute to the development of local value chains and market linkages. By diversifying income sources, farmers can participate in higher-value activities along the agricultural value chain, leading to improved market access, higher income, and enhanced agricultural productivity (Nkegbe *et al.*, 2022).

While non-farm income can bring various benefits, it also has certain limitations on agricultural productivity (Ming et al., 2022). Some key limitations to consider are: Time and Resource Constraints. Engaging in non-farm income activities may require farmers to allocate their time and resources away from agricultural production. This can lead to a diversion of labor, capital, and management attention from farming activities, potentially affecting productivity and farm efficiency. Non-farm income activities often require different skills and knowledge compared to agricultural production. Farmers may need to acquire new skills or seek training to engage in non-farm activities effectively. If there is a lack of access to training or limited knowledge transfer, it can hinder the successful integration of non-farm income activities and negatively impact agricultural productivity. Subsequently, agricultural activities are often seasonally intensive, requiring farmers' full attention during critical periods such as planting, harvesting, or livestock management. Engaging in non-farm income activities alongside agriculture can lead to conflicting demands and challenges in managing both effectively (Sun et al., 2024). Balancing the demands of both activities can be a limitation to achieving optimal agricultural productivity. Nonfarm income opportunities may depend on access to markets, infrastructure, and supportive business environments. In rural areas with limited market linkages, poor transportation, and inadequate infrastructure, the potential for viable non-farm income activities may be limited. This can restrict the ability of farmers to (Ming et al., 2022) diversify their income and have a significant impact on agricultural productivity. Non-farm income activities are not immune to risks and uncertainties. Economic fluctuations, market volatility, regulatory changes, and other external factors can affect the profitability and stability of non-farm income sources. If non-farm income activities face significant risks or experience downturns, farmers may become more vulnerable, and their agricultural productivity may be impacted. In some cases, a strong focus on nonfarm income activities may result in neglecting necessary investments in agricultural inputs, technologies, and infrastructure. Insufficient investment in farming can limit the adoption of modern agricultural practices, leading to lower productivity and reduced agricultural growth. If non-farm income opportunities attract agricultural labor away from farming, it can lead to labor shortages in the agricultural sector. This can impact agricultural productivity, especially during peak farming seasons when labor demand is high. Adequate availability and retention of skilled labor are essential for maintaining agricultural productivity. Also, certain non-farm income activities, such as small-scale enterprises or artisanal crafts, may have limitations in terms of scalability and growth potential. Scaling up nonfarm income activities to generate substantial income may be challenging, particularly in regions with limited market demand or saturated markets for specific products or services.

2. MATERIAL and METHODS

2.1. Data Source

In order to adequately address the determinants of non-farm income on Agricultural Productivity: Implication for sustainable agriculture and mitigating shocks among farming households in Nigeria, the data in Emergencies Monitoring Household Survey 2021 from the Food and Agriculture Organization (FAO), Data in Emergencies Hub, published on 8th February, 2023 was used³. The FAO developed a monitoring system in 26 food crisis countries to better understand the impacts of various shocks on agricultural livelihoods, food security and local value chains. The Monitoring System consists of primary data collected from households on a periodic basis (more or less every four months, depending on seasonality). Between the 20th May and the 25th June 2021, FAO led a household survey of five states in Nigeria: Borno, Katsina, Yobe and Zamfara. These five states were considered based on their agrarian peculiarities and being prone to shocks e.g., armed conflict, farmer herder clashes etc.⁴ Adamawa, Borno and Yobe States are in the Northeastern region of Nigeria (Food and Agriculture Organization (FAO) in Nigeria, 2020)

FAO describes the sampling procedure in the **Emergencies Monitoring Household Survey 2021** as follows: The sample design of this first round of data collection in Nigeria was Random Digital Dialing with no quotas. The total sample size was 2739 household and the sample size per state was: 556 in Adamawa; 568 in Borno; 535 in Yobe, 758 in Katsina and 322 in Zamfara. Data were disaggregated for comparison between Local Government Areas directly impacted by armed conflict and those not affected. The survey administered questionnaires covering the following information: Household information, income sources, crop production, crop marketing, livestock production, livestock marketing, fisheries production, fisheries marketing, food security and consumption, needs assistance.

2.2. Analysis of Data

To estimate the determinants of Agricultural Productivity, we proxied agricultural productivity as total income from farming households. This is the summation of both farm and non-farm income generated. In empirical studies, the primary theoretical framework explaining the linkage between nonfarm and farm sectors is articulated by (Singh *et al.*, 1986). Therefore, in order to

^{3:} https://microdata.worldbank.org/index.php

⁴https://data-in-emergencies.fao.org/pages/monitoring

estimate the determinants of non-farm income on agricultural productivity, the relationship between agricultural productivity and non-farm income, and determinant of agricultural productivity, the Tobit regression, probit regression, ordered logistic regression, linear regression and the multinomial logistic regression models were used, however, the probit and the linear regression models were the models of best fit for estimation. A Tobit regression⁵ or censored regression model belongs to a class of regression models designed for situations where the observed range of the dependent variable is censored, after the analysis, we encountered the problem of nonconvergence of both explanatory and the dependent variables. The error of only one variable defined and others not fully defined were obtained from probit, logit, ordered logit and multinomial regression model, respectively.

2.3. The Linear Regression Model

Agricultural Productivity proxied as farm and non-farm = total income (1)

 $\sum (farm + nonfarm income) = f$ unction of explanatory variables (2)

i.e.

$$\sum Zi = f (X_1 + X_2 + X_3 + X_4 + \dots X_n + e_n)$$
(3)

Where: Zi = Agricultural Productivity (proxied as total income-sum total of farm and non-farm income); X_1 = age of respondents; X_2 = gender (male =1, female = 0); X_3 = resident type (resident = 1, non-resident/displaced =0); X_4 = education (formal education =1, informal education =0); X_5 = activity (non-agricultural=0, agricultural = 1); X_6 = language (Hausa =1, English = 0); X_7 = Exposure to Shocks (yes = 1, no = 0); X_8 = where you called back after the shock/disaster (yes =1, no = 0); X_9 = Respondents' state (Borno=1, Yobe=2, Adamawa=3, Zamfara=4, Katsina=5). In order to estimate the determinants of shocks among respondents in the study area, the probit

regression model was used. Shocks were categorized as farmers affected (yes=1), or farmers not affected (no=0).

2.4. The Probit Regression Model⁶

This is one of the regression types used in modelling dichotomous or binary outcome variables⁷. Binary outcomes variables are those dependent variables with just two possibilities designated as yes or no (Nisbet, 2009; 2018) (Nisbet *et al.*, 2009); (Nisbet *et al.*, 2018).

To model a binary outcome, we have:

$$y^{*} = \alpha + \beta X + e$$
(5)
$$Y_{i} = \begin{cases} 1 \ if \ y \ * > \ r' \\ 0 \ if \ y \ * \leq \ r' \end{cases}$$
(6)

The Probit regression model is therefore specified as:

$$\Phi^{-1}(\mathbf{p}_{i}) = \sum_{k=0}^{k=n} \beta K X i k \tag{7}$$

Y= the dependent variable (Shocks: yes =1, no=0); Γ = the threshold; B = vector of parameter

 Φ is the normal distribution of errors; X= vector of explanatory variables; e_i = independent; distributed error term; $X_1 = age$ (continuous variable); $X_2 =$ Gender (male =1, female= 0); $X_3 =$ Education (formal education =1, informal education =0); X_4 = Total income (naira) [sum of farm and non-farm income); $X_5 =$ resident type (resident =1, non-resident/displaced =0); $X_6 =$ language (English =1, Hausa =0); X_7 = activity (Agricultural activities =1, non-agricultural activities = 0); X_8 = where you called back after the shock/disaster (yes =1, no = 0); $X_9 =$ Respondents' state (Borno=1, Yobe=2, Adamawa=3, Zamfara=4, Katsina=5).

Variable Specification

(i) Dependent variable: Exposure to Shocks. This study draws its inference from the studies of Takeshi and Tetsuji 2019; Tan *et al.*, 2021) the

⁵ Tobit Regression Model - What Is It, Examples, Applications (wallstreetmojo.com)

⁶ Probit Regression | Stata Data Analysis Examples (ucla.edu).

 ⁷ Probit Model (Probit Regression): Definition - Statistics How To

study of Takeshi and Tetsuji was centered on an economic crisis considered as man-made disaster which was characterized as an aggregate shock. The research focus as an investigation of the dynamics of productivity in prewar rural Japan. While in the case of Tan et al., their research was focused on the impact of climate change on rice yields in Malaysia. In this research, exposure to shocks (environmental-climate change, drought, floods-financial, health and work related) was classified into two major categories, Exposure to shocks-yes; or non-exposure to shocks-no; ii) The independent variables: were all other variables and their indicators that could explain the exposure or non-exposure of farming households to shocks.

3. RESULTS and DISCUSSION

3.1. Socio-economic characteristics of farming households

Farming households' mean age was ±33 years, while the mean total income was ₩277,076. The total income was a summation of all the incomes generated by the farming households. This consist of both agricultural incomes and non-agricultural incomes (Table 2).

Table 1: Demographic Characteristic of farming households

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
Age	2709	33.89	11.27	17	89
Total income	2709	277,076	535455.9	0	8,7000,005
Source: https://microdat	ta fao org				

Source: https://microdata.fao.org

Other socio-economic characteristics of farming households (Table 2) showed there were more males (92.80%) captured in the survey than females (7.20%) this is due to the cultural and religious background of the study area, where more males are exposed to the public than females. There were 526 respondents in Adamawa (19.4%), 568 respondents in Borno (21%), 758 respondents in Katsina (28%), 532 in Yobe (19.7%) and 322 respondents in Zamfara (11.9%). In order to fully understand the situation of farming households in the study area, there is need to scrutinize their residence types. Residents (93.38%) based on data surveyed live in the northern part of Nigeria, and are fully agrarian (80.62%). As at the time of this survey, they were plagued with shocks (70.58%) caused by natural disasters, farmer herder conflicts, droughts, etc. An overview of their type of residence showed that 93.8% were original occupants of the areas surveyed. More than ninety percent of respondents (93.28%) have been living in this particular area longer than two years after been displaced from their homes earlier. While recent migrants (6.69%) are those who have been living in this present place of residence for less than two years. Households (99.78%) were called by the authorities during or after their displacement, while 70.58% experienced shocks or natural hazards. Households' main sources of income was further neatly categorized into agricultural (crops and livestock production) and non-agricultural sources of income in shown in Table 2. Fifty-five percent of farming households engage in other non-farming activities as a way of augmenting income generated to the them, while 44.81% households obtain income from farming activities alone. Farming households (70.58%) were exposed to one shock or the other (see Table 3). The major shocks farming households in the study area were exposed to were sickness and death of household head (83.61%%), pest outbreak (96.71%), high food prices (72.61%), high fuel prices (85.75%), can't work or do business (92.36%), animal disease (96.60%), loss of farm employee (83.35%), no pasture (86.82%).

State	Frequency	Percent	Cumulative Percent
Adamawa	526	19.4	19.4
Borno	568	21.0	40.4
Katsina	758	28.0	68.4
Yobe	535	19.7	88.1
Zamfara	322	11.9	100.0
Gender			
Female	195	7.20	7.20
Male	2,514	92.80	100.00
Education			
Formal	2,443	90.18	90.18
No formal	266	9.82	100.00
Agricultural Activities			
Yes - both crop and livestock production	2,184	80.62	80.62
No	525	19.38	1000.0
Resident type			
Resident	2,527	93.28	93.28
Non-resident (displaced)	182	6.69	6.79
Income Source			
Agriculture	1214	44.81	44.81
Non-agriculture	1495	55.19	100.00
Language			
English	1520	43.89	43.89
Hausa	1189	56.11	100.00
Response call during/aftershock (call back by			
authorities)			
No	6	0.22	0,22
Yes	2703	99.78	100.00
Experienced Shock/natural hazard			
Yes	1912	70.58	70.58
No	797	29.42	100.00

Table 2: Socio-economic characteristics of respondents

Source: https://microdata.fao.org

3.2. Determinants of Shocks

This output from Table (3) provides information about the overall goodness of fit and evaluation of the model. Mean dependent variable represents the mean of the dependent variable, which in this case is exposure to shock. SD dependent variable. Pseudo R-squared this unlike the traditional Rsquared in linear regression, is used in logistic regression models (and sometimes other types of models) to measure the goodness of fit. It represents the proportion of variance in the dependent variable that is explained by the independent variables. In this case, the pseudo-R- squared is approximately 0.062, indicating that around 62% of the variance in exposure to shock is explained by the independent variables. Chisquare statistic is often used in logistic regression to assess the overall fit of the model. It compares the observed outcomes to the expected outcomes under the null hypothesis (that the model has no predictive power). Higher values of chi-square indicate a better fit of the model to the data. Prob > chi2: This is the p-value associated with the chisquare statistic. It indicates the probability of observing a chi-square statistic as extreme as, or more extreme than, the one computed from the data, under the assumption that the null hypothesis

is true. A low p-value (typically less than 0.05) suggests that the model provides a significantly better fit than a model with no predictors. Akaike Information Criterion (AIC) measures the relative quality of a statistical model for a given set of data. It balances the goodness of fit of the model with the complexity of the model (i.e., the number of parameters). Lower values of AIC indicate a better balance between goodness of fit and model complexity. Bayesian Information Criterion (BIC) similar to AIC, BIC is another measure used for model selection. It penalizes models with more parameters more heavily than AIC. Like AIC, lower values of BIC indicate a better balance between goodness of fit and model complexity. Based on all these statistics, the model appears to have a good explanatory power (pseudo-Rsquared of 0.620) and a good fit to the data (significant chi-square and low p-value). Pseudo R-squared is a measure used to assess the goodness of fit for models where traditional Rsquared isn't applicable, such as logistic

regression. Unlike R-squared in linear regression, pseudo R-squared doesn't represent the proportion of variance explained by the model but provides an indication of how well the model fits the data. A pseudo R-squared value of 0.620 suggests that the model explains a moderate amount of the variation in the dependent variable.

Furthermore, we can deduce that living Yobe, Adamawa and Katsina predisposes farming households to shocks. These variables are negative yet significant factors of exposure to shocks. We can also deduce from the table that older household heads are less likely to be prone to being exposed to shocks and other hazards than the younger family members. This therefore suggests that children and youth will bear the heat of shocks, natural disasters and hazards. This research outcome is similar to what was obtained in Brazil by Silva *et al.*, (2017) where the younger ones bore more the effect of drought causing them to be more vulnerable.

Table 3: Determinants of Shocks / Probit regression

Coaf	St Err	t volue	n volue	[05% Conf	Interval	Sig
0000	St.EII.	t-value	p-value	[9570 COIII	Interval	Sig
0	•	•	•	•	•	
-0.075	0.082	-0.91	0.364	-0.236	0.086	
-0.196	0.082	-2.40	0.017	-0.357	-0.036	**
-0.218	0.094	-2.31	0.021	-0.403	-0.033	**
-0.124	0.075	-1.65	0.099	-0.271	0.023	*
-0.010	0.002	-4.25	0.000	-0.015	-0.006	***
-0.376	0.064	-5.86	0.000	-0.501	-0.250	***
0.097	0.094	1.03	0.301	-0.087	0.282	
0.000	0.000	1.29	0.196	0.000	0.000	
-0.205	0.532	-0.39	0.700	-1.249	0.838	
0.386	0.056	6.95	0.000	0.277	0.496	***
0.275	0.106	2.59	0.09	0.067	0.482	***
-0.446	0.591	-0.76	0.45	-1.604	0.711	
	0.294	SD depende	ent var		0.456	
	0.620	Number of observations			2709	
	137.150	Prob > chi2			0.000	
	3169.473	Bayesian crit. (BIC)			3240.325	
	Coef. 0 -0.075 -0.196 -0.218 -0.124 -0.010 -0.376 0.097 0.000 -0.205 0.386 0.275 -0.446	Coef. St.Err. 0 . -0.075 0.082 -0.196 0.082 -0.218 0.094 -0.124 0.075 -0.010 0.002 -0.376 0.064 0.097 0.094 0.000 0.000 -0.205 0.532 0.386 0.056 0.275 0.106 -0.446 0.591 0.294 0.620 137.150 3169.473	Coef.St.Err.t-value0 -0.075 0.082 -0.91 -0.196 0.082 -2.40 -0.218 0.094 -2.31 -0.124 0.075 -1.65 -0.010 0.002 -4.25 -0.376 0.064 -5.86 0.097 0.094 1.03 0.000 0.000 1.29 -0.205 0.532 -0.39 0.386 0.056 6.95 0.275 0.106 2.59 -0.446 0.591 -0.76 O.294SD depended 0.294 SD depended 0.620 Number of 137.150 Prob > chi2 3169.473 Bayesian cr	Coef.St.Err.t-valuep-value0 -0.075 0.082 -0.91 0.364 -0.196 0.082 -2.40 0.017 -0.218 0.094 -2.31 0.021 -0.124 0.075 -1.65 0.099 -0.010 0.002 -4.25 0.000 -0.376 0.064 -5.86 0.000 0.097 0.094 1.03 0.301 0.000 0.000 1.29 0.196 -0.205 0.532 -0.39 0.700 0.386 0.056 6.95 0.000 0.275 0.106 2.59 0.09 -0.446 0.591 -0.76 0.45 O.294SD dependent var 0.620 Number of observations 137.150 Prob > chi2 3169.473 Bayesian crit. (BIC)	Coef.St.Err.t-valuep-value[95% Conf00.0750.082-0.910.364-0.236-0.1960.082-2.400.017-0.357-0.2180.094-2.310.021-0.403-0.1240.075-1.650.099-0.271-0.0100.002-4.250.000-0.015-0.3760.064-5.860.000-0.5010.0970.0941.030.301-0.0870.0000.0001.290.1960.000-0.2050.532-0.390.700-1.2490.3860.0566.950.0000.2770.2750.1062.590.090.067-0.4460.591-0.760.45-1.604Use of observations137.150Prob > chi23169.473Bayesian crit. (BIC)	Coef.St.Err.t-valuep-value $[95\%$ ConfInterval]00.0750.082-0.910.364-0.2360.086-0.1960.082-2.400.017-0.357-0.036-0.2180.094-2.310.021-0.403-0.033-0.1240.075-1.650.099-0.2710.023-0.0100.002-4.250.000-0.015-0.006-0.3760.064-5.860.000-0.501-0.2500.0970.0941.030.301-0.0870.2820.0000.0001.290.1960.0000.000-0.2050.532-0.390.700-1.2490.8380.3860.0566.950.0000.2770.4960.2750.1062.590.090.0670.482-0.4460.591-0.760.45-1.6040.711Number of observations2709137.150Prob > chi20.0003169.473Bayesian crit. (BIC)3240.325

3.3. Determinants of Agricultural Productivity

The determinants of agricultural productivity (Table 4) were estimated using the ordinary least squares (OLS) method, the dependent variable is "Total-Income" with several independent variables tested for their effect on total income. The Coefficients (Coef.) were estimated for each independent variable in the regression model.

They represent the change in the dependent variable for a one-unit change in the independent variable, holding all other variables constant. The Standard Error measures the accuracy of the coefficient estimate. Smaller standard errors indicate more reliable estimates, while the t-value also called the t-statistic, measures the number of standard deviations the coefficient is away from zero. Larger absolute t-values indicate that the coefficient is more likely to be statistically significant. The p-value indicates the probability of observing the t-statistic if the null hypothesis were true (i.e., if the true coefficient were zero). Lower p-values suggest stronger evidence against the null hypothesis. Typically, if the p-value is less than a chosen significance level (e.g., 0.05), the coefficient is considered statistically significant. The 95% Conf Interval provides the confidence interval for the coefficient estimate. It gives a range within which we are reasonably confident

the true coefficient lies with a certain level of confidence (usually 95%). Mean Dependent Variable, SD Dependent Variable represent the mean and standard deviation of the dependent variable, respectively. R-squared is a measure of how well the independent variables explain the variability of the dependent variable. It ranges from 0 to 1, with higher values indicating a better fit. In this case, the model explains around 42.3% of the variability in the dependent variable. F-test, Prob > F-test examines whether there is a statistically significant relationship between the independent variables and the dependent variable as a whole. The p-value associated with the F-test indicates whether the overall regression model is statistically significant. Akaike crit. (AIC), Bayesian crit. (BIC) are information criteria used for model selection. Lower values indicate a better trade-off between goodness of fit and model complexity.

Total- Income	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
: base Borno	0						
State							
Yobe	-21788.598	32636.853	-0.67	0.504	-85784.385	42207.189	
Adamawa	-4505.525	32454.174	-0.14	0.890	-68143.107	59132.057	
Zamfara	102804.71	37207.991	2.76	0.006	29845.635	175763.79	***
Katsina	76682.75	29921.051	2.56	0.010	18012.227	135353.27	**
Agric-activity HH	110564.68	26409.982	4.19	0.000	58778.817	162350.54	***
Gender	68080.032	39852.159	1.71	0.088	-10063.847	146223.91	*
Education	87449.098	35371.052	2.47	0.013	18091.972	156806.23	**
Exposure to	27245.869	22959.723	1.19	0.235	-17774.573	72266.312	
Shock							
Callback	-56667.928	217616.45	-0.26	0.795	-483379.9	370044.04	
Language	59842.986	21802.893	2.74	0.006	17090.907	102595.07	***
Age	2043.555	924.3880	2.21	0.027	230.9750	3856.136	**
Resident type HH	33382.075	40791.535	0.82	0.413	-46603.774	113367.93	
Constant	-101489.32	239601.58	-0.42	0.672	-571310.71	368332.07	
Mean dependent var		277075.978	SD depen	dent var		535455.854	
R-squared		0.423	Number of	of observati	ons	2709	
F-test		5.321	Prob > F			0.000	
Akaike crit. (AIC)		79117.549	Bayesian	crit. (BIC)		79194.305	
Source: https://microdata.fao.org;		*** p<0.01, *	* p<0.05, *	^r p<0.1			

Table 4: D	Determinants	of Agri	cultural	Productivity	/ Line	ar regression
		<i>(</i> 7				<i>C</i>

From Table 4, we can see that the male gender (p<0.1) earns more than the female gender, Agricultural activity (p<0.01) has highest positive

effect on income, residing in Zamfara State (p<0.01), residing in Katsina State (p<0.05), Being educated (p<0.05) positively impacts on

income. This signifies that education contributes significantly to higher agricultural earnings. language (p<0.01) and Age (p<0.05) are independent variables statistically significant predictors of total income, based on their coefficients and corresponding p-values, since their p-values are less than 0.05. Residing in Zamfara and Katsina shows a positive relation with an increase in the total income of faming households compared to those residing in Yobe and Adamawa states of the country. This result is a reflection and a representation of the present situation in these states were economic activities are going on smoothly without any hindrance or fear (Afouda et al., 2019). Households who engaged in other forms of non-farm income getting activities other than anticultural activities had a positive coefficient and higher total income. This is similar to the result obtained by Mazibuko and Antwi, (2019) where additional income increased the productivity of farmers this is however not similar with the research result of Sun et al., (2024) where non-farm income increased farm land abandonment and as such led to reduction in agricultural production.

Residents of respondents (State where farming households reside, Zamfara and Katsina) had a positive and significant relationship with increase in agricultural productivity. Households who were engaged in one agricultural activity or the other had a positive relationship with total income, proxied as agricultural productivity. This implies that household solely involved in agricultural activities had a increase in total income. Gender of households had a positive effect on agricultural productivity. In these study, more males were involved in agricultural activities than females, this is a result of the culture of people in the region (Kamara *et al.*, 2020).

4. CONCLUSION AND RECOMMENDATIONS

Overall, the combination of non-farm income opportunities and enhanced agricultural productivity can mitigate shocks, reduce poverty, enhance food security, create employment, promote sustainable resource management, and foster economic development in these five States. The synergy between non-farm income and agricultural productivity is crucial for achieving sustainable development goals and improving the well-being of farming families in these States. It is important to also note that the potential of nonfarm income to mitigate shocks and enhance agricultural productivity depends on various factors, including the availability of non-farm opportunities, state of residence of farming households, gender, educational status, language, whether respondents were called back after experiencing shock or natural disasters. Therefore, promoting non-farm income opportunities alongside agricultural development strategies will contribute to building absorbers to shocks, reduce vulnerability, and improve overall productivity among farmers.

In order to boost non-agricultural income sources, governments can implement a variety of policies and incentives. Skill Development Programs by investing in vocational training and skill development initiatives to equip individuals with the expertise needed for non-agricultural jobs, such as in manufacturing, IT, or services. Infrastructure Development- improve rural infrastructure, including roads, electricity, and internet connectivity, to support small businesses, tourism, and other non-agricultural activities. Interest loans, grants, or subsidies to entrepreneurs and small businesses in non-agricultural sectors to encourage innovation and expansion. Offer tax breaks or incentives to businesses that set up operations in rural or underdeveloped areas, creating job opportunities outside agriculture. Supporting the development of rural industries like handicrafts, textiles, and food processing marketing through assistance, technology upgrades, and export promotion.

Development of eco-tourism and cultural tourism in rural areas, which can generate income for local communities through Public-Private Partnerships (PPPs). Collaborate with private companies to invest in non-agricultural sectors, ensuring sustainable development and job creation. There is need to facilitate access to modern technology and digital tools for rural entrepreneurs to enhance productivity and market reach. Raise awareness about non-agricultural opportunities and provide career counseling to encourage diversification of income sources and establishment of safety nets like unemployment benefits or income support programs to reduce the risks associated with transitioning to non-agricultural livelihoods. These policies can help create a more diversified and resilient economy, reducing dependence on agriculture while improving overall living standards.

Limitations of the Study:

- 1. The data was sourced from external sources and it did not capture major agricultural productivity information like output, input, land area cultivated, labour used, farm management practices, time period, price data, economic indicators (such as inflation rate, interest on loans, government subsidies etc.), farm level data, other national and regional statistics (since majority of the farmers were displaced to other communities, states and neighboring countries).
- 2. This research was not able to capture agricultural productivity by $\frac{total output}{total input}$, since we didn't have information on these variables.
- 3. There is no assurance that the displaced farming households were the original occupants in the farming centers at the time the survey was carried out.
- 4. Because of the insurgencies in the region (banditry, farmer-herder clashes and other forms of conflict, so many farming household heads have been displaced to neighboring towns, villages and countries, there is the possibility that responses obtained would have emotional coloration.

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