



EMPIRICAL EVIDENCE ON CONTRACT FARMING IN NORTHERN NIGERIA: CASE STUDY OF TOMATO PRODUCTION

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Abstract

This study contributes to the scarce empirical evidence on contract farming in Northern Nigeria using a case study of tomato production. Using data from five Local Government Areas of Kano State in Northern Nigeria, a total of 116 tomato contract farmers and 84 non contract farmers were selected. The econometric result indicated that there was a high level of participation in contract farming. Participation in contract farming generated desirable causal effects on transaction costs, productivity, tomato income, total household income and poverty status of the farmers and this implies that the contract farming arrangement is very appealing to the farmers currently engaged in contract farming. The major factors that swayed the farmers' decision to engage in contract farming were education, farm size and extension indicating that these variables are key policy variables that could be leveraged to influence participation in contract farming in the study area. The study may give detailed information on how contract and noncontract tomato production is currently functioning in northern Nigeria.

1. INTRODUCTION

Contract Farming (CF) is defined as "an agreement between farmers and processing and/or marketing firms for the production and supply of agricultural products under forward agreements, frequently at pre-determined prices" (Eaton and Sherperd, 2011). CF refers to an agreement on agricultural production vis-à-vis buyers and farmers that institutes settings for the production and selling of farmhouse produce. Generally, the farmers agree to deliver certain quantities of a specific product at the quantified eminence criteria and time, and the buyer might also supply some inputs or hands-on backing to the farmer. In Southern and Eastern Africa, CF is synonymously referred to as "Out grower Scheme" and can be used for several products, even though in middle income economies, it is typical for staple crops like yams, plantain and rice.

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Empirical studies in middle income economies give mixed investigations about the safety and membership outcome of CF. Although the degree at which membership subsidizes to the wellbeing of smallholders endure a practical question, several authors found that partaking increases farmers' earnings (Barrett et al., 2012; Bellemare, 2012; Warning and Key, 2002). Singh (2002) was of the view of the exclusion of smallholders from partaking in CF. In this prospective, many researchers recommended the inclusion of smallholders in CF Warning and Key (2002) and Miyata et al. (2009). The literature similarly posits numerous complications startling CF performance, which include: deferred payments, cheating, high defaulting rate, biased terms and with no reimbursement for crop failure (Guo, 2005; Singh, 2002). Barrett et al. (2012) re-counted cases of high input turn over as both parties fail to honor their agreements. The double-hurdle model was used to standardize the drivers of engrossment in CF. It is a parametric synopsis of the Tobit model, in which two isolated stochastic processes regulate the certainty to partake in CF (Greene, 2007). Pronouncements in the Tobit model, participation and the level or extent of participation are presumed to be jointly and henceforth the factors affecting the two level decisions are equivalent. However, the choice to partake might lead to the conclusion level/intensity of participation and therefore the control variables may differ (Asfaw et al., 2011). The double-hurdle model is applied in a way that, both hurdles (the decision for input in CF and the continuous participation) have equations associated with them, incorporating the outgrowth of farmer's characteristics and circumstances. In estimating the double-hurdle model, a Probit regression (with complete observations) is tracked by a condensed regression on the non-zero observations (Cragg, 1971) and this was used to define the resolution to participate and the level/intensity of involvement in contractual arrangements in Zambia (Kiwanuka and Machethe, 2016). The double-hurdle assumes that households make two sequential decisions with regard to participating and level/intensity of a scheme like CF or the use of a technology. The number 1 is assigned to the first decision variable (D) for farmers who participated in contract farming and the value zero for otherwise. However, the expected utility of participating in CF (D_i^*) is latent. The PSM (Propensity Score Matching) was used to resolve the concussion of input in CF transaction costs and welfare. Basically, the PSM framework matches the observations of participants and non-participants of CF, conferring to the anticipated susceptibility of input in CF (Wooldridge, 2005). The underlying principle of PSM is that the predicted probabilities (propensity scores) from an estimated probit or logit model are used to find matches for farmers partaking in CF. The overall objective of the study is the empirical evidence on contract farming in Northern Nigeria using a case study of tomato production. The specific objectives are to:

- i) Determine the basis of involvement into tomato CF
- ii) Effect of partaking in CF on transaction cost
- iii) Influence of participation in CF on Output, Earnings and Wellbeing

2. METHODOLOGY

2.1. Sampling technique

A pre-survey was conducted to identify the tomato farmers under contract and those under the conventional farming system so as to establish a complete sampling frame and afterwards, a pilot survey was conducted to pre-test the questionnaire in order to help detect any fault that may surface in the questionnaire administration sample designs. The target populations were tomato farmers in the villages where tomato is mostly grown in the thirty villages of five local governments targeted in the study area, the population of tomato producers amounted to 2,143 farmers. Multi-stage sampling technique was employed. In the second stage, five local government areas, namely: Garun Mallam, Kura, Bunkure, Rano and Kiru were randomly selected and the third stage involved the purposive choice of six villages from each of the local government areas.

2.2. Data collection

Using a survey method encompassing a designed questionnaire, primary data were collected from farmers. The socioeconomic data collected included sex of the respondent, cropping pattern, household size, age, marital status and formal education levels. Production information collected included size of farmland owned, size of land under tomato production, type of labour used in production, varieties of seed planted, fertilizer application, cyclical yields and domestic income. Amount of credit, access to extension services were also among production information (number of visits), amount of fertilizers used. Market information was also collected which included prices of seeds, seasonal quantities produced, cost and returns, produce sold. Data about constraints faced by tomato farmers and suggestions to increase their output was also collected.

2.3. Double-hurdle model

This model outline the impact of drivers in CF. It is a parametric simplification of the Tobit model, in which dual distinct stochastic processes define the resolution and level to partake in CF (Greene, 2007). Decisions and level or extent of membership in the Tobit model, are supposed to be the same. Nonetheless, Asfaw et al. (2011), suggested that the proclamation to partake may lead the level/intensity of participation decision and therefore the control variables in both stages may vary. In this model, both hurdles (the decision for partaking in CF and the level of participation) have equations associated with them, integrating the accouterments of the farmer's physiognomies and surroundings. In estimating the double-hurdle model, a Probit regression (utilizing complete observations) is tracked by a condensed regression on the non-zero observations (Cragg, 1971) and this determine the resolution to partake and the level/intensity of involvement in contractual arrangements in Zambia (Kiwanuka and Machethe, 2016). The doublehurdle assumes that households make two sequential decisions for participating and level/intensity of contribution in a scheme like CF or the use of machinery. Each hurdle is habituated by the family circle socioeconomic characteristics and institutional variables. However, a diverse underlying variable is used in the double-hurdle model, to epitomize each resolution procedure. The first decision variable (D) is 1 for farmers who have partook in CF and zero for otherwise. The expected utility of participating in $CF(D_i^*)$ is latent however.

Evaluated with a Probit model, the first hurdle input equation is given as:

 $D_i = 1 \text{ if } D_i^* > 1 D_i = 0 \text{ if } D_i^* \le 1$

Where,

 $D_i^* = 1$ if the farmer participates in tomato CF and 0 otherwise,

 Z_i = descriptive vector variables (farmer/farm specific characteristics and institutional characteristics that influences the likelihood of partaking in CF),

a = vector of parameter estimates,

 $u_i = \text{error term.}$

The second hurdle of double-hurdle model involves an outcome equation, which uses a truncated model that determines the level of participation in CF measured in terms of the proportion of farm area allocated to tomato CF relative to the cumulative cultivable crop area owned. Therefore, the second hurdle uses observations only from those farmers who indicated a positive value on partaking in CF. It is worth stating that the farmers' involvement in CF does not partake at the same level of participation. Hence, the level/intensity of participation (level of participation hurdle) of in tomato contract farming is projected using a Tobit-like model given as:

 $Y_i = \begin{cases} Y_i^* \ if \ Y_i^* > 0 \ and \ D^* > 0 \\ 0 \ otherwise \end{cases}$

Where,

 Y_i = observed response on the proportion of land allocated to tomato contract farming, X_i = vector of explanatory variables, β = vector of parameter estimates, v_i = error term

The observed value of the proportion of land allocated to tomato contract farming is therefore given by:

The error terms of the two decision models (participation model and level of participation model) are distributed as follows:

The error terms u_i and v_i are usually assumed to be independently and normally distributed. It is assumed that for each respondent the decision whether to participate in contract farming and the decision about the participation level are made independently. The two decision processes are non-separable and thus both parts of the likelihood function must be maximized simultaneously.

Moffat (2005) was of the view that a variable appearing in both equations of the double-hurdle model have reverse effects.

2.4. Propensity score matching (PSM)

PSM was used to evaluate the impact of membership in contract farming transaction costs and welfare. PSM technique is a non-parametric approach that involves constructing a statistical comparison group by modeling the probability of participating in contract farming/adopting a technology on the basis of practical features that are unpretentious by the contract farming/technology. The underlying principle of PSM is that the predicted probabilities (propensity scores) from an estimated probit or logit model are used to find matches for farmers participating in contract farming (participants).

The estimation of average treated effect on the treated (ATT) is specified as follows:

The problem with estimation of the equation (6) is that $E\{H_0|D = 1\}$ is not observable. However, it is probable to appraise equation (6) by replacing $E\{H_0|D = 1\}$ with $E\{H_0|D = 0\}$ as follows

Valuation of equation (7) is a biased estimate of the causal effect of membership in CF. This leads to the modeling of a more reliable estimation by controlling observable characteristics (Z) to ensure that participation in CF is random and not connected with the outcome variables i.e restricted independence hypothesis is satisfied.

$$P(Z) = Pr\{D = 1|Z\} = E\{D|Z\}$$
(7)

$$ATT = E\{H_1 - H_0 | D = 1\}$$
 (8)

$$ATT = E\{E\{H_1 - H_0 | D = 1, P(Z)\}\}$$
 (9)

Where,

 H_1 = value of the outcome for participants in tomato contract farming,

 H_0 = value of the outcome for adopters of the new technology,

D = Participation (1 for participants in tomato contract farming and 0 otherwise),

Z = vector of explanatory variables.

This study employed two matching techniques (Nearest Neighbor Matching and Kernel Based Matching) instead of only one to ensure robustness of the impact of farmers' involvement in CF.

3. RESULTS AND DISCUSSION

3.1. Descriptive results of the continues variables

The result given in Table 1 shows that a larger proportion of the contract farmers (54.3%) and non-contract farmers (50%) respectively had no proper education. This matches cordially with the findings of Ayandiji (2011) who reported that 57% of the tomato farmers in Ogun State, Nigeria had no official education. This finding implies that the majority of the farmers are not favourably disposed to the influence of education on their farm production activities due to their lack of education. This is in accordance with the literature that education builds a supportive mental attitude for getting innovative practices, particularly information and management-intensive practices. Thus, the more educated the farmer is, the higher the likelihood of participating in CF as they are in a position to acknowledge the benefits and advantages of partaking. According to Beard (2005), the exceptional educated household head; is likely to participate in projects.

Educational qualification	Contrac	t farmers	Non-contract farmers			
Educational qualification	Frequency Percentage		Frequency	Percentage		
No formal education	63	54.3	42	50		
Primary education	18	15.5	17	20.2		
Secondary education	25	21.6	13	15.5		
Tertiary education	10	8.6	12	14.3		
Total	116	100	84	100		

 Table 1: Distribution of tomato farmers based on educational qualification

The results in Table 2 below shows that 98% of the non-contract farmers cultivated tomatoes in 0.1-1.0 hectares of farmland compared to 93% of the contract farmers. On the average, the contract farmers cultivated tomatoes on 1.0 hectares compared to 0.8 hectares for the non-contract farmers, signifying that tomato farming by both the contract and non-contract farmers were on a small scale. This result is in support of relates Maliwichi *et al.* (2014) who reported that 65% of the tomato farmers in Limpopo province, South Africa had farm size of at most 2 hectares. Thus the production of tomato on a small scale could be attributed to low access to large agricultural land which makes agricultural productivity growth through farm area expansion limited and therefore, productivity growth through sustainable intensification is a better option. This further validates the important role of CF in driving sustainable tomato production in the study area.

Farm size	Contrac	Contract farmers		act farmers
(Hectares)	Frequency	Percentage	Frequency	Percentage
0.1 – 1.0	108	93.1	82	97.6
1.1 - 2.0	8	6.9	2	2.4
Total	116	100.0	84	100.0
Mean	1.0		0.8	

 Table 2: Distribution of tomato farmers based on farm size

The result in Table 3 shows that most (97%) of the contract farmers had contacts with extension agents compared to 56% of the non-contract farmers. This result is expected as CF arrangement gives the contract farmers more access to agricultural extension support services as one of the benefits of the contractual agreement. This is not in tandem with Usman and Bakari (2013) who reported that a majority (64%) of the tomato farmers in Adamawa state, Nigeria had no access to extension. With CF, access to extension service is mostly made accessible to the contract farmers depending on the terms of the contract.

Extension	Contrac	t farmers	Non-contract farmers			
contact	Frequency	Percentage	Frequency	Percentage		
No contact	4	3.4	37	44.0		
Had contact	112	96.6	47	56.0		
Total	116	100.0	84	100.0		

3.2. Level of participation in tomato contract farming

Mwambi *et al.* (2016) pointed out that the concept of smallholder farmers' participation in CF is fundamental for policy makers pursuing to uphold rural economic activity and development. This makes understanding of tomato farmers' level of participation in contract farming in the study area a critical issue. The result presented in Table 4 indicates that a majority (60%) of the tomato contract farmers had high participation in contract farming in terms of allocating a larger proportion of their cultivable land to tomato contract farming and this implies that contract farming. Also, the result shows that there were farmers with very low, low and very high level of participation in tomato contract farming. This stipulates the level of disparity in membership in the study area of contract farming.

Table 4: Level of participation of farmers in tomato contract farming

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Level of participation	Frequency	Percentage					
Very low (1 – 25%)	15	12.9					
Low (26 – 50%)	21	18.1					
High (51 – 75%)	69	59.5					
Very high (76 – 100%)	11	9.5					
Total	116	100.0					

NB: Level of participation in contract farming was defined based on percentage of land allocated to tomato contract farming in relation to the total land cultivated by the farmers

3.3 Determinants of participation in tomato contract farming

Table 5 presents the result of the estimated Probit model of the determinants of participation in tomato contract farming. The Likelihood ratio (LR) of 152.03 of the estimated Probit model for tomato contract farming is significant at 1% probability level and this implies the joint significance of the explanatory variables included in the models. There is disparity in the factors that leverage the farmers' involvement in tomato CF. The coefficient for education was positive and significant in influencing farmer's participation in tomato contract farming at 1% level of

probability. This result is in support of Arumugam *et al.* (2011) whose findings indicated that education was positive and significantly influenced the farmers' likelihood of participation in fresh fruits and vegetable farming in Malaysia. Coefficient for farm size was positive and significant in influencing farmer's participation in tomato contract farming at 1% level of probability and this shows a direct relationship between farm size and participation in contract farming in Northern Ghana. Coefficient for extension contract was positive and significant in influencing farmer's participation at 1% level of probability relationship between farm size and participation in contract farming in Northern Ghana. Coefficient for extension contact was positive and significant in influencing farmer's participation in tomato contract farming at 1% level of probability. This result is in accordance with that of Anim (2011) who recounted that in the Limpopo province of South Africa, extension visits was absolutely important in swaying the maize farmers' input in CF

3.4. Level of participation in tomato contract farming

The result of the estimated truncated regression models in Table 5 shows that LR of 183.23 of the fitted models for data generated from tomato contract farming was significant at 1%. This indicates the joint significance of the explanatory variables in influencing the level or intensity of participation in tomato contract farming. The results revealed that there is some variation in the results of the estimated probit model and truncated regression models and this implies that the factors that influenced the farmers' decision to participate in tomato contract farming were not exactly the same factors that influenced the farmers' intensity of participation in tomato contract farming. This further justifies the use of double-hurdle model in examining farmer's participation in tomato contract farming in the study area as against the use of Tobit regression.

Variables	First hurdle: Probit model	Second hurdle: Truncated model
Intercept	4.335*** (2.94)	1.579** (2.20)
Gender	0.382 (1.32)	0.171 (1.54)
Age	-0.149** (-1.99)	-0.193 (-1.12)
Education	0.133*** (2.28)	0.027** (2.19)
Family size	-0.923 (-1.02)	0.017* (1.85)
Farm size	0.138*** (2.78)	0.062*** (2.41)
Farming exp	0.384* (1.77)	-0.049 (-0.37)
Farm assets	1.117 (0.89)	0.394* (1.76)
Access to credit	1.158** (3.79)	0.081 (1.60)
Extension contact	1. 750*** (2.50)	0.019*** (2.92)
Association	1.294*** (2.43)	0.315 (0.94)
Input subsidy	-0.283 (-0.66)	-0.055 (-1.04)
Market distance	0.443 (1.34)	-0.084 (-0.97)
Observations	200	116
LR chi ²	152.03	183.23
$Prob> chi^2$	0.00	0.00
Log likelihood	-58.95	-82.12
Sigma		1.656 (2.97*)
Pseudo R ²	0.56	

Table 5: Double-hurdle estimates of determinants of participation in tomato CF

NB: values in parenthesis are the t values

***, **, * implies significant at 1%, 5% and 10% probability levels respectively

The estimated coefficient of education was positive and significant in influencing the farmer's level of participation in tomato contract farming at 5% probability level, implying that more educated farmers had a higher probability of increasing their level of participation in contract farming. This outcome supports the findings of Kiwanuka and Machethe (2016). Kiwanuka and Machethe (2016) result showed that education positively influenced the level/intensity of participation in the interlocked contractual arrangement for dairy in Zambia. Also, Tongchure,

and Hoang (2013) found that a household members' level of education positively influenced farmers' likelihood to participate in contract participation in Thailand, noting that farmers who complete higher education would find it easier to understand the information given when receiving advice from the extension agents. The estimated coefficient of farm size was positive and significant in influencing the farmer's level of participation in tomato contract farming at 1% probability level. This is expected because the increasing level of participation in contract farming would mean increasing the land area allocated to tomato production. This means that as farm size accessible of farmers' increases, the probability of increasing their level of participation increases. This result is identical with the findings of other scholars who observed the direct relationship between increased levels of commercialization and increased land size. The estimated coefficient of extension contact was positive and significant in influencing farmer's level of participation in tomato contract farming at 10% probability level. This implies that farmers who are very much in contract farming. In addition, farmers with increased access to extension will be more informed on challenges and can upgrade their know-how on developmental projects or schemes (Sidibé, 2005).

3.5. Impact of participation in contract farming on transaction costs nexus

The two main assumptions underlying the consistency of propensity score matching techniques were evaluated based on results in Table 6 and 7 before proceeding to establish the causal effect of participation in contract farming on transaction costs. The balancing test is usually vital after matching to examine whether the alterations in covariates of both groups (contract farmers and non-contract farmers) in the coordinated sample have been excluded, in which case, the accorded corresponding group can be accorded a reliable counter to fact. The results of the simulation-based sensitivity analysis for PSM estimates as a test for the robustness of ATT for failure of the CIA as put forward by Ichino *et al.* (2008) is obtainable in Table 2. The results show that the matching method of the propensity score yields robust estimates of the ATT because the estimates with binary cofounder differ by less than 9% from the standard matching estimate since the simulated ATT exceeded 8.35% of the ATT baseline. This implies that the ATT is enthusiastic to potential deviations from the CIA and the potential confounder does not epitomize a real threat for the robustness of the standard estimate.

Matching	Outcome	Pseu	eudo R ² LR P-value Mean absolute bia		solute bias	s Absolute bias		
algorithm	indicators	BM	AM	BM	AM	BM	AM	reduction
NNM	Transaction cost	0.38	0.06	0.001	0.158	31.10	10.65	65.8
KBM	Transaction cost	0.35	0.05	0.001	0.167	29.84	7.11	76.2

 Table 6: PSM balancing properties of covariates before and after matching

NB: BM = before matching, AM = after matching, LR = likelihood ratio

Table 7: PSM estimates simulation-based sensitivity analy	ysis
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Outcome variable	Neu	itral confou	nder	Confounder calibrated to min access to credit		
Outcome variable	Estimate Outcon effect ^a effect ^b		Selection effect ^c	Estimator effect ^a	Outcome effect ^b	Selection effect ^c
Transaction costs (\mathbb{N})	1.02%	0.98	2.33	8.35%	1.61	2.10

^a The estimator effect indicates to what extent the baseline estimation result would change if we could observe an additional binary confounder.

^b The outcome effect measures the estimated effect of the simulated binary confounder on the outcome variable-transaction costs.

^c The selection effect measures the estimated effect of the simulated binary confounder on the selection into treatment-the propensity of participation in tomato contract farming.

The results of the mean treatment effects on the treated ATT appraised by both NNM and KBM matching methods are presented in Table 8. The results indicate that the transaction costs

(packaging, handling, transportation, communication costs etc.) incurred by the tomato contract farmers were significantly lower than that of the non-contract farmers with a mean difference of \approx 11429.62 and \approx 10130.67 for NNM and KBM matching methods respectively at 1% probability level. This implies that involvement in CF had an adverse effect on contract farmers by significantly decreasing the burden of transaction costs in the purchase of inputs for tomato production and also, disposal of the tomato output due to the contractual agreement. This result is in consonance with Tatlidil and Aktur (2004) who revealed that the transaction cost (proxied by transportation cost) of tomato contract farmers (\$25.90) was lower than the non-contract farmers (\$47.20) in the Bida district of Canakhale province, Turkey. Also, Birthal et al. (2008) reported that CF significantly reduced the transaction costs of dairy contract farmers. Noting that transaction costs were as high as 22 % of the total cost in the open market, and 9% under contract farming in India. Osebeyo and Aye (2014) described that policies in Nigeria that are intended at minimizing transaction costs will help in upholding tomato production, decreasing poverty among rural households there by sustaining agricultural growth. The transaction costs, reducing effect of tomato contract farming in the study area compare favourably with the findings of Setboonsaring et al. (2006) who reported that their results offer credibility to the debate that CF can be an operational institutional mechanism to ease transaction costs faced by small-scale rice farmers in Thailand. Other studies (Swinnen and Maertens, 2007; Oya, 2012) have equally indicated that contract farming is a veritable tool that can be explored for reducing transaction costs in food value chains.

Matching	Outcome indicator		ome indicator	ATT	
algorithm		CF	NCF		
NNM	Transaction costs(N)	22750.50	34180.12	11429.62***(12.38)	
KBM	Transaction costs(N)	22880.10	33010.77	10130.67***(5.22)	
ND * D . 0.1	** D .005 *** D .001				

NB: * P < 0.1, ** P < 0.05, *** P < 0.01

CF = contract farmers, NCF = non-contract farmers

3.6. Productivity, income and welfare gain of participation in contract farming

The results presented in Tables 9 and 10 were used to evaluate the balancing property and conditional independence assumptions respectively. The balancing property was satisfied based on the low pseudo- R^2 , insignificant p-values of the likelihood ratio test in comparison with the values before and after matching, high total bias decrease and lower mean standardized bias detected after matching in contrast with the values before matching. This implies that differences between the groups (contract farmers and non-contract farmers) in observed factors that could explain both selection into tomato contract farming as well as biased estimates for the outcome variables (productivity, tomato income, total household income and poverty) are properly controlled before the treatment effect valuation. To ensure there is substantial overlap in the distribution of the propensity scores for contract farmers and non-contract farmers, the common support condition was correspondingly enforced in the valuation process. As proposed by Heckman et al. (1997), individual annotations in the common support region were used in the analysis (region where the propensity score of the control units is greater than the minimum propensity score of the treated units and the propensity score of the treated units is less than the maximum propensity score of the control units).

Matching	Outcome	Pseudo R ²		LR P-value		Mean absolute bias		Absolute bias	
algorithm	indicators	BM	AM	BM	AM	BM	AM	reduction	
	Productivity (Kg/ha)	0.462	0.032	0	0.301	21.54	2.33	81.6	
NNM	Tomato income (N)	0.311	0.045	0.001	0.271	28.11	7.43	73.6	
	Total household income (N)	0.305	0.024	0.007	0.52	32.61	8.4	74.2	
	Poverty	0.49	0.011	0.004	0.281	25.33	5.64	77.7	
	Productivity (Kg/ha)	0.295	0.026	0.003	0.33	23.17	7.45	67.8	
KBM	Tomato income (ℕ)	0.431	0.012	0.001	0.461	29.01	9.14	68.5	
	Total household income (N)	0.413	0.035	0.004	0.459	33.5	12.1	63.9	
	Poverty (Headcount)	0.351	0.029	0.001	0.356	27.12	8.27	69.5	

Table 9: PSM balancing properties of covariates before and after matching

NB: BM = before matching, AM = after matching, LR = likelihood ratio

Table 10 presents the simulated-based sensitivity analysis result that reports robustness of matching estimators to failure of CIA. This indicates that the propensity score matching technique yields robust estimates of the ATT and therefore, the baseline ATT is robust to possible deviations from the CIA.

The matching results from both NNM and KBM matching techniques in Table 11 revealed that the contract farmers had significantly higher mean yield of 3.8 ton/ha and 3.7 ton/ha at 5% probability level suggesting that contract farming had a positive impact on the productivity of the farmers. This implies that participation in contract farming resulted in yield enhancing effect on tomato production and this stems from increased access to timely inputs, improved production technologies, credit, technical support and advisory services that contract farming guarantees the contract farmers.

Outcome variables	Neutral confounder			Confounder calibrated to mimic access to credit		
	Estimate effect ^a	Outcome effect ^b	Selection effect ^c	Estimator effect ^a	Outcome effect ^b	Selection effect ^c
Productivity (Kg/ha)	1.45%	1.34	1.68	4.51%	0.34	2.65
Tomato income (N)	-0.33%	1.02	1.21	11.63%	1.05	1.98
Total household income (N)	0.65%	1.59	1.33	2.11%	0.22	2.51
Poverty (Headcount)	2.81%	1.88	1.57	-3.78%	0.95	2.70

 Table 10: PSM estimates simulation-based sensitivity analysis

^a The estimator effect indicates to what extent the baseline estimation result would change if we could observe an additional binary confounder.

^b The outcome effect measures the estimated effect of the simulated binary confounder on the outcome variables-productivity, tomato income, total household income and poverty.

^c The selection effect measures the estimated effect of the simulated binary confounder on the selection into treatment-the propensity of participation in tomato contract farming.

The PSM results using NNM revealed that the ATT in tomato income and total household income between the two groups was estimated at $\frac{1}{N}$ 39879 and $\frac{1}{N}$ 39993 respectively and was statistically

significant at 1% probability level. This indicates that participation in contract farming generated positive income effects on the contract farmers which enable them to improve their standard of living. This positive income effect is expected through increased productivity, higher producer prices and reduced price risk. Also, the ATT in tomato income and total household income between the two groups using KBM produced similar result. This finding agrees with Vande velde and Maertens (2014) who reported that participation in contract-farming significantly increases rice income by 181.8 Euros in Benin republic. Other studies that established positive income effects of contract farming include (Cahyadi and Waibel, 2015; Wainaina et al., 2014; Sambuo, 2012; Saigenji and Zeller, 2009; Waswa et al., 2012; Sokchea and Culas, 2015). The positive income effect of tomato contract farming disagrees with the findings of Abdulai and Al-hassan (2016) who reported that contract farmers earn less from soybean cultivation as compared to their non-contract counterparts in Eastern corridor of the Northern Region, Ghana noting that the major reason for this outcome is because contractors apply more market power over the farmers. The results of the estimated ATT by NNM as shown in Table 10 indicates that poverty (incidence of poverty) among the tomato contract farmers (34%) was significantly lower than that of the noncontract farmers (45%) with a mean difference of -0.11(-11%) which was statistically significant at 5% probability level. Related result was also acquired using KBM. This result implies that contract farming had a significant poverty reducing effect on the tomato farmers and therefore, offers opportunity for alleviating poverty among tomato-based farmers in the study area. A plausible explanation for the poverty reducing effect of contract farming arises from the multiple production and marketing benefits that accrue to the tomato contact farmers as a result of the contractual agreement which led to increased productivity, income generation and invariably, reduced poverty incidence. The result of the poverty decreasing effect of CF is in line with Adjognon and Naseem (2012) who opined that CF is a tool for poverty alleviation in Africa.

Matching	Outcome indicators	Mean of outcome indicators		ATT
algorithm		CF	NCF	
NNM	Productivity (Kg/ha)	12510	8760	3750** (4.37)
	Tomato income (N)	205550	165671	39879***(8.01)
	Total household income (N)	491560	451567	39993***(1.89)
	Poverty (headcount)	0.34	0.45	-0.11**(2.23)
KBM	Productivity (Kg/ha)	12895	9224	3671**(2.41)
	Tomato income (N)	211455	184220	27235**(2.01)
	Total household income (N)	473880	463100	10780 ^{NS}
	Poverty (headcount)	0.35	0.48	-0.13**(2.37)

Table 11: PSM estimates of the impact of contract farming on productivity, income and welfare

NB: * P < 0.1, ** P < 0.05, *** P < 0.01, NS= not significant CF = contract farmers. NCF = non-contract farmers

4. CONCLUSIONS

This study contributes to the scarce empirical evidence on contract farming in Northern Nigeria using a case study of tomato production. The main factors that swayed the farmers' decision to partake in CF and level of involvement were education, farm size and extension implying that these variables are key policy variables that could be leveraged to influence participation in contract farming in the study area. As expected, there was high level of participation in contract farming and this implies that contract farming arrangement is very appealing to the farmers presently betrothed in it. In other words, these variables can be very instrumental in conditioning farmers participation behavior with respect to contract farming provided they are properly integrated in policy framework geared towards encouraging farmers' participation in contract farming. Participation generated desirable causal effects on transaction costs, productivity, tomato

income, total household income and poverty status of the farmers implying that with continued participation in contract farming, farmers are assured of reduced transaction costs and increased welfare gains. Thus, this research has contributed in supporting empirical evidence on contract farming as a strategy for farmers to realize welfare gains from their production.

Recommendations

Based on the findings of the study, the following recommendations have been put forward:

- i. In the light of delayed payment for crop produce which was indicated as a key challenge by some of the contract farmers, there should be interest payment for delay in payment to farmers as part of contractual agreement to curb the issue of intentional delay of payment by the contracting firms.
- ii. Appropriate measures should be put in place to ensure that barriers to inclusion of resource poor farmers in contract farming can be readily addressed. This can be achieved through farmer groups which gives poor farmers the opportunity of pooling their limited resources as a group and linking up with contracting firms.
- iii. To avoid default in meeting the terms of contract by both farmers and contractors, appropriate policy framework should be put in place by government to support small scale farmers involved in contract farming and also protect the interest of contractors.
- iv. Increasing farmers' access to land is a viable option for promoting participation in contracting farming because farm size influenced both decision to partake.

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References

- Abdulai, Y., & Al-hassan, S. (2016). Effects of contract farming on small-holder soybean farmers' income in the eastern corridor of the northern region, Ghana. *Journal of Economics and Sustainable Development*, 7, 103-113.
- Adjognon, S., & Naseem, A. (2012). Contract farming as a tool for poverty reduction in Africa. *Research to Practice Policy Briefs*, 2, 206-211.
- Anim, F. D. K. (2011). Small-scale maize farmers' decision to participate in contract farming: Implications for integration into the marketing chain. *African Journal of Business Management*, 5, 5065-5069.
- Arumugam, N., Arshad, F. M., Chiew, E. F.C., & Mohamed, Z. (2011). Determinants of fresh fruits and vegetables (FFV) Farmers' participation in contract farming in peninsular Malaysia. *International Journal of Agricultural Management & Development (IJAMAD)*, 1, 65-71.
- Asfaw, S., Shiferaw, B., Simtowe, F., & Haile, M. G. (2011). Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *Journal of Development and Agricultural Economics*, 3, 436-447.
- Ayandiji, A, Adeniyi, O. R., & Omidiji, D. (2011). Determinant post-harvest losses among tomato farmers in Imeko-Afon local government area of Ogun state, Nigeria. *Global Journal of Science Frontier Research*, 11, 23-28.
- Azumah, S. B., Donkoh, S. A., & Ehiakpor, D. S. (2016). Examining the determinants and effects of contract farming on farm income in the northern region of Ghana. *Ghana Journal of Science, Technology and Development*, 4, 1-10.

- Barrett, C. B., Bachke, M. E., Bellemare, M. F., Michelson, H. C., Narayanan, S., & Walker, T. F. (2012). Smallholder participation in contract farming: Comparative evidence from five countries. *World Development*, 40, 715–730.
- Beard, V. A. (2005). Individual determinants of participation in community development in Indonesia. *Environment and Planning C: Government Policy*, 23, 21-39.
- Bellemare, M. F. (2012). As you sow, so shall you reap: The welfare impacts of contract farming. *World Development*, 4, 1418-1434.
- Birthal, P. S., Jha, A. K., Tiongco, M. M., & Narrod, C. (2008). Improving farm-to-market linkages through contract farming: A case study of smallholder dairying in India. IFPRI Discussion Paper 00814.
- Cahyadi, E. R., & Waibel, H. (2015). Contract farming and vulnerability to poverty among oil palm smallholders in Indonesia. *Journal of Development Studies*, 52, 1-15.
- Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica*, 39, 829-844.
- Eaton, C., & Shepherd, A. W. (2001). Contract farming: Partnership for growth. *Agricultural Bulletin*, Volume 145, available at <u>www.google.com/books</u>.
- Greene, W. H. (2007). Econometric analysis. 6th Edition. Macmillan, New York, USA.
- Guo, H. (2005). An analysis of the influencing factors of Chinese farmers' participation in contract farming. *Chinese Rural Economy*, 3, 24-32.
- Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. *Review of Economic Studies*, 64, 605-654.
- Ichino, A., Mealli, F., & Nannicini, T. (2008). From temporary help jobs to permanent employment: What can we learn from matching estimators and their sensitivity?. *Journal of Applied Econometrics*, 23, 305–327.
- Kiwanuka, R. N. L., & Machethe, C. (2016). Determinants of smallholder farmers' participation in Zambian dairy sector's interlocked contractual arrangements. *Journal of Sustainable Development*, 9, 230-245.
- Maliwichi, L. L., Pfumayaramba, T. K., & Katlego, T. (2014). An analysis of constraints that affect smallholder farmers in the production of tomatoes in Ga-Mphahlele, Lepelle Nkumbi municipality, Limpopo province, South Africa. *Journal of Human Ecology*, 47, 269-274.
- Miyata, S., Minot, N., & Hu, D. (2009). Impact of contract farming on income: Linking small farmers, packers, and supermarkets in China. *World Development*, 37(11), 1781-1790.
- Moffat, P. G. (2005). Hurdle models of loan default. *Journal of the Operational Research Society*, 56, 1063-1071.
- Mwambi, M. M., Oduol, J., Mshenga, P., & Saidi, M. (2016). Does contract farming improve smallholder income? The case of avocado farmers in Kenya. *Journal of Agribusiness in Developing and Emerging Economies*, 6(1), 2-20.
- Osebeyo, S. O., & Aye, G. C. (2014). Transaction costs and marketing decision: A case study of smallholder tomato farmers in Makurdi, Nigeria. Urban, Planning and Transport Research, 2, 333-340.
- Oya, C. (2012). Contract farming in Sub-Saharan Africa: A survey of approaches, debates and issues. *Journal of Agrarian Change*, 12, 1–33.
- Saigenji, Y., & Zeller, M. (2009). Effect of contract farming on productivity and income of small holders: The case of tea production in north-western Vietnam. Contributed Paper presented for presentation at the International Association of Agricultural Economists Conference, Beijing, China, August 16-22.
- Sambuo, D. (2012). Tobacco contract farming participation and income in Urambo: Heckma's selection model. *Journal of Economics and Sustainable Development*, 5, 230-237.
- Setboonsarng, S., Leung, P., & Cai, J. (2006). Contract farming and poverty reduction: The case of organic rice contract farming in Thailand. Asian Development Bank (ADB) Institute, Discussion Paper No. 49.

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- Sidibé, M. (2005). Farm-level adoption of soil and water conservation techniques in northern Burkina Faso. Agricultural and Water Management, 71, 211-224.
- Singh, S. (2002). Contracting out solutions: Political economy of contract farming in the Indian Punjab. *World Development*, 30, 1621–1638.
- Sokchea, A., & Culas, R. J. (2015). Impact of contract farming with farmer organizations on farmers' income: A case study of reasmey stung sen agricultural development cooperative in Cambodia. *Australasian Agribusiness Review*, 23, 1-11.
- Swinnen, J., & Maertens, M. (2007). Globalization, privatization, and vertical coordination in food value chains in developing and transition countries. *Agricultural Economics*, 37, 89–102.
- Tatlidil, F. F., & Aktur, D. (2004). Comparative analysis of contract and non-contract farming model in tomato production. *Journal of Agronomy*, 3, 305-310.
- Tongchure, S., & Hoang, N. (2013). Cassava smallholders' participation in contract farming in nakhon ratchasrima province, Thailand. *Journal of Social and Development Sciences*, 4(7), 332-338.
- Usman, J., & Bakari, U. M. (2013). Profitability of small scale dry season tomato (lycopersicon esculentum mill.) production in adamawa state, Nigeria. *ARPN Journal of Science and Technology*, 3, 604-310.
- Vande Velde, K., & Maertens, M. (2014). Contract-farming in staple food chains: The case of rice in Benin (No. 189419).
- Wainaina, P. W., Okello, J. J., & Nzuma, J. M. (2014). Blessing or evil? contract farming, smallholder poultry production and household welfare in Kenya. *Quarterly Journal of International Agriculture*, 53, 319-340.
- Warning, M., & Key, N. (2002). The social performance and distributional consequences of contract farming: An equilibrium analysis of the Arachide de Bouche program in Senegal. World Development, 30(2), 255-263.
- Waswa, F., Gweyi-Onyango, J. P., & Mcharo, M. (2012). Contract sugarcane farming and farmers' incomes in the Lake Victoria basin, Kenya. *Journal of Applied Biosciences*, 52, 3685-3695.
- Wooldridge, J. M. (2005). Violating ignorability of treatment by controlling for too many factors. *Econometric Theory*, 21, 1026-1028.