

Article

Youth Participation in Agriculture and Poverty Reduction in Nigeria

Romanus Osabohien ¹, Alexander Nimo Wiredu ², Paul Matin Dontsop Nguezet ³,
Djana Babatima Mignouna ⁴, Tahirou Abdoulaye ⁵, Victor Manyong ⁶, Zoumana Bamba ⁷
and Bola Amoke Awotide ^{5,*}

¹ Department of Economics and Development Studies, Covenant University, Ota 112212, Nigeria; romanus.osabohien@covenantuniversity.edu.ng

² Social Science and Agribusiness, International Institute of Tropical Agriculture (IITA), Nampula 258, Mozambique; N.wiredu@cgiar.org

³ Social Science and Agribusiness, International Institute of Tropical Agriculture (IITA), Kalemie 570, Democratic Republic of the Congo; P.Dontsop@cgiar.org

⁴ International Institute of Tropical Agriculture (IITA), Cotonou 08 BP 0932, Benin; D.Mignouna@cgiar.org

⁵ Social Science and Agribusiness, International Institute of Tropical Agriculture (IITA), Bamako 91094, Mali; T.Abdoulaye@cgiar.org

⁶ Social Science and Agribusiness, International Institute of Tropical Agriculture (IITA), Dar es Salam 34441, Tanzania; v.manyong@cgiar.org

⁷ Country Representative, International Institute of Tropical Agriculture (IITA), Kinshasa 4163, Democratic Republic of the Congo; Z.Bamba@cgiar.org

* Correspondence: b.awotide@cgiar.org



Citation: Osabohien, R.; Wiredu, A.N.; Nguezet, P.M.D.; Mignouna, D.B.; Abdoulaye, T.; Manyong, V.; Bamba, Z.; Awotide, B.A. Youth Participation in Agriculture and Poverty Reduction in Nigeria. *Sustainability* **2021**, *13*, 7795. <https://doi.org/10.3390/su13147795>

Academic Editor: Luis Jesús Belmonte-Ureña

Received: 3 May 2021
Accepted: 9 June 2021
Published: 13 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract: With data from 683 systematically selected households, the study employed the Heckman two-stage model and the propensity score matching method (PSM) to examine the impact of youth participation in agriculture as a primary occupation on income and poverty in Nigeria. The results indicate that the gender of the youth and their determination to stay in agriculture significantly increases the probability that youth will participate in agriculture as a primary occupation. In addition, youth participation in agriculture as a main occupation contributes significantly to per capita household income and has the likelihood to reduce poverty by 17%. The daily wage rate of hired labor and the total farmland owned are the variables that positively explained the per capita income. Poverty was reduced by market access, having agriculture as a primary occupation, income from agricultural production, the total monetary value of all the household assets, determination to remain in agriculture, and the square of the respondents' age. These results imply that creating employment for youth by engaging them in agriculture as a full-time occupation can increase their income and reduce poverty. However, the promotion of other secondary occupations, land, and market access is also vital.

Keywords: agribusiness; per capita income; poverty reduction; sustainable development; youth unemployment

JEL Classification: D30; E24; J13; L30

1. Introduction

Africa has the highest proportion of people living in extreme poverty, comprising about 413.3 million in 2015 [1,2]. The high population growth rate has resulted in an increased level of unemployment, especially among the youth. Unemployment is believed to be one of the major causes of poverty. For Nigeria, about 86.9 million people are living in absolute poverty, which represents almost 60% of its estimated 200 million population [3]. Nigeria is experiencing a huge population increase, and it is projected to be the world's

third-largest country by 2050. This poses a threat to the actualization of the Sustainable Development Goals (SDGs), especially SDG-1 (to reduce extreme poverty by 2030) if urgent actions are not taken.

Globally, the unemployment rate is becoming a thing of deep concern, especially in Africa. In addition, the increasing rate of unemployment and poverty have caused the youth to venture into crimes or risk their lives to illegally migrate to developed countries in search of better opportunities [4]. According to United Nations, “youth are the persons between the ages of 15 and 24 years inclusive” [2]. On the other hand, the African Union (AU) defines youth as those individuals that fall within the age bracket of 15 to 35 years [5]. However, the National Policy on Youth Development in Nigeria defines youth as individuals between 18 and 35 years old. This subset of Africa’s teeming population constitutes about 60% of the total population [2,6,7]. By 2030, it is estimated that the African youth population will increase by 35%, which will further increase unemployment and poverty [2,7–9].

Similarly, the annual increase in the rate of youth unemployment in Nigeria is outrageous and worrisome. Hundreds of thousands of graduates are entering the labor market annually, where there is little or no hope of being gainfully employed. In 2009, the national unemployment rate in Nigeria was 19.7%, with the youth accounting for more than 75% [10]. As about 60% of Nigeria’s 200 million population are youths, with 55.4% being unemployed or underemployed, youth unemployment and poverty require urgent attention [8,9,11].

Nigeria’s government has attempted to stimulate youth interest in agricultural production and processing since the late 1980s. For instance, in 1986, the Federal Government established the National Directorate of Employment (NDE) to provide vocational training for the youth. In 1992, the Fadama program was initiated to enhance food self-sufficiency, reduce poverty, and create opportunities for employing youth in rural areas. In addition, in 2016, the Anchor Borrower’s Program (ABP), under the Agricultural Transformation Agenda (ATA), was launched to provide funds for youth interested in agriculture [6,12].

Studies have been conducted to examine some aspects of youth participation in agriculture; for example, Fawole and Ozkan [13] found that, with the required opportunities, such as creating a conducive environment for agribusiness, most respondents were willing to engage in agriculture. The study posited that if 22% of unemployed youth were involved in agriculture, particularly in all of the value chain nodes, there would be a reduction in unemployment. Similarly, Lyocks [14] found that inadequate incentives, limited agricultural skills, lack of agricultural training, limited access to finance, and low agricultural prospects were some of the factors hindering youth participation in agriculture. Another study, Libaisi, Marinda and Wakhungu [15] found that few youth are in agriculture compared with other segments of the population.

The study by Sakketa and Gerber [16] concluded that there is renewed hope for agriculture to provide sustainable livelihood prospects for the youth.

Presently, the focus on curtailing the threat of youth unemployment nationally and internationally is to fully engage youth in the agricultural sector. However, what is yet to be understood is how much better-off the youth are that participate in agriculture as a primary occupation compared with others in the population that are in agriculture as a secondary occupation. In other words, do the youth that is involved in agriculture or any activity along the agribusiness value chain as a primary occupation have a higher income compared with others (youth and non-youth) that participate in agriculture as a secondary occupation? In addition, how much impact does youth participation in agriculture as a primary occupation have on poverty reduction among the youth? These are some of the cogent questions that this study intends to answer.

In answering these questions, the study guides the policymakers concerning youth, poverty, and employment-related policies, especially projects targeted at creating employment for the youth within the agricultural value chain. Although, as mentioned previously, studies have been carried out in the area of youth employment and participation or engage-

ment in agriculture, to the best knowledge of the authors, the aspect of youth participation in agriculture as a primary occupation and its poverty effects, using the PSM and Heckman two-stage model, has not been considered in the extant literature. Thus, this study contributes to the literature by filling this gap.

2. Materials and Methods

2.1. Study Design, Study area, and Data

The study was conducted in two Nigerian geopolitical zones: North-Central and South-West. One state was selected from each region. In North-Central, Kwara State was selected, and in South-West, Ekiti State was selected. These two states are among the top states, with a substantial proportion of youth in agriculture in Nigeria. Kwara State covers a landmass of 32,500 km² and lies between latitudes 7°45'' and 9°30'' N and longitudes 2°30' and 6°35' E. The State comprises sixteen local government areas (LGA). Ekiti State covers an area of 8557 km² and consists of 16 LGAs.

The target population for the survey is the rural households who are engaged in agriculture, either as a primary or secondary occupation. The National Policy on Youth Development in Nigeria defines youth as individuals between 18 and 35 years. The total sample size of 1000 households, which comprised youth and adults, was collected through a multi-stage random sampling technique.

The first stage involved the purposive selection of the Kwara and Ekiti States. In the second stage, five LGAs were selected from each of the states, based on the reported large number of youths in these LGAs by the State Ministry of Agriculture. The third stage involved selecting five communities from the selected LGAs from each state, making a total of 25 communities for each state. The final stage involved the selection of twenty households per community. Five hundred respondents were collected from each state.

The data were analyzed using descriptive statistics, probit regression, propensity score matching (PSM), and the Heckman two-stage model. The t-statistic was used to test for significance in the differences in the socio-economic characteristics and poverty indicators of the respondents.

2.2. Analytical Framework and Estimation Techniques

This study is designed to evaluate the impact of youth participation in agriculture/agribusiness on poverty reduction. It seeks to determine whether youth that participates in agriculture as a primary occupation (treated group) have a higher income (calculated as the per capita average income from agricultural activities for three years and hence non-poor) compared with the other respondents that participate in agriculture as a secondary occupation.

Youth participation in agriculture (treated group) is defined as one, if the respondent is a youth, that is, falls within 18–35 years old, and participates in agriculture or agribusiness as a primary occupation. The control group consists of the other respondents in the sample that participate in agriculture or agribusiness as a secondary occupation, irrespective of age. Participation in agriculture/agribusiness includes not only crop or livestock production, but also any activities along the agricultural value chain, such as inputs marketer, supplier of farm implements, output marketer, transporter of farm produce, and farm output processor.

The study specified the basic relationship of the impact of youth participation in agriculture as a primary occupation on per capita income as a linear function of a vector of explanatory variables (X_i) and the youth participation in agriculture as a primary occupation dummy variable (D_i). Thus, the linear regression model is specified in Equation (1), as follows:

$$G_i = X_i'\lambda + \gamma D_i + \varepsilon_i \quad (1)$$

where G_i represents per capita income, ε_i is the normal random distribution term, D_i is a dummy variable representing youth participation in agriculture as a primary occupation. The dummy variable takes the value of 1 if the respondent is aged 18–35 years and

participates in agriculture as a primary occupation, and 0 if the respondent participates in agriculture as a secondary occupation, irrespective of age. The dichotomy in this paper is participation in agriculture as a primary or secondary occupation. Similarly, X_i is the vector of household and farm characteristics.

Youth participation in agriculture/agribusiness as a primary occupation was viewed as a function of socioeconomic and farm characteristics. It is believed that the fact that a youth decided to participate in agriculture as a primary occupation implies that the youth has self-selected to participate in agriculture instead of through a random assignment. Therefore, following the study by Becerril and Abdulai [17], this present study assumed that the respondents were risk-neutral. The index function used to estimate the respondents' participation in agriculture was therefore expressed in Equation (2), as follows:

$$D_i^* = X_i' \alpha + v_i \quad (2)$$

where D_i^* is a latent variable, denoting the difference between utility from participation in agriculture as a primary occupation (U_{iA}) and the utility from participating in agriculture as a secondary occupation (U_{iN}). The youth participate in agriculture as a main occupation if $D_i^* = U_{iA} - U_{iN} > 0$. $X_i' \alpha$ provides the estimate of the difference in utility from participation in agriculture ($U_{iA} - U_{iN}$) using the household socioeconomic and farm-level characteristics, with X_i as explanatory variables, while v_i is an error term.

When estimating Equations (1) and (2), it is essential to appreciate the fact that the relationship between youth participation in agriculture as a primary occupation and income and poverty could be interdependent. Specifically, there is the possibility of the occurrence of selection bias, which can arise because of the unobservable and observable factors influencing both error terms of the farm income and poverty equations (e_i), and the participation in agriculture as a primary occupation equation (v_i), thus resulting in the correlation of error terms of the outcome and the youth participation in agriculture as a primary occupation specification. Therefore, an attempt to estimate Equation (1) using the ordinary least squares (OLS) will lead to biased estimates.

OLS regression will either underestimate or overestimate the impact of participation in agriculture as a primary occupation on farm income and poverty, depending on whether the youth that participates in agriculture as a primary occupation can realize the potential benefits of participation in agriculture as a primary occupation because of certain unobservable factors [18]. Moreover, the income difference between the youth that participates in agriculture as a primary occupation (treated group) and the respondents in the control group that are in agriculture as a secondary occupation cannot be attributed to participation in agriculture as a primary occupation alone, as long as the selection bias problem exists. To overcome the selection bias and attempt a robust estimator, the best solution is to conduct an experiment or carry out a randomized control trial (RCT).

In the absence of an experimental setting or RCT, the study used observational data in which the estimation of the causal effect of the treatment was constructed using data on treated and control groups, and adopted an econometric approach to eliminate the possible issue of selection bias or endogeneity. Furthermore, the study adopted the two most widely used estimation strategies in the literature to eliminate the biases. Firstly, the study adopted the propensity score matching (PSM) and the Heckman two-stage model as a robustness check.

In recent years, propensity score matching (PSM) has gained popularity as a potential method for assessing the impact of public policy and programs when faced with the absence of experimental assessments due to its competencies to deal with the bias associated with the observable characteristics of the respondents. Secondly, the study used the Heckman two-stage model, a two-stage estimation approach, and requires an identification variable to remove the bias due to the unobservable characteristics of the respondents. These two estimation strategies (PSM and Heckman's two-stage model) were adopted in this study to evaluate the impact of youth participation in agriculture as a primary occupation on the per capita income and poverty reduction.

2.2.1. Propensity Score Matching (PSM)

The main goal of this study is to calculate the average impact of participation in agriculture as a primary occupation on those youth that participates in agriculture as a primary occupation, that is, the average effect of the treatment on the treated (ATT). This is achieved by comparing their income and poverty outcomes to an estimate of what would have happened if those youth had not participated in agriculture as a primary occupation. The reason for targeting this, rather than the average impact for all of the respondents (even those who participate in agriculture as a secondary occupation), is that participation in agriculture as primary occupation is not randomly assigned, and so an estimation of the impact of participation in agriculture as a primary occupation may be less plausible and so have fewer practical implications. There is an unobserved outcome, that is the counterfactual, which is the income or poverty reduction that would have occurred had the youth that participated in agriculture as a primary occupation not participated. The propensity score matching (PSM) method is applied to generate a control group and deal with bias due to selection-on-observables (overt bias).

The advantage of the PSM is that it is still valuable even in the absence of baseline data or panel surveys. In addition, PSM is also one of the non-parametric estimation techniques that do not depend on the functional form and distributional assumptions. The PSM approach has gained popularity in program, policy, and technology adoption evaluation studies for many decades. It has been utilized by many researchers, such as [19–27], among many others.

PSM controls for the differences in observable covariates that might influence the decision of the youth to participate in agriculture as a primary occupation and is based on the conditional independence assumption (CIA) [28], which states that conditional on the observable characteristic of the respondents (X), the outcome of the youth is independent of participation in agriculture as a primary occupation and is written as follows: $TY, Y_o \perp T \mid X$. Another assumption is the common support or overlap condition: $0 < P(T = 1 \mid X) < 1$. This condition ensures that the youth participation in agriculture as a primary occupation observation have comparison observations “nearby” in the propensity score distribution [25,26]. The study by Heckman [15]; Heckman, Ichimura, Smith and Todd [26] and encourages dropping treatment observations with weak common support. Only in the area of common support can inferences be made about causality. It is also important to conduct a balancing test. That is to check the following:

$$\hat{P}(X \mid T = 1) = \hat{P}(X \mid T = 0) \quad (3)$$

The propensity score ($P(x)$), which is the probability that a youth participates in agriculture as a primary occupation, given as X , is written as follows:

$$P(x) = \Pr(T = 1 \mid X = x) \quad (4)$$

where T is youth participation in agriculture as a primary occupation and X is the observable characteristics of the respondents. Instead of comparing individuals across multiple characteristics, the approach matches on a single dimension, namely, the probability of participation in agriculture as a primary occupation [20,21]. As Rubin [20], Rubin [21], Rosenbaum and Rubin [23] demonstrated, matching on the probability of covariate occurrence is equivalent to directly matching on covariate existence. Using a set of predictors, the study estimates a logistic regression model to determine each youth propensity score, i.e., the probability of participating in agriculture as a primary occupation.

After estimating the propensity for each youth participating in agriculture as a primary occupation, the study derives the ATT through the most adopted matching methods in the literature—the nearest neighbor and kernel-based matching, as developed by Heckman [26]. The study adopts the kernel-based approach as a robustness check for the result from the nearest neighbor matching. Evidence suggests that the kernel-based approach to matching is more precise than the most common alternatives, such as radius and one-to-

one matching [29]. Kernel-based matching is a non-parametric estimation approach that uses multiple observations from the comparison population (in this analysis, those who did not participate in agriculture as a primary occupation) to generate the counterfactual for each youth that participated in agriculture as a primary occupation.

The nearest neighbor matching matches the treated and control group with the nearest propensity scores. These matched control units are then used to construct the counterfactual for the treated units. Kernel matching measures the treatment effects by subtracting a weighted average of outcomes from each outcome observation in the treated group from the control group. Each control group is weighted based on its distance from the treated unit. Heckman, Ichimura, Smith and Todd [27], Dehejia and Wahba [28], Frölich [30] provide a general outline for understanding different matching estimators. Using their framework, all three matching estimators of ATT can be represented in line with [31], as follows:

$$ATT = \frac{1}{n^1} \sum_1 \{ (Y_{1i}|T_i = 1) - \sum_j r_{1,0}(Y_{0i}|T_i = 0) \} \quad (5)$$

where n^1 is the number of treatment cases, and r represents a set of scaled weights that measure the distance between each control unit and the target treatment unit. These estimators are reportedly different primarily in the number of matches designated for each to-be-matched target case and how these multiple matches are weighted, r , if more than one is used [32]. The average treatment effect on the treated (*ATT*) is then estimated by averaging the within-match differences in the outcome variable between the treated and control group [23,27], as follows:

$$E(Y_1 - Y_0|T = 1) = E[E(Y_1 - Y_0|T = 1, P(x))] = E[E(Y_1|T = 1, P(x)) - E(Y_0|T = 0, P(x))] \quad (6)$$

Bassi [23] showed that the treated and control groups with the same propensity scores have identical distributions for all of the baseline variables. This “balancing property” means that, if we control for the propensity score when we compare the groups, we have effectively turned the observational study into a randomized block experiment, where “blocks” are groups of subjects with the same propensities.

2.2.2. Heckman Two-Stage Model

To circumvent the problem of selection on unobservables, the study adopted the two-step regression model suggested by Friedlander, Greenberg and Robins [25], Heckman [26] to analyze the factors affecting the probability of the youth participating in agriculture/agribusiness as a primary occupation. The Heckman two-stage model has been widely used. and it relies on powerful assumptions such that the unobserved determinants of the outcome and selection equations are jointly and normally distributed, with zero means, constant variances, and a covariance term [18,33,34].

The Heckman two-stage model involves a two-step procedure. This approach is deemed the most appropriate for this study, because of its capability to overcome simultaneity. The Heckman two-stage procedure has been used extensively in the literature to address selection bias, especially when the correlation between the two error terms is greater than zero [33,35,36]. Basically, according to Dehejia and Wahba [28], this approach relies on the restrictive assumption of normally distributed errors.

The analytical procedure was carried out in two stages. In the first stage, we estimated the selection equation using the probit model (youth participation in agriculture as a primary occupation using Equation (2)), and in the second stage, the study estimated the income using Equation (1). The identification variable is the determination of the respondents to continue to participate in agriculture as a primary occupation, even if a respondent has the opportunity to leave agriculture. The respondents were asked if they would leave agriculture if they had the opportunity to do so, and those respondents that said “no” were categorized as “determined to stay in agriculture”.

Based on the well-known challenges confronting agriculture in Africa, it is only a strong-minded and resolute individual that can venture into agriculture as a primary

occupation. It is obvious that youth participation in agriculture will not be possible without the determination to participate and remain in agriculture. However, determination despite any challenge is not sufficient to influence youth income or poverty. The income or poverty of the youth can only be impacted if the youth are keenly involved or participate in agriculture/agribusiness as a primary occupation. Thus, the identification variable has fulfilled the exclusive restriction condition to be a valid instrument in this study. The youth participation equation (Equation (2)) was therefore estimated as follows:

$$D_i^* = X_i' \alpha + v_i \quad (7)$$

The latent variable D_i^* represents the propensity of youth participation in agriculture as a primary occupation, and X_i is the vector of explanatory variables that influences the decision to participate in agriculture/agribusiness as a primary occupation. The probit model was adopted to predict the probability of youth participation in agriculture as a primary occupation, and was also used to obtain the inverse Mill's ratio (IMR) (λ), which, according to Heckman [25], Heckman [26], Hoffman and Kassouf [35], is the ratio of the ordinate of a standard normal to the tail area of the distribution, and can be computed as shown below:

$$\lambda_i = \frac{\varphi(\rho + \alpha X_i)}{\Phi(\rho + \alpha X_i)} \quad (8)$$

where φ and Φ are the standard normal density function and standard normal distribution functions, respectively. λ_i is the calculated IMR term to provide OLS selection corrected estimates [37].

The second step involves the inclusion of the inverse Mills ratio into the income equation to test for selection bias in the model. If the coefficient of the inverse Mills ratio is significant, then there is selection bias in the model and the OLS estimates of the outcome equation will be inconsistent and biased. Hence, preference will be given to the results from the second stage of the Heckman model, as this leads to robust estimators. In the case where the coefficient of the inverse Mills ratio is not significant, then this means the absence of selection bias in the data. Therefore, OLS estimates are consistent and unbiased, and close to the results from the second step of the Heckman model. The variables included in the PSM and Heckman two-stage model are presented in Table 1.

Table 1. Summary statistics of the explanatory variables for the youth participation in the agriculture model.

Variable	Description	Mean	Standard Deviation
Youth in agriculture	Dummy variable for respondents between 15 and 35 years of age participating in agriculture/agribusiness as a primary occupation, 0 if otherwise	0.53	0.49
Age	Age of the respondents in years	29.42	4.55
Gender	A dummy variable for the gender of the respondent. 1 if the respondent is male, 0 if otherwise	0.76	0.43
Ekiti State	Dummy variable for the respondent that is from Ekiti State. 1 if the respondent is from Ekiti State, 0 if otherwise		
Household size	Total number of members of the household	4.11	2.42
Formal education	A dummy variable that takes 1 if the youth has a formal education, 0 if otherwise.	0.74	0.44
Years of schooling	Total number of years of schooling	10.37	3.93
Attended training	A dummy variable that takes 1 if the respondent has attended at least one training, 0 if otherwise	0.16	0.37
Marital status	Dummy variable for the marital status of the respondent. 1 if the respondent is married, 0 otherwise	0.58	0.49

Table 1. Cont.

Variable	Description	Mean	Standard Deviation
Land acquisition by inheritance	Dummy variable for the mode of land acquisition. 1 by inheritance and 0 otherwise	0.52	0.49
The main reason for participating in agriculture	Dummy variable to capture the main reason for choosing to participate in agriculture 1 if the main reason is unemployment, and 0 otherwise	0.46	0.49
The total size of farmland owned	The total area of land owned by the respondent in hectares	5.99	4.99
Determined to stay in agriculture	Dummy variable to capture the youth determination to remain in agriculture if given other opportunities. 1 if the youth is willing to remain in agriculture, and 0 if not willing	0.67	0.47
The total monetary value of household assets	The total monetary value of all household assets owned by the respondent	141,372.20	156,677.50
The total monetary value of productive assets	The total monetary value of all the productive assets owned by the respondent	131,304.70	144,533.40
Daily labor wage rate gender	The daily wage rate of hired labor in Naira	1314.25	2287.44
Per capita annual food expenditure	The per capita annual expenditure on food in Naira	81,370.32	75,532.20
Cost of land	The average cost of land purchased for farming in Naira	141,375.00	158,377.10
Non-farm income	The average non-farm income in Naira	13,137.46	17,869.24

Source: Authors, 2020.

2.3. Poverty Measurement

Income and consumption expenditure are the two most common indicators used in poverty assessment across the globe. However, in this study, the per capita average household income for three years (2017–2019) was used. This income includes income from all sources, such as crop production and livestock, processing, marketing, and non-farm income. One of the most important variables in poverty analysis is the poverty line, which defines the income level needed for a household to escape poverty. Absolute and relative poverty lines are the most adopted in the literature. In this study, the relative poverty line using two-thirds of the mean per capita income was adopted.

Different poverty measurements have been developed and used in the literature [38–41]. Observably, the FGT method, often called the p-alpha class of poverty measure, is the most popular, because the α is a policy parameter that can be varied to approximately reflect poverty “aversion”, and the P_α class of poverty indices is subgroup decomposable [39–41]. Thus, this study adopted the standard FGT method [39–41] to generate the poverty profile of the selected respondents. According to United Nations [2], the FGT indices are based on partial moments for the income distribution. If $F(\cdot)$ is the income distribution and l is the poverty line, then for a given α , this family of poverty indices is defined as follows:

$$P_\alpha = \int_0^l (1 - x/l)^\alpha f(x) dx \quad (9)$$

Some other important poverty indices are also obtained from Equation (9) by allowing α to vary between 0 and 2. For instance, when α is equal to zero, we have the following headcount measure:

$$P_0 = \int_0^l f(x) dx = F(l) \quad (10)$$

For headcount, the simplest and commonest measure that is usually adopted is the Headcount index, which gives the proportion of the population below the poverty line. If we multiply P_0 by the population size, the number of poor people is obtained. Nevertheless,

the study cannot differentiate between poor and very poor people. With α equal to one, we introduced the poverty gap or the poverty deficit $l - x_i$:

$$P_1 = \int_0^l (1 - x/l)f(x)dx \quad (11)$$

The poverty gap index, which is the gap between poor people's income and the poverty line, is expressed as a ratio to the poverty line. It shows the average depth of poverty. This index fulfills the principle of transfer, contrary to the headcount measure P_0 . It is continuous in x , while P_0 is not. However, it is not sensitive to some type of transfer between the poor. For α equal to two, the study arrives at a measure, which is sensitive to the income distribution among the poor.

$$P_2 = \int_0^l (1 - x/l)^2 f(x)dx \quad (12)$$

The squared poverty gap (poverty severity) index reveals the inequality in income among the respondents. The higher the value of this index, the more unequal the distribution of income among the poor. Thus, the standard FGT [39–41] is operationalized as follows:

$$P_\alpha(y, z) = \frac{1}{N} \sum_{i=1}^n \left(\frac{Z - Y_i}{Z} \right)^\alpha \quad (13)$$

where Z is the relative poverty line, n is the number of respondents below the poverty line, N is the number of respondents in the reference population, Y_i is per capita average income of the i th household, and $Z - Y_i$ is the poverty gap of the i th household, $\frac{Z - Y_i}{Z}$ is the poverty gap ratio. α is the poverty aversion parameter and takes values 0, 1, and 2, $\alpha = 0$, Equation (13) gives the poverty headcount $\alpha = 1$, Equation (13) gives the poverty depth $\alpha = 2$, and Equation (13) gives the poverty severity index.

Understanding the determinants of poverty is of key importance for designing an effective poverty reduction strategy. Therefore, using the computed relative poverty lines, the respondents were classified into poor and non-poor, and the Logit model was subsequently adopted to examine the determinants of the probability of a respondent being poor. The Logit model has been widely used in the empirical literature for such an assessment by many past researchers [42–44]. The dependent variables in the models are binary and postulated that the probability of a respondent being poor is a function of some socioeconomic, demographic characteristics, etc. The Logit model can be expressed as follows:

$$\text{Log} \left(\frac{p(y = 1)}{1 - p(y = 1)} \right) = \alpha_0 + \sum_{i=1}^n \alpha_i Z_i \quad (14)$$

The empirical model of the effect of a set of explanatory variables on being poor maximum likelihood estimation techniques is thus specified using the following linear relationship:

$$y_1 = \alpha_0 + \alpha_1 + \alpha_2 Z_2 + \alpha_3 Z_3 \dots \alpha_n Z_n + \xi_i \quad (15)$$

where G is a dichotomous dependent variable, which is explained as $y_1 = 1$; if the likelihood estimation technique is used, it is thus specified using the following linear relationship: if the respondent is poor, $y_0 = 0$, and if the respondent is non-poor, α_0 is the intercept, α_1 is the regression coefficients, μ_i is the error term, and Z_1 to Z_n are the explanatory variables/observable characteristics, respectively. The explanatory variables included in the logistic regression were based on a literature review on the determinants of poverty. In this study, the probability of a respondent being poor was postulated as a function of some socioeconomic and demographic characteristics and financial variables.

3. Results and Discussion

3.1. Socioeconomic Characteristics of the Respondents

The summary statistic of the socioeconomic characteristics of the respondents is presented in Table 2. About 53% of the total respondents participate/are involved in agriculture as a primary occupation. About 46% of the respondents are in agriculture/agribusiness because of unemployment, although a higher percentage (51%) of them are interested in agriculture and are passionate about being in agriculture/agribusiness. In addition to crop production, aquaculture, and livestock rearing, the respondents are also involved in agribusiness activities along the agricultural value chain, such as input and output marketing, transporting, and processing. However, the majority (47%) are into agricultural processing.

The average age of the total sample is 29 years, and a higher percentage (76%) are male. About 58% of the respondents are married, with an average household size of four persons. About 74% have a formal education with an average of ten years of education. However, only 17% have tertiary education, 40% have secondary education, and the illiteracy rate is about 26%. Participation in training is also low. Only 16% of the total respondents reported having participated in the training. Land access is largely by inheritance, as 52% of the respondents obtained their land through inheritance. Some respondents, however, claimed to obtain land by purchase at an average cost of ₦141,375.00.

Table 2. Socioeconomic characteristics of the respondents.

Variables	Frequency	Percentage	Mean
Youth in Agriculture as a Primary Occupation			
No	323	47.29	-
Yes	360	52.71	-
Age (Years)			
15–25	138	25.32	29.42
26–35	545	79.79	-
Gender			
Female	166	24.30	-
Male	517	75.70	-
Marital Status			
Single	287	42.02	-
Married	396	57.98	-
Household Size			
0–5	508	74.38	-
6–9	165	24.16	-
10–18	10	1.46	-
Education Level			
No School	175	25.62	-
Primary	121	17.72	-
Secondary	270	39.53	-
Tertiary	114	16.69	-
Others	3	0.44	-
Land Acquisition Mode			
Gift	126	18.45	-
Inherited	355	51.98	-
Land purchase	183	26.79	-
Others	78	11.42	-
Attended Training			
Yes	110	16.15	-
No	571	83.85	-

Table 2. Cont.

Variables	Frequency	Percentage	Mean
Primary Occupation			
Agriculture	360	52.79	
Civil servant	65	9.53	-
Artisan	93	13.64	
Trading	138	20.23	
Others	26	3.81	
Secondary Occupation			
Agriculture	406	59.44	
Civil servant	37	5.42	-
Artisan	86	12.59	
Trading	149	21.82	
Others	5	0.73	
Types of Agribusiness			
Input marketer	36	5.27	
Output marketer	142	20.79	
Transporter	98	14.35	-
Processor	320	46.85	
Others	87	4.83	
Market Access			
No	598	87.55	-
Yes	85	12.45	
Reason for Participating in Agriculture			
Unemployment	314	46.31	-
Passion/interest	348	51.33	
Others	16	2.36	
Farming Types			
Aquaculture	96	14.06	
Crop	369	54.03	
Livestock	202	29.58	-
Horticulture	86	12.59	
Others	29	4.25	

Source: Authors, 2020.

3.2. Test of Mean Differences in Poverty Indicators

The difference in some selected poverty indicators between the treated and control group was assessed using a *t*-test; the results are presented in Table 3. The results show that the treated group had a higher per capita average household income, agricultural income, farmland, asset value, and market access compared with the control group. Under the assumption of random assignment, this would have been interpreted as the impact of youth participation in agriculture as a primary occupation on per capita income and poverty status. However, the treated variable—youth participation in agriculture as a primary occupation—was not random in the population. Therefore, there is the need to control for all of the observables and unobservable characteristics of the respondents that make it not to be random.

3.3. Poverty Indices

Poverty indices measure the level of poverty among the respondents. The relative poverty line was computed using two-thirds of the mean per capita total asset values. The poverty line determines the threshold of income, separating the poor and non-poor respondents. The estimated relative poverty line was ₦66,373.55. As shown in Table 4, the results reveal that about 40% of the total sample is poor. The proportion of poor (40%) among the youth who participate in agriculture as primary occupation is relatively

lower compared with the other respondents that are involved in agriculture as a secondary occupation (41%).

Table 3. Test of mean differences in poverty indicators.

Variable	Total N = 683	Treated Group N = 360	Control Group N = 323	Mean Difference	t-Test
Per capita average household income (Naira)	105,543.60	116,988.80	93,088.43	23900.39	3.06 ***
Agricultural income (Naira)	56,270.40	61,102.74	50884.52	10218.22	3.14 **
Non-farm income	13,137.46	12,400.35	1,3956.72	1,556.37	1.14
Income from processing	3302.43	3539.64	3038.79	500.85	0.4584
Per capita annual food expenditure (Naira)	81,370.32	75,529.70	87,726.29	12,196.58	
Total farmland owned	5.91	6.82	4.91	1.91	5.07 ***
Total farmland cultivated	4.11	4.62	3.54	1.07	5.05 ***
Monetary value of total household assets (Naira)	141,372.20	140,231.20	142,634.80	2403.59	0.19
Per capita monetary value of total household assets (Naira)	41,626.21	35,924.53	47,781.00	11,856.46	2.41 **
Monetary value of productive assets (Naira)	131,304.70	143,834.90	117,339.20	26,495.70	2.40 **
Per capita monetary value of productive assets (Naira)	43,724.69	41,682.88	45,946.65	4263.76	0.64
Years of schooling	10.37	10.29	10.43	0.14	0.40
Access to market (%)	12.00	15.00	9.00	5.00	1.91

Source: Authors, 2020. Note: *** and ** imply significance at 1% and 5%, respectively.

Table 4. Estimates of poverty by participation in agriculture status.

Poverty Indices	Total Sample N = 683	Treated N = 360	Control N = 323
Poverty headcount (P_0)	0.4038	0.3964	0.4118
Poverty depth (P_1)	0.1547	0.1509	0.1589
Poverty severity (P_2)	0.0827	0.0805	0.0850

Source: Authors, 2020.

The poverty depth or gap, which measured the average shortfall in the income of the respondents below the poverty line and poverty severity—that gives the indication of inequality among the respondents living below the poverty line; in other words, a measure of the severity of deprivation of those living in absolute poverty—is also higher among the control compared with the treated group. This implies that the youth who participated in agriculture/agribusiness as a primary occupation are less poor compared with the youth that participates in agriculture as a secondary occupation. Thus, youth participation in agriculture as a primary occupation has the potential of contributing significantly to a reduction in poverty among the youth.

Determinants of Poverty

The approaches aimed at eradicating poverty ought to recognize the factors that are correlated with poverty and are flexible to adjustment by the policy. The study assessed the factors that determine the probability of a respondent being poor, using the logit model; the results are presented in Table 5. The dependent variable is the poverty status of the respondents. The poverty status is a binary variable and is represented by 1 if the respondent is poor, and 0 if otherwise. The results of the logit model are presented

in Table 5. The log-likelihood of -287.012 , the pseudo-R-squared of 0.26, and the LR (Chi^2) of 202.06 (significant at 1% level) imply that the overall model is well-fitted, and the explanatory variables used in the model were collectively able to explain the likelihood of poverty among the respondents.

Table 5. Logit regression predicting the likelihood of being poor.

Variable	Coefficient	Std. Error	Z-Value	p-Value
Youth in agriculture (1 = primary occupation is agriculture)	−0.597 ***	0.229	−2.6	0.009
Married (1 = yes)	0.147	0.311	0.47	0.635
Inherited land (1 = yes)	0.404 *	0.218	1.85	0.064
Gender (1 = male)	0.441 *	0.253	1.74	0.081
Total farmland owned (ha)	0.005	0.028	0.19	0.849
Determination (1 = yes)	−0.640 ***	0.239	−2.67	0.008
log of total household asset value (₦)	−0.288 ***	0.099	−2.89	0.004
log of productive asset value (₦)	0.0226	0.089	0.25	0.799
Daily labor wage rate (₦)	−0.000	0.000	−0.32	0.747
EKITI State (1 = yes)	−0.654 **	0.286	−2.28	0.022
Age of respondents (year)	0.559 *	0.288	1.94	0.053
Square of respondents' age	−0.009 *	0.005	−1.74	0.083
Formal education (1 = yes)	0.065	0.284	0.23	0.819
Household size (number)	0.463 ***	0.069	6.73	0.000
Market access (1 = yes)	−0.942 ***	0.341	−2.76	0.006
Attended training (1 = yes)	0.375	0.302	1.24	0.215
Non-farm income (₦)	−5.21E−06	0.000	−1.07	0.284
Total livestock unit	0.135 ***	0.046	2.95	0.003
Income from agriculture only (₦)	−0.000 ***	0.000	−4.03	0.000
Constant	−7.295 *	4.425	−1.65	0.099
Number	572			
Log Likelihood	−287.012			
LR Chi^2 (19)	202.06			
Prob > Chi^2	0.000			
Pseudo R^2	0.2604			

Source: Authors, 2020. Note: ***, ** and * imply significance at 1%, 5%, and 10%, respectively.

Poverty among the respondents is determined by some socioeconomic/demographic characteristics and institutional and financial variables. Among the socioeconomic/demographic variables. The coefficient of household size was found to be positive and significant. This implies that as the household size increases, the probability of a respondent falling below the poverty line also increases. A large household size indicates that a respondent would have more “mouths” to feed and would constitute a reduction in the per capita household income. This result is in agreement with the findings of Anyanwu [45], and Oyekale et al. [46], which concluded that the size of the household size increases the likelihood of a household being poor.

A respondent's involvement in a secondary occupation aside from agriculture could serve as a source of non-farm income. However, this could be a disincentive to agricultural production, as this could compete for the respondents' time and resources needed to develop agriculture. Land access by inheritance is positive and statistically significant; this means that poverty is higher among those respondents that accessed land through inheritance. This could be because land accessed through inheritance is usually very fragmented and limits the respondents to cultivating a small plot of land.

Market access is negative and statistically significant, implying that market access has a poverty-reducing potential. Having agriculture as primary occupation is negative and statistically significant. Poverty is lower among the respondents who participated in agriculture as a primary occupation. This implies that the youth that is participating in agriculture as a primary occupation are less poor compared with the others. In the same

vein, income from agricultural production is negative and statistically significant. The higher the income from agricultural production, the less poor the respondents.

The total monetary value of all of the household assets is negative and statistically significant, suggesting that asset ownership has a poverty-reducing effect. Poverty was higher in Kwara State compared with Ekiti State. The determination to stay in agriculture even if there is an opportunity to leave has the potential to reduce poverty among the respondents. This “determination to stay” could make the respondents resilient in the face of the numerous challenges confronting agriculture in Nigeria, and hence contribute to increased productivity and income.

3.4. Impact of Youth Participation in Agriculture on Income and Poverty—PSM

The idea behind the PSM is to match each treated group with an identical control group in the sample, and to then measure the average difference in income and poverty between the two groups after controlling for individual and farm characteristics, which may influence the outcome. The common support was imposed in constructing the matching estimates. This reduced the sample size, as it dropped treatment observations with a propensity score higher than the maximum or less than the minimum propensity score of the controls. In addition, the balancing property of the covariates was satisfied. As a robustness check, two matching methods, the nearest neighbor and kernel-based matching were employed to estimate the impact.

Table 6 presents the average treatment effect on the treated (ATT) across the two matching methods. The results indicate that youth participation in agriculture as a primary occupation has a significant impact on per capita income. The nearest neighbor matching method was used with replacement and concluded that youth participation in agriculture as a primary occupation contributes to a significant increase in household income of about ₦31,301.224. On the other hand, the kernel-based matching method shows that youth participation in agriculture as a primary occupation significantly increases household income by about ₦32,150.526. The results further show that if the youth currently participating in agriculture as a secondary occupation had participated in agriculture as a primary occupation, they would have obtained an increase in household income of between ₦22,382.146–34,113.215. This is the ATU.

Table 6. Impact of youth participation in agriculture on per capita income.

Variable	Sample	Treated	Control	Difference	Std. Err	T-Stat
Nearest Neighbor Matching						
Per Capita Income (₦)	Unmatched	120,779.526	88,641.649	32,137.876	8423.385	3.82 ***
	ATT	120,779.526	89,478.301	31,301.224	13,651.691	2.29 **
	ATU	88,641.649	111,023.796	22,382.146		
	ATE			27,231.999		
Kernel-Based Matching						
Per Capita Income (₦)	Unmatched	120,779.526	88,641.649	32,137.876	8423.385	3.82 ***
	ATT	120,779.526	88,629.000	32,150.526	11,855.588	2.71 **
	ATU	88,641.649	122,754.864	34,113.215	-	-
	ATE			33,045.979		

Source: Authors, 2020. Note: *** and ** imply significance at 1% and 5%, respectively.

The effect of youth participation in agriculture as a primary occupation on poverty reduction is also estimated using the two most common matching methods (nearest neighbor matching (NNM) and the kernel-based matching (KBM) methods). The results are shown in Table 7. The NNM results show a negative and significant effect of the treatment on poverty reduction. This is the average difference between the poverty headcount of similar pairs of households and different participation in agriculture *n* status.

Table 7. Impact of youth participation in agriculture on poverty reduction.

Variable	Sample	Treated	Control	Difference	Std. Err	T-Stat
Nearest Neighbor Matching						
Poverty reduction	Unmatched	0.3664	0.5306	−0.1642	0.0425	−3.86 ***
	ATT	0.3664	0.5342	−0.1678	0.0789	−2.13 **
	ATU	0.5306	0.4939	−0.0367		
	ATE			−0.1080		
Kernel-Based Matching						
Poverty reduction	Unmatched	0.3664	0.5306	−0.1642	0.0425	−3.86 ***
	ATT	0.3664	0.5319	−0.1654	0.0632	−2.62 **
	ATU	0.5306	0.3873	−0.1433		
	ATE			−0.1533		

Source: Authors, 2020. *** and ** imply significance at 1% and 5%, respectively.

The ATT is the average treatment effect on the treated. The nearest neighbor and kernel-based matching show a poverty-reducing effect of about 17%. In the same vein, the youth that participated in a secondary occupation would have obtained a reduction in the poverty headcount of between 3–14% if they had participated in agriculture as a primary occupation. Therefore, youth participation in agriculture as a primary occupation has a potential poverty-reducing effect.

3.5. Factors Influencing Youth Participation in Agriculture and Its Effect on Income—Heckman Two-Stage Model

The results of the probit regression predicting the likelihood of youth participation in agriculture as a primary occupation from the first stage of the Heckman two-stage model are presented in Table 8. The sample shows that 360 of the respondents are classified as a youth in agriculture as a primary occupation. However, this may be a non-random sample of the youth in agriculture as a primary occupation if there are variables that affect youth participation in agriculture as a primary occupation. If this is so, then the OLS on the sample of the youth working full time in agriculture will be biased and inconsistent.

To determine if there is a problem of selectivity in the dataset, first, the study estimated the probability of youth participating in agriculture as a primary occupation (the probability of being treated) as a function of the original control variables and additional identifying variables—in this study, we used the variable that captures the youth willingness to remain in agriculture, even if there is an opportunity to leave. This variable captures the youth's determination to be in agriculture despite all of the challenges associated with agriculture. This variable is assumed to positively affect youth participation in agriculture as a primary occupation but is assumed not to influence income or poverty.

Estimates of the probit model derived from the first stage of the Heckman model revealed that the model has a good fit with its explanatory variables, as the chi-square test is significant at 1%. This implies that the exogenous variables are relevant for explaining the likelihood of youth participation in agriculture. Seven of the included variables are either positively or negatively statistically significant. However, only two variables are positively and statistically significant in determining the youth's participation in agriculture as a primary occupation. These variables are gender and the youth's determination to remain in agriculture even if there is an opportunity to leave. These two variables increase the youth's likelihood to participate in agriculture as a primary occupation, and the participation rate is higher among males compared with females. On the other hand, the youth that is not married have a low per capita annual food expenditure (food insecure), lack formal education, cannot access land through inheritance, have a higher probability of participating in agriculture as a primary occupation, and the participation rate could be higher in Kwara State compared with Ekiti State.

Table 8. Probit regression predicting youth participation in agriculture as a primary occupation: Heckman first step.

Variable	Coefficient	Standard Error	Z-Value	p-Value
Marital status (1 = married)	−0.297 *	0.179	−1.66	0.097
Inherited land (1 = yes)	−0.612 ***	0.175	−3.5	0.000
Gender (1 = male)	0.515 **	0.181	2.84	0.005
Attended training (1 = yes)	−0.206	0.236	−0.87	0.383
Access to market (1 = yes)	0.498	0.373	1.34	0.181
Log of per capita annual food expenditure (₦)	−0.400 ***	0.096	−4.18	0.000
Wage labor rate (N)	−0.000	0.000	−0.06	0.948
Formal education (1 = yes)	−0.375 *	0.196	−1.92	0.055
Log of productive asset value (₦)	−0.009	0.069	−0.13	0.896
Total livestock unit	0.025	0.032	0.76	0.448
Non-farm income (₦)	−0.000	0.000	−1.05	0.293
Total farmland owned (ha)	0.032	0.020	1.58	0.114
Determination (1 = yes)	3.850 ***	0.395	9.75	0.000
EKITI State (1 = yes)	−0.803 ***	0.206	−3.9	0.000
Constant	2.241	1.370	1.63	0.102
Wald chi ² (13)	131.66			
Prob > chi ²	0.000			

Source: Authors, 2020. Note: ***, ** and * imply significance at 1%, 5%, and 10%, respectively.

3.6. Factors Affecting Income: Heckman Second-Step

The estimation of the factors affecting income from the Heckman second step is presented in Table 9. The dependent variable is the log of per capita income. The Lambda term is significant and positively signed, which implies that the error terms in the selection and primary equation are positively correlated, and indicates the presence of selection biases in the equation. This suggests that (unobserved) factors that make youth more likely to participate in agriculture as a primary occupation tend to be associated with increased income. Therefore, the use of the Heckman two-stage model in this study instead of OLS is appropriate. The IMR was incorporated in the second stage of the model. However, the analysis showed that the IMR (Lambda) is positive and statistically significant, implying that the increase in the per capita farm income is conditional on the probability of the youth participating in agriculture as a primary occupation.

Table 9. Factors affecting income: Heckman's second step.

Variable	Coefficient	Standard Error	Z-Value	p-Value
Marital status (1 = married)	−0.129	0.217	−0.6	0.552
Gender (1 = male)	0.084	0.238	0.35	0.725
Formal education (1 = yes)	−0.242	0.231	−1.05	0.295
Labor wage rate (₦)	0.000 ***	0.000	2.91	0.004
Log of productive asset value (₦)	0.129	0.082	1.58	0.115
Total farmland owned (ha)	0.089 ***	0.025	3.54	0.000
Inherited land (1 = yes)	−0.411 *	0.238	−1.73	0.084
Log of per capita annual food expenditure (₦)	−0.366 ***	0.123	−2.97	0.003
Attended training (1 = yes)	−0.229	0.351	−0.65	0.514

Table 9. Cont.

Variable	Coefficient	Standard Error	Z-Value	p-Value
Access to market (1 = yes)	0.192	0.337	0.57	0.569
Non-farm income (₦)	0.000	0.000	0.07	0.943
Total livestock unit	−0.329 ***	0.038	−8.67	0.000
EKITI State (1 = yes)	−0.802 ***	0.296	−2.71	0.007
Constant	13.925 ***	1.547	9.00	0.000
Lambda	0.808 *	0.475	1.70	0.089

Source: Authors, 2020. Note: *** and * imply significance at 1%, 5%, and 10%, respectively.

The Heckman two-stage model estimates support the results of the PSM model, that youth participation in agriculture as a primary occupation has a positive effect on farm income. Other variables that are positive and statistically significant in explaining per capita household income are the daily wage rate of hired labor and the total farmland owned. Inherited land, per capita annual food expenditure, total livestock unit, and residence in Ekiti State are negative and statistically significant in determining the income of the respondents. These results imply that access to a reasonable size of farmland would be an important factor in the achievement of higher income for those that decided to participate in agriculture as a primary occupation.

4. Summary, Conclusions, and Policy Recommendations

The study assesses youth participation in agriculture as a primary occupation on income and poverty reduction in Nigeria. It uses PSM and the Heckman two-stage procedure to control for selection bias due to the observable and unobservable characteristics of the respondents. The results from the probit estimates indicate that the youth's gender and the determination to stay in agriculture are positive and statistically significant for influencing participation in agriculture as a primary occupation. The results from the Heckman second-stage estimates show that youth participation in agriculture as a primary occupation contributes significantly to per capita household income.

For robustness checks of the estimated effect of youth participation in agriculture as a primary occupation, the propensity score matching method was used. The results indicate that the increase in per capita farm income due to youth participation in agriculture as a primary occupation varies between ₦31,301.22 and ₦32,150.526. This confirms the finding of the Heckman two-stage model estimates. Similarly, youth participation in agriculture as a primary occupation can reduce poverty by 17%.

The variables that are negatively correlated with poverty are market access, having agriculture as a primary occupation, income from agricultural production, the total monetary value of all the household assets square of the age of respondents, and the youth's determination to remain in agriculture, while the variables that are positively and statistically significant in explaining per capita income are daily wage, rate of hired labor, and total farm size. Per capita annual food expenditure, total livestock unit, and inherited land are negative and statistically significant in determining the income of the respondents. These results imply that besides the youth participation in agriculture as a primary occupation, access to substantial farmland for meaningful production activities would be needed to achieve the objective of income improvement.

The Heckman second stage estimates reveal that youth participation in agriculture as a primary occupation positively affects income, and this view was also supported by the PSM results. Hence, youth participation in agriculture as a primary occupation can help generate an increase in household income and reduce poverty. Although non-farm income is positive, but not significant, it could imply the need to also support youth participation in other secondary activities to supplement the household income, especially during the off-season. The implication of these, thus, is that any policy that focuses on

engaging the unemployed youth in agriculture should also ensure their access to farmland, especially where access to land through inheritance is lacking, as well as also promote their engagement in other non-farm activities to supplement their income.

Author Contributions: Conceptualization, R.O.; methodology, B.A.A. and R.O.; validation, A.N.W., P.M.D.N., D.B.M., T.A., V.M., and Z.B.; B.A.A.; resources, Z.B.; writing—original draft preparation, R.O.; writing—review and editing, All authors; supervision, B.A.A.; funding acquisition, Z.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the International Fund for Agricultural Development (IFAD) under the grant 2000001374 “Enhancing Capacity to Apply Research Evidence (CARE) in Policy for Youth Engagement in Agribusiness and Rural Economic Activities in Africa” Project in the International Institute of Tropical Agriculture (IITA).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the International Institute of Tropical Agriculture (IITA).

Acknowledgments: The authors are grateful to the International Fund for Agricultural Development (IFAD) and the International Institute of Tropical Agriculture (IITA) for the financial support. The usual disclaimers apply.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Beegle, K.; Christiaensen, L.; Dabalen, A.; Gaddis, I. *Poverty in a Rising Africa*; The World Bank: Washington, DC, USA, 2016.
2. United Nations (UN). Youth population trends and sustainable development. *Popul. Facts Work.* **2015**, 2015.
3. Kazeem, Y. Nigeria Has Become the Poverty Capital of the World. 2008. Available online: <https://qz.com/africa/1313380/nigerias-has-the-highest-rate-of-extreme-poverty-globally/> (accessed on 22 February 2021).
4. Bellow, J.; Miguel, E. War and local collective action in Sierra Leone. *J. Public Econ.* **2009**, *93*, 1144–1157. [CrossRef]
5. African Union. African Youth Charter. 2006. Available online: [fromhttp://africa-youth.org/sites/default/files/african_youth_charter.pdf](http://africa-youth.org/sites/default/files/african_youth_charter.pdf) (accessed on 12 September 2019).
6. Olanrewaju, O.; Osabohien, R.; Fasakin, J. The Anchor Borrowers Programme and youth rice farmers in Northern Nigeria. *Agric. Financ. Rev.* **2021**, *81*, 222–236. [CrossRef]
7. Yami, M.; Feleke, S.; Abdoulaye, T.; Alene, A.D.; Bamba, Z.; Manyong, V. African Rural Youth Engagement in Agribusiness: Achievements, Limitations, and Lessons. *Sustainability* **2019**, *11*, 185. [CrossRef]
8. Adesugba, M.; Mavrotas, J. *Youth Employment, Agricultural Transformation, and Rural Labor Dynamics in Nigeria*; IFFPRI Discussion Paper No. 01579; International Food Policy Research Institute: Washington, DC, USA, 2016.
9. Haggblade, S.; Chapoto, A.; Drame-Yayé, A.; Hendriks, S.; Kabwe, S.; Minde, I.; Mugisha, J.; Terblanche, S. Motivating and preparing African youth for successful careers in agribusiness. *J. Agribus. Dev. Emerg. Econ.* **2015**, *5*, 170–189. [CrossRef]
10. Nations Bureau of Statistics—NBS. Delta, 2nd Least Poor State in Nigeria—NBS, Vanguard Newspaper. 2020. Available online: <https://www.vanguardngr.com/2020/05/delta-2nd-least-poor-state-in-nigeria-nbs/> (accessed on 4 May 2020).
11. Garba, A.S. Refocusing education system towards entrepreneurship development in Nigeria: A tool for poverty eradication. *Eur. J. Soc. Sci.* **2010**, *15*, 140–150.
12. CBN. Financial Inclusion Newsletter, 1, A. Quarterly Publication of the Financial Inclusion Secretariat. 2016. Available online: <https://www.cbn.gov.ng/FinInc/FinIncNewsletter.asp> (accessed on 22 February 2021).
13. Fawole, W.; Ozkan, B. Examining the willingness of youths to participate in agriculture to halt the rising rate of unemployment in Southwestern Nigeria. *J. Econ. Stud.* **2019**, *46*, 578–590. [CrossRef]
14. Lyocks, J.S.W.; Tanimu, J.; Dauji, Z.L. Growth and yield parameters of ginger as influenced by varying populations of maize intercrop. *J. Agric. Crop. Res.* **2013**, *1*, 24–29.
15. Libaisi, K.J.; Marinda, A.P.; Wakhungu, W.J. Common Interest Youth Groups and Their Contribution to Food Security Among Small Holder Farm Households in Western Kenya. *Future Agric.* 2012. Retrieved February, 2016, 2021 from Future Agricultures. Available online: <http://www.futureagricultures.org/publications/search-publications> (accessed on 22 February 2021).
16. Sakketa, T.G.; Gerber, N. Rural Shadow Wages and Youth Agricultural Labor Supply in Ethiopia: Evidence from Farm Panel Data. In *Change at Home, in the Labor Market, and On the Job (Research in Labor Economics)*; Polachek, S.W., Tatsiramos, K., Eds.; Emerald Publishing Limited: Bingley, UK, 2020; Volume 48, pp. 61–105. [CrossRef]
17. Becerril, J.; Abdulai, A. The impact of Improved Maize Varieties on Poverty in Mexico: A Propensity Score-Approach. *World Dev.* **2009**, *38*, 1024–1035. [CrossRef]

18. Bacha, D.; Namara, R.E.; Bogale, A.; Tesfaye, A. Impact of small-scale irrigation on household poverty: Empirical evidence from the Ambo district in Ethiopia. *Irrig. Drain.* **2011**, *60*, 1–10. [CrossRef]
19. Cochran, W.; Rubin, D. Controlling bias in observational studies. *Sankhya* **1973**, *35*, 417–446.
20. Rubin, D.B. The Use of Matched Sampling and Regression Adjustment to Remove Bias in Observational Studies. *Biometrics* **1973**, *29*, 185–203. [CrossRef]
21. Rubin, D.B. Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies. *J. Am. Stat. Assoc.* **1979**, *74*, 318–328.
22. Bassi, L.J. Estimating the Effect of Training Programs with Non-Random Selection. *Rev. Econ. Stat.* **1984**, *66*, 36–43. [CrossRef]
23. Rosenbaum, R.P.; Rubin, B.D. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *Am. Stat.* **1985**, *39*, 33–38.
24. Friedlander, D.; Greenberg, H.D.; Robins, K.P. Evaluating government training programs for the economically disadvantaged. *J. Econ. Lit.* **1997**, *35*, 1809–1855.
25. Heckman, J. Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations. *J. Hum. Resour.* **1997**, *32*, 441–462. [CrossRef]
26. Heckman, J.; Ichimura, H.; Smith, J.; Todd, P. Characterizing Selection Bias Using Experimental Data. *Econometrica* **1998**, *66*, 1017–1098. [CrossRef]
27. Dehejia, R.H.; Wahba, S. Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Rev. Econ. Stat.* **2002**, *84*, 151–161. [CrossRef]
28. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT Press: Cambridge, MA, USA, 2010.
29. Frölich, M. Finite-Sample Properties of Propensity-Score Matching and Weighting Estimators. *Rev. Econ. Stat.* **2004**, *86*, 77–90. [CrossRef]
30. Smith, J.A.; Todd, P.E. Does matching overcome LaLonde’s critique of nonexperimental estimators? *J. Econom.* **2005**, *125*, 305–353. [CrossRef]
31. Hosny, A.S. Theories of economic integration: A survey of the economic and political literature. *Int. J. Econ. Manag. Soc. Sci.* **2013**, *2*, 133–155.
32. Morgan, S.L.; Harding, D.J. Matching estimators of causal effects: Prospects and pitfalls in theory and practice. *Sociol. Methods Res.* **2006**, *35*, 3–60. [CrossRef]
33. Adeoti, A. Factors Influencing Irrigation Technology Adoption and its Impact on Household Poverty in Ghana. *J. Agric. Dev. Trop. Subtrop.* **2008**, *109*, 51–63.
34. Sinyolo, S.; Mudhara, M.; Wale, E. The impact of smallholder irrigation on household welfare: The case of Tugela Ferry irrigation scheme in KwaZulu-Natal 2009. *S. Afr. Water SA* **2014**, *40*, 145–156. [CrossRef]
35. Hoffman, R.; Kassouf, A.L. Deriving conditional and unconditional marginal effects in log earnings equations estimated by Heckman’s procedure. *Appl. Econ.* **2005**, *37*, 1303–1311. [CrossRef]
36. Siziba, M. Strategies on Women Entrepreneurship Survival: A Case Study of Women Entrepreneurs in Zimbabwe between 2007–2009. *JWEE* **2010**, *3–4*, 71–79.
37. Greene, W.H.; Hensher, D.A. A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transp. Res. Part B Methodol.* **2003**, *37*, 681–698. [CrossRef]
38. Sen, A. Poverty: An Ordinal Approach to Measurement. *Econom. J. Econom. Soc.* **1976**, *44*, 219–231. [CrossRef]
39. Foster, J.; Greer, J.; Thorbecke, E. The Foster–Greer–Thorbecke (FGT) poverty measures: 25 years later. *J. Econ. Inequal.* **2010**, *8*, 491–524. [CrossRef]
40. Foster, J.; Greer, J.; Thorbecke, E. A Class of Decomposable Poverty Measures. *Econometrica* **1984**, *52*, 761–766. [CrossRef]
41. Foster, J.E.; Shorrocks, A.F. Poverty Orderings. *Econom. J. Econom. Soc.* **1988**, *56*, 173–177. [CrossRef]
42. Lubrano, M. The Econometrics of inequality and Poverty. Lecture 3, Welfare Functions, Inequality, and Poverty. September 2016. Available online: <http://132.206.230.228/dominance/milu3.pdf> (accessed on 25 February 2021).
43. Grootaert, C. The Determinants of Poverty in Cote d’Ivoire in the 1980s. *J. Afr. Econ.* **1997**, *6*, 169–196. [CrossRef]
44. Crouch, M.; McKenzie, H. The logic of small samples in interview-based qualitative research. *Soc. Sci. Inf.* **2006**, *45*, 483–499. [CrossRef]
45. Anyanwu, J.C.; Erhijakpor, A.E. Do international remittances affect poverty in Africa? *Afr. Dev. Rev.* **2010**, *22*, 51–91. [CrossRef]
46. Oyekale, A.S.; Adeoti, A.I.; Ogunnupe, T.O. Sources of income inequality and poverty in rural and urban Nigeria. In Proceedings of the 3rd Annual Workshop of Poverty and Economic Policy (PEP) Network, Dakar, Senegal, 11–20 June 2004.