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POST-HARVEST TECHNOLOGY CHANGE IN CASSAVA PROCESSING: A CHOICE PARADIGM

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Abstract

This study employed a choice model to examine the factors influencing the choice of post-harvest technologies in cassava starch processing, using a sample of five hundred and seventy (570) processors in the forest and guinea savanna zones of Nigeria. In addition, the profitability of various post-harvest technologies in the study area was assessed using the budgetary technique while the impact of improved post-harvest technology on processors' revenue and output was analysed using the average treatment effect model. Sex of the processor, processing experience, income, and cost of post-harvest technology, the capacity of post-harvest technology and access to credit amongst others significantly influence the choice of post-harvest technologies. Although the use of improved post-harvest technology comes with a high cost, the net income from its use was higher than the other types of post-harvest technologies, suggesting that the use of improved techniques was more beneficial and profitable. In addition, using improved post-harvest technology had a positive and significant effect on output and income. These findings shows that investment in improved post-harvest technologies by cassava starch processors and other stakeholders would increase income, thus, improving welfare.

Keywords

Cassava starch;Post-harvest technologies; Profitability; Treatment effect model

1.0 Introduction

The potentials inherent in cassava processing is enormous. Cassava, as a crop, if adequately harnessed, has the prospect of industrializing Nigeria. Nweke *et al*. (2012) indicated that Nigeria is the most advanced of the African countries poised to expand production and utilization of cassava products. With an annual output of over 40 million metric tonnes, Nigeria is widely recognized as the largest producer of cassava in the world, accounting for over 70% of the total production in West Africa (Oguntade, 2013). Cassava is available all year round, and this makes it preferable to small-scale farmers and processors alike compared to other seasonal crops such as grains, peas, and beans which are only available at certain times of the year. Cassava products such as starch, ethanol, etc have both local and international demands, thus making cassava a highly valuable crop.

A major cassava product on the world trade market and used, as an industrial raw material is starch. The immense use and applications of starch, especially cassava starch in various industries has made necessary adequate investment in the starch processing business. Cassava starch has many remarkable characteristics, including high paste viscosity, high paste clarity and high freeze-thaw stability, which are advantageous to many industries (Adetunji *et al*. 2015). Also, cassava is mostly made up of starch (70-85%, dry base and 28-35%, wet base) and thus gives high and better quality of starch compared to other starch sources such as maize, rice and wheat (Ogundari *et al.* 2012). While production and processing of cassava into starch is very lucrative and attractive, post-harvest losses in the production and processing of cassava into starch are enormous. As stated by Oguntade (2013), there are two sources of loss during the processing of cassava into starch: spillage during processing and spoilage during storage, with the quantity of starch that is lost due to spillage and spoilage estimated at 106,212 mt, with a value of ₦ 13.8 billion (₦ 130,000 per mt). The magnitude of these losses depends mostly on cassava production and processing techniques. For example, the traditional technology mostly used by small-scale cassava starch processors, is characterized by high post-harvest loss, low productivity, and high labour intensity. In addition, quality of specific cassava products could be compromised through traditional processing methods, based on the simple ways they were transformed.

As a result of the various constraints of using conventional processing technology, efforts have been made in the mechanization of some of the laborious and time-consuming cassava processing operations. Mechanizing processing operations becomes necessary to improve on the potentials and prospect of cassava especially as it relates to post-harvest losses. A technology change from traditional technology to improved technology would lead to increase income, expansion of processing enterprises, increased output and improved productivity. Technological change which is mostly arrived at through research is influenced by the level of awareness, knowledge, preferences, and expectations.

However, the choice of any of these technologies depends on individual factors such as preferences, perceptions, beliefs, and experience. Several studies on adoption of agricultural technologies have employed choice models in understanding the decisions of individuals as it reflects on their choice of technology. Most commonly used are the binary choice models (Saka and Lawal 2009; Adejumo *et al*. 2014; Abdoulaye *et al*. 2014; Boniphace *et al*. 2015). These models are however limited in that they do not allow for choices amongst more alternatives.

The extension of the binary choice model is the multinomial logit model and the multinomial probit model. When selection is over a large number of exclusive choices, the multinomial logit specification is appealing in applied work, due to its simplicity, at the cost of parametric and (testable) independence assumptions (Bourguignon *et al*. 2007). In developing countries, studies such as Bayard *et al*. (2006), and Ojo *et al*. (2013), have used the multinomial logit model to express the probability of an individual being in a particular category. However, these studies focus only on the socio-economic indicators influencing the choice of technologies without taking cognizance of the characteristics of the technology itself. Thus, the present study differs from these past studies in that it included both socio-economic and technology-specific characteristics in examining the choice of post-harvest technologies.

1.1. The Concept of Technological Change

As opined by Jaffe *et al*. (2003), the mensuration of the rate of technological change rests basically on the notion of transformation function given as T (Y, I, t) ≤0, where Y and I stand for a vector of outputs and inputs, respectively, with t representing time.

The equation above sketches a group of combinations of inputs and outputs that are possible at a point in time. The movement of this frontier that makes it feasible over time to use supplied input vectors to give output vectors that were not previously feasible designates technological change. As stated by Beaudry *et al.* (2006), the configuration of the technological change model comes from the reflection that an individual often encounters several choices in the mix of techniques used to produce a good such as cassava starch and the selection of techniques is influenced by the factor prices facing the individual.

The technological improvement as a result of a technical change is depicted in Figure 1 (see supplementary material). Production function I represent the new technology while production function II represents the old technology. With the same level of input OX, the output is increased from OG to OH as a result of shift in production function which is due to the adoption of the new technology. Conversely, the same output level G can be produced with a lower level of input OP, due to the introduction of new technology.

If a setting where individuals such as cassava processors have access to a set of technologies to produce a final good (cassava starch) denoted by Y_t is considered, the production of Y_t requires inputs X_{t}, where these inputs can be organized in different ways to produce output and each of these alternative organizations correspond to a different technology (improved or traditional technology). If the different technologies are represented by $\theta \in \tau$, then the production function is assumed to satisfy constant returns to scale and concavity. A price-taking individual will aim to maximize profits by solving the following problem

$$\max_{X_t, \theta_t} F(X_t, \theta_t) - w_t X_t \quad (2)$$

Where w_t is the vector of factor prices. In this setting, definition of a competitive equilibrium can be extended to include the choice of technologies.

2.0 Materials and methods

2.1 Data sources

The present study used humid forest and the guinea Savannah Agro-ecological zones of Nigeria. These zones span across the southern and north central parts of Nigeria where a high cassava production output has been reported and hence, a high level of cassava processing. Following Salganik and Heckathorn (2004), the snowballing (chain referral) methodology was employed in choosing a total of five hundred and seventy (570) cassava starch processors. These processors were interviewed using a structured questionnaire. Post-harvest technologies (PHT) in the study area were classified into Traditional, Trad-improved, and Improved (PHT) based on characteristics such as rate of turnover, capacity level, and output level.

2.2 Empirical model of Post-harvest technology choice.

The examination of a processor's choice behaviour is a function of his/her characteristics, attributes of the available alternatives and a decision criterion (Kroh and Eijk, 2003). The interpretation of a decision among a given set of options is often in two ways. Firstly, individuals consider the utility derivable from an alternative and then make a choice based on the observed utility maximization. The concept of utility, therefore "assumes commensurability of attributes. This implies that the attraction of an alternative mostly depends on its qualities. (Ben-Akiva *et al.* 1985 as cited by Kroh and Eijk., 2003).

Utility theory thus gives an in-depth understanding of individuals' choice through utility maximization behaviour (Parkin, 1997), as individuals would choose an alternative that gives the highest utility. Excerpting from Acheampong *et al.* (2013), in a random utility framework, an individual, v_i in this case, a cassava processor receives utility U from choosing an alternative equal to $U_{njt} = U(X_{njt})$ from a finite set of j alternatives in a choice set, t. This occurs if and only if, this alternative gives at least as much utility as any other alternative, with X_{njt} denoting a vector of the attributes of j. The following equation expressing an individual's utility formalizes the basic relationship where (v_{njt}) is the observable component and (ε_{njt}) represents the error component of utility. That is,

$$u_{njt} = v_{njt} + \varepsilon_{njt} \qquad (1)$$

Decomposing the above equation further gives:

$$U_{njt} = V(z_{njt}, s_n) + \varepsilon_{njt} \qquad (2)$$

Equation (4) indicates that utility is a function of the attributes of the relevant good (z_{njt}) and the characteristics of the individual (s_n), together with the error term (Rolfe *et al*. 2000). However, as difficulty may arise in understanding and predicting preferences of individuals, the choice made between alternatives can be expressed in the form of probability such that a processor n chooses the alternative j over other alternatives within a choice set, such that:

$$P_{njt} = p_{rob}[(V_{njt} + \varepsilon_{njt}) > (V_{njh} + \varepsilon_{njh})] \ \forall_{j} \neq h \qquad (3)$$

The probability of choosing this alternative is estimated by the following multinomial logit framework:

$$\Pr(y_i = 1 \mid X_i) = \frac{1}{1 + \sum_{h=2}^{j} \exp(X_i' \beta_h)} \qquad (4)$$

$$\Pr(y_i = j) = \frac{\exp(X_i' \beta_j + \sigma_j \mu_i)}{1 + \sum_{h=2}^{j} \exp(X_i' \beta_h + \sigma_h \mu_i)}, \ j = 2, \ldots, J \qquad (5)$$

Where: $\Pr(y_i = j)$ is the probability of choosing either trad-improved or improved post-harvest technologies with traditional technology as the reference group. J is the number of alternatives, i.e., post-harvest technology in the choice set; $j = 0$ is the reference group; X_i is a vector of the predictor (exogenous) social factors (variables), and β_i is a vector of the estimated parameters

In this model, the utility derived from choosing alternative j (with j=1,…, J (J=3) is stated as:

$$V_{ij} = X_i^1 \beta_j + \varepsilon_{ij,} \qquad (6)$$

Where $X_i$the vector of processors' characteristics that influence choice decisions, ε_{ij} are random errors assumed to be independent and identically distributed across the *J* alternatives.

The choice of the multinomial logit model was based on its ability to perform better with discrete choice studies as it examines choice between a set of mutually exclusive alternatives (McFadden, 1974 and Judge *et al.* 1985). Adapting from Nguyen-Van *et al.* (2016), the estimation of the multinomial logit model is obtained by maximizing the log-likelihood function given below:

$$\ln L = \prod_i^n \prod_j^J 1(y_i = j) \ln Pr(y_i = j | X_i), \qquad (7)$$

Where $1(y_i = j)$ is the indicator of the processor's choice (i.e., it takes one if $y_i = j$, 0 otherwise)

As the parameter estimates of the MNL model provide only the direction of the effect of the independent variables on the dependent variable, the marginal effects from the MNL, which measure the expected change in probability of a particular category with respect to a unit change in an independent variable was calculated (Greene, 2000; Wooldridge, 2002). This is stated as:

$$\frac{\partial P_j}{\partial P_j} = P_j\left[B_{jk} - \sum_{j-1} P_j B_{jk}\right] \qquad (8)$$

2.3 Empirical model of the impact of improved post-harvest technology

The estimation of causal effects is a comparison between likely outcomes, in which a cassava processor has two potential outcomes taking the value of 0 or 1. If the binary outcome variable represented by 'd' stands for improved post-harvest technology adoption status, with d=1 representing adoption and d=0 represents non-adoption, then the observed outcome of y of cassava processors as a function of two potential outcomes can be written as $y = d_{yi} + (1-d)y_o$. For any household i, the causal effect of using improved post-harvest technology on output and income is defined by $y_i - y_o$. The average causal effect of adoption within a specific population (the average treatment effect) can be determined as $E(y_i - y_o)$, where y_i denotes an outcome in which improved technology is adopted, y_o denotes an outcome when not adopting, and E is the mathematical expectation.

In this study, the estimation of average treatment effect used the propensity score matching method. The propensity score was defined as the conditional probability of receiving a treatment assignment (such as the use of improved post-harvest technology) with given covariates X (Rosenbaum and Rubin (1983) such that:

$$e(X) = P[Z = 1|X] \qquad (9)$$

The estimation of the propensity score matching method usually follows two steps. In the first step, the propensity score is estimated using probability models such as logit, probit or multi-nominal logit can be used (Dehejia and Wahba, 2002). However, the appropriateness of the choice of model depends on the nature of the program being evaluated. Also, models with flexible functional forms in the independent variables tend to work well (Okoruwa *et al*. 2015). In this study, using the logit model, we examined the factors that influence the probability of using improved post-harvest technologies while the matching algorithms used both the logit and probit probability models. The logit model for propensity score estimation is expressed as:

$$PS(X_i) = P(D_i = 1|X_i) = \frac{\exp(X_i'\ \beta)}{1+\exp(X_i'\ \beta)} \qquad (10)$$

Following from the estimation of the propensity score, the average treatment effect on the treated was specified as:

$$\tau_{ATT} = E(\tau|D = 1) = E[Y(1)D = 1] - E[Y(0)|D = 1] \quad (11)$$

By rearranging and subtracting $E[Y(0)|D = 0]$ from both sides, the specification of the ATT becomes:

$$E[Y(1)|D = 1] - E[Y(0)|D = 0] = \tau_{ATT} + E[Y(0)|D = 1] - E[Y(0)|D = 0] \quad (12)$$

The terms in the left hand side are observables and ATT can be identified if and only if $E[Y(0)|D = 1] - E[Y(0)|D = 0]$=0. That is, when there is no self-selection bias.

The dependent variable for this study is the use of improved post-harvest technology which takes the value of 1 if the cassava starch processor uses improved post-harvest technology and zero otherwise. The covariates include: age, the square of age, gender, the total number of years spent in school, household size, number of income earners in the household, processors' experience, total cost of acquisition of technology, access to credit, and the total quantity of cassava roots purchased. The apriori expectations of these variables are presented in Table 1.

Variable	**Measurement of the variables**	**Expected sign**
Age	In years (continuous)	+
Age2	In years (continuous)	-
Gender	Dummy (0=male, 1=female)	+
Years spent in schooling	In years (continuous)	+
Household size	In numbers (continuous)	-
Number of income earners	In numbers (continuous)	+
Years of processing experience	In years (continuous)	+
Cost of acquiring technology	In naira (continuous)	-
Access to credit	Dummy (yes=1, no=0)	+
Capacity of technology	In kilogram per hour (continuous)	+

Table 1. Variable measure and a-priori expectations of covariates

3.0 Results and discussion

3.1 Characteristics of cassava starch processors

The summary of socioeconomic characteristics of starch processors is given in Table 2. Female entrepreneur and a small fraction of men (about 31%) mostly dominate the cassava smallholder starch processing industry in Nigeria. The mean age of 48 years indicates the youthful nature of the cassava starch processors which is an added benefit regarding the longevity of the trade and the inclination to innovation adoption. The average total number of years of education was seven years with 17 years of processing experience. The household size for all categories of technology users was six, indicating a high level of labour accessibility. More than half of processors using trad-improved technology had access to credit with the majority belonging to a social group. The capacity of processing machinery for improved post-harvest technology is about three times greater than traditional post-harvest technology.

	Traditional (n=157)	Trad-improved (n=346)	Improved (n=67)	Pooled	F-statistics
Sex (%)					
Male	21.7	35.3	29.8	30.9	
Female	78.3	64.7	70.2	69.1	
Age (mean)	48	48	48	48	0.06
Years of processing experience (mean)	18	16	19	17	3.99**
Years of education (mean)	7	7	8	7	0.94
Household size (mean)	6	6	6	6	4.67***
Number of income earners (mean)	2	2	2	2	4.98***
Access to credit (%)					
No	70.1	44.8	41.8	51.4	
Yes	29.9	55.2	58.2	48.6	
Belong to a social group (%)	29.9	57.4	12.7	65.1	
Capacity of machines in kg (mean)	2603.3	3281.4	6162.9	3433.3	12.30***

Table 2. Distribution of Socio-Economic Characteristics of Cassava Starch Processors. *Statistical significance levels: *** 1%; **5%*

The budgetary technique was used to obtain information on profitability among the different post-harvest technologies. In estimation of the depreciation cost on fixed assets, we employed the straight-line method. For simple assets such as cutlasses, knives, bowls etc. a useful life of two years and salvage value of zero Naira (N0.00) was assumed, however, in line with existing literature (Oluka, 2000), the useful life of 10 years and a salvage value of 5% was assumed for more massive and large processing assets. As presented in Table 3, the total variable cost took the most significant share of the total value ranging from 79.6% to 87.0% across the various post-harvest technologies. The total revenue, total cost, gross margin and net profit significantly differ amongst the three categories of post-harvest technologies. In addition, the benefit-cost ratio (BCR) indicate that the use of improved post-harvest technologies is more economically attractive than the other groups.

Items	**Traditional PHT**		**Trad-improved PHT**		**Improved PHT**		**F-statistics**
Quantity of cassava starch	519		1018.9		2723.9		
Price of cassava starch/kg	300		300		300		
Total revenue	155700		305670		817170		56.22***
Variable cost		%VC		%VC		%VC	
Cost of cassava roots	26740.29	49.3	19308.54	37.84	23824.35	23.73	
Cost of loading and off-loading	10934. 6	20.1	4357. 6	8.54	5998.53	5.98	
Cost of transportation	4087.90	7.54	2597.38	5.09	4477.94	4.46	
Cost of Water	2560.03	4.72	814.87	1.60	2536.77	2.53	
Cost of labour	3349.80	6.18	3569.35	6.99	9133.07	9.10	
Cost of energy (fuel/electricity)	520.29	0.96	1581.49	3.10	3487.11	3.47	
Maintenance	6035.90	11.13	18801. 00	36.84	50923.71	50.73	
Total variable cost (TVC) (B)	54228.88		51030.23		100381.48		
Depreciation cost on fixed assets	8100.58		11992.7		25319.66		
Total cost (B+ C)	62329.46		63022.93		125701.14		137.23***
% of TVC to total cost	87.0		81.0		79.6		
% of TFC to total cost	13.0		19.0		20.1		
Gross Margin (A-B)	101471.12		254369.77		716788.4		97.32***
Net profit	93370.54		242377.07		691468.86		129.63***
BCR	1.50		3.85		5.50		

Table 3. Comparative Costs and Returns Structure (Naira) profitability analysis of PHT

**** Statistical significance at 1% level; VC= variable cost*

3.2 Determinants of choice of post-harvest technologies.

The factors influencing the choice of post-harvest technologies used by the processors were identified using the MNL model. The effect of coefficients was estimated with respect to the traditional post-harvest technology category, as the reference group (Table 4). The explanatory variables possessed a Chi-squared value of 264.76. This connoted that the approximated model was very significant at 1% level with a log likelihood of -386.2. This indicated a well-fitted model. As it is more convenient to interpret the marginal effects on individual expectations (Nguyen-Van *et al*. 2016), the marginal effects from the MNL model, which shows the actual magnitude of the change of probabilities among variables were presented.

Sex of the cassava starch processor which is a dummy variable had a significant but negative effect on the choice of trad-improved post-harvest technology relative to the reference group. Although the response of processors to this change is inelastic, the marginal effect implies that an increase in the number of female cassava starch processors would increase the probability of choosing the reference group by 10.5%. Generally, processing of cassava is usually done by women using traditional technology, and this fact may predispose them to accept conventional post-harvest technologies over other categories. Also, Jera and Ajayi (2008) and Kassie *et al*. (2012) noted that women may not adopt new technologies like their male counterparts as a result of differences in their earnings as well as cultural factors. Also, a unit increase in the household size of processors would lead to 2.0% increase in the choice of trad-improved post-harvest technology relative to traditional post-harvest technology (which is more labour intensive), respectively. The response of processors to such increase is however inelastic.

In the case of the choice of improved post-harvest technology, a year increase in the processing experience of cassava starch processors and a unit increase in income from processing activities would cause 0.3% and 0.0001% increase in the probability of choosing improved post-harvest technology relative to the reference group. While processors response was elastic to increase in processing experience, it was inelastic to a change in income from processing activities. Moreover, a kilogram per hour increase in the capacity of post-harvest technologies would lead to 3.2% increase in the probability of using improved post-harvest technology. Increase in the capacity of technology, observed as the volume of cassava roots a technology can take, would lead to more output (quantity of cassava starch produced). The importance of this change was further buttressed by the elastic response of processors to such increase.

Variable	**Coefficient**	**Std. error**	**P-value**	**Marginal effect**	**Elasticity**
Trad-improved PHT					

Age	-0.781	0.01	0.43	-0.013	-0.855
Age^2	0.458	0.602	0.45	0.078	1.654
Sex	-0.479	0.265	0.07*	-0.105	-0.108
Processing experience	-0.015	0.014	0.30	-0.005	-0.125
Years of education	0.008	0.027	0.78	-0.002	-0.002
Household size	0.093	0.054	0.08*	0.020	0.173
Cost of PHT	-1.062	0.133	0.00***	-0.124	-2.109
Capacity of PHT	0.38	0.238	0.11	0.043	0.492
Income from processing	0.344e-5	0.282e-5	0.22	0.153e-6	0.016
Access to credit	0.951	0.238	0.00**	0.167	0.115
Constant	7.091	4.723	0.133		
Improved PHT					
Age	-0.092	0.142	0.52	-0.002	-1.527
Age^2P	0.416	0.847	0.62	0.004	1.054
Sex	0.295	0.439	0.50	0.031	0.426
Processing experience	0.056	0.022	0.01**	0.003	1.078
Years of education	0.045	0.04	0.27	0.002	0.262
Household size	-0.018	0.082	0.82	-0.005	-0.510
Cost of PHT	-2.446	0.424	0.00***	-0.086	-18.862
Capacity of PHT	0.899	0.315	0.00***	0.032	4.673
Income from processing	0.142e-4	0.312e-5	0.00***	0.611e-6	0.701
Access to credit	0.724	0.371	0.05**	0.001	0.006
Constant	16.479	7.768	0.03		
Number of observations	570				
Log likelihood	-386.2				
LR $chi^2(20)$	264.76				
Pseudo R^2	0.255***				

Table 4. Parameter Estimates of Choice of Post-Harvest Technologies.

*Statistical significance levels: ***1%; **5%; *10%*

Furthermore, the marginal impacts of the cost of acquiring technology which significantly affects both the choice of trad-improved and improved post-harvest technology suggest that a 1% increase in the cost of acquiring technology will decrease processors probability of choosing these two categories relative to the reference group. The responses of processors to this changes were observed to be highly elastic when evaluated at the mean values of the independent variable. Similarly, a unit increase in access to credit of cassava starch processors increases the probability of choosing trad-improved post-harvest technology by 16.7% and improved post-harvest technology by 1.0%. However, the partial elasticity of response of processors to these change was inelastic across the categories.

3.3 Impact of Improved Post-Harvest Technology use

The logit regression estimations of the propensity score adoption equation are shown in Table 5. By employing the binary logit regression model, the essential variables explaining the decision to use improved post-harvest technology were identified. The pseudo R^2 value of 0.16 correctly predicts 65.67% of users of improved post-harvest technology and 77.53% non-users. Correct predictions were greater for non-users than users. The likelihood ratio test of the hypothesis that the coefficients of all the explanatory variables are zero has a Chi-square value of 63.97 with 11 degrees of freedom, suggesting that the estimated model is significant.

Variables	**Coefficient**	**P-value**	**Marginal effect**
Age	-0.070 (0.10)	0.50	0.004
Age2	0.513 (0.61)	0.40	-0.030
Gender (male=0, female=1)	0.244 (0.31)	0.43	0.014
Years of education	0.042 (0.03)	0.17	0.002
Household size	0.090 (0.07)	0.18	0.005
Number of income earners	-0.508 (0.18)	0.00***	-0.029
Years of processing experience	0.051 (0.02)	0.00***	0.003
Cost of acquiring technology	-1.524 (0.36)	0.00***	-0.088
Access to credit (1=yes, 0=no)	0.190 (0.31)	0.54	0.011
Membership in social group	0.208 (0.34)	0.54	0.012
Capacity of technology (kg/hr)	0.639 (0.22)	0.00***	0.037
Chi2(10)	63.97***		
Log likelihood	-174.36		
Pseudo R2	0.16		
Non-users correctly predicted	65.67		
Users correctly predicted	77.53		

Table 5. Parameter estimates of propensity to use improved post-harvest technology.*** *Significance at 1% level; standard error in parentheses*

The result shows that the years of processing experience and capacity of technology covariates, both had a positive and significant influence on the decision to use improved technology at 1% level while the number of income earners and cost of acquiring technology exert negative but significant influence, also at 1% level.

After estimating the propensity scores, the quality of the matching process was assessed by checking if the common support condition was satisfied. Figure 2 (see supplementary material) shows substantial overlap in the distribution of the propensity scores for the two groups as neither plot indicates too much probability mass near 0 or 1.

Since balancing the distribution of relevant variables between non-users and users of improved post-harvest technology is the main reason for propensity score estimation (Menale *et al*. 2011; Okoruwa *et al.*2015), covariate balancing test was done and presented in Table 6.

Matching algorithm	**Model type**	**Pseudo R^2 before matching**	**Pseudo R^2 after matching**	**LR X^2(p-value) before matching**	**LR X^2(p-value) after matching**	**Mean standardized bias before matching**	**Mean standardized bias after matching**
NNM[a]	Logit	0.074	0.004	30.50(p=0.00)	0.64(p=1.00)	12.5	3.9
	Probit	0.074	0.004	30.50(p=0.00)	0.68(p=1.00)	12.5	4.1
NNM[b]	Logit	0.074	0.008	30.50(p=0.00)	1.41(p=0.99)	12.5	5.4
	Probit	0.074	0.003	30.50(p=0.00)	0.56(p=1.00)	12.5	4.8
KBM[c]	Logit	0.074	0.009	30.50(p=0.00)	1.54(p=0.99)	12.5	3.7
	Probit	0.074	0.009	30.50(p=0.00)	1.58(p=0.99)	12.5	3.9
KBM[d]	Logit	0.074	0.002	30.50(p=0.00)	0.33(p=1.00)	12.5	2.5
	Probit	0.074	0.002	30.50(p=0.00)	0.41(p=1.00)	12.5	2.5
KBM[e]	Logit	0.074	0.004	30.50(p=0.00)	0.69(p=1.00)	12.5	2.9
	Probit	0.074	0.002	30.50(p=0.00)	0.32(p=1.00)	12.5	1.6
RM[f]	Logit	0.074	0.003	30.50(p=0.00)	0.62(p=1.00)	12.5	2.8
	Probit	0.074	0.003	30.50(p=0.00)	0.54(p=1.00)	12.5	2.3

Table 6. Matching quality indicator before and after matching.

[a]*NNM = five nearest neighbor matching with replacement and common support*
[b]*NNM = five nearest neighbor matching with replacement, caliper 0.02 and common support.*
[c]*KBM = kernel based matching with bandwidth 0.1 and common support.*
[d]*KBM = kernel based matching with bandwidth 0.06 and common support.*
[e]*KBM = kernel based matching with bandwidth 0.03 and common support.*
[f]*RM = radius matching with caliper 0.02 and common support.*

The test revealed the mean standardized bias before matching which was about 12.5% reduces to 1.6 -5.4% after matching. The likelihood tests prior to matching were all significant at 1% level, showing that the joint significance of the covariates was accepted. Further, the pseudo-R^2 after matching was fairly low with none of the p-values being significantly different from zero. This suggests that the propensity score is successful in terms of equilibrating the distribution of covariates between the two groups (Sianesi, 2004).

The report of the impact of the use of improved post-harvest technology on outcome variables, i.e., total output (measured in kilogram) and income (measured in naira) of cassava starch processors, are reported in Table 7. Estimators used were based on five nearest neighbours with replacement, the Epanechnikov kernel estimator with a bandwidth of 0.06 and the radius matching estimator with a caliper of 0.02. Although the matching algorithms were based on two probability models (probit and logit), the result from the probit model was chosen for lead discussion as all the matching algorithms were more significant. As seen from Table 7, the use of improve post-harvest technology had a positive and significant impact on the total output and income of cassava starch processors. That is, the production of cassava starch processors when they use improved technology increases by approximately 463kg while net income of cassava starch processors increases within a range of ₦138, 454.5 ($453.21) and ₦138, 738.5($454.14) per month. This finding is in agreement with past studies such as Okoruwa *et al*. (2015); and Afolami *et al.* (2015); amongst others that showed that adoption of improved agricultural technologies had positive impacts on welfare.

Matching algorithm	**Outcome**	**ATT**		**Critical level of hidden bias**	
		Logit	Probit	Logit	Probit
NNM[a]	Total output	462.5(1.28) *	462.5 (2.99) ***	1.4	2.3
	Net income	138738.5 (1.28) *	138738.5(2.99) ***	1.4	2.3
KBM[d]	Total output	462.5 (2.18) **	461.5(2.23) **	1.0	1.1
	Net income	138738.5 (2.18) **	138454.5(2.23) **	1.0	1.1
RM[f]	Total output	462.5 (2.16) **	462.5 (2.16) **	1.2	1.2
	Net income	137910.4(2.16) **	138738.5(2.16) **	1.2	1.2

Table 7. Impact estimates of improved post-harvest technology use on smallholders' total starch output and net income. ****significance at 1%, **significance at 5% and * significance at 10%*

At the time of the study, the amount in Naira were converted to a dollar equivalent using a bank exchange rate of ₦324.24 to one US$.

A sensitivity analysis was further carried out for the presence of hidden bias using the Rosenbaum bounds (rbounds test). The result of the test as shown in Table 7 reveals how hidden biases may distort interpretations about treatment effects but does not show if and when biases are present or what scales are possible. The Rosenbaum sensitivity analysis results show that the critical level of hidden bias range between T=1.0 - 2.3; where T is the critical level when the question of a positive impact of improved technology on output and income of cassava processors can be queried. This denotes the fact that individuals with the exact covariates differ in their odds of acceptance and adoption by a factor of 50-70%, the impact of the adoption effect on the outcome variables may come into question. Thus, it can be inferred that the ATT is not sensitive to unobserved selection bias and are a pure effect of using improved post-harvest technology.

4.0 Conclusion

Cassava starch processors in the study area were mostly female. The type of post-harvest technology commonly used was the trad-improved post-harvest technology which combines traditional techniques with some improved post-harvest technology. Cost of post-harvest technology and access to credit were some of the factors that determine the choice of post-harvest technologies in Nigeria. Accordingly, efforts must be made to encourage the development of affordable technologies especially to poor rural dwellers about 90 percent of who depend on agriculture for their livelihoods. Also, this study recommends policies targeted at provision of credits that are affordable and easily accessible by cassava starch processors in order for them to procure the more expensive technologies.. Sex of cassava starch processor also determines the choice of post-harvest technologies. Therefore, there is a need to empower women to enable them to have access to improved techniques. Although the use of improved post-harvest technologies for processing cassava is associated with high variable costs, the benefits embedded in its use is far higher than the costs. As shown by the impact analysis result, a change from the use of either traditional post-harvest technology or trad-improved post-harvest technology to the improved post-harvest technology is highly beneficial. Using improved post-harvest technology will help improve the quality of cassava products and possibly place cassava in Nigeria on the World market. Investments in improved post-harvest technologies, increase small-holders' income, increase output and also improve food availability in Nigeria.

Declaration of interest

none

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References.

Abdoulaye T, Abass A, Maziya-Dixon B, Tarawali G, Okechukwu R, Rusike J, Alene A, Manyong V and Ayedun B (2014) Awareness and adoption of improved cassava varieties and processing technologies in Nigeria. *Journal of Development and Agricultural Economics* 6(2): 67-75.

Adejumo OA, Ojoko EA and Yusuf SA (2014) Factors influencing choice of pesticides used by grain farmers in Southwest Nigeria. *Journal of Biology Agriculture and Healthcare*, 4 (28): 31-38.

Afolami CA, Obayelu AE and Vaughan II (2015) Welfare impact of adoption of improved cassava varieties by rural households in South Western Nigeria. *Agricultural and Food Economics* 3(1):18 doi:10.1186/s40100-015-0037-2

Acheampong PP, Owusu V and Gyiele KN (2013) Farmers' preferences for cassava variety traits: empirical evidence from Ghana. *Contributed paper prepared for presentation at the Fourth International Conference of the African Association of Agricultural Economists (4th ICAAAE) 22-25th September, 2013*. Hammamet, Tunisia.

Adetunji A, Isadare D, Akinluwade K. and Adewoye O (2015) "Waste-to-Wealth Applications of Cassava–A Review Study of Industrial and Agricultural Applications". *Advances in Research* 4(4): 212–229.

Bayard B., Jolly M. C. and Shannon A. D (2006) The adoption and management of soil conservation practices in Haiti: the case of rock walls. *Agricultural Economic Review* 7(2): 29-39

Beaudry P, Doms M and Lewis E (2006) "Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution". available at:http://doi.org/10.3386/w12521.

Boniphace NS, Fengying N and Chen F (2015) An analysis of smallholder farmers' socio-economic determinants for inputs use: a case of major rice producing regions in Tanzania. *Russian Journal of Agricultural and Socio-Economic Sciences* 2(38): 41-55

Bourguignon F, Fournier M and Gurgand, M (2007) Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys* 21(1): 174-205.

Dehejia RH and Wahba S (2002) Propensity score matching methods for nonexperimental causal studies. *The Review of Economics and Statistics* 84(1): 151-161.

Greene WH (2000) *Econometric analysis*. Fourth edition. Prentice Hall, New Jersey.

Jaffe AB, Newell RG and Stavins, RN (2003) Technological change and the environment. *Handbook of Environmental Economics* 1:461-516.

Jera R and Ajayi OC (2008) Logistic modelling of smallholder livestock farmers' adoption of tree-based fodder technology in Zimbabwe. *Agrekon* 47(3): 379-392.

Judge GG, Hill RC, Griffiths WE, Lűtkepohl H and Lee TC (1985) *Theory and practice of econometrics*. 2nd ed. New York: John Wiley and Sons.

Kassie M, Jaleta M, Shiferaw B, Mmbando F and Muricho G (2012) *Plot and Household-Level Determinants of Sustainable Agricultural Practices in Rural Tanzania*. Environment for Development. Discussion paper series. Retrieved from http://www.rff.org/RFF/Documents/EfD-DP-12-02.pdf

Kroh M and Eijk C (2003) Utilities, Preferences and Choice. *Paper prepared for the joint sessions of workshops of the ECPR in Edinburgh*, March 2003.

Mcfadden D (1974) Conditional Logit Analysis of Qualitative Choice Behaviour. Zarembka P., (Eds.), Frontiers in Econometrics, Academic Press, New York. 105-142.

Menale K, Shiferaw B and Muricho G (2011) Agricultural technology, crop income and poverty alleviation in Uganda. *World Development* 39(10):1784-1795.

Nguyen-Van P, Poiraud C and To-The N (2016) Modeling farmers' decisions on tea varieties in Vietnam: a multinomial logit analysis. *Agricultural Economics* 48(3): 291–299

Nweke FI, Spencer DSC. and Lynam JK (2012)*The Cassava Transformation Africas Best-Kept Secret*. Michigan State University Press, East Lansing.

Ogundari I, Momodu A, Famurewa A, Akarakiri J and Siyanbola W (2012) Analysis of Sustainable Cassava Biofuel Production in Nigeria. *Energy & Environment* 23(4): 599–618.

Oguntade AE (2013) *Food losses in cassava and maize value chains in Nigeria analysis and recommendations for reduction strategies.* GIZ, Bonn.

Ojo MA, Nmadu JN, Tanko L and Olaleye RS (2013) Multinomial Logit Analysis of Factors Affecting the Choice of Enterprise Among Small-holder Yam and Cassava Farmers in Niger State, Nigeria. Journal of Agricultural Sciences, 4(1):7-12. doi: 10.1080/09766898.2013.11884695

Okoruwa VO, Ogheneruemu OE. and Lydia OA (2015) Root and tuber expansion programme and poverty reduction among farmers in Southwest Nigeria. *Journal of Development and Agricultural Economics* 7(10): 332–343. doi:10.5897/jdae2015.0656

Olayide SO and Heady EO (1982) *Introduction to agricultural production economics.* Ibadan University Press, University of Ibadan, Ibadan, Nigeria.

Oluka SI (2000) "Costs of tractor ownership under different management systems in Nigeria". *Nigerian Journal of Technology* 19(1):15-28.

Parkin, M. (1997) *Microeconomics*. 3rd Ed. Updated Edition. The Addison-Wesley Series in Economics. New York:Addison Wesley Longman Inc.

Rolfe, J., Bennett J., and Louviere J. (2000) Choice modelling and its potential application to tropical rainforest preservation. *Ecological Economics* 35: 289-302.

Saka, JO and Lawal, BO (2009) Determinants of adoption and productivity of improved rice varieties in southwestern Nigeria. *African Journal of Biotechnology* 8(19): 4923-4932.

Salganik MJ and Heckathorn DD (2004) Sampling and Estimation in Hidden Populations Using Respondent-Driven Sampling. *Sociological Methodology* 34(1):193–240.

Sianesi B (2004) An evaluation of the active labour market programmes in Sweden. *The Review of Economics and Statistics* 86(1):133–155.

Wooldridge JM (2002) Econometric Analysis of Cross Section and Panel Data. Cambridge: MIT Press.

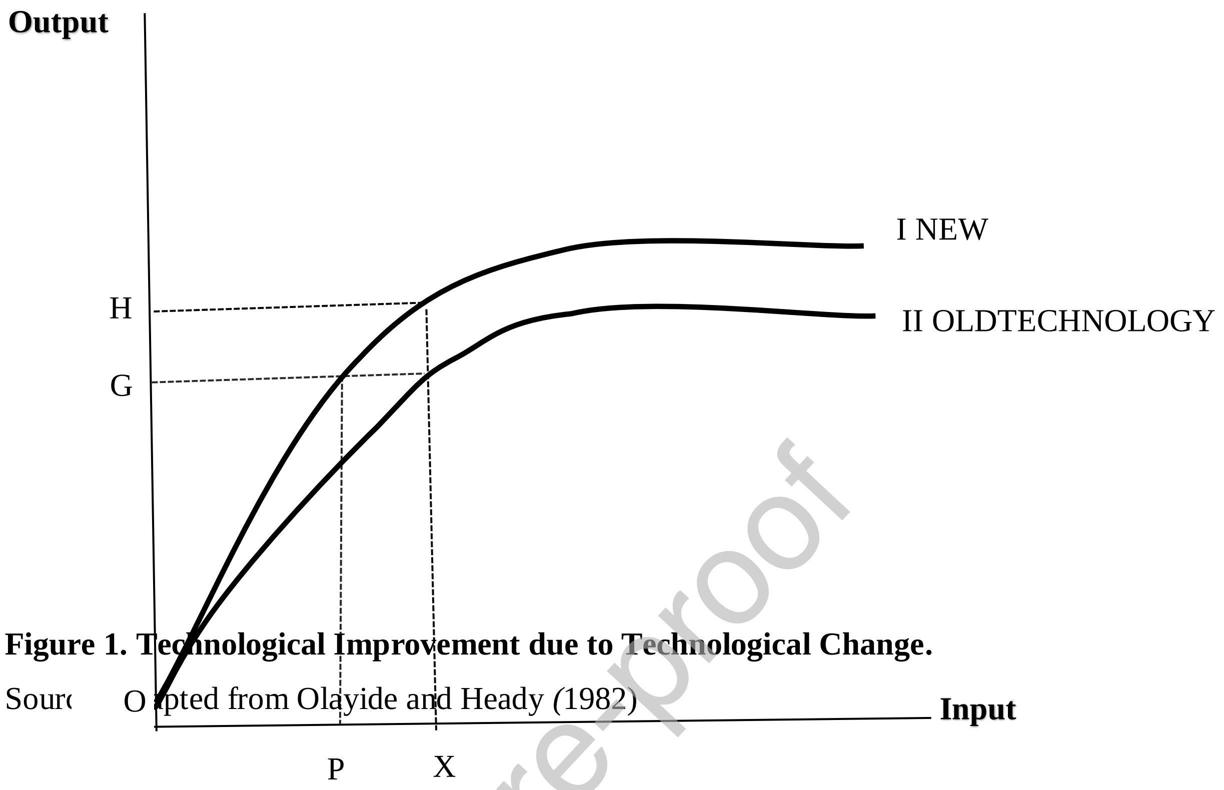

Figure 1. Technological Improvement due to Technological Change.

Source: Adapted from Olayide and Heady (1982)

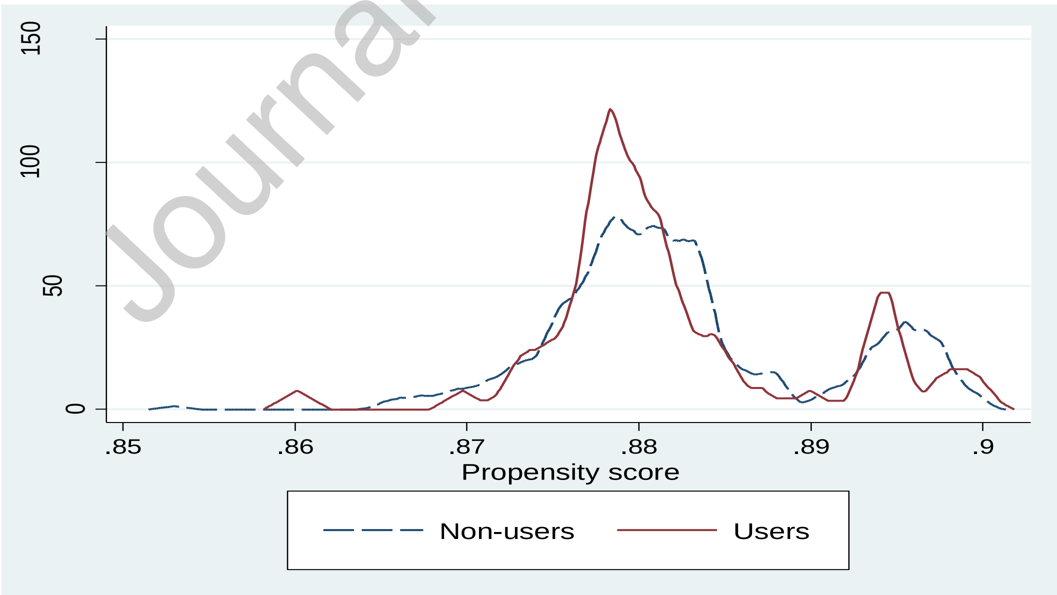

Figure 2. Propensity score distribution for overlap assumption.