Estimating causal effects of cassava based value-webs on smallholders' welfare: a multivalued treatment approach

T. Adeyemo; V. Okoruwa; V. Akinyosoye

University of Ibadan, Department of Agricultural Economics, Nigeria

Corresponding author email: adeyemotemitayo@gmail.com

Abstract:

The aim of the paper is to evaluate the impact of value-webs as an innovation in agricultural production on welfare of cassava smallholders in Nigeria. The estimation procedure involved the alternative process of multivalued treatment models when treatment units have multiple values. The study thus extends previous impact studies which focused on estimating causal effects from binary treatment units. The treatment units were determined from the extent of utilization of cassava which informed the classification of households into value-web groups. Value-web is defined here as a measure of joint linkages of product chains within the cassava system. The determinants of the choice of utilization were also estimated. Results show that value-web groups include non-cassava based households; low-level, middle-level and high-level value web groups at 32.4%, 34.1%, 24.4% and 9.1%, respectively. Resource allocation to cassava, farming experience, and access to improved cassava varieties increased probability of higher value-web activities. The ATE estimated from the model shows significant increases of up to N11, 560.14 (USD 37.9) and N11, 296.57(USD 37.04) in monthly farm income if non-cassava based and low-level web households became high-level web households. Keywords: Cassava, Value-webs, Causal effect, Smallholders, Multivalued treatment JEL: C31; D13; O31, Q12

Acknowledgement: The authors wish to acknowledge the BiomassWeb Project funded by the German Federal Ministry for Education and Research (BMBF) and the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH. The Research Fellowship offered by the International Institute of Tropical Agriculture, Ibadan, Nigeria to the first author is gratefully acknowledged. The research is supported by CGIAR Program on Humidtropics and, the Roots, Tubers and Bananas (RTB).

JEL Codes: O31, C31

#755

Estimating causal effects of cassava based value-webs on smallholders' welfare: a multivalued treatment approach.

Abstract

The aim of the paper is to evaluate the impact of value-webs as an innovation in agricultural production on welfare of cassava smallholders in Nigeria. The estimation procedure involved the alternative process of multivalued treatment models when treatment units have multiple values. The study thus extends previous impact studies which focused on estimating causal effects from binary treatment units. The treatment units were determined from the extent of utilization of cassava which informed the classification of households into value-web groups. Value-web is defined here as a measure of joint linkages of product chains within the cassava system. The determinants of the choice of utilization were also estimated. Results show that value-web groups include non-cassava based households; low-level, middle-level and high-level value web groups at 32.4%, 34.1%, 24.4% and 9.1%, respectively. Resource allocation to cassava, farming experience, and access to improved cassava varieties increased probability of higher value-web activities. The ATE estimated from the model shows significant increases of up to ₦11, 560.14 (USD 37.9) and ₦11, 296.57(USD 37.04) in monthly farm income if non-cassava based and low-level web households became high-level web households.

Keywords: *Cassava, Value-webs, Causal effect, Smallholder households, Multivalued treatment*

JEL: *C31; D13; O31, Q12*

1.0 **Introduction**

Cassava has taken centre stage in provision of staple food to the teeming population in Nigeria (Fuller, 2011; FAO, 2017). The importance of cassava in the Nigerian economy is seen in her continued leadership in global cassava production, with fresh cassava roots production of about 20% of world's cassava, and up to 34% of Africa's cassava (Abass *et al.*, 2014). Although, there is a great unmet need for high valued cassava products for food and non-food uses, value addition to cassava has been limited to the production of locally available food staples, and limited raw materials for cottage industries within the economy.

Considering the importance of cassava as a versatile source for food, feed, pharmaceutical, industry and biofuel uses (Ashante-Pok, 2013), it become imperative for stakeholders to constantly find ways of improving productivity, output and continued sustainability within the cassava system. In view of this, the Federal government of Nigeria has come up with various initiatives aimed at moving the current agricultural practices from subsistence to market based. From the agricultural development plans of the 1960s-1980s, to the more recent Agricultural Transformation Agenda (ATA) and Agricultural Promotion Policy (APP) which focused on cassava as one of the mandate crops for growing the economy (Akinyosoye, 2005; Anyanwu *et al.*, 2011, Kuku- Shittu *et al.*, 2013). Most of these interventions revolve around the value chain approach whereby efficiency is advocated at each node of productive activity for the agricultural system in question. However, on-farm wastages, postharvest losses, low standard products still characterize the cassava system at different nodes of its various product chains (Onyenwoke and Simonyan, 2014). This may be an indication that the nodal focus of the value chain may not be sufficient to maximize cassava as an agricultural biomass; and hence the exploration of value web.

The value web concept is derived from business models; where businesses have opted for effective resource management through full oversight of critical functions within the system. In a typical business value web, processes that were formally outsourced are brought into the core of the business, so that productive resources can be optimally used without wastages, leading to a reduction in total costs of production, and increase in business profit. Now, bringing this to agricultural systems, value webs mean the use of available resources within a system to link available product chains in such a way as to maximize outputs and minimize wastes. Biomass based value webs links biomass value chains in a cycle of cascading resource use in such a way as to reduce waste and ensure full utilisation of agricultural biomass (Virchow *et al.*, 2014). Value-webs thus offers agricultural actors the opportunity of higher levels of maximizing their returns by increasing their product lines within the biomass/agricultural system (see Figure 1 for a typical economy wide cassava value web). The basis of analysis is the physical flow of agricultural biomass as well as the uses to which actors within the system make of the biomass. The biomass based value web explores joint production of an agricultural biomass within cascading resource use in a circular economy (Scheiterle *et al.*, 2017). The sustainability of this type of production concept is hinged on the rational nature of farmers, who typically make production and consumption decisions, within their limited resources based on expectation of returns on their investment (Rapsomanikis, 2015).

In response to the demand of emerging bioeconomies, re-orienting agricultural systems as value web models is expected to ensure that the food demand by smallholder producer-based, economies is not neglected in the global demand for biomass for industrial uses (Virchow *et al,* 2016). Scheiterle *et al*., (2017), examined the development of sugar cane within a value web concept and found that re-orienting the sugarcane system in Brazil as a value web has the potential to increase economic growth. Likened to the development of a circular economy, value-webs in agricultural systems are expected to ensure that declining resources are effectively utilized in a multi-layered reverse network, thus ensuring full use of the biomass. There is however scant evidence of how value-webs work among the smallholders who form the bulk of biomass production in developing economies. This study therefore explores value-web production processes among cassava smalholders in Nigeria. Specifically, the empirical research questions in this study were; what is the extent of utilization of cassava among smallholder households in the study areas; what factors determine the choices of smallholders' levels of utilization of cassava and what is the impact of the choices made on the welfare of the farm households?

Empirical estimation of impact of interventions or programs follows the classical binary form of a treated unit and the counterfactual (Rosenbaum and Rubin, 1983). However, when treatment units take on multiple values, there is a need to rethink the parametric estimation of causal effects. This study explores the growing literature of estimating causal effects from multiple treatment units (Cattaneo, 2010; Cattaneo *et al*, 2013; Uysal, 2014 and Eposti, 2014 and Linden *et al*, 2016). In this way, we contribute to the causal inference literature since the basis for treatment in this study is the multiple levels of smallholder value-web participation in the cassava system.

The rest of the study us organized as follows. Section 2 explores the methodological framework of causal effect estimation in multivalued treatments; section 3 is the variable measurement and methodology; while section 4 present and discusses the empirical results. Section 5 concludes the study and offers recommendation.

2.0 Methodological Framework

2.1 Causal Effects Estimation

The conventional models for estimating causal effect are based on the potential outcome framework of Rubin (1974), in which case, each observational unit has ex-ante potential outcome for the treatment.

Let *di* denote the treatment, where *di*=1 if individual is in treatment group and 0 otherwise. For the individual *I*, (for *i*=1,2,…*N*), there are two potential outcomes given as: *Yi(1)* and *Yi(0)*, where *Yi(1)* is the outcome realized by the individual for being in the treatment group, while *Yi(0)* is the outcome for the individual if he was not in the treatment group. However, an individual can either be treated or untreated, never both, therefore, only one outcome is observed, and that is the potential outcome, the other outcome being the counterfactual. Thus, if *Yi (0)* is observed for an individual, his counterfactual is *Yi (1);* and if *Yi (1)* is observed, then his counterfactual is *Yi (0)*.

The potential outcome is denoted as:

$$Y_i = Y_i(d_i) = Y_i(0)(1-d_i) + Y_i(1)d_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The causal effects of being treated is thus Y_1-Y_0. However, these individual effects cannot be observed for a single household, therefore, the expected value is estimated and given as:

i. $E\ (Y_1\text{-}Y_0)$, this is the Average Treatment Effect.
ii. $E\ (Y_1\text{-}Y_0/d=1)$; the effect of the treatment on the sub population of the treated alone
iii. $E\ (Y_1\text{-}Y_0/d=0)$: the expected effect of the treatment on the untreated sub population

There are two basic assumptions underlying the potential outcome framework;

i. The Conditional Independence Assumption (CIA): this states that after conditioning on covariates (*Xi*), and there are no more unobserved variables that affect the outcome or the treatment, then the potential outcomes are independent of the treatment. This means that we have no measured unconfoundness or selection on observables.

$$(Y_1, Y_0) \perp d|X \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

ii. Overlap assumption: there is a non-zero (positive) probability of each individual being treated in a sample population.

$$0 < p(d=1|X) < 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In this study however, the focus is in estimating the impact of utilizing the concept of a biomass based value web in the smallholder agricultural household production and consumption decision matrix. Thus, the treatment is developed from the extent of utilization of cassava in a value web concept; in which few households are considered as non-treated (not a cassava based smallholder household) and then there are different intensity of treatment for the remaining observational units (differing levels of use of the biomass based value web concept of production in the cassava system). This is a classic case of a multivalued treatment model (Cattaneo, 2010 and Eposti, 2014).

2.2 **Parametric Estimation of Multivalued Treatment Effect Model**

Multivalued treatment effects arise as a result of increase in number of treatment regimens in the observational units of choice. The estimation of multivalued treatment lie in the causal effects of the treatment levels on an outcome variable when the treatment, T_i, takes on finite values between *0* and *K* (Bia and Mattei, 2008).

Therefore, consider *N* observational units, $i=(1, \ldots, N)$ exposed to given treatment level, $Ti = (0, \ldots K)$, and, the following is observed:
(Yi, Ti, Xi); for receiving treatment *Ti*, when;
$D_{it}(T_i)= \{1, \text{if } T_i=t; 0 \text{ otherwise}\}$

Also, for each individual household, there is a set of potential outcomes Y_{it} ($Y_{i0} \ldots Y_{iK}$). The outcome *Yi* given the treatment options $D_{it}(T_i)$, in the potential outcome Y_{it} is :

$$Y_i = \sum_{t=0}^{K} D_{it}(T_i) Y_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

In multivalued treatment effect model, there is no true counterfactual, thus, it become possible to estimate pairwise treatment effects between the different treatment units; '*m'* and *'l'* (Uysal, 2014, Eposti, 2014). Therefore, given different levels of treatment *'m'* and *'l'*; the following obtains:

i. The average treatment effect of the treatment *m* relative to treatment *'l'*,

$$\tau^{ml} = \mathrm{E}[Y_{im} - Y_{il}] = \mu_m - \mu_l \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

ii. The average treatment effect for an individual from among the treatment group, *m*

$$\gamma^{ml/m} = \mathrm{E}[Y_{im} - Y_{il} / T_i = m] = \mu_{m/m} - \mu_{l/m} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

iii. The symmetric treatment effects for the other treatment level 'l', i.e average treatment of treated (ATT) with respect to treatment 'l'; such that;

$$\tau^{m/l} = -\tau^{l/m} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

iv. The average treatment effect (ATE) of treatment ‘m’ with respect to treatment ‘l’ on the subpopulation of units under treatment ‘l’ is :

$$-\tau^{lm/l} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

The assumptions of potential outcome framework for binary treatment units are reformulated to multiple treatment units. Thus, the assumptions of conditional independence and overlap form the basis for causal effects estimation in this model.

The CIA requires additional conditioning on covariates (Xi), which is expected to contain all confounders that allow us to make treatment effect estimates in observational studies. Referred to as ‘weak uncounfoundedness’ (Imbens, 2000), stated as:

$$Y_{it} \perp D_{it}(T_i)/X_i, \forall t \in \Im \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Where, $\perp$ implies independence, and $\forall t \in \Im$, (0… K) - the treatment levels ranging from finite values of 0 to ‘K. The expected potential outcome (μi) estimates based on the CIA assumption follows the following estimation procedure:

$$\begin{aligned} &E[Y_{it}|X_i] = E[Y_{it}|D_{it}(T_i) = 1, X_i] \\ &= E[Y_i|D_{it}(T_i) = 1, X_i] \\ &= E[Y_i|D_{it}(T_i) = t, X_i]; \forall t \in \Im \end{aligned} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

The potential outcome is estimated by a regression function as:

$$\mu_t = E[Y_{it}] = E[E[Y_{it}|X_i]] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (11)$$

The treatment effect estimates can thus be defined as:

i. The average treatment of individual units of treatment *‘m’* relative to *‘l’.*

$$\hat{\tau}^{ml} = \hat{\mu}_m - \hat{\mu}_l \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

ii The average treatment effect of individuals in the ‘m’ treatment ($ATET_m$).

$$\hat{\tau}^{m/m} = \hat{\mu}_{m/m} - \hat{\mu}_{l/m} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (13)$$

The overlap assumption implies positive probability of observational units receiving any of the treatment regimen. Imbens, (2000) extended the estimation of the overlap assumption in the case of multivalued models as the General propensity score (GPS). Accordingly, following the notations of classical propensity score, the GPS is the positive probability of receiving a treatment level given the conditioning variables.

$$\begin{aligned} r(t,x) &= \Pr\left[T_i = t \middle| X_i = x\right] \\ &= E\left[D_{it}(T_i) \middle| X_i = x\right] \end{aligned} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14)}$$

The potential outcome means can thus be determined by weighting the observed outcomes with the estimated GPS weights (Davidian *et al*, 2011) expressed as:

$$E[Y_{it}] = \left[\frac{Y_i D_{it}(T_i)}{r(t, X_i)}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(15)}$$

Where; $r(t, Xi) > 0$

The overlap assumption is typically considered together with the CIA assumption, in order to develop what Rossembaum and Rubin, (1983) calls the Strong Ignorability; that is a complete overlap in the distribution of covariate between the treatment levels (Linden *et al.*, 2016). Based on the notations established from the assumptions, there are a number of approaches to estimating treatment effects in multivalued models. These are generally referred to as treatment effect estimators briefly discussed as follows.

2.2.1 ***Treatment effects estimators in multivalued effect models***

We examine the three main treatment effect estimators used in multivalued treatment effects models. These are the Regression Adjustment (RA) estimators; Inverse Probability weighting (IPW) estimators and the doubly robust estimators (DRE).

i. ***Regression Adjusted (RA) estimators***

The RA estimators are built on the validity of the weak unconfoundness, using regression models to predict the potential outcomes after adjusting for the X_i, which are assumed to contains all the confounders in the observational study as to make inferences unbias. The RA is based on specifying a regression function for determining the potential outcome of equation 11 ($\mu_t = E[Y_{it}] = E\left[E\left[Y_{it} \middle| X_i\right]\right]$). The conditional mean function to estimate the potential outcome is thus given as:

$$E[Y_{it} / X_i] = E[Y_i / T = t, X_i] = \beta_{0t} + X'_i\beta_{1t}, \forall_t \in \Im \ldots\ldots\ldots\ldots\ldots (16)$$

The treatment effects are then estimated by contrasting the potential outcome means for each treatment level (See Uysal, 2014 for full derivation).

$$\tau_{RA}^{ml} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\beta}_{1m} + X'_i\hat{\beta}_{1m}) - (\hat{\beta}_{1l} + X'_i\hat{\beta}_{1l}) \ldots\ldots\ldots\ldots\ldots.. (17)$$

The RA is however constrained by the specification of correct functional forms. Notwithstanding, it is more robust in providing stable estimates even when the sample size is small (Statacorp, 2013).

ii. ***Inverse Probability Weighting (IPW) Estimators***

The inverse probability weighting estimators uses weighted means to determine the treatment effect when covariates have been accounted for. Following the notation of the GPS in equation 15, $E[Y_{it}] = \left[\frac{Y_i D_{it}(T_i)}{r(t, X_i)}\right]$

Where, $E[Y_{it}] = \mu$; if the probability of receiving treatment level $r(t, Xi) > 0$

The ATEs between treatment levels *'m'* and *'l'* is given as:

$$\hat{\tau}_{IPW}{}^{ml} = \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i D_{im}(T_i)}{\hat{r}(m, X_i)} - \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i D_{il}(T_i)}{\hat{r}(l, X_i)} \ldots\ldots\ldots\ldots\ldots\ldots (18)$$

The importance of the IPW estimators lies in it being able to present graphical illustration of the overlap of the covariates distribution among the treatment levels. However, a violation of the overlap assumption leads to biased estimates.

iii. ***Doubly robust estimator (DRE)***

Increase in treatment levels (multivalued treatments) may imply missing observation and hence the need for more efficient estimators (Bang and Robin, 2005), inherent in the doubly robust approach (Cattaneo, 2010, Uysal, 2014). The DRE combines the usefulness of the RA and IPW by modelling the probability of receiving treatment as well as the outcome simultaneously in a way as to estimate asymptotically unbiased estimates even when one of the two models is not correctly specified (Sloczyński and Wooldridge, 2014; Linden *et al.*, 2016). Two main DRE used in treatment effect literature include the Augmented Inverse probability weighted (AIPW) estimators and the Inverse Probability Regression Adjusted (IPWRA) estimators (Statcorp, 2013).

The AIPW is basically built on the principle of the IPW model, with an augmentation term that helps correct for a misspecification of the treatment model (Drukker, 2014). The augmentation term tends to zero if the treatment model is correctly specified as the sample size increases. The AIPW model on the other hand corresponds to the Efficient Influence Function (EIF); a non-parametric estimation of treatment effects (Cattaneo *et al*., 2013; Farrell, 2015). Following Linden *et al.*, (2016); the AIPW is estimated in three steps. In the first step, the GPS parameters and consequently the inverse is estimated. In the second step, separate regression model for the outcomes of each treatment level as well as treatment specific outcomes for each observation are computed. The final step is the computation of the unconditional means from the estimated GPS (step1) and the estimated conditional mean function (step 2). The unconditional mean (μ) is specified as follows:

$$AIPW(\mu_i) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Y_i D_{it}(T_i)}{\hat{r}(t_i, X_i)} - \frac{D_{it}(T_i) - \hat{r}(t_i, X_i)}{\hat{r}(t_i, X_i)}\hat{m}_i(X_i)\right] \text{……. (19)}$$

The IPWRA estimator is mainly a RA model weighted by the inverse of the GPS. Similar to the AIPW, the IPWRA is also operationalized in three steps. First, the GPS scores and corresponding inverse propensity weights are estimated for each treatment level. Second, with the estimated IPW, the regression outcome models (equation 17) are fitted with the IPW weights, so that specific outcomes for each treatment levels are obtained for each observation from the estimated coefficients of the weighted regression. At the final stage, the means of the treatment specific predicted outcomes are estimated as the unconditional means.

In this study, the 'teffect' package in STATA 14 was explored for the parametric estimation of causal effects across the four approaches discussed above. The discussion is however based on the estimates of the doubly robust procedure, based on the superiority in providing consistent estimates. We also explored the Efficient Influence Function (Cattaneo *et al.*, 2013) to further validate the parametric results. This was done with the aid of the user-written command 'poparms' on STATA 14.

3.0 Data and Variable Measurement

3.1 Data and Descriptive Statistics

The sampling unit for this study is the Agricultural household. Following the household model (see Sadoulet and Janvry, 1995), we assume that the farm household is made up of units who are related and use production factors collectively in order to generate resources, under the supervision of the household head, who may be a male or a female. The aim of the household is thus to sustain welfare from the collective actions of the household members under the headship of a key individual. The head of the household was thus the pivot person in the household survey carried out.

The data for this study was based on a survey of smallhlolder farming households carried out in 2015. The survey covered three states across the guinea savanna and forest zones of Nigeria. These include Kwara state in the guinea savanna zone as well as Edo and Ogun states representing the forest agro-ecological zone. The sampling procedure was multi-stage. In each state, 2 Agricultural Development Zones (ADZs) were selected from the lists of ADZs. From each ADZ, blocks were randomly selected, proportionate to the sizes of the ADZs. From the blocks, cells, were also randomly selected proportionate to the size of the blocks. The cells formed the primary sampling units, from which a random sample of cassava based households were selected. In total, a sample of 800 households were selected across the study areas. Data on household socioeconomic and entrepreneurial characteristics as well as activities within the cassava system and income from each cassava product line were collected.

3.2 Variable Measurement and Household Characteristics

The treatment variable in this study was a measure of the extent of utilization of cassava biomass by smallholder households in the study areas. First, however, we identified smallholder households whose primary sources of income was not within the cassava system. These smallholders (non-cassava based households-NCH) formed the control group ($t=0$) within the treatment unit. For the households who indicated that cassava was their main source of income, we estimated the extent of utilization of cassava within their productive system using a cluster analysis. Based on reconnaissance survey, we came up with 13 items that contains the activities and products obtainable from the cassava system in Nigeria (See appendix 1). Responses of the household to these activities were then subjected to clustering analysis and used to place them into one of the three value-web groups (low, middle and high).

In this study, we used the hierarchical cluster analysis, specifying the agglomerative wards linkage method in order to minimize the sum of square error between the two groups.

The results of the cluster analysis presented three distinct clusters (I, II and III) as shown in the Dendogram (Figure 2). However, there is no clear indication for which of the three clusters represent low, mid-level or high-level value-web groups, giving rise to a need to profile and define each cluster. In defining each cluster, we follow the cluster profiling of Yim and Randeem, (2015), and used certain variables with apriori expectations as regards value-webs. Specifically, we ascertained that value-webs are synonymous with increased income, increased resource allocation to a venture (land allocation), as well as increased sources of income (number of activities) (Dufey *et al.*, 2007; Virchow *et al.*, 2016).

The profiling presented in Table 1 shows that cluster I was synonymous with low income, low resource allocation and below average level of activities in their cassava systems. Cluster II on the other hand, showed reasonable higher income and number of activities than cluster I; while it has the highest level of resource allocation to the cassava system. Although cluster III had lower resource allocation to the cassava system than II, its participants had higher income as well as the highest number of income generating activities from their cassava system. Using these criteria, we conclude that cluster I, II and III respectively are classified as low-level, middle- level and high-level cassava value-web households.

The overall treatment units are therefore 4 levels, with $t=0, 1, 2, 3;$ representing non-cassava households (NCH), low-level value-web (LL); middle-level value-web (ML) and high-level value-web (HL), each making up 32.38%; 34.13%, 24.38% and 9.13% respectively (Figure 3). Description of confounding variables was made across these 4 classes of observational units.

On the other hand, the outcome variable in this study was the monthly income of smallholder households from their agricultural activities. The monthly income was a culmination of all income accruing from all possible product lines within the farming systems of the households for each productive cycle. All income was aggregated into monthly income for ease of analysis.

The description of sampled smallholder households by value-web groups is presented in Table 2. Tests of differences in means of outcome across the groups was done using the Kruskall Wallis rank test. The finding showed that overall, about 72% of the households had male heads, with only 28% being female headed households; with no significant difference across the value-web groups. The average age of the household heads was 51 years, varying across the groups at $p<0.05$. Household heads in the high level participating group had an average age of about 52 years, while those in the mid-level group had average ages of about 50 years. There was however no significant difference across the groups in terms of household size where the average household size was about 7 members. Educational achievements of the household revealed differences across the groups with majority of the household heads with non-formal education among the high-level value-web participants (42.47%), while the majority with primary, secondary and tertiary educations were largely represented among the middle-level (37.95%), low-level (33.7%) and the non-cassava based households (12.74%) respectively.

The results also showed high proportion of households who saved (71.38%); for which the high-level participant households accounted for 83.56%. Membership in social group was found to be highest among the high-level participant's households (93.15%). Table 2 also shows that high-level value web households had the highest number of years of total farming experience of about 28 years. The lowest years of total farming experiences was found among the low-level participants households (21.64 years) and the non-cassava based households (21.85 years).

Categorization by land area cultivated shows that up to 56.25% of the households used between 1.5ha-3ha of farm land for the farming activities, varying significantly across the value-web groups. There was also significant difference ($p<0.01$) across the participating groups in terms of land resources allocated to cassava. The proportion of land allocated to cassava out of the total land area cultivated for non-cassava households and low-level cassava households were 28% and 59% respectively, while those for mid-level and high-level cassava households were 70% and 65% respectively.

Average farm income was ₦55, 940.24, which varied across the value-web households at $p<0.01$, with the ₦46, 075; ₦57, 364; N62, 021 and ₦69, 368 for Non-cassava, low-level, middle-level and high-level value-web households respectively.

About 46.3% of the households had access to credit for their productive activities. The result showed that 67.12% of the high-level participants' households had access to credit while only 41.03%, 47.6%, and 42.86% of the mid-level, low-level and non-cassava based households had access to productive credit. It was also seen that 97.2% and 95.5% respectively of the high-level participant households' plant and process improved cassava varieties. However, while there was a higher proportion of low-level participants (79.85%) who planted improved cassava variety, there were more of the mid-level participants who processed improved cassava variety (54.873%). Wealth distribution[1] showed that high-level value-web households made up 45% of the richest wealth quintile, while about 23% of the low-level and mid-level participant households made up the poorest wealth quintile. The non-cassava households make up the highest percentage (28%) of smallholder households in the poor wealth quintile.

4.0 Empirical Results and Discussion

4.1 Determinants of Level of Cassava Value-web Participation

An ordered probit model was used to isolate factors that determine level of participation of households at different levels in the cassava value-web. The results are presented in Table 3. The estimated model has a maximum likelihood of -809.35, and LR chi^2 of 452.59 which is significant at 1% ($p<0.01$), implying that the model as a whole is well fitted. Ordered probit estimates are based on the parallel assumption that allows us to make inference for all discrete groups in the model from a single result (William, 2008). Thus, the probability of being in successively higher levels of participation in the cassava biomass value web was found to have increased significantly ($p<0.01$) with increased land resources allocated to cassava (3.5%) and number of years of farming experience (1.7%), increased income from activities within the cassava value web (51.7%) as well as increased asset (8. 8%). The probability also increased at $p<0.05$ with access to credit (20.4%) and access to improved cassava variety (23.2%). However, the probability of successively increasing participation in the cassava value web reduced at $p<0.05$ for an increase in age of household head (8.2%) and for households who had savings (24.1%).

[1] Principal component analysis was employed to determine the asset index from which the wealth status is determined. :

$$CI_j = \sum \frac{F_i(X_{ji} - X_i)}{S_i}$$

Where, C_{ij} =asset index value for the jth household participating in the series of 'i' activities; F_i is the weight of the ith variable from the PCA; X_{ji} is the jth household value for the ith variable; X_i and S_i are the mean and standard deviations of the values of the ith variables.

The marginal effect estimates provided the information for determinants of assignment to each of the treatment units. A percentage increase in the age of household head significantly ($p<0.05$) increased the probability of the household being in the non-cassava group by 2% and by 0.2% for the low level cassava value web group at $p<0.1$. It however significantly ($p<0.05$) reduced the probability of being in mid-level and high level participating households respectively by 1% and 0.1% respectively.

Also, a 1% increase in the proportion of land allocated to cassava significantly ($p<0.01$) reduced the probability of being in the non-cassava households and low-level value-web groups by 0.84% and 0.08%. However, it significantly ($p<0.01$) increased the probability of participating in the mid-level and high-level groups within the cassava biomass value web by 0.44% and 0.47% respectively. This follows a study by Hichaambwa *et al.,* (2015), where increasing land resources allocation implies expansion of productive capacity of the households' holdings, which may translate to increased output, for which the smallholders are consequently able to leverage on the different value addition options inherent in the cassava value web and hence to increase revenue from cassava biomass.

Similarly, a 1% increase in the number of years of farming experience of the household head significantly increased the probability of being in the mid-level and high-level participating groups by 0.3% and 0.2% respectively. More years of experience has been hypothesized to increase investment and value addition in agricultural systems, (Guo *et al*., 2015); likely as a result of the ability to leverage on established contacts, market, trade route and information to increase their revenue.

The results in Table 3 also show that households who had access to credit had higher probability ($p<0.05$) of 2.6% of being in the mid-level group and 2.7% of being in the high-level participant groups. Literature has established that access to credit increases the capital base of the smallholders, enabling investment I n improved methods and technologies of production and value addition which are key to increased participation in the cassava value web, (Arias *et al*., 2013). Similarly, smallholders who had access to improved cassava varieties had significant ($p<0.05$) probability of 2.9% and 3.1% of being in the middle-level and-high level groups respectively. Evenson and Gollin, 2002 reported that access to improved cassava variety for production and processing encourages increased value addition since they are expected to be higher yielding, of better quality and thus marketability.

A percentage increase in the asset index of the households significantly ($p<0.01$) increased the probability of being in the middle-level and high-level groups by 1.1% and 1.2% respectively. Some researchers have asserted that asset ownership is a prerequisite for increased leverage in investing in agricultural activities with prospects of higher returns (Johnson *et al.*, 2016). A unit increase in the income that accrues to the smallholders from their agricultural activity also significantly ($p<0.01$) reduced the probability of being in the non-cassava and low-level participating cassava value web group by 12.4% and 1.2% respectively. A percentage increase in farm income also significantly ($p<0.01$) increased the probability of being in the mid-level and high-level participating groups by 6.6% and 7.0% respectively. This follows economic theory of rationality (Hall, 1991); where expectation of increased utility (e.g income), informs the decision of individual in production of investment as also observed in a study by Samson *et al.*, 2016. Savings was however found to be a disincentive to increased investments in higher level activities in cassava value web. Households who had savings had significantly ($p<0.01$) lower probability of being in the middle (0.031) and high (0.032) level groups in the cassava value web. The intuition behind this may be related to the inverse relationship between savings and investment (Mankiw, 2009).

4.2 **Impact estimates of cassava value-web**

The multivalued treatment effect model estimated in this study was based on the assumptions of strong ignorability. One of the vital assumption inherent in this is the overlap assumption, which is graphical depicted as the estimated probabilities of being assigned to a treatment unit (Figure 4). The density graph shows that none of the treatment units has estimated probabilities at the extreme points of '0' and/or '1'. There was also considerable overlap of the density curves. We therefore ascertain that we could make unbiased inference on the parameters of the treatment effect model estimated.

Estimates of potential outcomes means (POMs) are presented in Table 4 for each treatment group across the treatment effect estimator used. The estimates across each of the approaches was found to be similar in terms of signs, magnitude and significance. However, the parameters for the RA was found to be biased upwards across the treatment units than the other estimator. Using estimates from the AIPW, we find that the monthly income that would accrue to smallholder households if they participated in the cassava value-web would be ₦45, 967.91 (USD 150.71); ₦57, 528.04 (USD188.62); ₦62, 309.74 (USD 204.29) and ₦68, 824.61 (USD

225.65) respectively for households in non-cassava, low-level based, middle-level based and high-level value-web groups. While these are only slightly different from the current average monthly farm income for the households (See Table 1); they provide the true impact of the value-webs when contrasted between pairwise treatment units after causal estimation assumptions have been met.

In Table 5, we present pairwise treatment effect for each group across treatment effect estimators. However, we discuss the results of the doubly robust estimators (AIPW), since they have been found to give consistently unbiased parameters even if either of the treatment or outcome model is not correctly specified. We find that increasing participation in the value web increases the income of the smallholder households significantly. The results show that for households who were in the control group, (NCH); there would be an increase of ₦11, 560.14 (USD 37.9) if they decided to participate at even the lowest value-web level in the cassava system. Moreover, if non-cassava based households moved to middle-level and high-level groups in the cassava value-web, the household income would significantly increase by ₦16, 341.84 (USD 53.58) and ₦22, 856.7 (USD 74.94), respectively. This indicates the versatility of cassava within the Nigerian agriculture (Nweke *et al.*, 2002), and the importance of value-webs as a production innovation in raising income and hence welfare of the households. The more of the cassava biomass that is utilized by the households within their productive resource base, the more diverse the product lines and hence the higher the income that would accrue to the households.

Furthermore, the result shows that if households who were low-level value-web increased participation in cassava value-web activities to become middle-level web group, their monthly income would increase by ₦4781.14 (USD 15.68), and by as much as ₦11, 296.57 (USD 37.04) if they became high-level value-web participants. Households who hitherto participated at middle-level value-web activities would have their household income increase by as much as ₦6, 514 (USD 21.36) if they increased value-web activities to become high-level participants.

When we examined the treatment effect across the other estimators of RA and IPW, we found almost similar effects, in terms of the direction and signs of the impact. However, we found that while the impact using the RA was lower than the other estimators; that of the IPW were slightly exaggerated. Only the parameters of the IPWRA and AIPW were consistently close to each other. We also used the non-parametric estimation procedure of Cattaneo *et al.*, (2013) to validate the treatment effects parameters that were estimated. The estimates of the semi-parametric Efficient Influence Function (EIF) were much closer to those of the doubly robust estimators (especially that of the AIPW) than either of the single estimation procedure.

5.0 **Conclusion and Recommendation**

This study examined an agricultural innovation-the biomass based value web, in bringing about maximum utility to smallholder households within the cassava system in Nigeria. We conclude that although subsistence is the case among majority of the smallholders, there is a substantial effort to improve production using the value web concept.

Our study further extended the literature on potential outcome framework to a multivalued treatment effect model. We estimated different approaches within the model and found that consistent and unbiased results were more likely to be found when the doubly robust estimates are employed as also found in the works of Cattaneo *et al.*, (2013) and Linden *et al.*, (2016). The estimation parameters show significant increases in income to smallholders with successive increase in value-web participation.

The study recommends opening up opportunities for smallholders to increase resource base through access to affordable credits, improved cassava varieties and adequate land use rights which will encourage higher investment within the cassava value web.

References

Abass A. B.,Towo E., Mukuka I., Okechukwu R., Ranaivoson R., Tarawali G., and Kanju E., 2014. Growing cassava: *A training manual from production to postharvest. International Institute for Tropical Agriculture (IITA), Ibadan, Nigeria.*

Akinyosoye V.O., 2005. Government and Agriculture in Nigeria: Analysis of Policies, Programmes and Administration. *Macmillan Publishers.*

Anyanwu, C., Amoo, B., Odey, L. And Adebayo, O., 2011. An Assessment of the Operations of the Presidential Initiatives on Agriculture in Nigeria: 2001-2007. *Central Bank of Nigeria (CBN), Occasional Paper, 40;* June, 2011.

Arias P, Hallam D., Krivonos E., and Morrison J., 2013. Smallholder Integration in Food Markets. *Food and Agricultural Organization (FAO),* 2013. E-ISBN 978-92-5-107663-7.

Ashante-Pok A, 2013. Analysis of Incentives and Disincentives for Cassava in Nigeria. *Technical Notes Series, MAFAP, FAO, Rome*.

Bang H., and Robins J. 2005. Doubly robust estimation in missing data and causal inference models. *Biometrics*, 61(4):962-973. DOI: 10.1111/j.1541-0420.2005.00377

Bia M. and Mattei A., 2008. A Stata Package for the Estimation of the Dose Response Function through Adjustment for the Generalized Propensity Sore'. *The Stata Journal*, 8(3): 354-373.

Cattaneo M. D., 2010. Efficient Semiparametric Estimation of Multivalued Treatment Effects under Ignorability. *Journal of Econometrics*, 155:138-154, 2010.

Cattaneo, M., Drukker D., and Holland A., 2013. Estimation of multivalued treatment effects under conditional independence. *The Stata Journal (2013*) 13 (3): 407–450

Davidian, M., Tsiatis, A. A., and Cao, W. 2011. More Robust Doubly Robust Estimators. In *BOOK OF ABSTRACTS* (p. 16). http://www.stat.ncsu.edu/_davidian

Drukker D.M., 2014. Estimating Treatment Effects from Observational Data using TEFFECTS. *Presented at STATA Conference, July 31-August 1, 2014, Boston, United States of America.*

Dufey A, Vermeulen S, and Vorley B., 2007. Biofuels: strategic choices for commodity dependent developing countries. *Common Fund for Commodities, Amsterdam*

Eposti R., 2014. The Impact of the 2005 First Pillar Reform as a Multivalued Treatment Effect. Alternative Estimation Approaches *Paper prepared for the European Association of Agricultural Economics (EAAE), August 26-29, 2014; Ljubljana, Slovenia*

Evenson, R.E. and Gollin, D., 2002. Crop variety improvement and its effect on productivity. The impact of International Agricultural Research. *Food and Agricultural Organization (FAO); CABI Publishing; ISBN 0-85199-549-7.*

Food and Agricultural Organization (FAO), 2017. Nigeria at a Glance. FAO, 2017. *Retrieved online at http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/; on 18/06/2017*

Farrell, M.H., 2015. Robust inference on average treatment effects with possibly more covariates than observations. *Journal of Econometrics*, 189(1): 1-23.

Fuller, D. 2011. Case Study on Potential for Scaling Up: Adding Value to Waste in the Cassava Processing-Goat Keeping Systems in Nigeria. *Washington, DC: the World Bank. Accessed December*, 23 (2017).

Guo G., Wen Q and Zhu J, 2015. The Impact of Aging Agricultural Labor Population on Farmland Output: From the Perspectives of Farmer Preferences. *Mathematical Problems in Engineering, Vol 2015, 7 pages*. http://dx.doi.org/10.1155/2015/730618.

Hall R. E.,1991. The Rational Consumer: Theory and Evidence. *MIT press, Cambridge, Massachusetts, United Kingdom.*

Hichaambwa M., Chamberlain J, and Sitko N., 2015. Determinants and Welfare Effects of Smallholder Participation in Horticultural Markets in Zambia. *African Journal of Agriculture and Resources Economics,* 10(4): 279-296.

Imbens, G. W. 2000. The role of the propensity score in estimating dose-response functions. *Biometrika*, 87(3): 706–710. doi:10.2307/2673642

Johnson, N.L., Kovarik, C., Meinzen-Dick, R., Njuki, J. and Quisumbing, A., 2016. Gender, assets, and agricultural development: Lessons from eight projects. *World Development*, 83: 295-311.

Kuku- Shittu O, Mathiassen A., Wadhwa A. ,Myles L and Ajibola A., 2013.Comprehensive Food Security and Vulnerability Analysis: Nigeria. *IFPRI Discussion Paper 01275,* July 2015.

Linden A., Uysal S. D., Ryan A. and Adams J, L.,(2016). Estimating Causal Effects for Multivalued Treatments: a Comparison of Approaches. *Statistics in Medicine, 2016, 35:534-552.*

Mankiw N. G., 2009. Macroeconomics. 6th *Edition*. *South-Western Cengage Learning, United States of America.*

Nweke, F.I. Spencer D.S.C., Lynan J.K., 2002. The Cassava Transformation: Africa's Best Kept Secret'. *Michigan State University Press, East Lansing, United States, ISBN, 0-87013-602-X*

Onyenwonke C., and Simonya K. J. 2014. Cassava Post-harvest Processing and Storage in Nigeria: a Review. *African Journal of Agricultural Research*, 9(53):3853-3863.

Rapsomanikis G., 2015. The Economic Lives of Smallholder Farmers: an Analysis based on Household Data from Nine Countries. *Food and Agricultural Organization (FAO),* Rome, 2015.

Rosenbaum, P.R. and Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41-55.

Rubin, D. B. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*. 66:688–701.

Sadoulet, E., and De Janvry, A. 1995. Quantitative development policy analysis (Vol. 5). *Baltimore: Johns Hopkins University Press.*

Samson, G.S., Gardebroek, C. and Jongeneel, R.A., 2016. Explaining production expansion decisions of Dutch dairy farmers. *NJAS-Wageningen Journal of Life Sciences*, *76*:87-98.

Scheiterle L., Ulmer A., Birner R., and Pyka A., (2017). From Value Chains to Biomass-Based Value Webs: the Case of Sugarcane in Brazil's Economy. *Journal of Cleaner Production (In press)*

Sloczyński T. and Wooldridge J. M., 2014. General Double Robustness Result for Estimating Average Treatment Effects. *Institute for the Study of Labour (IZA) Discussion Paper No. 8084*

StataCorp. 2013. Stata: Release 13. Statistical Software. College Station, TX: *StataCorp LP.*

Uysal S. D., 2014. Doubly Robust Estimation of Causal Effects with Multivalued Treatments. *Economic Series, 297; Institutes for Advanced Studies, Vienna, Austria' June 2014.*

Virchow D., Beuchelt T., Denich M., Loos T. K., Hoppe M., and Kuhn A., 2014. The Value Web Approach. *Rural Focus, 21, March, 2014*.

Virchow D., Beuchelt T.D., Kuhn A., and Denich M., 2016. Biomass-Based Value Webs: a Novel Perspectives for Emerging Bio economies in Sub-Saharan Africa. *In F.W. Gatzweiker and J. von Braun (eds.), Technological and Institutional Innovations for Marginalised Smallholders in Agricultural Development.* DOI: 1.1007/978-3-319-25718-1_14.

Williams R, (2008), 'Ordinal Regression Models: Problems, Solutions and Problems with Solutions'. *German Stata User Group Meeting, Notre-Dame Sociology*, June 20, 2008

Yim O., and Randeem K. T., 2015. Hierarchical Cluster Analysis: Comparison of three linkage measure and application to psychological data. *Quantitative Methods in Psychology,* 11(1): 8-21

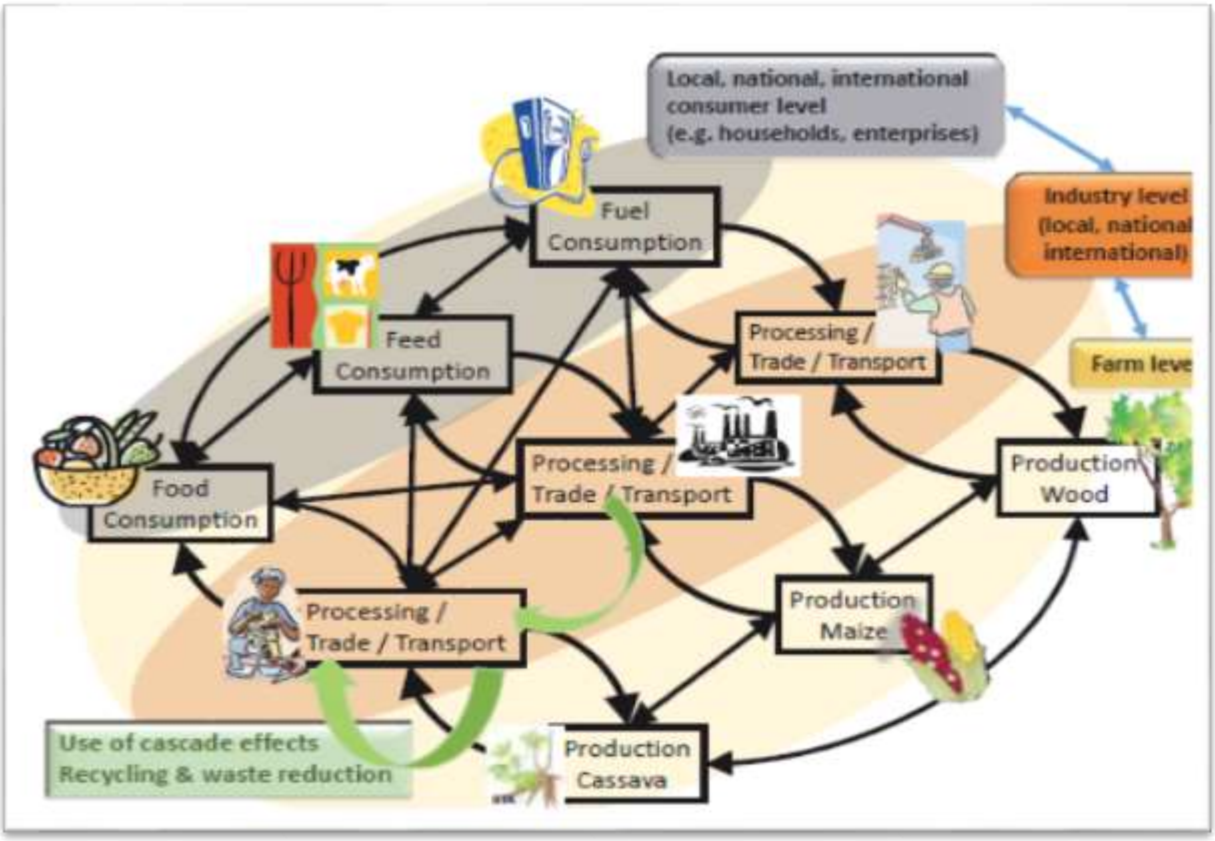

Fig. 1: A Hypothetical Cassava Value Web Concept

Source: Virchow *et al.*, 2014

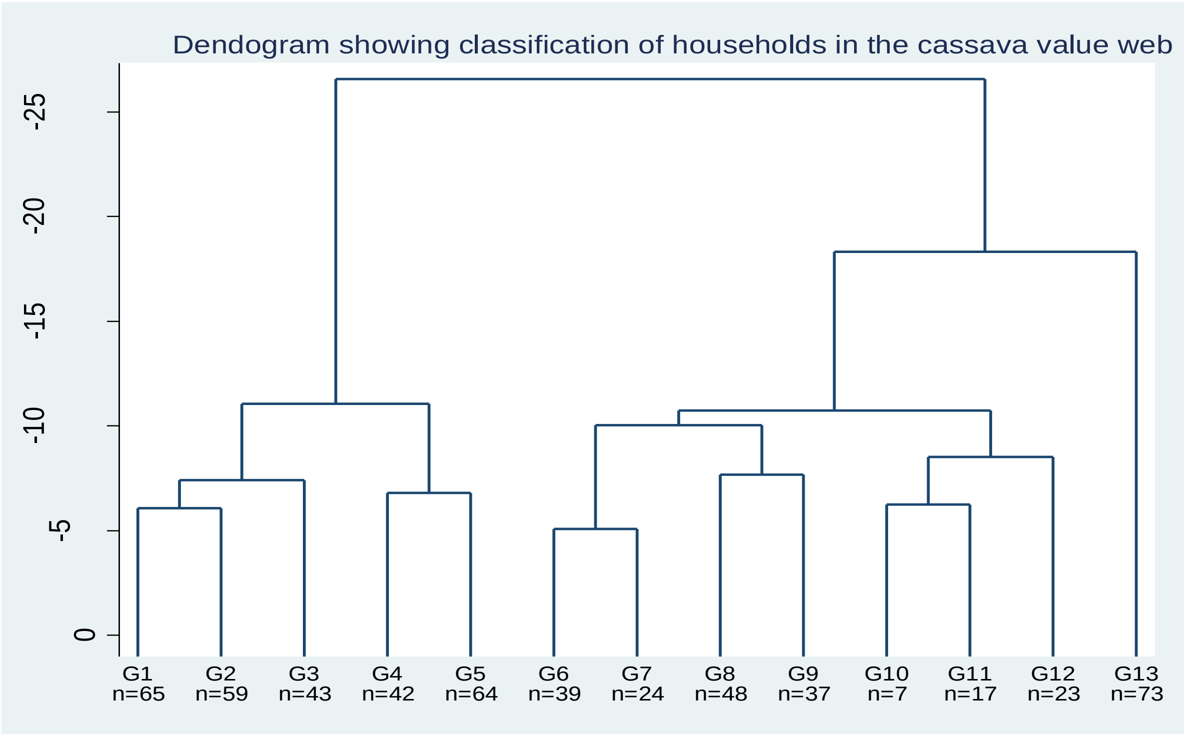

Figure 2: Dendogram showing three distinct clusters of cassava smalholders by utilization of cassava

Table 1: Profile of Clusters using selected variables

Indicator variables	Cluster					
	I (n=273)		II(n=195)		III(n=73)	
	Value	Rank	Value	Rank	Value	Rank
Number of activities	4.73	3	6.31	2	8.97	1
Proportion of Land allocated to cassava	0.59	3	0.70	1	0.65	2
Income from agricultural activities(₦ /(USD)	57364.42 (188.08)	3	62021.8 (203.35)	2	69368.97 (227.44)	1
Overall cluster rank	3		2		1	

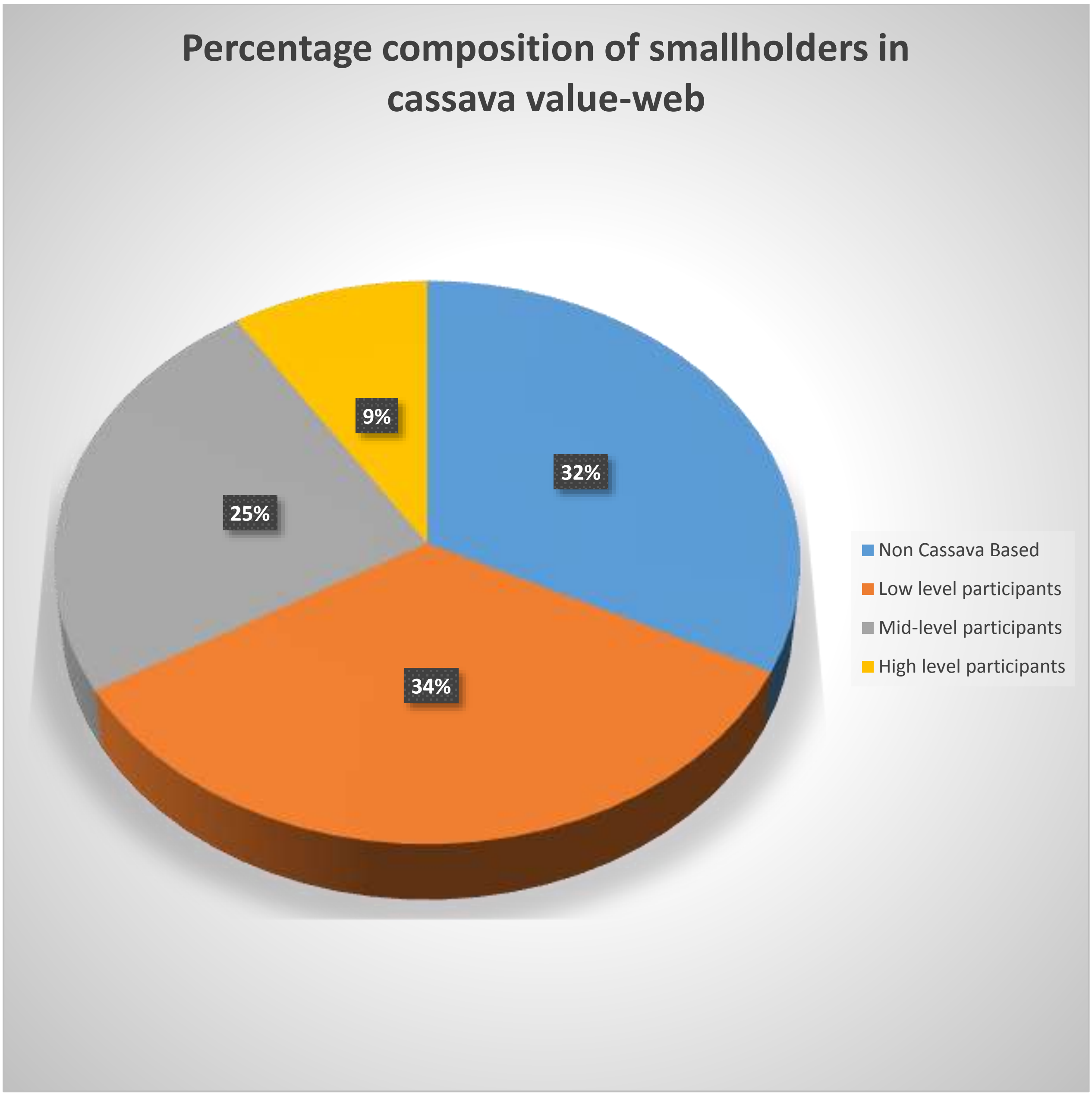

Figure 3: Percentage Composition of Smallholders within Cassava Value-web

Table 2: Socioeconomic Characteristics of Respondents across Cassava Value Web Groups

Characteristics	NCH (n=259)	LL (n=273)	ML (n=195)	HL(n=73)	Total(N=800)	Difference test
Gender						
Male (%)	75.68	67.40	73.85	71.23	72.00	4.95
Female (%)	24.32	32.60	26.15	28.77	28.00	
Age in years (average)	50.51	51.25	50.32	51.85	50.84	2.65
Household size(average)	6.25	7.03	6.51	6.84	6.63	16.59***
Education						
Non-formal education (%)	23.94	29.67	21.03	42.47	26.88	
Primary education (%)	36.29	26.74	37.95	31.51	33.00	12.62***
Secondary education (%)	27.03	33.70	29.23	23.29	29.50	
Tertiary education (%)	12.74	9.89	11.79	2.74	10.63	
Savings (%)	73.36	70.70	65.13	83.56	71.38	9.59**
Membership in social group (%)	77.61	75.09	70.77	93.15	76.50	15.30***
Years of farming experience (average)	21.85	21.64	22.84	28.12	22.59	81.025***
Proportion of Land allocated to cassava activities	0.28	0.60	0.70	0.65	0.54	418.13***
Land area cultivated						
<0.5ha	7.34	15.02	18.97	10.96	13.13	23.13***
0.5ha-1.5ha	38.22	29.67	25.13	21.92	30.63	
1.5ha-3ha	54.44	55.31	55.90	67.12	56.25	
Farm Income* (average)	46075.36	57364.42	62021.81	69368.97	55940.24	118.00***
Access to credit (%)	42.86	47.62	41.03	67.12	46.25	16.34***
Plant improved variety (%)	49.42	79.85	64.62	97.26	67.88	88.27***
Process improved variety (%)	34.75	34.13	54.87	94.52	58.13	123.19***
Wealth class (quintile)						
Poorest (%)	20.46	23.08	23.08	8.22	20.88	
Poor (%)	28.57	20.51	24.62	12.33	23.38	59.90***
Middle class (%)	18.53	16.48	19.49	16.44	17.88	
Rich (%)	22.01	16.12	16.41	16.44	18.13	
Richest (%)	10.42	23.81	16.41	46.58	19.75	

*Exchange rate: ₦305/1 USD

Table 3: Parameter Estimates of Determinants of Participation Levels in Cassava Value web in Nigeria

	Coefficients		Marginal Effects			
	Parameters	**Standard Error**	**NCH**	**LL**	**ML**	**HL**
Age of household head	-0.082**	0.041	0.020** (0.010)	0.002* (0.002)	-0.010** (0.005)	-0.011** (0.003)
Age sq	0.439*	0.253	-0.105* (0.060)	-0.01 (0.007)	0.056* (0.032)	0.059* (0.034)
Gender of household head (Base=Female)	-0.006	0.098	0.001 (0.023)	-0.000 (0.002)	-0.001 (0.012)	-0.001 (0.013)
Education (Base= Non formal education)	-0.006	0.099	0.002 (0.004)	0.001 (0.002)	-0.001 (0.003)	-0.001 (0.013)
Household size	0.004	0.019	-0.001 (0.006)	-0.000 (0.000)	0.002 (0.004)	0.001 (0.002)
Proportion of Land allocated to cassava	3.500***	0.213	-0.838*** (0.037)	-0.079*** (0.027)	0.444*** (0.032)	0.473*** (0.041)
Number of years of farming experience	0.017***	0.004	-0.004*** (0.001)	-0.000*** (0.000)	0.003*** (0.007)	0.002*** (0.001)
Access to credit (Base =No)	0.204**	0.093	-0.049** (0.022)	-0.005* (0.004)	0.026** (0.012)	0.027** (0.013)
Access to improved cassava variety	0.232**	0.099	-0.055*** (0.024)	-0.005* (0.003)	0.029** (0.013)	0.031** (0.014)
Membership of social group (Base =No)	0.041	0.108	-0.009 (0.026)	0.001 (0.002)	0.005 (0.014)	0.006 (0.015)
Asset index	0.088***	0.028	-0.021*** (0.007)	-0.002** (0.009)	0.011*** (0.004)	0.012*** (0.004)
Income from agricultural activities	0.517***	0.101	-0.124*** (0.024)	-0.012*** (0.004)	0.066*** (0.013)	0.070*** (0.014)
Savings (Base=No)	-0.241**	0.101	0.058*** (0.024)	0.005** (0.003)	-0.031*** (0.013)	-0.032*** (0.014)
Agro-ecological zone (Base=Forest zone)	-0.016	0.102	0.004 (0.024)	0.000 (0.002)	-0.002 (0.013)	-0.0 02 (0.014)
Cut 1	9.981***					
Cut 2	11.280***					
Cut 3	12.373***					
Number of Observations	800					
Log Likelihood	809.35					
LR chi2	452.59***					
Pseudo R2	0.219					

* p<0.10; ** p<0.05; *** p<0.01; standard errors are in parentheses

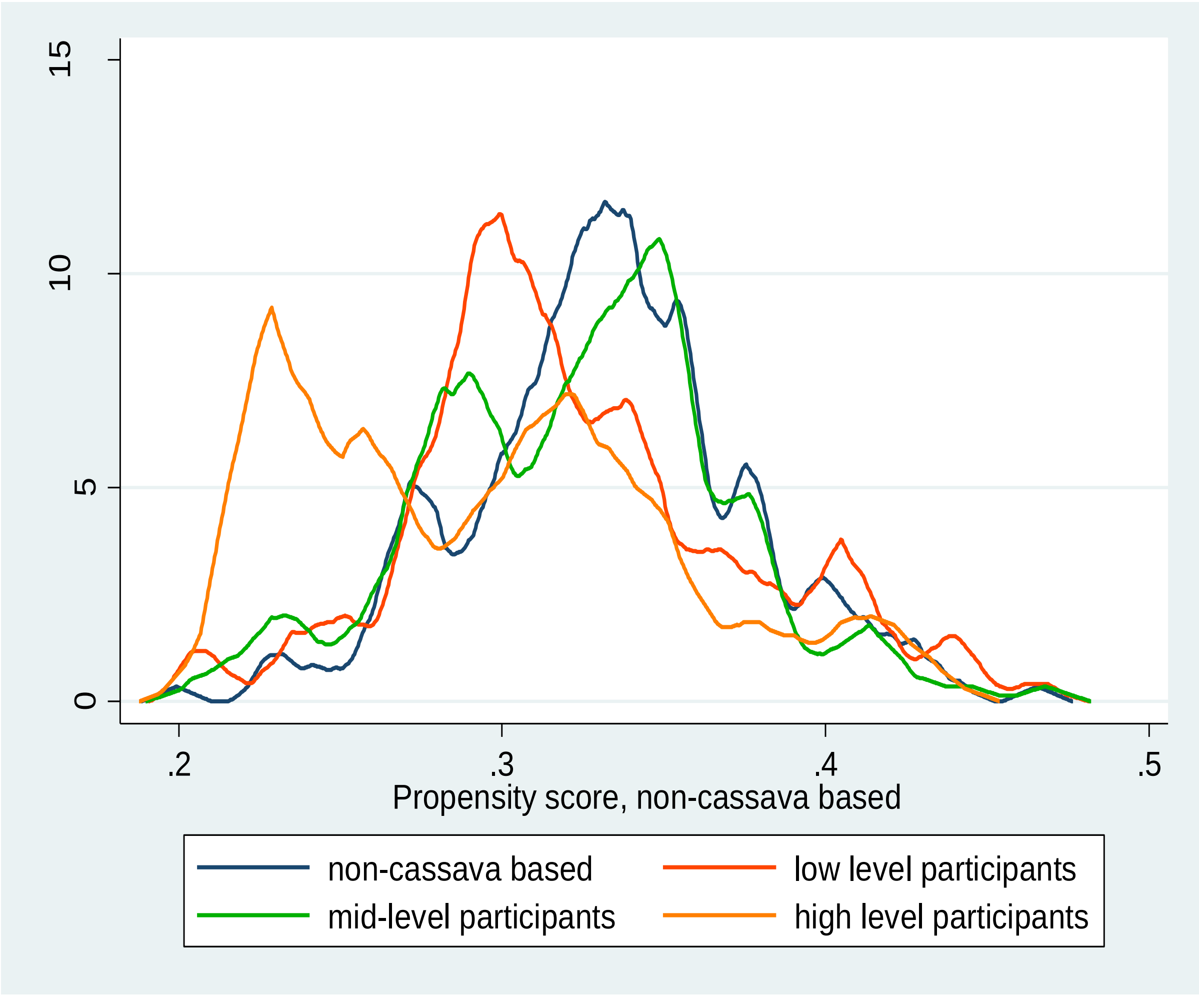

Figure 4: Estimated Probabilities of Assignment to Treatment Units

Table 4: Potential outcome means of income across treatment units and estimators

Estimator/Treatment unit	Parameter	Robust Standard error
RA		
NCH	46059.55***	744.9525
LL	57454.39***	1289.104
ML	62287.03***	1666.07
HL	71481.73***	3446.083
IPW		
NCH	45957.26***	756.587
LL	57548.5***	1271.075
ML	62311.24***	1670.479
HL	68731.23***	3850.647
IPWRA		
NCH	45961.95***	757.6774
LL	57528.88***	1270.45
ML	62323.14***	1666.525
HL	69293.67***	3330.718
AIPW		
NCH	45967.91***	757.2523
LL	57528.04***	1270.612
ML	62309.74***	1668.232
HL	68824.61***	3556.919

*** $p<0.01$

Table 5: Treatment effects estimates across treatment effect estimators

Pairwise treatment effect (l→m)[#]	Average treatment effect (ATE)	Robust Standard errors
RA		
NCH→LL	11394.84***	1488.418
NCH→ML	16227.48***	1822.931
NCH→HL	25422.18***	3528.236
LL→ML	4832.64***	2104.636
LL→HL	14027.34***	3681.11
ML→HL	9194.70***	3833.78
IPW		
NCH→LL	11591.25***	1483.697
NCH→ML	16353.99***	1830.833
NCH→HL	22773.98***	3934.579
LL→ML	4762.74***	2097.6
LL→HL	11182.73***	4053.527
ML→HL	6419.99	4208.495
IPWRA		
NCH→LL	11566.93***	1482.37
NCH→ML	16361.19***	1827.308
NCH→HL	23331.72***	3423.685
LL→ML	4794.25***	2093.941
LL→HL	11764.78***	3560.408
ML→HL	6970.53*	3733.21
AIPW		
NCH→LL	11560.14***	1482.312
NCH→ML	16341.84***	1828.735
NCH→HL	22856.7***	3647.707
LL→ML	4781.70***	2095.432
LL→HL	11296.57***	3776.295
ML→HL	6514.87*	3934.477
EIF (non-parametric)		
NCH→LL	11560.14	1492.649
NCH→ML	16341.84	1834.261
NCH→HL	22856.7	4054.691
LL→ML	4781.698	2111.773
LL→HL	11296.57	4186.978
ML→HL	6514.87	4324.854

* p<0.10; *** p<0.01; #: m is a higher level of treatment

Appendix 1

Cluster Items for Classifying Cassava Value-Web Groups

S/N	ITEM	Response(Yes/No)
1	I produce cassava for home consumption alone	
2	I produce cassava both for home consumption and sale of cassava roots to processors	
3	I process my cassava roots both for home consumption and market sales	
4	I process cassava into garri alone	
5	I process cassava into fufu alone	
6	I process cassava into lafun alone	
7	I process cassava into garri and fufu alone	
8	I process cassava into starch	
9	I process cassava into high quality cassava flour	
10	I sell cassava roots alone	
11	I sell cassava roots and process for home consumption and market	
12	I use cassava leaves and residue as manure and mulch on my farm	
13	I have access to ready market for my high quality cassava products	