Impact of Agro-Industrial Development Strategies on Smallholder Rice Farmers' Productivity, Income and Poverty: The Case of Contract Farming in Nigeria

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Abstract

This study assess the impact of agro-industrial strategy in the form of Contract Farming (CF) arrangement on the participating farmers' productivity, income and poverty in rural Nigeria. The data for this study was collected 2014 through multistage random sampling techniques of 300 rural farming households. In addition to the PSM, the study uses the Endogenous Switching Regression (ESR) with sample selection model. The empirical impact assessment shows that the CF arrangement increases the output of the participating farmers by 80%. The study also shows that contract farmers have higher average output and per capita income from rice production than they would have earned if they had not participated in the CF. Poverty headcount also reduced significantly by 14%. This implies that CF is an effective agro-industrial development strategy and has important policy implication to enhance welfare and eradicate poverty in rural Nigeria. Thus, CF should be encouraged and its implementation adequately monitored by the government to eliminate default by the farmers and the contracting agribusiness firms.

Keywords: Farmers, Rice, Contract, Poverty, Income, Productivity, Nigeria

JEL Classification: B12, C12, D86, H43

1.1.Introduction

Agricultural growth and development is paramount to economic and political stability of Nigeria. This is not only because of its contribution to the Gross Domestic Product (40%), but also due to the fact that it's the largest employer of labour; employing about 75% of the Nigerian labour force, particularly the rural dwellers. The high rate of poverty in Nigeria (Table 1) is worrisome and the deplorable standard of living in the rural areas is of a great concern to

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the policy makers. Worthy of note is the fact that poverty is prevalent among the rural dwellers (Table 2) majority of who are farmers. This observed high rate of poverty has been attributed to low output, lack of market access and low income.

Table 1: Poverty profile in Nigeria: 1980-2010

Year	Non-poor	Moderately poor	Extremely poor	Poverty incidence	Estimated population	Population in Poverty
1980	72.8	21.0	6.2	27.2	65.0	17.1
1986	53.7	34.2	12.1	46.3	75.0	34.4
1992	57.3	28.9	13.9	42.7	91.5	39.2
1996	34.4	36.3	29.3	65.6	102.3	67.1
2004	43.3	32.4	22.0	54.4	126.3	68.7
2010	31.0	30.3	38.7	69.0	163.0	112.47

Source: National Bureau of Statistics (NBS). HNLSS 2010

Table 2: Incidence of Poverty in Nigeria, by Sector (2010)

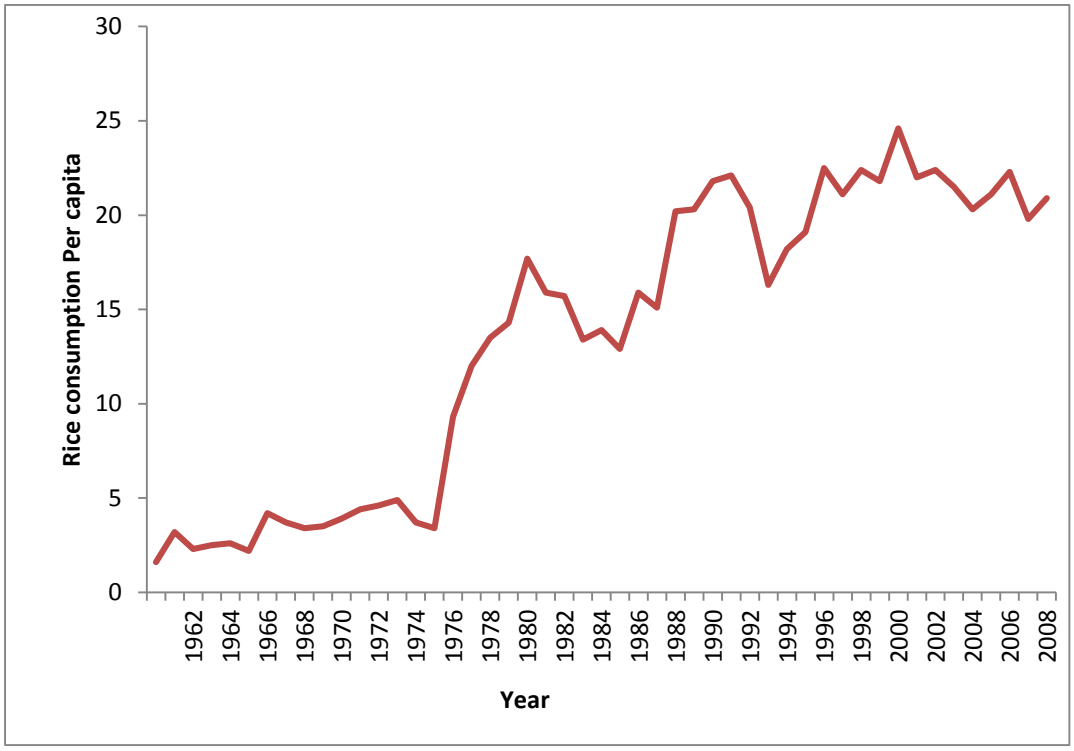
Sector	Food poverty		Absolute poverty		Relative poverty		Dollar per day	
	Food poor	Non-food poor	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
Urban	26.7	73.3	52.0	48.0	61.8	38.2	52.4	47.6
Rural	48.3	51.7	66.1	33.9	73.2	26.8	66.3	33.7
National	41.0	59.0	60.9	39.1	69.0	31.0	61.2	40.3

Source: National Bureau of Statistics (NBS). HNLSS 2010

Nigerian farmers cultivate many staple food crops, but rice is the most important staple food crop in Nigerian diets. It is a crop that is highly important in the attainment of national food security and eradication of rural poverty and overall economic growth. For several decades successive Nigerian government have tried to avert any food insecurity crisis that could be engendered by rice scarcity, in view of the fact that the local production of rice has never been able to meet the local demand. One of the adopted strategies is the huge importation of rice from other notable rice exporting countries across the globe. It was however realised that this approach takes so much foreign exchange from the external foreign reserve and it is also not a sustainable approach. Hence, to curtail rice importation, successive Nigerian governments

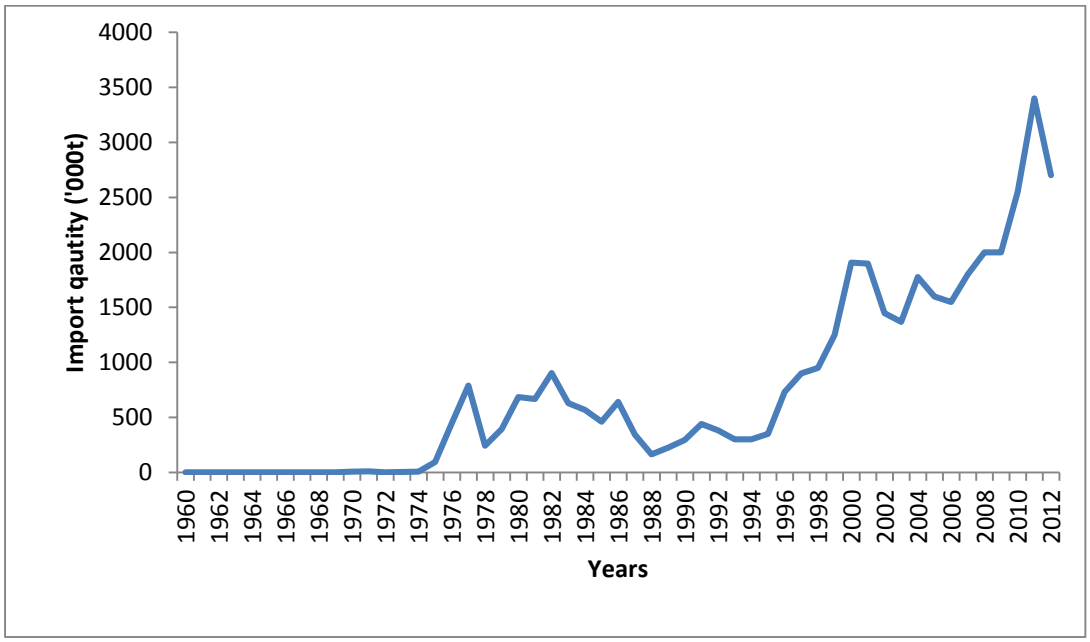
have adopted many trade policies such as increase in tariff, ban and unban of rice importation and import quota.

Figure 1: Rice consumption per capita



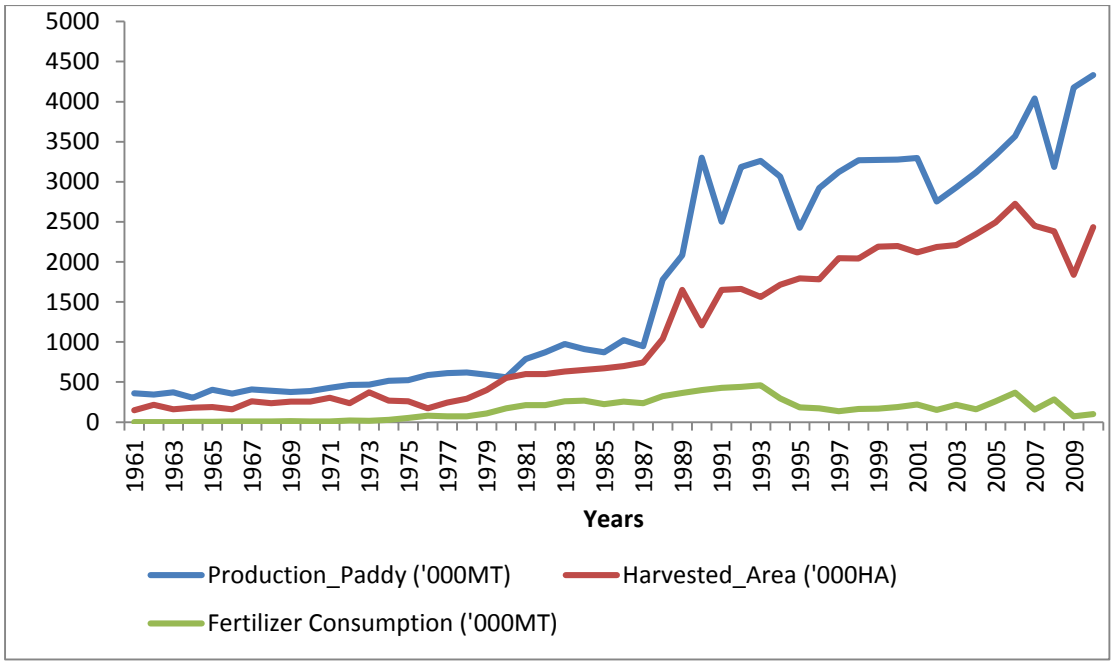
Source: Underlying data from FAO, 2012

Figure 2: Import Quantity: 1960-2011



Source: Underlying data from FAO, 2012

Figure 3: Paddy production, Area harvested and Fertilizer consumption



Source: Underlying data from FAO, 2012

Observably, the best solution to the aforementioned problems is to increase efforts that could generate improvement in rice productivity. However, rice productivity does not just depend on yield alone, but also determined by the efficiency of post-harvest processing and access to profitable output markets. Market access is particularly very important to smallholder farmers because it signifies that their production is not limited by their consumption or the local markets. Thus, a sustainable effort to improve the rice sector will also need to be complemented with modern processing techniques to get polished rice that could compete favourably with the imported rice in terms of quality. Therefore, what is essentially required is huge investment in modern rice mills and the empowerment of the farmers to be able to produce large quantity of paddy rice to meet the need of these mills. Consequently, under the current Agricultural Transformation Agenda (ATA), the strategy adopted is the use of Private Partnership (PPP) approach. This approach has brought into operation companies like Olams Ltd., Ebony rice mill, and Veetee Nigeria Ltd., that focus on the use of modern rice processing techniques. These companies adopt the contract farming approach in order to get continuous supply of paddy rice.

Contract farming is an institutional arrangement widely adopted in agricultural production (Glover and Kusterer, 1990). Under contract farming, farmers usually agree to deliver specific

commodities in predetermined quantities and to meet predetermined quality standards, while contractors agree to provide production support (e.g., supply of agricultural inputs and provision of agricultural technologies) and accept products at predetermined prices (Eaton and Shepherd, 2001).

1.2. Contract Farming arrangement in Nigerian Rice Sector

The adoption of agricultural input market liberation policy in many developing countries created a wide gap that can be filled by CF arrangement as the state hands off the procurement and distribution of vital inputs such as extension services, credit, and price supports at subsidised rate, this provide the opportunity for the private sector to assume a similar role in more efficient manner than the states. However, many researchers (Glover and Kusterer, 1990; Little and Watts, 1994) are of the opinion that CF can be a tool through which multinational agro-industrial companies can take undue advantage of the smallholder farmers.

The adoption CF dates back to the 19th century in the United States and at least to the 1940s in Latin America, in recent years the practice has undergone substantial expansion throughout the developing world. Contracting agreement in Nigeria is most commonly practiced by large scale processing and seed companies. In the case of the large scale rice processors the processing plants have high fixed costs and therefore the focus of these companies is on how to achieve a steady flow of paddy supply throughout the year. Obviously, dependence on open market purchases does not guarantee the achievement of this laudable objective. The contract agreement can include a specification of the planting dates (and thus delivery dates) as well as total quantities to be delivered. According to Prowse (2012), contract farming can be understood as a firm lending inputs such as seed, fertilizer, credit or extension to a farmer in exchange for exclusive purchasing rights over the specified crop. It can further be described as a form of vertical integration within agricultural commodity value chains whereby the agro-allied industry exert the highest control over the production process and final product.

The adoption of CF in Nigeria, particularly for important staple food crops like rice is a relatively new idea. CF within the rice sector is gaining attention in view of the urgent response to achieve increase production of rice to meet the need of the teeming population in addition to the fact that Nigeria need to produce, process and release a local rice that is highly competitive with the imported rice that has dominated Nigerian diet. This is with a view to

reduce the overdependence on imported rice to meet local demand and thus, cut down the huge foreign exchange that goes into rice importation in particular and food importation in general.

Lately, Nigerian government have come to realised the fact that the supply of quality rice that can meet international standard and compete favourably with the imported rice cannot be achieved through the smallholder farmers alone. Apart from the fact that the local rice production is low compared with the demand, the quality is also substandard due to the poor and crude indigenous post-harvest techniques adopted by the farmers. The desired major breakthrough in Nigeria rice sector can only be achieved through the use of modern large scale processing machines. Consequently, through the private-public partnership arrangement many international organisations have shown interest in upgrading the Nigerian rice sector to international standard. Hence, modern large scale processing machines were imported into the country by notable companies such as Olam, Veetee and Ebony rice mill. This large scale rice processing plants will require continuous supply of large quantity of paddy rice all the year round. The best option to get this done is to enter into a contract agreement with some small holder rice farmers who are either contacted to participate through the extension agents, but in most cases the farmer must be a member of a recognised and registered cooperative society such as the Rice Farmers Association of Nigeria (RIFAN).

The aforementioned agro-allied industries supply certified improved rice seed in addition to fertilizer to the farmers at subsidised rate. They also train the farmers on the best-bet production techniques and supervise the farms in order to obtain high quality paddy. However, there is no reason, of course, for a company not to use more than one method of obtaining its supplies, and some companies use a combination of company farms, contract growers, and open market purchases.

Rice contract farming in Nigeria falls under the multipartite arrangements involving private firms (usually foreign, but occasionally local), the national government, international aid or lending agencies, such as the United States Agency for International Development (USAID), and the World Bank. Although, reports reveal that there is high rate of default on the part of the contracting firms and the farmers. The contracting firms can decide to pay farmers lower price different from the agreed price at time of signing the contract agreement. In the same vein, farmers also default by not meeting the requirements of the contracting firm either in terms of quality specification or quantity of output. Farmers can also default by selling their

produce to other organisations or individuals that promise better price. However, despite these shortcomings in CF arrangement it has many positive effects. A key feature of contract farming, which bears on production response, is risk sharing and risk reduction. In fact, contracting is fundamentally a way of allocating risk between the agro-allied industry and the farmers. The latter assume most of the risks associated with production, while the former assumes the risks of marketing the final product. Total risk is reduced relative to a non-contract situation of that crop. In addition, it guaranteed the farmers timely and profitable access to output market, reduces production and transaction costs and increase productivity. All these are expected generate increase in productivity which is expected to translate into improve household income, bring more cash inflows to the cash strapped farm sector and contribute to poverty reduction among the contract farmers.

1.3.Research Question

The contract agreement in most cases involves no written agreement and where there is, due to the low level of education of the farmers, which implies that they are mostly illiterates and may not really understand the written agreement before going into such an agreement with the agro-allied industries. This weakness engendered high rate of default on both sides of the partners. Although contract farming arrangement is expected to generate increase in agricultural production and open up more profitable market access for the farmers, however, the extent to which this notable arrangement has impacted the farmers in terms of income, poverty reduction and household welfare improvement in Nigeria is not yet known. Therefore, this study intends to provide answers to the following pertinent research questions:

1. Does contract farming arrangement generate increase in rice productivity among the contract farmers compared with the non-contract farmers?
2. What is the impact of contract farming arrangement on rural farming households' income and poverty reduction?

In order to provide answers to the foregoing questions, this study empirically investigates the impact of contract farming on rice productivity, farmers' income and overall poverty reduction in rural Nigeria.

1.4.Contribution to the Literature

The growth and development of Nigeria agro-allied industries especially those that are into rice processing is very important to the nation's overall development agenda. Many foreign direct investments have been attracted into Nigeria, especially to boost rice production and processing in order to make the nation self-sufficient in rice production and for export. The adoption of contract farming to ensure adequate supply of raw materials to agro-industries in Nigeria especially rice processing plants is still relatively a new idea. However, it is believed that this is a good step in the right direction, if one examined it from the point of view of industrial growth and development. However, deep quantitative empirical analysis would be required to actually pin down its effect (positive or negative) on the welfare of the participating farmers.

Although several literature abound on contract farming, particularly in developed countries such as USA, but studies that have looked into the impact of contract farming on farmers' welfare and poverty is still very scanty and in Nigeria non-exist to the best knowledge of the authors. Thus, there is still a gap in the literature that this study intends to fill. In Nigeria, many agro-allied industries established through the Public-Private Partnership (PPP) are now utilising the contract farming arrangement to get continuous supply of raw materials, making this study a great importance to Nigeria government; as it will shed light on the potential impact of this relatively new agro-industrial strategy on the government efforts to achieve increase in agricultural productivity, better access to profitable markets for the rural farmers, boost rural households' income and eradicate the endemic poverty situation in rural Nigeria.

Additionally, this study will not rely essentially on sheer comparison of output, income or poverty situation between the contract farmers and the non-contract farmers only , it will also use the Propensity Score Matching (PSM) method that controls for bias due to selection-on-observables and in addition adopt the endogenous switching regression model which is an instrumental variable estimation technique capable of eliminating the bias due to unobservable characteristics of the farmers to provide a consistent estimate of the impact of contract farming on productivity, income and poverty reduction among the farmers selected from the notable rice producing areas of Nigeria.

The rest of the paper is organised as follows: The analytical framework and estimation techniques are presented in section two. Section three presented the data and the descriptive

statistics. Section four contains the results and discussion. A brief summary, conclusion and policy recommendation is presented in section five.

2.0.Analytical Framework and Estimation Techniques

2.1. Poverty Assessment

One of the most important variable in poverty analysis is the poverty line which defines the level of consumption expenditure or income needed for a household to escape poverty. Absolute and relative poverty line are the most commonly adopted in the literature. In this study we adopt a relative poverty line computed as two-third of the mean per capita income. In assessing poverty at any level many different approaches been utilised in the literature (Sen, 1976; Foster, 1984; Foster and Shorrocks, 1988 and Foster-Greer-Thorbecke (FGT), 1984). However, the FGT (1984) often called the p-alpha class of poverty measure appears to be the most commonly use. This is based on the fact that the α parameter has a policy influence as it can be varied to approximately reflect poverty "aversion" and also the P_α class of poverty indices is subgroup decomposable. Thus, this study adopted the standard FGT (1984) to generate the poverty profile of the rice farming households. According to Lubrano (2013), the FGT indices are based on partial moments with respect to the income distribution. If F (.) represents the income distribution and l is the poverty line, then for a given α this family of poverty indices is defined as follows:

$$P_\alpha = \int_0^l \left(1 - x/l\right)^\alpha f(x)dx \qquad (1)$$

By allowing the parameter α to vary between 0 and 2 we can derive the other notable poverty indices from equation (1). The headcount measure is obtained if α is equal to zero:

$$P_0 = \int_0^l f(x)dx = F(l) \qquad (2)$$

The simplest and commonest measure of poverty that is usually adopted in the literature is the *Headcount index*, which gives the proportion of the population below the poverty line. Multiplying P_0 by the population size, will give the number of poor. However, this will not tell us the exact difference between those households that are poor and those that are very or extremely poor. This can however be improved upon by making α to be equal to one, thus providing the poverty gap or the poverty deficit $l - x_i$ which shows the average depth of poverty:

$$P_1 = \int_0^l (1 - x/l) f(x) dx \qquad (3)$$

The *Poverty Gap Index,* which is the gap between the poor people's income and the poverty line, expressed as a ratio to the poverty line. This index fulfil the principle of transfer, contrary to the headcount measure P_0. It is continuous in x, while P_0 is not. But it is not sensitive to some type of transfers between the poor. Furthermore, if we set α to be equal two, we obtain another measure which is sensitive to the income distribution among the poor:

$$P_2 = \int_0^l (1 - x/l)^2 f(x) dx \qquad (4)$$

The Squared Poverty Gap (Poverty *Severity) Index* reveals the inequality in income among the rice farmers and the higher the value of this index, the more unequal is the distribution of the income among the poor. As underline in Atkinson (1987) and Foster and Schorrocks (1988), these indices are useful for ranking distributions, to determine for instance in which of the regions or sectors we have more poor households. Although the answer might depend on the l (poverty line). One region or sector might have more poor households than the other for a given poverty line, but just the reverse for another value of l .

2.2. The Impact Evaluation Framework

The potential outcome framework proposed by Rubin (1974), labelled the Rubin Causal Model (RCM) by Holland (1986) was adopted in this study to assess the impact CF on productivity, farmers' income and poverty reduction. The potential outcome framework is by now standard in both the statistics and econometrics literature. One of the attractions of the potential outcomes setup is that from the outset it allows for general heterogeneity in the effects of the treatment. Such heterogeneity is important in practice, and it is important theoretically as it is often the motivation for the endogeneity problems that concern economists. One additional advantage of the potential outcome set up according to Imbens and Wooldridge (2008), is that the parameters of interest can be defined, and the assumptions stated, without reference to particular parametric models.

The potential outcome framework assumes, for simplicity, that the rice farmers can only be in two states: contract and non-contract (participating and non-participating). In this study, our outcome of interest is rice productivity, farmers' income and poverty reduction. The treatment

is CF. Let $T = 1$ for the contract farmers and $T = 0$ for the non-contract farmers. Each of the rice farmers status is associated with a potential outcome Y_{0i} *and* Y_{1i}. Y_{1i} represents the potential outcome if the farmer participate in CF and Y_{0i} the potential outcome if the farmer did not participate in CF. Thus, each rice farmer has a Y_{1i}, Y_{0i} pair that represents the outcomes that would be realized in the two states. However, a rice farmer can only be in one state at a time, at most one of the two states is observed at any given point in time. This implies that farmer i can either be a contract farmer or non-contract farmer. Meaning that it is impossible for farmer i to be both contract and non-contract at the same time. This suggests that one of the states of the farmer is counterfactual and this lead to what is referred to as missing data problem in programme impact evaluation (Morgan and Winship, 2007).

The observed outcome is: $Y = TY_{1i} + (1 - T_i)Y_{0i}$. The gain or impact of participating in CF can be stated as follows: $Y = Y_{1i} - Y_{0i}$. Due to this aforementioned missing data problem, observing this gain for an individual rice farmer becomes an impossible task. It is therefore an essential condition to find a solution to this missing data problem in order to evaluate the gain or impact of participating in CF on all the outcomes of interest. The methods to control for this evaluation problem are broadly classified into two: experimental (randomization) and quasi-experimental approach. In randomized experiments, the probability of assignment to treatment (CF) does not vary with potential outcomes, and is a known function of covariates. The leading case is that of a completely randomized experiment where, in a population of N units $N1 < N$ randomly chosen units are assigned to the treatment and the remaining $N0 = N - N1$ units are in the control group. If the participation in the CF were randomly assigned, the unobserved counterfactual outcome denoted by $E(Y_{1i} \mid T_i = 0)$ could be replaced with the actual outcome denoted by $E(Y_{1i} \mid T_i = 1)$ since the two would almost be the same. Hence, the impact of CF would be the mean difference in the productivity, income and poverty between the contract and non-contract farmers. One of the major challenges of observational study is the fact that the treatment (CF) may depend on other factors that also affect the response variable. Moreover, T may be endogenous as well. In this study a rice farmer can decide to participate or not in the CF. Therefore, T is not a random assignment. That is, T may depend on some observable characteristics of the rice farmers.

As noted by Mendola (2007) one of the main weaknesses of many empirical impact evaluation studies is the failure to establish an appropriate *counterfactual* situation that could facilitate true identification of the causality of change. In this study, being able to assess what the situation would be like if the farmer did not participate in CF; which is the counterfactual scenario, is an important condition in order to assess the impact of CF on productivity, income and poverty reduction. Specifically, the Average Treatment Effect (ATE) and the Average Treatment Effect on the Treated (ATT) are defined as follows:

$$ATE = E\left(Y_{1i} - Y_{oi}\right) \quad (5)$$

$$ATT = E\left(Y_{1i} - Y_{0i} \mid T_i = 1\right) \quad (6)$$

In this context, the ATE asks the question: what would the productivity, income and poverty status have been in this sample had the farming households been randomly treated (Participate in CF)? On the other hand, the ATT asks the following question: what would the outcomes of the contract farmers have been in this sample had they decided to participate in CF? A necessary assumption in this context is the following: $Y_{1i}, Y_{0i} \mid T_i \perp X_i$. Where $\perp$ denotes independence. Different versions of this assumption has been identified in the literature. It has been referred to as the un-confoundedness assumption (Rosenbaum and Rubin, 1983), selection-on-observables (Heckman and Robb, 1985), or the conditional independence assumption (Lechner, 1999). It simply implies that conditional on the observed pre-treatment characteristics of the farmer i, a vector of variables X_i, the assignment of the treatment is independent of potential outcomes. This assumption guarantees the identification of the ATE and ATT.

Another requirement is the common support condition: $0 < P(T_i = 1 \mid X_i) < 1$. This condition rules out the perfect predictability of T given the covariates *X*. It simply states that the units with the same pre-treatment observables characteristics will have a positive probability of being both treated and control units. Instead of conditioning on X_i, it is possible to condition on the propensity score. Rosenbaum and Rubin (1983) defined the propensity score $P(X)$, as the conditional probability of receiving the treatment given the covariates. They further showed that if potential outcomes are independent of the treatment assignment conditional on

covariates X_i, then they are also independent of the treatment conditional on the propensity score, $P(X)$

$$P(X) = \Pr(T_i = 1 | X_i) = E(T_i | X_i) \quad (7)$$

The unconfoundedness assumption can now be written as: $Y_{1i}, Y_{0i} | T_i \perp P(X)$. Under these assumptions, ATE and ATT can be re-written as follows:

$$ATE_{psm} = E(Y_{1i} - Y_{0i} | P(X)) = E(Y_{1i} | T_i = 1, P(X)) - E(Y_{01} | T_i = 0, P(X)) \quad (8)$$

$$\begin{aligned} ATT_{psm} &= E(Y_{1i} - Y_{0i} | T_i = 1, P(X)) \\ &= E(E(Y_{1i} | T_i = 1, P(X)) - E(Y_{0i} | T_i = 0, P(X))T_i = 1) \end{aligned} \quad (9)$$

Simply computing the ATT using the PSM estimator boils down to calculating the mean difference in outcomes of the treated and control units, appropriately weighted by the propensity score distribution of the participants.

2.2.1. The Propensity Score Matching (PSM) Approach

The Propensity-Score Matching (PSM) method is applied to generate a control group and also deal with bias due to selection on-observables (overt bias). The PSM does not require a baseline data or panel survey and it is also one of the non-parametric estimation techniques that do not depend on functional form and distributional assumptions. Since it was introduced by Rosenbaum and Rubin (1983), the PSM has been widely utilised by economists, medical scientists, and financial scholars, sociologists, and political scientists among many others. Specifically, Cochrane and Rubin (1973a), Rubin (1973b), Rubin (1979), Bassi (1984), Rosenbaum and Rubin, (1985), Friedlander *et al.,(*1997), Heckman *et al.,* (1997), Heckman *et al.,*(1999), Dehejia and Wahba (1999; 2002), Heckman and Navarro- Lozano (2004), Wolfe and Michaud (2004), Campello et al., (2010), Gangl (2006), Grodsky (2007) and Arceneaux et al., (2006) are some of the researchers that have used PSM to assess the impact of various programs, policies, adoption of improved technologies on different kinds of outcomes of interest.

Essentially, PSM estimates each farmer's propensity to receive a binary treatment (with a logit) as function of observables and matches farmers with similar propensities. When farmers have similar propensity scores, their assignment to the treated group is largely random with respect to the relevant covariates, and thus mimics a controlled experiment, making it possible to

accurately identify causal effects. More importantly, the estimation of the propensity is not sufficient to calculate the Average Treatment Effect (ATE). There is need to search for the appropriate counterfactual(s) that matches with each participant depending on its propensity score. Different propensity score matching estimators have been proposed in the literature. Morgan and Harding (2006) and Caliendo and Kopeinig (2008) provide extensive discussions of practical and theoretical issues in propensity score estimation and comparisons of different types of matching estimators used to estimate the treatment effects.

The nearest neighbour, stratification, and the kernel matching are commonly used matching methods. Nearest-Neighbour Matching (NNM) matches participants and non-participants with the nearest propensity scores (Davis *et al.*, 2010). The NNM searches for control units with the nearest propensity score to those of each treated unit (Rubin 1973a; 1973b; Rosenbaum and Rubin, 1983). These matched control units are used to construct the counterfactual for the treated units. Since a control unit can be a best match for more than one treated unit, this method can be applied with or without replacement. With replacement, every matched control unit will be returned to the pool after the match and can subsequently be used as a match again. However, without replacement, every matched control unit is considered only once. Caliendo and Kopeinig (2008), however, argue that matching with replacement involves a trade-off between efficiency and bias. The difference between the outcomes of the treated and the matched control units is computed, and the ATT is then obtained by averaging these differences. Another problem that could arise in this context is that some matches may be fairly poor. It is possible that some treated units may have a nearest neighbour that is not so near, i.e.; may have a very different propensity score. This is why the kernel matching method was introduced.

In kernel matching, the counterfactual for each treatment case is constructed using all possible control units, but each control unit is weighted based on its distance from the treated unit. Specifically, these weights, represented by $\phi_{1,0}$, are calculated using a kernel function that transforms the distance between the selected target treatment unit and control units in the study (Heckman et al., 1997; 1998; Smith and Todd, 2005). The non-parametric Kernel Matching estimator is thus a natural extension of stratification sand NNM methods, since it simply matches all control units to each treatment unit but weights it so that those closest to the treatment unit are given the greatest weight. Kernel matching measures treatment effects by subtracting from each outcome observation in the treatment group a weighted average of

outcomes in the comparison group. The Average Treatment Effect on the Treated (ATT) is then estimated by averaging within-match differences in the outcome variable between the participants and the non-participants (see, e.g., Rosenbaum, 1995; Dehejia and Wahba, 1999).

Heckman *et al.*, (1997, 1998) and Smith and Todd (2005) provide a general outline for understanding different matching estimators. Using their framework, all three matching estimators of the ATT can be represented as follows:

$$ATT = \frac{1}{n^1}\sum 1\{(y_{1i} \mid T_i = 1) - \sum_j \phi_{1,0}(y_{0i} \mid T_i = 0)\} \qquad (10)$$

Where n^1 is the number of treatment cases and ϕ_i represents a set of scaled weights that measure the distance between each control unit and the target treatment unit. According to a survey of Morgan and Harding (2006), these estimator differ primarily in (a) the number of matches designated for each to-be-matched target case and (b) how these multiple matches are weighted, $\phi_{1,0}$ if more than one is used (Hosny, 2013).

2.2.2. Endogenous Switching Regression Model

To complement the PSM techniques and to assess consistency of the results to different assumptions, endogenous switching regression technique was applied. An econometric model that specifies a decision process and the regression models associated with each decision option is the endogenous switching regression model and it is used to address issues of self-selection and the estimation of treatment effects when there is non-random allocation of subjects to treatment and control groups as is generally the case with observational (as opposed to experimental) data. The sample-selection and disequilibrium models belong to this general class of switching models with the switch determined endogenously (Maddala and Nelson, 1975). In this study we specify the binary decision choice of farmers to participate in CF conditioned on observed covariates as follows:

$$P_i^* = \beta Z_i + \varepsilon_i$$

$$P_i = 1 \text{ if } \quad P_i^* > 0 \qquad (11)$$

$$P_i = 0 \text{ if } P_i^* \le 0$$

Due to the selection biases this study utilized an endogenous switching regression model of the outcomes of interest (productivity, income and poverty reduction) where the rice farmers faces two regimes (1) to participate and (2) not to participate in CF defined as follows:

$$G_{1i} = \lambda_1 H_i + \phi_1 C_{1i} + \nu_{1i} \quad (12a)$$

$$G_{2i} = \lambda_2 H_i + \phi_2 C_{2i} + \nu_{2i} \quad (12b)$$

Where G_i is productivity, per capita income and poverty level of the farmers in regimes 1 and 2, H_i represent a vector of exogenous variables thought to influence the outcomes function. ϕ_1 and ϕ_2 are the parameters to be estimated and ν_1 and ν_2 are the error terms. Finally, the error term are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as:

$$\text{cov}(\varepsilon_i, \nu_1, \nu_2) \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_2^2 & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & \sigma^2 \end{bmatrix} \quad (13)$$

Where

$\sigma_1^2 = \text{var}(\nu_1); \sigma_2^2 = \text{var}(\nu_2); \sigma^2 = \text{var}(\varepsilon_1); \sigma_{12} = \text{cov}(\nu_1, \nu_2); \sigma_{1\varepsilon} = \text{cov}(\nu_1, \varepsilon_i);$

$\sigma_{2\varepsilon} = \text{cov}(\nu_2, \varepsilon_i); \sigma^2$ represent variance of the error term in the selection equation and σ_1^2, σ_2^2 represents variance of the error term in the outcome equations.

According to Maddala (1983), when there are unobservable factors associated with selection bias, the important implication of the error structure is that, because the error term (ε_i) of the selection equation (11) is correlated with the error terms (ν_1, ν_2) of the outcome functions 11a and 11b, the expected values of ν_{1i}, ν_{2i} conditional on the sample selection are non-zero:

$$E(\nu_{1i} \mid P_i = 1) = E(\nu_{1i} \mid \varepsilon_i > -Z_i\beta) = \sigma_{1\varepsilon}\left[\frac{\theta(Z_i\beta/\sigma)}{\varphi(Z_i\beta/\sigma)}\right] \equiv \beta_{1\varepsilon}\gamma_1 \quad (14a)$$

$$E(\nu_{2i} \mid P = 0_i) = E(\nu_{2i} \mid \varepsilon_i \leq -Z_i\beta) = \sigma_{2\varepsilon}\left[\frac{-\theta(Z_i\beta/\sigma)}{1-\varphi(Z_i\beta/\sigma)}\right] \equiv \beta_{2\varepsilon}\gamma_2 \quad (14b)$$

Where θ and φ are the probability density and cumulative distribution functions of the standard normal distribution, respectively. The ratio of θ and φ evaluated at βZ_i, represented by γ_1 and γ_2 in equations 14a and 14b is referred to as the inverse mills ration(IMR) which denotes selection bias terms. Previous studies have used a two-stage method to estimate the

endogenous switching model (e.g. Lee, 1978; Feder *et al*., 1990; Fuglie and Bosch, 1995; Freeman *et al*., 1998). In the first stage, a probit model of the criterion equation is estimated and the inverse mills ratios γ_1 and γ_2 are derived according to definitions in equation 14a and 14b. In the second stage, these predicted variables are added to the appropriate equation in 12a and 12b, respectively to yield the following sets of equations.

$$G_{1i} = \lambda_1 H_i + \beta_{1\varepsilon}\gamma_1 + \phi_1 P_{1i} + \eta_1 \qquad (15a)$$

$$G_{2i} = \lambda_2 H_i + \beta_{2\varepsilon}\gamma_2 + \phi_{21} P_{2i} + \eta_2 \qquad (15b)$$

The coefficient of the variables γ_1 and γ_2 provide estimates of the covariance terms $\beta_{1\varepsilon}$ and $\beta_{2\varepsilon}$, respectively. Since the variables γ_1 and γ_2 have been estimated, however, the residuals η_1 and η_2 cannot be used to calculate the standard errors of the two-stage estimates. While lee (1978) suggested a procedure to derive consistent standard errors most especially for the two stage approach, Maddala (1983) argue that such procedure require potentially cumbersome and complicated process which most studies using earlier two stage approach failed to implement. Thus in this study we utilise a single stage approach where full information maximum likelihood (FIML) method proposed by Lokshin and Sajaia (2004) using the movestay command in the statistical software STATA is employed for the empirical analysis.

The FIML considers the entire system of equations, and all the parameters are jointly estimated. Estimators obtained by FIML enjoy all the properties of maximum likelihood estimators. They are consistent and asymptotically normally distributed. Most important of all these properties is that the estimators are asymptotically efficient and achieve the Cramer-Rao lower bound. Thus, FIML estimators are most efficient among estimators of the simultaneous equations model which is the endogenous switching regression model in this case. The FIML simultaneously fit the selection (equation 11) and outcomes (12a and 12b) equations in order to yield consistent standard errors, thus making γ_1 and γ_2 in equation 15a and 15b, respectively homoscedastic. The FIML's log likelihood function for switching regression model employed in this study proposed by Lokshin and Sajaia (2004) is described below:

$$\ln P_i = \sum_{i=1}^{N} \left\{ \begin{array}{c} P_i t_i \left[\ln F\left(\frac{(Z_i\beta + \alpha_{1\varepsilon}(G_{1i} - H_{1i}\lambda/\pi_1))}{\sqrt{1-\alpha_{1\varepsilon}^2}}\right) + \ln(f(G_{1i} - H_{1i}\lambda/\pi) \right] \\ + (1-P_i) t_i \left[\frac{\ln(1 - F(Z_i\beta + \alpha_{2\varepsilon}(G_{2i} - H_{21}\lambda)/\phi_2)}{\sqrt{1-\alpha_{2\varepsilon}^2}} + \ln(f((G_{2i} - H_{2i}\lambda)/\phi_2) \right] \end{array} \right\} \quad (16)$$

The sign of the correlation coefficients $\alpha_{1\varepsilon}$ and $\alpha_{2\varepsilon}$ have economic interpretations (Fuglie and Bosch, 1995). If $\alpha_{1\varepsilon}$ and $\alpha_{2\varepsilon}$ have alternate signs, then individual participate in CF on the basis of their comparative advantage: those farmers that participated in contract farming have above average returns from participation and those who choose not to participate have above –average returns from non-participation. On the other hand, if the coefficient have the same sign, it indicates hierarchical sorting: contract farmers have above-average returns whether they participate or not, but they are better off participating in contract farming, whereas non-participants have below-average returns in either case, but they are better off not participating in contract farming. The ATT of non-contract farmers can be calculated as:

$$ATT = E(G_{1i} - G_{2i} \mid P_i = 1) = H_i(\lambda_1 - \lambda_2) + (\sigma_{1\mu} - \sigma_{2\mu})\gamma_1 \quad (17)$$

In equation 17, $E(G_{1i} \mid P_i = 1) = H_i\lambda_1 - \sigma_{1\mu}\gamma_1$ represent the expected outcome for households that participated, had they chose to participate in contract farming.

$E(G_{2i}P = 1) = H_i\lambda_2 - \sigma_{2\mu}\gamma_1$ represents the expected outcomes for households who participated, had they chose not to participate in contract farming. For convenience, the estimation of the above equations was carried out using the add on procedure movestay , written by M. Lokshin (DECRG, The World Bank) and Z. Sajaya (Stanford University) in 2004, which was designed especially for this type of endogenous switching regressions model. The definition and description of the variables used in the model is presented in Table 3.

Table 3: Description and definition of the variables used in the model.

Variable	Description and definition
Participation	Dummy=1 if farmer participated in CF, 0 otherwise
Age	Age of the farmers in years
Gender	Dummy=1 if household head is male, 0 otherwise
Hsize	Number of people in the household
Educ	Years of formal education
Age2	Square of age
Tfarmland	Total farmland cultivated in hectares
Extension agents	Dummy=1 if farmer had contact with extension agents, 0 otherwise
Awareness	Dummy=1 if farmer is aware of CF
Accredit	Dummy=1 if farmer has access to credit, 0 otherwise
Distmrk	Distance to output market (km)
output	Total rice output (kg)
farmexp	Number of years of farming experience
income	Total agricultural income (Naira)
totagexp	Total agricultural expenditure (Naira)
Transpcost	Total cost of transportation (Naira)
Memorga	Membership of any cooperative society

3.0. Data and descriptive Statistics

This study utilised a primary data collected in 2013 through multistage random sampling technique. The primary data was also supplemented with Focus Group Discussion (FGD) and Key Informant Interview. In the first stage, six prominent rice producing States were purposively selected, thus Niger, Osun, Ekiti, Ebonyi, Benue and Ogun were selected. Two major rice producing Local Government Areas (LGAs) were also selected from the six selected States. The next stage was the selection of two villages from each of the LGAs selected. In the final stage, farmers were selected proportional to the size of rice farmers in each of the selected villages. Overall, this selection design generated about 350 farmers. However, after data cleaning and management, only 341 respondents were used for the analysis.

The result of the descriptive statistics as presented in Table 1 shows that 150 farmers among the respondents participated in the contract farming, while the rest are non-participants (191).

Majority of the respondents (59%) are males. The average age of the respondents is 43years. The average years of rice farming experience and formal education is 20 and 5 years, respectively. This suggests that the farmers have good farming experience and are not illiterates and thus capable of making appropriate farming decisions. The average farmland was 2.91ha, with an average output of 2356kg**.** The average distance to the nearest market was 14km. This long distance coupled with the high transportation cost and the poor rural access roads are disincentives to agricultural marketing in rural Nigeria and tends to discourage large scale production and discourages commercialised agriculture. However, with the adoption of CF, farmers will not only be able to produce more, they are more likely to have good and profitable markets for their outputs thus, enabling agricultural commercialisation, rural development and industrial growth.

Table 4: Socio-economic Characteristics of the Respondents

Variable	Mean	Standard Deviation	Minimum	Maximum
Average Age	43.00	12.13	18	76
Average household size	8.00	4.70	2.00	30.00
Average years of education	5.00	4.93	0.00	16.00
Average output (kg)	2356.04	1621.13	120.00	5700.00
Average distance to the market(km)	14.00	10.76	1.00	45.00
Years of farming experience	20.30	11.02	3.00	60.00
Average farm size (Ha)	2.91	1.59	0.19	7.00

Source: Field survey, 2013

4.0. Results and Discussion

4.1. Summary Statistics of the Variables by participation Status

The summary of the descriptive statistics of some important welfare and poverty indicators and the test of the mean differences, using the t-test is presented in Table 5. The result shows that the contract farmers perform better than the non-contract farmers in most of the variables except in the number of persons per households, expenditure per hectare, and per capita income. In particular, the contract farmers have significantly higher output and income, compared with the non-contract farmers. However, as the above comparisons do not control for the rice farmers' characteristic differences, the mean differences in the performance between contract and non-contract farmers may be caused by the rice farmers' characteristics rather than their contract or non-contract status. In the following we use the "propensity score matching" method to conduct a more refined comparison by controlling for the rice farmers'

characteristic differences and hence, provide the average treatment effect on the treated estimate.

Table 5: Summary Statistics of the Variables by contract Status

Variable	**Total N=341**	**Contract farmers N=150**	**Non-contract farmers N=191**	**Difference**
Age	43.22(0.66)	44.73(1.03)	42.03(0.84)	2.06**
Household size	8.32(0.25)	8.37(0.35)	8.28(0.36)	0.09
Education(years)	5.59(0.27)	7.77(0.36)	3.87(0.33)	3.89***
Total output	2932.31 (236.63)	4556.28 (498.28)	1657.96 (80.34)	2898.31***
Distance to market	14.28(0.58)	16.92(0.82)	12.20(0.78)	4.72***
Farming experience (years)	20.3(0.59)	21.93(0.96)	19.03(0.74)	2.91**
Farm size	3.08(0.13)	3.69(0.25)	2.61(0.10)	1.07***
Production expenditure(₦)	94465.10 (4330.31)	126447.00 (7626.41)	69348.43 (4066.88)	57098.57***
Per capita expenditure(₦)	15216.25 (879.30)	19444.49 (1672.70)	11895.64 (784.25)	7548.85***
Expenditure/hectare((₦/ha)	45640.25 (4329.91)	49669.62 (5817.84)	42475.81 (6239.50)	7193.81
Rice income (₦)	229553.40 (9330.23)	310513.30 (15611.60)	165972.30 (8924.60)	144541.10***
Per capita income(₦)	87129.70 (13496)	106474.00 (21122.93)	71937.86 (17446.12)	34536.11
Income/hectare((₦/ha)	151598.30 (21353.13)	222263.20 (45251.48)	96102.27 (12598.77)	126161.00***
Amount of credit obtained	48186.92 (4029.58)	60537.31 (5308.84)	27500.00 (4543.24)	33037.31***

Source: Field survey, 2013

Note: Standard error in parentheses

4.2. Average Variable Costs of Rice Production by participation in Contract Farming

One of the main reasons for the endorsement and the popularity of the contract farming arrangement is its potential to generate a reduction in the cost of production. In most cases, farmers get important production inputs at subsidized price and also training on how to best apply these inputs for maximum output. In this study we examined the rice production cost structure in order to see if there is any significant difference in the variable costs of production between the contract and non-contract farmers. The result as presented in Table 6 shows that the contract and non-contract farmers seem to have similar cost of production in many of the farm activities. However, there is observed significant differences in the cost of labour,

ploughing, threshing and bagging. This could be related to the additional farmland cultivated and the ensued increase in output as a result of contract farming.

Table 6: Average Variable Cost of Rice Production in Nigeria

Variable cost (₦)	**Total N=341**	**Participants N=150**	**Non-participants N=191**	**Difference**
Labour	46687.76 (2232.86)	50833.33 (3598.43)	43413.16 (2795.50)	7420.18* (4485.48)
Fertilizer	32480.00 (3366.60)	38342.86 (6514.23)	27350.00 (2550.78)	10992.86 (6671.35)
Herbicide	24566.28 (3475.01)	40320.00 (6571.07)	10867.39 (1066.52)	29452.61 (6228.17)
Ploughing	36685.71 (8211.42)	50036.36 (14167.25)	22000.00 (4857.98)	28036.36* (15594.23)
Planting	28828.95 (3792.21)	34131.58 (7204.02)	23526.32 (2209.75)	10605.26 7535.30)
Weeding	18734.69 (2160.74)	22200.00 (3964.37)	17205.88 (2571.79)	4994.12 (4681.56)
Harvesting	29218.13 (3014.10)	33983.82 (4505.43)	25695.65 (4010.72)	8288.17 (6063.96)
Threshing	8897.14 (1019.27)	11193.33 (1927.38)	7175.00 (983.61)	4018.33* (2016.72)
Winnowing	2409.09 (523.93)	2300.00 (757.19)	2500.00 (753.78)	200.00 (1077.27)
Bagging	4714.63 (940.53)	8184.62 (2607.73)	3103.57 (461.06)	5081.04* (1878.29)
Transportation	10884.27(418.36)	10720.64(816.49)	10977.64(464.99)	257.00

Source: Field survey, 2013

4.3. Poverty Indices

Using an estimated relative poverty line of ₦58086.00 ($US352.04) per annum; approximately $1.00 per day, we estimated the poverty indices for the contract and non-contract farmers and the results is presented in Table 6. It is not surprise to note that majority of the farmers fall below the poverty line. About 69%, and 82% of the contract and non-contract farmers, respectively are poor. In other words, poverty is still a big issue among the farmers in Nigeria. However, contract farming appears to exert a reduction on all the poverty indices. The results show that poverty headcount, depth and severity reduce by 15.65%, 20.53% and 21.85% respectively due to participation in contract farming. This result suggests that contract farming has the potential to generate a reduction in the prevalence of poverty among the rural small holder rice farmers in Nigeria. However, this has no causal interpretation, due to the problem of hidden and overt biases.

Table 7: Poverty Indices of the Respondents by Contract Participation Status

Poverty Indices	**Total sample**	**Contract farmers**	**Non-contract farmers**	**%Change**
Headcount *(P0)*	0.7654	0.6933	0.8219	-15.65
Poverty depth *(P1)*	0.5011	0.4378	0.5509	-20.53
Poverty Severity *(P2)*	0.3599	0.3112	0.3982	-21.85

Source: Field survey, 2013

4.4. Impact of Contract Farming on Rice Productivity, Income and Poverty Reduction

We adopted the PSM technique to estimate the impact of CF on all the outcomes of interest: rice productivity, income and poverty reduction. The Propensity Scores (PS) are generated using the logit model. First, it estimated the determinants of participation in contract farming and then matched the contract farmers with the non-contract farmers based on their PS. The result of the determinants of farmers' decision to participate in CF is presented in Table 8 and it reveals that the decision of the farmers to participate in CF is statistically and significantly influenced by distance to the nearest output markets, years of formal education and access to credit. This implies that farmers that have to travel to far distance markets, highly educated and can access credit easily have the highest probability to participate in CF. Hence, the desire for easy access to profitable output market, education of the household's head and financial security in form of access to credit are important factors that will encourage farmers to participate in CF. The PS and the result of the balancing test is also presented in Table 9. The non-significance of the coefficients and the low percentage bias shows that the covariates between the contract and non-contract farmers are actually balanced after matching.

Table 8: Determinants of Participation in Contract Farming

Variable	Coefficient	Std. Error	z-value	P>z
age	0.038	0.063	0.61	0.543
House size	-0.011	0.028	-0.39	0.698
age2	-0.000	0.001	-0.58	0.563
Farming experience (years)	0.013	0.022	0.59	0.554
Distance to market(Km)	0.029**	0.012	2.49	0.013
Education (years)	0.280***	0.084	3.35	0.001
Education2	-0.008	0.006	-1.45	0.148
Membership of organisation	0.166	0.401	0.41	0.679
Extension contact	-0.191	0.359	-0.53	0.595
Access to credit	0.884**	0.280	3.16	0.002
Constant	-3.061	1.458	-2.1	0.036
Number	339.00			
Log likelihood ratio	-192.32			
Pseudo R2	0.172			
LR chi2(10)	79.84***			

Source: Field survey, 2013

Note: ***, **,significant at 1%, and 5%, respectively

Table 9: Propensity Score and Test of Balancing

	Mean			t-test	
Variable	**Treated**	**Control**	**%bias**	**t**	**p>t**
age	44.723	43.52	9.9	0.83	0.406
age2	2161.5	2040.1	10.9	0.89	0.372
Household size	8.2973	7.6892	13.1	1.34	0.181
Years of experience	21.926	21.453	4.3	0.33	0.744
Distance to market	16.878	17.507	-6	-0.46	0.645
Education	7.6892	7.8243	-3	-0.26	0.795
Square of education	78.608	81.257	-4.1	-0.32	0.749
Member of organisation	0.91216	0.90541	2	0.20	0.841
Extension agent	0.87162	0.91892	-13.5	-1.33	0.185
Access to credit	0.39865	0.34459	12	0.96	0.338

Source: Field survey, 2013

4.4.1. Impact of Contract Farming on Productivity

As a form of sensitivity analysis and robustness check for the PSM estimates, we adopted the two most widely used matching algorithm: the Nearest Neighbour Matching (NNM) and the Kernel Based Matching (KBM). The most interesting and relevant estimate to us in this study is the Average Treatment effect on the Treated (ATT), which provides the impact of contract farming on the farmers that participate in contract farming. The result of the PSM is presented in Table 10. The result of the NNM shows that the productivity (output per hectare) of the participating farmers increased by 378.11kg/ha. In percentage term, the result shows 56% increase in productivity among the contract farmers. This result was also validated by using the KBM. This is with a view to ensure that the impact estimate is not sensitive to the matching technique adopted. The KBM result also shows a positive and significant increase in productivity of about 395.02kg/ha among the contract farmers. Similarly, the result also shows that contract farming increases rice productivity by 58% among the participating farmers. This suggests that contract farming can generate the desired increase in rice productivity in Nigeria.

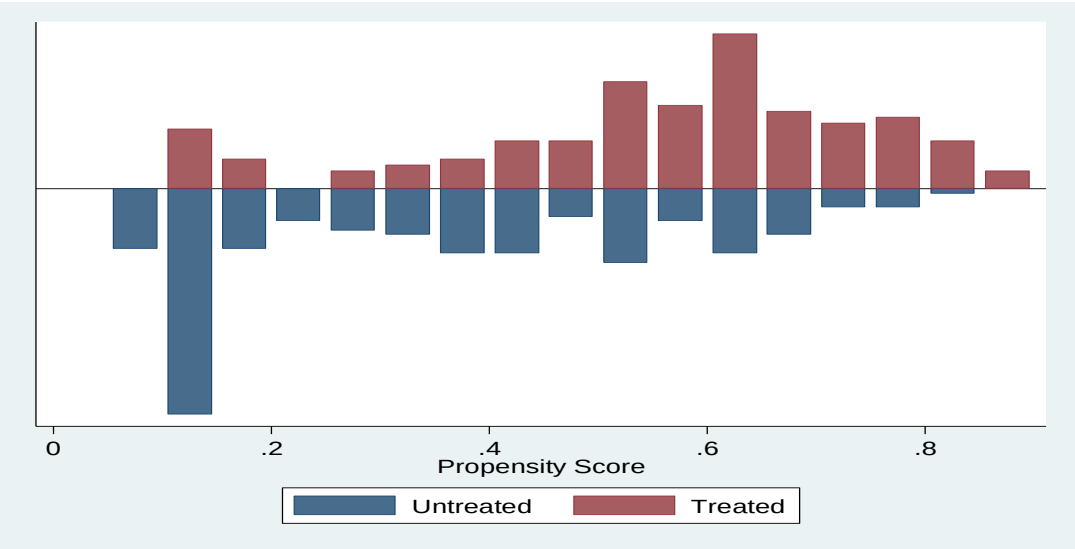
Table 10: Impact of CF on Productivity

Sample	Contract farmers	Non-contract farmers	Difference	S.E.	T-stat
Nearest Neighbour Matching (NNM)					
Unmatched	1066.23	656.65	409.58	46.54	8.80
ATT	1066.23	688.12	378.11***	77.11	4.90
% Impact	6.85	6.29	0.56***	0.12	4.73
ATU	656.65	1058.61	401.96		
ATE			391.55		
Kernel Based Matching (KBM)					
Unmatched	1066.23	656.65	409.58	46.54	8.80
ATT	1073.31	678.29	395.02***	56.62	6.98
% impact	6.86	6.28	0.58***	0.08	6.93
ATU	656.65	1089.17	432.53		
ATE			416.28		

Source: Field survey, 2013

Note: ***, significant at 1%.

Figure: Area of Common Support: Impact on Productivity



4.4.2. Impact of Contract Farming on Income from Rice Production

The income from rice production is calculated as total output multiplied by the prevailing market price or the price paid by the contracting firm per kilogram. The impact of contract farming on income from the rice production is also estimated using the NNM and KBM techniques. The result is presented in Table 11. The results of the NNB and KBM show that income of the contract farmers increased significantly by ₦127854.70 and ₦131722.70, respectively. In percentage term, contract farming generated about 64% increase in rice income.

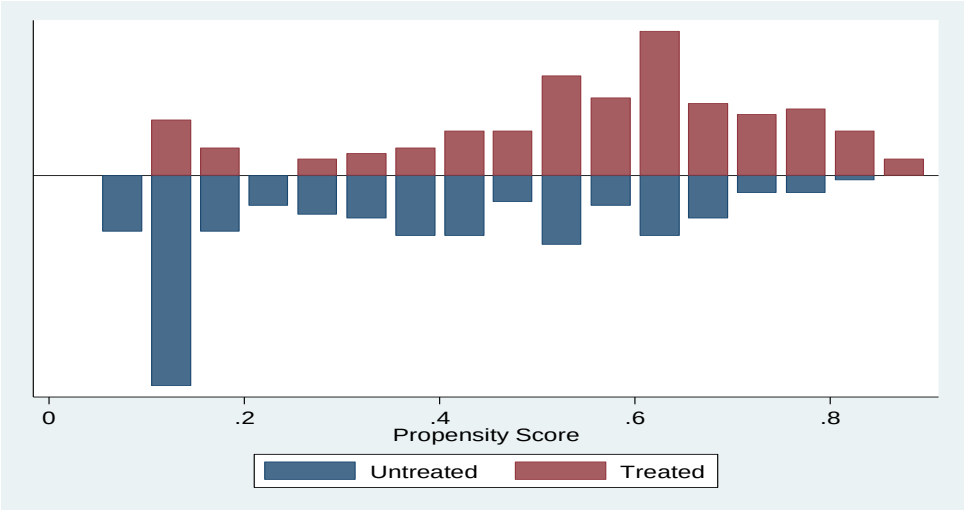
Table 11: Impact of Contract Farming on Income from Rice Production

Sample	Contract farmers	Non-contract farmers	Difference	S.E.	T-stat
Nearest Neighbour Matching (NNM)					
Unmatched	308628.38	165972.30	142656.10	17137.54	8.32
ATT	308628.38	180773.60	127854.70***	26739.50	4.78
% impact	12.42	11.77	0.64***	0.17	3.89
ATU	165972.25	222479.10	56506.81		
ATE			87655.75		
Kernel Based Matching (KBM)					
Unmatched	308628.38	165972.30	142656.10	17137.54	8.32
ATT	310876.71	179154.00	131722.70***	20661.48	6.38
% impact	12.43	11.79	0.64***	0.10	6.25
ATU	165972.25	229786.40	63814.12		
ATE			93234.45		

Source: Field survey, 2013

Note: ***, significant at 1%.

Figure: Area of Common Support: Impact on Income from Rice Production



4.4.3. Impact of Contract Farming on Poverty Reduction

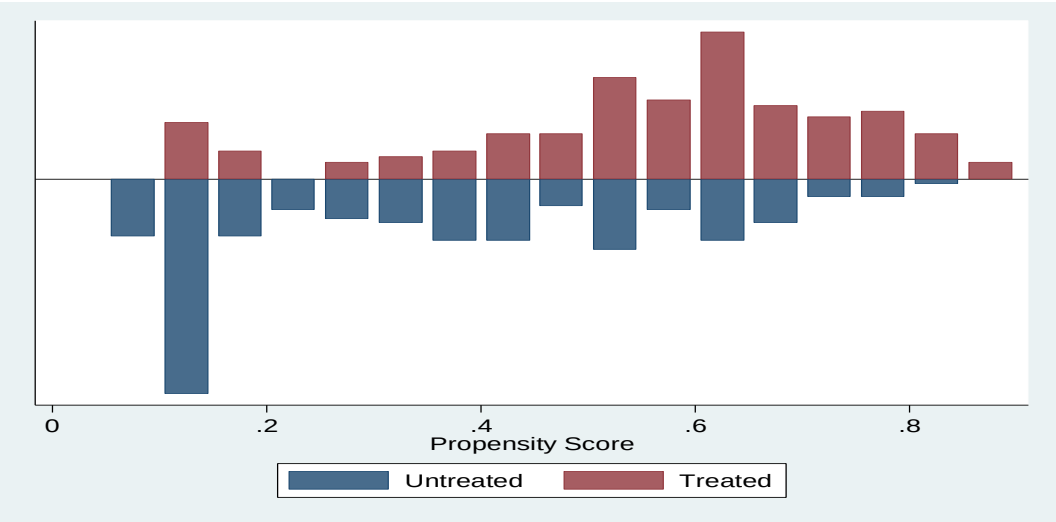
Using the poverty line of about ₦ 58086.00 per annum the rice farming households were classified into poor and non-poor. Households with mean per capita income lower than the poverty line were classified as poor. The variable poor, which is binary; taking the value of one if the household is poor and zero otherwise is used as the dependent variable for the estimation of the impact of contract farming on poverty reduction. Essentially, the estimate is expected to show by how much the proportion of the poor households reduced due to participation in contract farming. Both the results of the NNM and the KBM show that contract farming reduced poverty headcount by 14% and 8% respectively. This is an indication that apart from the fact that CF increases output, which translate into increase in income, it also have a resultant poverty reduction effect on the contract farmers.

Table 12: Impact of Contract Farming on Poverty Reduction

Sample	Contract farmers	Non-contract farmers	Difference	S.E.	T-stat
Nearest Neighbour Matching (NNM)					
Unmatched	0.69	0.82	-0.13	0.05	-2.74
ATT	0.69	0.83	-0.14**	0.07	-1.95
ATU	0.82	0.84	0.02		
ATE			-0.05		
Kernel Based Matching (KBM)					
Unmatched	0.69	0.82	-0.13	0.05	-2.74
ATT	0.69	0.77	-0.08	0.06	-1.44
ATU	0.82	0.85	0.02		
ATE			-0.02		

Source: Field survey, 2013

Figure: Area of Common Support: Impact on Poverty Reduction



4.4.4.. Endogenous Switching Regression

The results of the endogenous switching regression are presented in Table 13. The results of the participation selection equation are reported in the section output headed contract. The results of the rice output regression among the contract farmers are reported in the logoutput_1 section, and the rice output among the non-contract farmers is presented in the logouput_0 section. The correlation coefficients rho_1 and rho_2 are both negative, but are statistically significant only for the correlation between contract choice equation and the contract farmers' rice output. Since rho_1 is negative and statistically significantly different from zero, the model suggests that farmers who choose to participate in contract farming obtain higher output than a random farmer from the sample would have obtained.

The non-contract farmers are not better or worse than a random farmer. The likelihood ratio test for joint independence of the three equations is statistically significant at 1%. The variable sigma**,** /lns1 , /lns2, /r1/r2 are the ancillary parameters used in the maximum likelihood procedure. sigma_1, and sigma_2 are the square roots of the variables of the residuals of the regression part of the model. The result of the Average Treatment Effect on the Treated (ATT) shows a positive and significant increase in yield due to participation in contract farming.

Table 13: FIML Estimates of the Endogenous Switching Regression

	Coefficient	Std. Err.	z-value	P>z
logoutput_1				
age	-0.049	0.038	-1.330	0.185
hhsize	-0.035	0.058	-0.600	0.55
yearsexp	-0.021	0.013	-1.570	0.117
hhsize2	0.002	0.002	1.120	0.261
farmsize	0.104***	0.028	3.770	0.000
gender	0.162	0.172	0.940	0.345
credit	-0.217	0.161	-1.340	0.179
educatio	-0.029	0.020	-1.480	0.140
age2	0.001	0.000	1.520	0.128
Constant	9.712***	0.905	10.740	0.000
logoutput_0				
age	-0.021	0.029	-0.710	0.477
hhsize	0.002	0.039	0.060	0.949
yearsexp	0.003	0.009	0.280	0.781
hhsize2	0.000	0.001	0.370	0.71
farmsize	0.327***	0.046	7.100	0.000
gender	-0.049	0.131	-0.370	0.708
credit	-0.191	0.161	-1.180	0.236
educatio	-0.004	0.019	-0.230	0.820
age2	8.66E-05	0.000	0.240	0.810
Constant	6.834***	0.623	10.970	0.000
Contract				
age	0.055	0.037	1.480	0.138
hhsize	0.032	0.056	0.570	0.566
yearsexp	0.012	0.013	0.970	0.334
hhsize2	-0.002	0.002	-1.010	0.313
farmsize	0.182***	0.050	3.610	0.000
gender	-0.315*	0.169	-1.860	0.063
credit	0.547***	0.171	3.200	0.001
educatio	0.103***	0.017	6.040	0.000
age2	-0.001	0.000	-1.410	0.159
memborg	0.219	0.205	1.070	0.286
awarenes	-0.002	0.155	-0.010	0.992
Constant	-2.941***	0.912	-3.230	0.001
/lns1	-0.017	0.089	-0.190	0.847
/lns2	-0.289**8	0.063	-4.560	0.000
/r1	-1.146***	0.213	-5.390	0.000
/r2	-0.215	0.343	-0.630	0.530
sigma_1	0.983	0.088		
sigma_2	0.749	0.047		
rho_1	-0.816***	0.071		
rho_2	-0.212	0.328		

Source: Field survey, 2013

Note: ***, **,*, significant at 1%, 5%, and 10%, respectively

5.0. Summary, Conclusion and Policy Recommendations

Contract farming is becoming one of the vital approach to agro-industrial development and agricultural productivity increase in developing countries like Nigeria. This study empirically assess the impact of CF on rice productivity, farmers' income and poverty reduction in rural Nigeria. The study adopted the FGT poverty measurement, endogenous switching regression and PSM approaches using the two widely adopted matching techniques (NNM and KBM) to provide the estimates of the impact of CF on all the outcomes of interest. The results of the poverty assessment show that poverty is still highly endemic among the rural farmers. Contract farmers have higher output than the non-contract farmers. Contract farming impacted productivity and income positively. CF also reduced poverty headcount significantly among the contracting farmers. Hence, this study conclude that CF has the potential to generate the desired increase in rice productivity, increase farmers' income and contribute to the reduction of poverty in rural Nigeria. Since the results show that contracted farmers generally perform better than the non-contracted farmers, these findings seem to disagree with the notion that contract farming is 'exploitative' to smallholder farmers (Key and (Runstern, 1996). Therefore, it is recommended that farmers should be encouraged to participate in CF. The CF agreement should also be made explicit enough for the farmers to understand in order to reduce the high default rate among the farmers. The Government should also moderate and supervise the contract agreement to prevent the firms from cheating the farmers by deviating from the agreed price after harvest.

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Appendix A.

Map of Nigeria showing all the selected States and Regions