FARMER ADOPTION OF CASSAVA TRAITS:

A CASE STUDY OF IMPROVED VARIETIES IN NIGERIA

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ABSTRACT

Adopting improved varieties is key for improving agricultural productivity and farmers' quality of life in developing countries. The objective of the study was to examine determinants of Nigerian farmers' decisions to adopt improved cassava variety (ICV) traits, classifying the traits into three different groups: resilience, marketability, and cooking quality. The data used in this study come from a survey of 1,087 households conducted in four regions of Nigeria in 2015, focusing on adoption of ICVs. Using Tobit and Seemingly Unrelated Regression (SUR) models, the results showed that the determinants of adoption vary across traits. For instance, adoption of ICVs with superior cooking quality traits is affected by extension agency contact, and credit availability. On the other hand, determinants of trait adoption with resilience characteristics are household size and household's cooperative membership. Furthermore, living in the North region has a positive effect on adoption of resilience trait, while it negatively affects adoption of marketability and cooking quality traits. Besides, the proportion of cassava used for home consumption purposes shows a negative correlation with adoption of ICVs and traits.

BIOGRAPHICAL SKETCH

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I. Introduction

Cassava is one of the major staple crops in developing countries, mainly in Africa. According to the Food and Agriculture Organization of the United Nations (FAO), cassava is cultivated by small-scale farmers mostly for home consumption and to sell the surplus because it grows well in poor soils and requires less labor than other crops (FAO, 2005). Also, cassava is usually intercropped with vegetables, plantation crops (such as coconut, oil palm, and coffee), yam, sweet potato, melon, maize, rice, groundnut, or other legumes. As a result, cassava supports the livelihood of over 300 million Africans and provides 37% of dietary energy. Cassava has rich carbohydrates, and is the main source of calcium, vitamins B and C, and essential minerals for the population. For this reason, improving cassava production and productivity in Africa is directly related to sustainable food security and people's wellbeing (Moyo, 2016). Area planted to cassava reached 27.5 million hectares worldwide in 2019, of which 78.6% were planted in Africa. However, of the 303.6 million tons of cassava were produced worldwide, only 63.3% were produced in Africa (FAO, 2019). This suggests that African productivity in cassava production is lower than the world's average.

The productivity of staple crops has been an essential part of food security and agricultural development in developing countries, and researchers and international organizations have sought to increase their productivity (Doss, 2006; Feder et al., 1985; Rahm & Huffman, 1984). One of the main strategies to increase productivity was to develop improved varieties with specific traits (e.g., pest resistance or high yields). However, fewer farmers adopted the improved varieties than expected, which led to a low adoption rate (Wossen et al., 2015). Therefore, researchers have found

determinants of farmer adoption of improved varieties. (Adesina & Baidu-Forson, 1995; Feder et al., 1985).

The previous literature has limitations in understanding farmer adoption behavior. First, many studies measure adoption as a binary (yes/no). However, it is advantageous to use continuous adoption variables that provide more information - e.g., intensity of adoption (Doss, 2006; Mwangi & Kariuki, 2015). Second, previous literature measures trait adoption indirectly, by eliciting farmer preferences for specific traits of improved varieties, and it assumes that a higher preference for a given trait would lead to a higher adoption of ICV with such trait. (Otieno et al., 2011; Ouma et al., 2007). However, this indirect measurement lacks consideration of actual adoption behavior. Lastly, previous research focuses mainly on the adoption of the production or processing-related traits, but largely ignores consumption and market-related traits. Considering that consumption and market-related traits are important, analyzing adoption of these traits is necessary (Odemero, 2015; Otieno et al., 2011). Furthermore, despite farmers usually produce cassava for home consumption purposes, the existing research does not consider the effects of cassava's home consumption on farmers' improved variety adoption or trait adoption.

To address this gap in the literature, this research examines determinants of Nigerian farmers' decisions to adopt ICVs with specific traits. To do this, we use household-level cross-sectional data from The Cassava Monitoring Survey (CMS) in Nigeria conducted by the International Institute of Tropical Agriculture (IITA) in 2015. Based on the data, we calculate the percentage of land used for ICV and traits to have continuous adoption variables. Classifying traits according to three distinct characteristics (resilience, marketability, cooking quality), this study aims to understand farmer decision-making on consumption-related attributes. It also introduces a

new explanatory variable indicating cassava usage for home consumption to identify its effect on trait adoption.

This study follows three research steps. First, we conducted Factor analysis to construct a set of traits with common characteristics, since a large number of traits makes the study difficult. Second, it calculates a continuous adoption variable in the form of the Adoption Index, which indicates the adoption rate based on land usage for cassava and improved cassava variety (Phillip et al., 2000; Saka et al., 2005). Third, this research uses the Tobit model and Seemingly Unrelated Regression (SUR) model to estimate partial effects of explanatory variables on each trait adoption and compares the results across traits regarding determinants of trait adoption.

Examining the socio-economic and institutional factor effects on trait adoption, this research finds that the determinants of adoption vary across traits. For instance, living in North region has a positive effect on adoption of ICVs with resilience trait. However, it shows a negative effect on adoption of marketability and superior cooking quality traits. Furthermore, frequency of contact with extension agencies is associated with the marketability and cooking quality traits. At the same time, adoption of the resilience trait is significantly correlated with household size and association membership. Besides, home consumption rate shows negative correlations with ICV and trait adoption. It implies that an increase in cassava usage for home consumption purposes instead of sales will likely decrease adoption of ICVs and traits.

II. Literature Review

The literature review consists of five sections. The first section discusses adoption measurements used in the literature. The second section reviews studies focusing on framer preferences and adoption of specific improved cassava variety (ICV) traits. The third section examines models used to measure farmer adoption behavior. The fourth section analyzes factors affecting farmer ICV adoption decisions. Finally, the final section states the contribution of this study to the literature.

Measuring Adoption

Defining adoption and selecting how to measure it is complicated, as they depend upon the technology being adopted (Mwangi & Kariuki, 2015). In terms of agricultural technologies, definitions of adoption also vary by studies. For example, the definition of adoption can consider farmers' selection or perceptions of a technology, or level of a technology adopted (Adesina & Baidu-Forson, 1995; Jain et al., 2009).

In the improved variety adoption studies, adoption is defined as a binary or as a continuous variable. The binary variable measures a farmer's decision to adopt or not (Rahm & Huffman, 1984). The continuous variable measures, for its part intensity of adoption (i.e., percentage of land allocated to ICVs) as well as what binary variable measures (Phillip et al., 2000). The majority of earlier studies used a simple dichotomous adoption variable (Chandio & Yuansheng, 2018; Feleke & Zegeye, 2006; Shiyani et al., 2002). Some farmers can grow more than one variety. In this case, measuring how much the improved variety is adopted is important, in addition to whether it is adopted or not. It implies that the measurement for the binary variable does not contain sufficient

information. Thus, using a binary adoption variable is suitable for adoption of only one crop variety. In other words, the binary definition is appropriate such a case that farmers replace local varieties with the improved variety in all land (Doss, 2006).

In contrast, defining adoption as a continuous variable is more appropriate when considering the intensity of adoption or intercropping of different varieties (Doss, 2006; Rahman & Chima, 2016). Using a continuous adoption variable can provide much more information about adoption status compared to the binary variable, such as the proportion of area under cultivation of a target variety (Feder et al., 1985). As a measurement of continuous adoption variable, Feder et al. (1985) suggested a share of farm area under the improved variety. Similarly, Phillip et al. (2000) and Saka et al. (2005) used an adoption index using a proportion of land in their maize and rice study. The adoption index was computed for individual farmers as follows:

$$ADOPTION_i = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} T_i}$$

Where:

$ADOPTION_v =$ The adoption rate for a specific technology or improved variety by farmer i,

$P_i =$ Land area under a specific technology or improved variety by farmer i,

$T_i =$ Total land area grown to crop by farmer i

i = [1, n]

Due to difficulties in data collection, many previous studies specified adoption as a discrete variable (Doss, 2006). However, we use continuous adoption variables with the assumption that farmers follow a sequential decision process: first, farmers choose "whether to

grow improved varieties with a particular trait". Second, they consider "what is the level or intensity of such choice?" (Rahman and Chima, 2016). Then, the current study generates trait adoption variables by using the Adoption Index.

Adoption of Traits

Some studies have focused on the adoption of traits rather than on the adoption of ICVs, finding that certain traits increase improved variety adoption. This occurs when an improved variety has attributes that farmers prefer or perceive positively. Adesina and Baidu-Forson (1995) showed that farmers' preferences for varietal attributes are important determinants of adoption and use-intensities,

Furthermore, Smale et al. (2001) argued that farmers' decisions on crop variety adoption are not associated with individual varieties but with a set of traits of the varieties. To choose this set of traits, farmers maximize their utility by responding to production constraints, considering consumption preferences, and satisfying specific market requirements. Otieno et al. (2011) examined the role of varietal attributes in farmers' adoption of improved pigeon pea (Cajanus cajan) varieties in the Taita District, Kenya. The study showed that the major traits of pigeon pea variety driving its rapid adoption included drought tolerance, pest tolerance, yield, ease of cooking, taste, and price. Researching sorghum varieties in Kenya, Timu et al. (2014) also found that farmers not only focused on production-related traits but also on non-production-related traits including taste, brewing qualities, and ease of cooking.

To measure trait preferences of farmers, the literature estimated farmers' willingness to pay (WTP) for traits. The WTP indicates benefits farmers' benefits from adopting an improved

variety. Using the choice experiment approach, Asrat et al. (2010) evaluated farmers' WTP for traits of sorghum varieties and found socio-economic and institutional variables are important determinants of the WTP. Acheampong et al. (2013) used a choice experiment approach to investigate farmers' preferences. The study estimated the value (WTP) that farmers placed on different traits, and then identified farm household-specific and institutional factors that affected farmer preferences.

Furthermore, many studies analyzing trait preferences have emphasized production-related traits (Abebrese et al., 2019; Acheampong et al., 2013; Asrat et al., 2010; Ouma et al., 2007). However, some studies argued that it is essential to pay attention to traits related to consumption and market characteristics, because these traits increase improved variety adoption and farmer satisfaction (Otieno et al., 2011; Timu et al., 2014). Understanding the improved variety adoption considering the end-user preferences have received little attention from the literature as well (Dziedzoave et al., 2006).

In the extensive examinations on farmers' preferences of improved varietal attributes, relevant data tend to include survey items only on farmers' preferences, but do not capture actual adoption. To address this limitation, this study uses actual measures of ICV adoption. Furthermore, it examines the adoption of specific traits with marketability and cooking quality characteristics to consider the value chain from production to consumption.

Models to Examine Adoption Behavior

Many studies have investigated the influence of various socio-economic factors on decision-makers' willingness to use a new technology (Feder et al., 1985; Flinn & Shakya, 1985;

Rahm & Huffman, 1984). Rahm and Huffman (1984) use random utility theory, to develop an adoption behavior model that econometrically explains differences in farmers' decisions. The model defined ad new technology adoption as a choice between two alternatives, namely the traditional technology and the improved technology. Farmers adopt either of the two technologies to maximize their utility. Similar to Rahm and Huffman (1984), most studies used a binary variable (yes/no) and specify adoption univariate and multivariate logit or probit models to explain adoption (Feleke & Zegeye, 2006; Kebede et al., 1990; Nerlove & Press, 1973; Otieno et al., 2011; Ouma et al., 2007). However, as Lynne et al. (1988) pointed out, the binary outcome variables provide limited information about the effects of explanatory variables. The logit and probit model's coefficient interpretations cannot provide information about the intensity of adoption due to loss of information.

Therefore, in response to the necessity of using a continuous adoption variable that captures the adoption intensity, the Tobit estimation method's extension has been suggested and used (A Gara, 2020; Flinn & Shakya, 1985; J Lamichhane, 2017; Kebede et al., 1990; Lynne et al., 1988; McDonald & Moffitt, 1980; YL Idrisa, 2012). Tobit provides 1) estimates of the probability that a specific farmer becomes an adopter, and 2) the estimates of the level of adoption for the adopter, which were not available in the previous research (Amemiya, 1984; Flinn & Shakya, 1985). The Tobit model is specified as equation (1) where μ_i is an independently, normally distributed error term with zero mean and constant variance σ^2 (Wooldridge, 2010):

$$(1)\ Y^* = X\beta + \mu \ , \quad Y_i = \begin{cases} Y_i{}^* & if\ \ Y_i{}^* = X_i\,\beta + \mu_i > T \\ 0 & if\ \ Y_i{}^* = X_i\,\beta + \mu_i \leq T \end{cases}$$

where Y_i is the probability of adoption and the intensity of use and $Y_i{}^*$ is a non-observable latent variable, and T is a non-observed threshold level. If the $Y_i{}^*$ is greater than T,

observed variable Y_i becomes a continuous function of the explanatory variables, and 0 otherwise (i.e., no adoption) (Adesina & Zinnah, 1993).

According to McDonald and Moffitt (1980), the Tobit model uses all observations, those at the limit, usually zero (e.g., no adoption), compared to other frameworks using only observations above the limit value. Moreover, it captures the intensity level of adoption, which reduces the loss of information (McDonald & Moffitt, 1980). To examine farmer trait adoption, this research thus uses the Tobit model, a censored regression model with threshold zero.

Factors Affecting Farmers Improved Variety Adoption Decisions

Previous literature on determinants of improved variety adoption showed that education has a significant positive effect on adopting improved variety. That is, highly educated farmers are more likely to be early adopters (Abdoulaye et al., 2014; Feder et al., 1985; Nkonya et al., 1997; Weir & Knight, 2000). Household size is also positively associated with the adoption, as large household size implies high availability of labor (Bonabana-Wabbi, 2002; Doss, 2006; Feder et al., 1985). In addition, Kalinda et al. (2014) found that households with a male head are more likely to adopt improved crop varieties. Information accessibility, including farmers' participation in cooperative and extension services, also increases improved variety adoption (Abdoulaye et al., 2014; Feder et al., 1985; Kalinda et al., 2014; Nkonya et al., 1997). Credit access is also positively associated with the adoption (Doss, 2006; Feleke & Zegeye, 2006). Distance to market negatively affects the adoption of improved maize varieties in Southern Ethiopia (Feleke & Zegeye, 2006; Ramasamy et al., 1999). Meanwhile, the relationship between age of farmer and adoption is not clear. Langyintuo and Mekuria (2008) noted that younger farmers are more likely to adopt

improved varieties than older farmers since they have more chances to access new knowledge and technologies. On the other hand, older farmers may be better positioned to adopt new technologies because of their accumulated comparative advantages in capital and knowledge (Langyintuo & Mekuria, 2008; Mwangi & Kariuki, 2015).

The literature has also examined determinants of trait preferences, finding significant and positive effects of extension services (Asrat et al., 2010; Timu et al., 2014). Farmer trait preferences vary by geographical regions where households are located. Primary production constraints are linked to trait preferences (Smale et al., 2001). Gender is also found as a determinant of adoption. Women are more likely to prefer traits reducing labor input for processing, such as easiness to peel (Bentley et al., 2017; Wossen et al., 2017).

According to the FAO, cassava farming in Nigeria is done mostly by small farmers to for home consumption and to sell the surplus in the market (FAO, 2005). However, the correlation between improved variety adoption and the level of home consumption (i.e., proportion of output allocated to household consumption has not received much attention in adoption studies. Therefore, this study expands the literature on trait adoption by examining how the level of self-sufficiency affects adoption decisions.

Contribution to the Literature

Literature has shown that several socio-economic, institutional, and policy factors affect farmer decisions to adopt improved agricultural technologies. These findings are also applied to the improved variety adoption (Feder et al., 1985; Jain et al., 2009). However, the methodological

limitations of measuring adoption and the necessity of examining a correlation between adoption and consumption remain largely unknown.

This study contributes to filling such gaps in the literature by 1) using a continuous adoption variable and the Tobit approach, 2) examining actual adoption of specific traits (resilience, marketability, superior cooking quality), 3) examining the impact of a new explanatory variable, the level of self-sufficiency, on adoption intensity.

In conclusion, this study seeks to comprehensively understand farmers' decision-making on the improved variety traits, focusing on the case of cassava in Nigeria. It identifies the effects of determinants on trait adoption, and then compares similarities and differences of determinants of each trait. Since a thorough understanding of farmers' decision-making processes is of genuine interest to policymakers and academics, this study contributes not only to the literature on farmer adoption of improved varieties and traits, but also to identify ways to increase improved cassava variety adoption.

III. Empirical Model and Data

To achieve the goals, this research examines the determinants of framer adoption for traits of ICVs. The first section explains the Factor Analysis used in the research to group traits into three typologies. Based on the results of factor analysis, three factors grouping three individual relevant variables are identified. Each factor group indicates a different characteristic of the traits: resilience, marketability, and cooking quality. In the second section, this study calculates the

adoption ratio of 1) overall improved variety adoption, 2) each of three aggregated traits, and 3) nine individual traits. The third section introduces the Tobit and Seemingly Unrelated Regression models used to estimate the determinants of trait adoption. The last two sections discuss the data sampling and describe the variables used in this research.

Factor Analysis

To define typologies of traits, the current study uses the factor analysis. The factor analysis is constructed with statistical techniques to simplify complex sets of data or to reduce the number of traits included in the econometric analysis (Kline, 2014). The results of factor analysis identify factors by classifying traits that are strongly correlated with each other. Following Kline (2014), therefore, the factors are dimensions or constructs which are condensed statements of the relationships between a set of variables. Using factor analysis, we identify subsets of the traits with common characteristics and define typologies for the current study.

Our factor analysis was conducted based on the CMS data that respondents rated 21 attributes relevant to improved cassava variety upon their preferences. We used factor analysis, employing a Varimax factor rotation. Kaiser–Meyer–Olkin (KMO) tests indicated that the rates of the traits were free from multicollinearity and were suitable for factor analysis (i.e., KMO > 0.6). The results of the factor analysis showed two factors with an eigenvalue greater than one. The research considered two additional factors with an eigenvalue greater than 0.7.

The research found that each factor has its unique characteristics. Factor 1, resilience trait, includes traits required during the farming stage. Factor 2, marketability trait, indicates attributes primarily essential in the market. Factor 3, cooking quality, represents traits closely related to the

consumption stage. The fourth factor was excluded as it was out of the current study's interest. Table 1 shows the factor loadings for the three factors.

[Insert Table 1 here]

Based on the factor analysis results, this research constructed three typologies of ICV traits. These indicate three different trait characteristics: resilience, marketability, and cooking quality. Then, each typology consists of three individual traits. The individual traits are primarily assigned with each factor, mostly following the factor analysis results. Meanwhile, the CMS data about farmer adoption does not contain all ICV traits covered in factor analysis. For instance, there is no data about adoption with traits related to the resilience factor (i.e., responsiveness to fertilizers, herbicide ready, and compatibility with mechanization). Thus, we assigned the drought resilience trait to the resilience in addition to the pest trait and disease trait.

Therefore, individual trait assignments to the typologies are as follows: The resilience trait has pest trait, disease trait, and drought trait. The marketability trait has a high yield trait, early maturity trait, and big tuber size trait. The cooking quality trait consists of good pounding ability trait, good taste of Gary trait, and good taste of fufu trait. Upon the typologies, we also define aggregated traits. The aggregated traits are the traits with common characteristics that their individual traits have,

Figure 1 provides a conceptual model of improved cassava variety and a relation diagram of the traits upon typologies identified. Based on these traits, this research sets our dependent variable of interest as improved variety adoption rate and trait adoption rate of each household that adopted improved variety. It includes two levels of trait adoption rate: aggregated trait adoption rate and individual trait adoption rate. Thus, our multi-dependent variable set consists of improved

variety adoption rate, three aggregated trait adoption rates, and nine individual trait adoption rates. And all these variables are constructed at the household level.

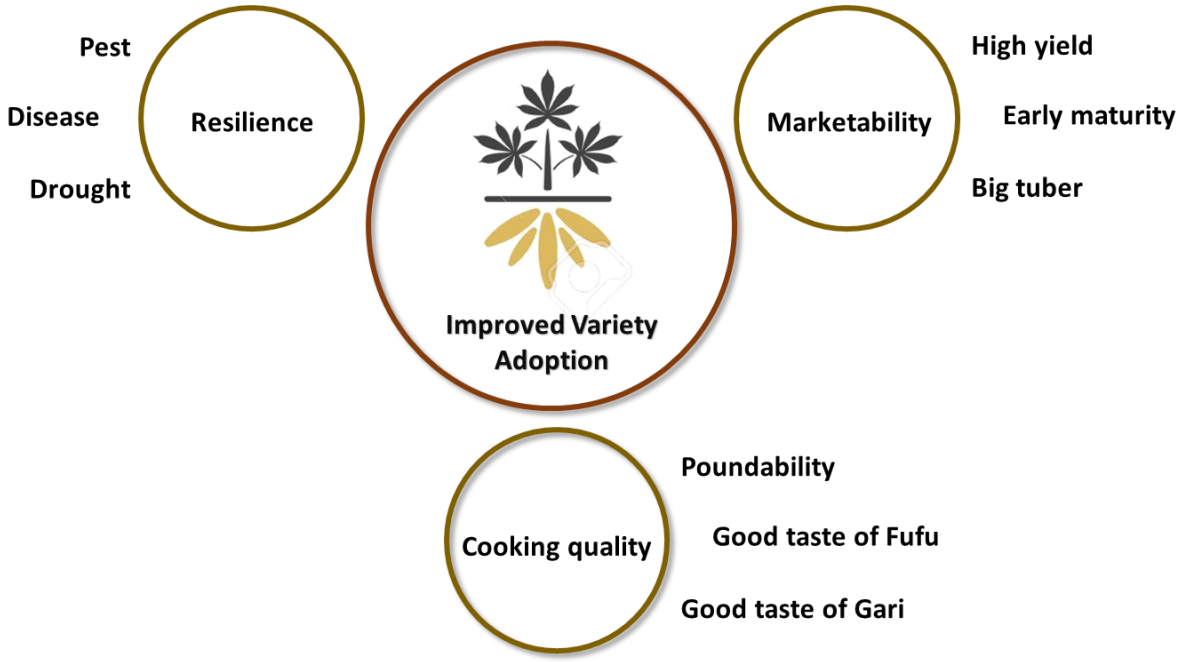

Figure 1. Traits of Improved Cassava Variety

Measuring Improved Variety Adoption Rate

To measure improved variety adoption, the current study uses data from the Cassava Monitoring Study (CMS), which contains each household's farming area for improved variety as well as the total area planted to cassava cultivation. The total area data in particular contains summation of local cassava variety's area and improved variety's area. The improved variety adoption rate is calculated by dividing the area for improved variety adopted by the total area planted to cassava, ranging from zero to 100.

(2) Improved Variety Adoption Rate $= \frac{Area\ for\ improved\ variety\ adopted}{Total\ area\ for\ cassava} \times 100$ *(%)*

To calculate the trait adoption rate, we first measure each adoption rate of the nine individual traits that were selected from above. The CMS questionnaire asked the households to select three traits that they liked the most about the improved cassava variety they adopted. They were asked to select from production traits, processing traits, and consumption traits each (Wossen et al., 2017). This gives the individual trait adoption information under improved variety cultivation. Dividing the area for individual trait adopted by the total area for cassava gives an individual trait adoption rate for every nine individual traits as indicated below.

(3) Individual Trait Adoption Rate $= \frac{Area\ for\ individual\ trait\ adopted}{Total\ area\ for\ cassava} \times 100$ *(%)*

To measure the aggregated trait adoption rate, we add up the adoption of improved varieties with traits associated with a specific aggregated trait as shown in figure 1. For example, adoption of varieties with high cooking quality is calculated as the adoption rate of all varieties with cooking quality related traits, divided by the total area planted to cassava. The research constructed three aggregated trait adoption rates (Figure 1), using the area under aggregated trait adoption and total area for cassava. Mathematically,

(4) Aggregated Trait Adoption Rate $= \frac{\text{Area for aggregated trait adopted}}{\text{Total area for cassava}} \times 100$ (%)

Tobit and Seemingly Unrelated Regression models

To study farmers' behavior on trait adoption, the current study employs the Tobit model because it captures both whether to adopt improved varieties or a particular trait or not and the rate (or percent) of the adoption. The Tobit regression of trait adoption is specified as a function of

these variables as:

(5) $Y_i^* = X_i\beta + \mu_i, \quad Y_i = \max(0, Y_i^*)$

where Y_i^* denotes adoption rate of an i-th farmer who grew cassava, X_i is the matrix of regressors, β is the vector of the estimable parameters for each independent variables, and μ_i is a normally and independently distributed error term with zero mean and has constant variance σ^2. Also, the regression equation shows $y^*{}_i$ is observable only when it is greater than zero, which means the threshold of the Tobit model is zero.

To examine the adoption of traits with different characteristics, we run Tobit regression on three levels of adoption. First, it runs a Tobit regression on aggregated improved cassava variety adoption rate, enabling us to examine the factor that affect adoption of improved varieties. Then, the research runs the model for three grouped traits aggregated based on the factor analysis's results (resilience, marketability, and cooking quality). The results of aggregated trait adoptions show more precise effects of explanatory variables to better understand cassava farmers' trait adoption behaviors. To examine the determinants of adoption more precisely, the research evaluates the effect of the explanatory variables on each of nine individual traits that consist of one of three aggregated traits, using the Tobit model.

There is no firm economic theory that instructs the choices of independent variables in adoption studies. However, the adoption literature suggests that farmers' decision to adopt an agricultural technology depends on economic factors and the institutional environment (Feleke & Zegeye, 2006). Hence, the choice of explanatory variables in this study is based on a review of past adoption studies. A farmer's socio-economic characteristics that influence adoption include region, gender, age, years of education, and percentage of cassava production used for home

consumption. Additionally, distance to the main markets and the price difference between improved traditional varieties are included as explanatory variables. A farmer's institutional environment is characterized by the number of extension services contacts, group membership participation, and accessibility to credit.

Furthermore, this research employs the Seemingly Unrelated (SUR) model to consider the possibility that error terms of each trait adoption regression are correlated. This approach enables us to accommodate farmer's decisions to choose a single or a combination of varieties simultaneously. The formulation of the SUR model is as:

$$(6)\ \begin{cases} Y_1 = X\beta_1 + \varepsilon_1, \\ \quad\vdots \\ Y_m = X\beta_m + \varepsilon_m \end{cases}, \text{ m = 1, ..., M}$$

where a matrix of regressors is identical to (4) of the Tobit model. It is assumed that the error terms for different traits, ε_n and ε_m, may be correlated. Two SUR regressions are employed in this research. The first SUR is on the three aggregated trait adoption rates and is formulated as:

$$(7)\ \begin{cases} Y_{Production} = X_{Production}\beta_{Production} + \varepsilon_{Production} \\ Y_{Marketablility} = X_{Marketability}\beta_{Marketability} + \varepsilon_{Marketability} \\ Y_{Cooking-quality} = X_{Cooking-quality}\beta_{Cooking-quality} + \varepsilon_{Cooking-quality} \end{cases}$$

Then, the second SUR consists of nine equations having nine individual trait adoption rates as dependent variables having m = 9.

Data and Sampling Procedures

Our cross-sectional data comes from the Cassava Monitoring Survey (CMS) conducted between June and September 2015 in Nigeria (Wossen et al., 2017). Nigeria is the largest cassava-

producing country in the world, with $1.46 million of export value, making up 19.4% of global production (FAO, 2009–2019). The cassava yields in Nigeria increased by 43% in the last decade, and the area of land used to cultivate cassava almost doubled. The IITA developed a CMS questionnaire to assess the comprehensive adoption status of improved cassava varieties among Nigerian cassava farms.

The subjects were Nigerian cassava-producing households from 16 major cassava-growing states, covering 80% of the total cassava production in Nigeria. These 16 states are stratified across four geopolitical regions: Southeast, South-South, Southwest, and North, and the distribution of the states is provided in Figure 1. The respondents consisted of owners of both large and small farms in order to achieve data randomization (Wossen et al., 2017).

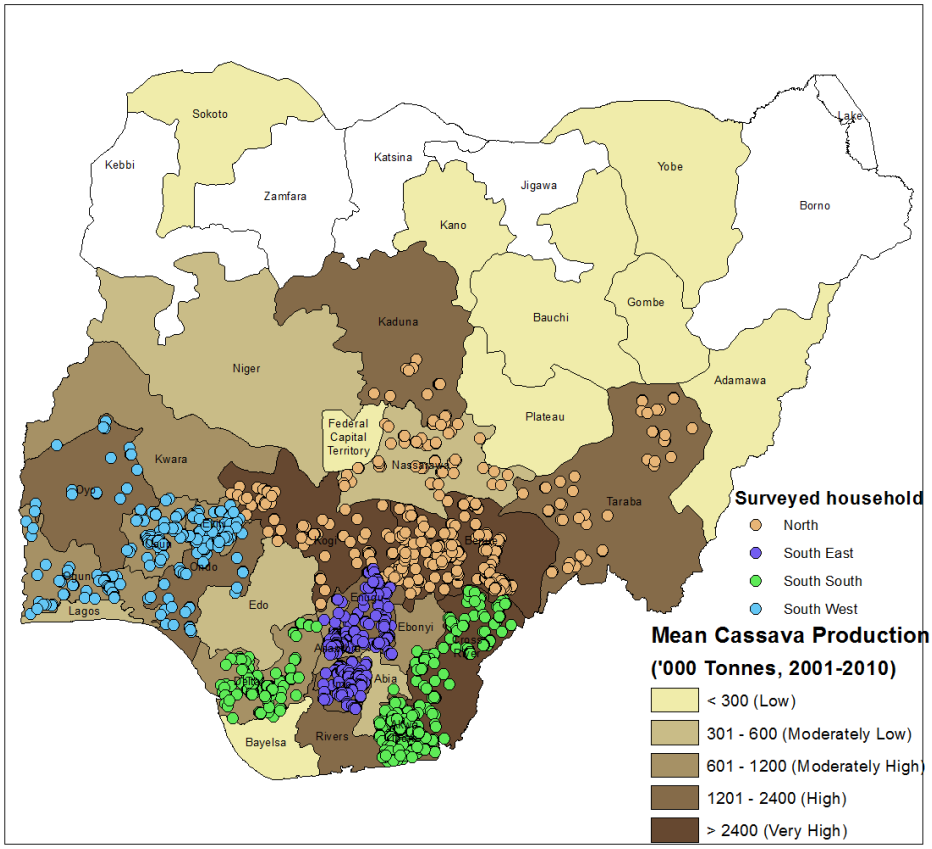

Figure 2. CMS Study Areas

A stratified multistage random sampling approach was adopted for the survey. The IITA randomly selected 125 villages from each region based on the list of villages provided by the National Population Commission of Nigeria (NPCN). From each village, it chose 50 cassava-growing households at random. Of these 50 households, five heads of household were randomly selected for the survey. Thus, the data contained the responses of 625 households per region and a total of 2500 randomly selected households. Of the 2500 households, 1087 reported that they were adopting improved varieties. The information of respondents was anonymized (Wossen, Girma, et al., 2017).

Descriptive Statistics

Using the data collected via the approach described above, the current study examines the effects of determinants on the adoption of each improved variety trait. Also, to compare the adoption of each trait with those of the other traits, we examined total improved variety adoption, aggregated trait adoption, and individual trait adoption. Thus, this study expands the findings on improved variety adoption to three different aggregated trait adoptions and nine individual trait adoptions as dependent variables. Table 2 provides descriptive statistics of the dependent variables. All variables are constructed as household-level data.

[Insert Table 2 here]

The construction of the adoption rates was based on the farmers' responses to the survey. This study also examined farmer trait adoption based on the cassava variety used, matching each variety to its traits. The specific explanations and model results are presented in the Appendix.

Table 3 presents summary statistics of the regressors employed in this paper. Two broad

categories—the socio-economic factors and the institutional factors—have been selected to explain farmers' decisions regarding ICV traits. The choice of these explanatory variables is primarily based on the literature (Doss, 2006; Mwangi & Kariuki, 2015) and studies with similar justifications (Otieno et al., 2011; Rahman & Chima, 2016; Wossen et al., 2017).

[Insert Table 3 here]

Of the 1087 households whose heads responded to questionnaires related to this entire research, 27% were located in the North, 34% in the Southwest region, 15% in the Southeast region, and 25% in the South-South region. Table 3 indicates that almost 92% of the households had male heads, with an average age of 50.82 years and 9 years of education. On average, the size of the households (counting individuals over 12) was four.

The table also shows that approximately 34.8% of households used cassava production for home consumption purposes instead of selling the product in the market or using it in other way. Table 3 shows that, per 10 pounds of weight, the price of the improved cassava variety was 0.36 naira higher than that of the local (traditional) variety, and households were located approximately 11.1 miles from the main market. On average, households had contacted extension agents at least two times in the yar and are member of two farmer groups and associations on average during the year before the survey was conducted. Only 44% of households stated that had access to credit.

IV. Results

This chapter presents the results of the Tobit model. To understand farmers' decisions regarding ICV traits, the effects of the determinants of ICV adoption, three aggregated trait adoptions, and nine individual adoptions are identified (see Figure 1). Since the magnitude of the parameter estimates does not precisely reflect the correct regression coefficients for observed adopters, this chapter also presents the decomposed results of the Tobit regression on the marginal effects of trait adoption (McDonald & Moffitt, 1980).[1]

Adoption of Improved Varieties

Table 4 presents the estimates of the Tobit model in column 2 and the marginal effects in column 3. The Tobit parameter estimates showed that households in the Southwest and Southeast are expected to adopt ICVs in a greater percentage of the area than households in the North. Also, cassava usage for home consumption can be expected to decrease the likelihood of ICV adoption. With regard to institutional and policy factors, Extension Agency shows a statistically significant effect. Frequent contact with extension agencies is associated with the increase in ratio of land usage of ICVs to that used for total cassava cultivation, consistent with previous literature. However, credit accessibility has a negative effect on improved variety adoption, in contrast with the results of previous studies.

[Insert Table 4 here]

[1] The Tobit and decomposed results for the adoption of aggregated traits and individual traits based on cassava varieties are presented in Tables A1 to A4 in the Appendix.

Among marginal effects of Tobit estimation, marginal effects conditional on being uncensored are nearly identical to the Tobit estimates in size and significance. Column 3 shows that households in the Southwest and Southeast are expected to adopt ICVs by 19.49 and 8.43 percent more households in the North. A 10 percent increase in cassava usage for home consumption decreases the percentage of the improved variety on the land by 2.40 percent. A unit increase in Extension Agency is likely to increase ICV adoption by 0.235 percent, while farmers who have credit access have an ICV adoption rate that is 5.24 percent less than those of farmers who lack credit availability.

Adoption of Aggregated Traits

This section presents the estimation results from the Tobit and the decomposed results in Table 5. Given that the SUR model results are very close to those from the Tobit model, from here on, this section only discusses the results from the Tobit model. Table 5 shows that several variables' (e.g., South-South, age, size of household, association membership) coefficients in resilience trait adoption are statistically significant in the Tobit model for aggregated trait adoption. However, these variables are not significant in the improved cassava variety adoption analysis. This difference in significance indicates that the Tobit regression on the adoption of trait groups (i.e., resilience, marketability, cooking quality) captures underlying effects, which may be masked or offset in the error terms of the improved variety adoption models.

[Insert Table 5 here]

Turning to the specific estimation results of the Tobit model for aggregated trait adoption, Table 5 shows that a number of socio-economic factors and institutional and policy factors have

statistically significant effects on each aggregated trait adoption rate. Column (2) shows the results for the resilience traits. Households in the Southwest, Southeast, and South-South are likely to decrease their adoption rate compared to households in the North. The head of household's age has a positive effect on the resilience trait adoption rate. Results also indicate that household size and home consumption ratio are negatively correlated with adoption of resilience traits, while the households' social participation in associations is statistically significant and positively associates with higher rate of adoption for resilience trait.

The marketability trait and the cooking quality trait show similar parameter estimates in terms of statistical significance and signs of the estimates. Results are shown in columns (3) and (4) of Table 5. The effects of living in the southwest and southeast on the adoption of both traits are positive and statistically significant. The cassava home consumption ratio has a significant and negative effect on adoption of ICVs with both marketability and cooking quality traits. Among institutional and policy factors, the frequency of contact with extension agencies is positive and statistically- significant in the adoption of marketability traits. Finally, access to credit is negatively associated with the adoption of cooking quality traits.

The marginal effects are presents in columns (5), (6) and (7), Table 5. The results exhibit large heterogeneous regional differences, and the direction of the region effects differs upon the characteristics of traits. Some institutional and policy factors are statistically significant. A one unit increase in belonging to an association increases the adoption of resilience traits by 1.39 percent. A one unit increase in the number of contacts with extension services would increase the adoption of marketability traits and cooking quality traits by 0.25 and 0.23 percent, respectively. On the other hand, credit availability would significantly decrease the likelihood of adoption of ICVs with

cooking quality traits. Moreover, one unit increase in household size would decrease the adoption of resilience traits by 1.17%, which is contrary to previous findings in ICV adoption studies.

Adoption of Individual Traits

This section presents the estimation results of the individual trait adoption rates from the Tobit model and marginal effects (Tables 6,7,8). Each table presents the estimated parameters from the Tobit model and marginal effects in the same format as in Table 5. Similar to what was done for the aggregated trait adoption evaluation and since the SUR model results are very close to those from the Tobit model, this section will only discuss the Tobit model results with the same variables.

Resilience Traits

Table 6 presents the results for individual traits associated with resilience. Results suggest that several socio-economic factors and institutional and policy factors significantly affect adoption rates of these traits. Results show that adoption of ICVs with pest traits is negatively affected by living in the southwest region instead of the north region. Likewise, the disease trait adoption is negatively affected by living in the Southwest and Southeast regions. Living in the Southwest, Southeast, and South-South has negative effects on the drought-resilient trait adoption. Household size can be expected to influence disease and drought trait adoption negatively. The home consumption ratio is likely to decrease the adoption of the drought trait. The adoption rate of the pest trait is negatively affected by credit availability, and association membership positively affects drought trait adoption.

[Insert Table 6 here]

In columns (5), (6), and (7) of Table 6, the marginal effect of Tobit estimates is presented. The results show the large heterogeneous effects of regional differences, and the direction of the effects differs based on the characteristics of the traits. Living in the North increases the adoption of all resilience traits compared to the other three regions, and this effect is statistically significant. The regional effects on the drought trait adoption are greater than pest and disease trait adoptions. Household size is expected to decrease the disease and drought trait adoption rates by 0.67 percent and 0.59 percent, respectively. A 10% increase in the home consumption ratio negatively influences the drought trait adoption rate by 0.96 percent. Households' social group participation significantly affects drought trait adoption, increasing adoption rate by 0.99 percent. Credit availability is only significant for the adoption of the pest trait and decreases the rate by 1.53 percent.

The effects of regional differences on the aggregated resilience trait are averse to the effects of ICV adoption and the other two aggregated trait adoptions. When it comes to individual trait adoptions, signs of the regional effects follow the aggregated traits' results. However, living in the Southeast is not significant for pest trait adoption. Similarly, the South-South region is not significant for pest or disease trait adoption. Household size is negatively significant for resilience, disease, and drought traits. The home consumption ratio also has a significant negative effect on the resilience trait and can be expected to decrease drought trait adoption. Association membership positively affects the aggregated trait adoption and the drought trait adoption. Credit access, which is negative for ICV adoption and insignificant for resilience trait adoption, is likely to decrease pest trait adoption.

Marketability Traits

Tobit results for the individual marketability trait adoption are presented in Table 7. The marketability trait adoption is significantly affected by most regional differences. Living in the Southwest will likely increase the adoption rates of high-yield and early maturity traits, and living in the Southeast is more likely to affect the adoption of high-yield and big tuber traits compared to living in the North. Living in the South-South is expected to be positive for the high-yield trait and negative for the early maturity trait. Households with male heads are significantly positive for the big tuber trait. The home consumption ratio has a negative effect on high-yield and early maturity trait adoption. Increases in extension agency contact and association membership are positive and significant for the early maturity trait and big tuber trait, respectively, and the effect of credit is negative for the early maturity trait.

[Insert Table 7 here]

Table 7 also shows the decomposed results of Tobit regression for individual marketability traits. According to the results, if farmers live in the Southwest, they are likely to increase their adoption of high-yield and early maturity traits by 5.35 percent and 11.76 percent, respectively, compared to those living in the North. Households in the Southeast seem to adopt 16.54 percent and 15.18 percent more high-yield and big tuber traits, respectively, than households in the North. Compared to living in the North, living in the South-South has a positive effect on the adoption of high-yield traits but a negative effect on the adoption of the early maturity trait with estimated effects of 10.13 percent and -8.27 percent, respectively. Households with male heads are 8.03 percent more likely to adopt the big tuber trait than those with female heads. The high-yield and

early maturity trait adoption rates decrease by 1.14 percent and 2.67%, respectively, with every 10 percent increase in the home consumption rate. A unit increase in frequency of contact with extension agencies increases the adoption rate of the high-yield trait by 0.31 percent. Additionally, a unit increase in the number of association memberships is expected to increase the big tuber trait adoption rate by 1.86 percent. Credit availability will decrease the early maturity adoption rate by 5.54 percent. Household size positively affects high-yield adoption by 0.93 percent, and this is consistent with other adoption research results.

A number of variables are not statistically significant for aggregated trait adoption but are statistically significant for individual trait adoption. With regard to regional variables, the Southwest and Southeast were statistically significant and positive for the aggregated marketability trait adoption. At the individual trait level, most of the regional effects, which are statistically significant, follow the ICV adoption and the aggregated adoption. Compared to these trends, the effect of living in the South-South is negative for early maturity trait adoption. The presence of male heads of households, which is not statistically significant for ICV and aggregated adoption, favors big tuber trait adoption. Households that use their produced cassava for private purposes are likely to decrease high-yield and early maturity traits, the adoption of ICV, and marketability trait adoption. Frequency of contact with extension agencies has a positive effect on high-yield trait adoption, which is identical to its effect on ICV adoption. However, the number of group memberships and credit accessibility, which are not statistically significant for ICV and aggregated adoption, are positive and negative for the big tuber and high-yield traits, respectively.

Cooking Quality Traits

Tobit results of individual trait adoption for cooking quality traits are shown in Table 8. Living in the Southwest instead of the North is statistically significant for all three individual traits. However, the effect is negative for the poundability trait, which is different from those for the other two traits. Living in the Southeast instead of the North has a statistically significant and positive effect on the poundability trait and a negative effect on the gari taste trait. Households in the South-South, compared to those in the North, are less likely to adopt the poundability trait. The home consumption ratio has a statistically significant and negative effect on the fufu and gari taste traits, respectively. Distance to the market has a statistically significant and negative effect on the fufu taste trait. The extension service has a negative influence on poundability trait adoption and a positive effect on gari taste. Credit access is expected to negatively affect fufu and gari taste traits.

[Insert Table 8 here]

For the cooking quality-related traits, the directions of some trait coefficients are not consistent. Overall signs of the effect for poundability trait adoption are averse to adoptions of other traits or the aggregated trait. Columns (5), (6), and (7) of Table 8 show the difference with other trait adoption more closely by presenting the marginal effects of the Tobit estimates. Poundability trait adoption rate is the highest in the Southeast, and the difference in adoption rate compared to the North is 14.23 percent and around 20 percent compared to the Southwest and Southeast. If 10 percent of the home consumption ratio is increased, the effects of home consumption ratio on the intensity of trait adoptions for fufu and gari taste will be -1.32 percent and -1.55 percent, respectively. For every 10-mile increase in distance to the main market, the trait adoption rate of fufu taste decreases by 1.54 percent. For every unit increase in the number of extension agency contact, the poundability trait adoption rate will likely be decreased by -0.26

percent, and that of gari taste will be increased by 0.25 percent. Credit access is expected to negatively influence the adoption rate of fufu and gari taste traits by 5.42 percent and 5.12 percent, respectively.

Compared to the aggregated cooking quality trait adoption and ICV adoption, Table 8 shows the difference in significance level for coefficients of cooking quality-related traits. Moreover, the signs of the likelihood and marginal effects are not identical to all three traits, and this becomes very clear in the regional differences. When the poundability trait is negatively affected by regional variables, the regional differences between the Southwest and South-South are positive or statistically insignificant to the other two individual traits. Likewise, living in the Southeast has positive effects on poundability trait adoption but negatively influences the gari taste trait. The home consumption ratio, which is statistically significant and negative for cooking quality adoption, also has a statistically significant and negative effect on the taste of fufu and gari, respectively. While distance to market was not statistically significant for aggregated adoption, it has a statistically significant and negative effect on the taste of fufu. The use of extension services, which was expected to positively affect aggregated adoption, has a negative effect on poundability and a positive effect on gari taste. In addition, credit access, which was not statistically significant in the cooking quality trait adoption, is expected to negatively affect fufu and gari tastes, in line with the ICV adoption results.

V. Discussion and Conclusion

This study used Tobit models to examine the determinants of farmer adoption of improved cassava varieties (ICVs) with different traits in Nigeria. Since the determinants of the adoption of ICV traits have not been examined in previous studies, the results will be valuable for both researchers and policymakers. The study revealed significant differences in the determinants of adoption across traits.

Significant differences were evident in the aggregate and trait adoption of ICVs across regions. In addition, adoption of ICVs with resilience traits correlated with the household head's age. Among institutional and policy factors, frequency of contact with extension agencies had positive effects on ICV adoption and the adoption of ICVs with marketability and cooking quality traits. Households' social group participation, indicated as an Association variable, was significant and had a positive effect on the adoption of the resilience trait.

The study examined the effect of the portion of cassava that is produced for home consumption. The consumption ratio showed a negative correlation with ICV and overall trait adoption. This result may have occurred because households are not linked to the market, they are more remote, they have less access to different varieties, or they prefer the local variety. As Bonabana-Wabbi (2002) suggested, cassava production for household consumption is likely to decrease ICV adoption; the results of our research corroborate this finding: The more cassava is produced for household consumption, the less farmers are likely to adopt ICVs. Therefore, our results indicate that the purposes of cassava after cultivation are critical for future research and policymaking.

Some of our results differ from those of previous adoption studies. We find that access to credit is negatively correlated with total ICV adoption and with the adoption of ICVs with good cooking quality traits. The results indicate that having credit access also has negative effects on individual trait adoption (e.g., pests, early maturity, the taste of gari, the taste of fufu). This is surprising because previous studies reported a positive relationship between credit availability and ICV adoption (Doss, 2006). Similarly, the present results indicate that household size has a negative effect on the adoption of ICVs with resilience-related traits. Previous literature found that larger households have more labor ability, which correlates with the ability to adopt new technologies, including ICVs. Thus, the literature generally reports positive effects of household size on ICV adoption.

Not surprisingly, the adoption of ICVs with resilience and marketability traits had similar effects to the adoption of ICVs with these trait components considered individually. However, determinants of the adoption of ICVs with individual cooking quality traits tend to vary. For example, the adoption of ICVs with traits for taste of gari and fufu (poundability) was higher (lower) in the Southwest compared with the North. In contrast, the adoption of ICVs with poundability (taste of gari) traits was higher (lower) in the Southwest compared with the North. In addition, the availability of extension services likely increases the adoption of ICVs with a good taste of gari. Unlike the other traits, the variation among individual cooking quality traits was relatively large. This was more evident in terms of regional differences.

This study contributes to the literature by providing insights into farmers' decisions on the adoption of ICVs with a variety of traits in Nigeria. The results suggest common and different aspects of farmers' decision making on the adoption of different trait characteristics. The first main

policy implication of this study is that in an effort to develop new improved cassava varieties, it is important to be aware that farmer trait adoption is not always the same as total ICV adoption, and it varies across traits.

As a second policy implication, studying the farmers' adoption of ICVs with specific traits can help policymakers design the right policies to facilitate a rapid increase in the adoption of improved varieties. Understanding farmers' determinants of adoption for ICVs with specific traits can inform decision makers' choices (e.g., in breeding programs) when it comes to selecting the right combination of varietal attributes to focus on. To be specific, a farmer's geographical location and trait adoption are highly correlated, and the regional effects vary across ICV traits. This suggests that future policy should consider regional differences when developing ICVs. In addition, the size of households is likely to increase the adoption of high-yield traits and decrease the adoption of resilience trait characteristics. Extension services were found to have a positive effect on the adoption of most traits but a negative effect on poundability trait adoption. Therefore, when designing new ICVs, extension services should consider the heterogeneous preferences for traits across farmers.

The third policy implication relates to the importance of farmers' consumption preferences on the adoption of ICVs with specific traits. The more households produce cassava for their home consumption, the less they tend to adopt ICVs and new varietal traits. This can enhance their production mass or the overall quality of their cassava. Here, that cassava farming contributes to households' food security and nutrition in developing countries seems to contradict the finding that cassava for home consumption purposes has a negative relationship with the adoption of ICVs

targeting quality traits. Still, research examining these important issues is lacking. Further research on this topic would help elucidate how to increase the adoption of ICVs.

Finally, the negative correlation found between adoption of certain traits and household size and between adoption of certain traits and credit availability have important implications for future research. Previous studies have shown that household size and credit access increase the adoption of agricultural technologies (Doss, 2006). This study found the contrary. Analyzing this contradictory finding warrants further research because the CMS only provides cross-sectional data for 2015. Thus, future research should use panel data approaches to further examine the impact of these two variables on ICV adoption.

APPENDIX

The research in the appendix aims to elucidate farmers' decision making on improved cassava variety (ICV) traits. The specific purpose in this work as a whole was to examine determinants of trait adoption with trait information given by each ICV. In other words, this research tried to identify the name of the ICV first, followed by traits of the ICV. However, most CMS respondents did not correctly remember the names of the varieties they were cultivating. Bentley et al. (2017)'s report offered information about the names of ICVs adopted by households in Nigeria and the traits that each of the ICVs includes. The information about the ICV's name and traits was collected based on four regions—the North, Southwest, Southeast, and South-South. Based on this information, this research assumed that if a specific variety were adopted, the traits involved in the variety would also be adopted.

While the main chapter used trait adoption information answered by each household, the current research uses information collected on a regional basis. Therefore, there are two primary limitations in the study in this appendix compared with the main chapter. First, there is a possibility of endogeneity in regional variables. Since the data used in the appendix are initially constructed based on regions, trait information given by variety may naturally reflect regional characteristics. When considering trait adoption data, regression with regional variables can cause endogeneity issues. The second primary limitation is distortion in sampling. The data based on regional responses did not entirely cover the 2,500 samples. It is because a limited number of households remember the correct name of ICVs that they chose. Only 45 varieties and 714 households that

adopt these ICVs were identified. Therefore, whether these partial samples can represent the whole sample should be carefully considered.

The empirical model of this appendix uses the trait adoption data of these 714 households among the full sample of 2,500 households. Based on this data, we use the same methodology adopted in the main research. Following the results of factor analysis done in the main chapter (see Table 1 and Figure 2), it calculates the percentage of land planted with ICVs and their traits. The approach to constructing the land ratio planted with ICVs and the traits used is also identical to that used in the main study above (see Measuring improved variety adoption rate in Chapter 3). The results of the calculation indicate adoption rates of three grouped traits (resilience, marketability, and cooking quality) and nine individual traits (pest, disease, drought, high yield, early maturity, big tuber size, poundability, good taste of gari, and good taste of fufu). Using the Tobit model, this appendix runs regressions on two levels of trait adoption—aggregated and individual traits. Moreover, the Seemingly Unrelated Regression (SUR) model was run to check the multi-correlation between trait adoption variables.

The Tobit estimation results of this appendix are presented in Table A1 to Table A4. Since the Tobit and SUR model results show that each estimate has identical signs, the four tables only contain the Tobit results. Furthermore, the study estimated marginal effects of Tobit results then presented the marginal effects in the rate of trait adoption. The Tobit results for most regional variables and home consumption ratio showed identical signs to those of the main chapter's results (see Table 5,6,7,8). However, in several trait adoptions, household size is positively correlated with trait adoption if it is statistically significant. Moreover, the price difference, which was not significant in the main study, was found to be significant in many trait adoptions, which implies that the

likelihood of trait adoption will rise if the cassava price of ICVs is higher than that of traditional cassava.

Table A- 1. Tobit Estimation Results for Aggregated Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Resilience Trait	**Marketability Trait**	**Cooking-quality Trait**	**Resilience Trait**	**Marketability Trait**	**Cooking-quality Trait**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	-6.476	0.671***	0.367***	-0.944***	0.563***	0.303***
	(105.628)	(0.107)	(0.111)	(0.060)	(0.089)	(0.091)
Southeast	-1.861***	0.745***	-0.970***	-0.863***	0.630***	-0.622***
	(0.195)	(0.147)	(0.169)	(0.068)	(0.127)	(0.097)
South-South	-0.845***	0.346***	0.116	-0.549***	0.278***	0.093
	(0.131)	(0.127)	(0.133)	(0.079)	(0.104)	(0.106)
Male	-0.103	0.085	0.295*	-0.037	0.072	0.228*
	(0.184)	(0.162)	(0.175)	(0.067)	(0.138)	(0.135)
Age	-0.001	-0.006	-0.010***	-0.000	-0.005	-0.008***
	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Edu	0.006	0.001	-0.014	0.002	0.001	-0.011
	(0.011)	(0.009)	(0.010)	(0.004)	(0.008)	(0.007)
Size of Household	0.020	0.054***	0.067***	0.007	0.046***	0.052***
	(0.023)	(0.019)	(0.020)	(0.008)	(0.016)	(0.016)
Home Consumption	-0.018	-0.053**	-0.054**	-0.007	-0.046**	-0.042**
	(0.028)	(0.023)	(0.024)	(0.010)	(0.019)	(0.019)
Price Difference	0.063	0.042	0.018	0.023	0.036	0.014
	(0.040)	(0.040)	(0.041)	(0.015)	(0.034)	(0.032)
Distance to Market	0.028	0.020	0.008	0.010	0.017	0.006
	(0.028)	(0.027)	(0.028)	(0.010)	(0.023)	(0.022)
Institutional and policy factors						
Extension Agency	-0.000	0.000	0.002	-0.000	0.000	0.002
	(0.005)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)
Association	0.042	0.049	0.023	0.015	0.041	0.018
	(0.043)	(0.033)	(0.034)	(0.016)	(0.028)	(0.027)
Credit	0.025	0.014	0.032	0.009	0.012	0.025
	(0.117)	(0.092)	(0.097)	(0.042)	(0.078)	(0.075)
Intercept	0.699**	0.754***	1.069***			
	(0.309)	(0.268)	(0.284)			

Notes: N=714, The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table A- 2. Tobit Estimation Results for Individual Resilience Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Pest	**Disease**	**Drought**	**Pest**	**Disease**	**Drought**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	-5.468	-5.432	1.768	-0.937***	-0.903***	0.000
	(97.345)	(97.633)	(779.725)	(0.054)	(0.054)	(0.000)
Southeast	-1.774***	-1.881***	10.017	-0.879***	-0.863***	0.095**
	(0.166)	(0.177)	(191.604)	(0.060)	(0.058)	(0.038)
South-South	-5.594	-5.513	11.639	-0.937***	-0.903***	0.474***
	(126.662)	(130.793)	(191.604)	(0.054)	(0.054)	(0.074)
Male	-0.130	-0.042	0.188	-0.038	-0.012	0.016
	(0.185)	(0.192)	(0.501)	(0.053)	(0.054)	(0.043)
Age	0.004	0.003	-0.007	0.001	0.001	-0.001
	(0.004)	(0.004)	(0.013)	(0.001)	(0.001)	(0.001)
Edu	0.012	0.010	0.037	0.003	0.003	0.003
	(0.010)	(0.011)	(0.032)	(0.003)	(0.003)	(0.003)
Size of Household	-0.012	0.001	0.107	-0.004	0.000	0.009
	(0.022)	(0.022)	(0.067)	(0.006)	(0.006)	(0.006)
Home Consumption	0.019	0.019	-0.062	0.005	0.005	-0.005
	(0.028)	(0.029)	(0.073)	(0.008)	(0.008)	(0.006)
Price Difference	0.099***	0.073*	-0.035	0.029***	0.020*	-0.003
	(0.037)	(0.037)	(0.154)	(0.011)	(0.010)	(0.013)
Distance to Market	-0.049	-0.033	0.074	-0.014	-0.009	0.006
	(0.041)	(0.042)	(0.058)	(0.012)	(0.012)	(0.005)
Institutional and policy factors						
Extension Agency	-0.003	-0.003	0.021	-0.001	-0.001	0.002
	(0.005)	(0.005)	(0.020)	(0.001)	(0.001)	(0.002)
Association	0.020	0.029	0.166	0.006	0.008	0.014
	(0.040)	(0.041)	(0.125)	(0.012)	(0.012)	(0.011)
Credit	0.026	0.071	0.018	0.007	0.020	0.002
	(0.114)	(0.116)	(0.320)	(0.033)	(0.033)	(0.028)
Intercept	0.632**	0.486	-13.064			
	(0.297)	(0.304)	(191.605)			

Notes: N=714 The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table A- 3. Tobit Estimation Results for Individual Marketability Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	High yield	**Early maturity**	**Big tuber**	**High yield**	**Early maturity**	**Big tuber**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	0.450***	0.536***	2.495***	0.357***	0.429***	0.179***
	(0.112)	(0.115)	(0.506)	(0.089)	(0.091)	(0.036)
Southeast	0.746***	0.340**	4.623***	0.616***	0.265**	0.866***
	(0.153)	(0.160)	(0.624)	(0.130)	(0.127)	(0.145)
South-South	0.321**	-0.289**	-7.320	0.251**	-0.201**	-0.014**
	(0.133)	(0.142)	(205.430)	(0.105)	(0.096)	(0.007)
Male	0.047	0.059	0.095	0.038	0.046	0.012
	(0.170)	(0.177)	(0.586)	(0.139)	(0.138)	(0.076)
Age	-0.003	-0.004	-0.017	-0.003	-0.003	-0.002
	(0.004)	(0.004)	(0.012)	(0.003)	(0.003)	(0.002)
Edu	-0.002	0.007	-0.011	-0.001	0.006	-0.001
	(0.009)	(0.010)	(0.031)	(0.008)	(0.008)	(0.004)
Size of Household	0.047**	0.061***	-0.020	0.038**	0.048***	-0.003
	(0.020)	(0.021)	(0.073)	(0.016)	(0.016)	(0.009)
Home Consumption	-0.059**	-0.031	-0.091	-0.048**	-0.024	-0.012
	(0.024)	(0.025)	(0.078)	(0.019)	(0.019)	(0.010)
Price Difference	0.044	0.057	0.307**	0.036	0.045	0.040**
	(0.041)	(0.043)	(0.135)	(0.034)	(0.033)	(0.018)
Distance to Market	-0.006	-0.039	0.059	-0.005	-0.030	0.008
	(0.028)	(0.032)	(0.130)	(0.023)	(0.025)	(0.017)
Institutional and policy factors						
Extension Agency	0.002	0.002	0.009	0.001	0.001	0.001
	(0.005)	(0.005)	(0.020)	(0.004)	(0.004)	(0.003)
Association	0.029	0.012	-0.188*	0.024	0.009	-0.024*
	(0.034)	(0.036)	(0.112)	(0.028)	(0.028)	(0.014)
Credit	0.128	0.042	0.581*	0.104	0.033	0.075*
	(0.096)	(0.100)	(0.308)	(0.078)	(0.077)	(0.040)
Intercept	0.731***	0.627**	-3.295***			
	(0.281)	(0.291)	(1.045)			

Notes: N=714 The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table A- 4. Tobit Estimation Results for Individual Cooking Quality Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Poundability	**Taste of Fufu**	**Taste of Gari**	**Poundability**	**Taste of Fufu**	**Taste of Gari**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	-1.441***	0.157	0.316***	-0.882***	0.126	0.247***
	(0.098)	(0.114)	(0.114)	(0.059)	(0.091)	(0.089)
Southeast	-2.455***	-0.991***	-1.613***	-1.032***	-0.630***	-0.785***
	(0.223)	(0.173)	(0.197)	(0.056)	(0.098)	(0.076)
South-South	-5.892	0.053	-0.035	-1.048***	0.042	-0.025
	(148.560)	(0.136)	(0.137)	(0.055)	(0.107)	(0.101)
Male	0.129	0.325*	0.125	0.050	0.244*	0.087
	(0.179)	(0.179)	(0.182)	(0.070)	(0.135)	(0.127)
Age	0.000	-0.009**	-0.011***	0.000	-0.007**	-0.008***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)
Edu	-0.012	-0.014	-0.013	-0.005	-0.011	-0.009
	(0.009)	(0.010)	(0.010)	(0.004)	(0.007)	(0.007)
Size of Household	0.027	0.064***	0.051**	0.011	0.048***	0.036**
	(0.019)	(0.021)	(0.021)	(0.007)	(0.016)	(0.015)
Home Consumption	-0.018	-0.055**	-0.037	-0.007	-0.041**	-0.026
	(0.025)	(0.025)	(0.026)	(0.010)	(0.019)	(0.018)
Price Difference	0.075**	0.028	-0.017	0.029**	0.021	-0.012
	(0.037)	(0.042)	(0.043)	(0.014)	(0.032)	(0.030)
Distance to Market	-0.017	0.004	0.029	-0.006	0.003	0.020
	(0.036)	(0.029)	(0.029)	(0.014)	(0.022)	(0.020)
Institutional and policy factors						
Extension Agency	-0.001	0.001	-0.004	-0.000	0.001	-0.003
	(0.004)	(0.005)	(0.006)	(0.002)	(0.004)	(0.004)
Association	0.041	0.018	-0.000	0.016	0.013	-0.000
	(0.032)	(0.035)	(0.036)	(0.013)	(0.026)	(0.025)
Credit	-0.067	0.061	0.084	-0.026	0.046	0.058
	(0.094)	(0.099)	(0.101)	(0.037)	(0.074)	(0.070)
Intercept	0.827***	1.020***	1.148***			
	(0.273)	(0.291)	(0.296)			

Notes: N=714 The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

TABLES

Table 1. Defining ICV Trait Factors Based on Farmers' Trait Preferences

Factor	Traits in factor	Factor loadings
Resilience Eigenvalue = 3.250 Reliability α = 0.685	Pest and disease resistance	0.537
	Responsiveness to fertilizers	0.447
	Herbicide ready	0.676
	Compatibility with mechanization	0.501
Marketability Eigenvalue = 1.009 Reliability α = 0.588	High market demand	0.419
	Big root size	0.522
	High root yield	0.551
	Earliness of maturity	0.308
Cooking quality Eigenvalue = 0.653 Reliability α = 0.519	Easiness in pounding	0.428
	Good quality gari	0.433
	Good quality Fufu/Akpu	0.587

Table 2. Descriptive Statistics for Dependent Variables of Tobit Regressions Measuring Adoption Intensities in Nigeria, 2015

N = 1087

Adoption Rate	Mean	Std. Deviation	Min	Max
Improved variety	64.23	32.24	0.00	100.00
Resilience trait (Aggregated)	13.64	27.23	0.00	100.00
Market preference (Aggregated)	59.54	33.77	0.00	100.00
Cooking quality (Aggregated)	58.48	33.81	0.00	100.00
Pest	2.57	12.83	0.00	100.00
Disease	6.65	19.84	0.00	100.00
Drought	5.97	18.94	0.00	100.00
High yield	35.05	35.54	0.00	100.00
Early maturity	38.68	36.57	0.00	100.00
Big tuber	32.58	34.34	0.00	100.00
Poundability	9.85	22.65	0.00	100.00
Good taste of Fufu	38.47	36.84	0.00	100.00
Good taste of Gari	51.52	35.65	0.00	100.00

Table 3. Summary Statistics for Household Characteristics of Tobit Regressions Measuring Adoption Intensities in Nigeria, 2015

N = 1087

Variable	Definition of Variable	Mean	Std. Deviation	Min	Max
Socio-economic factors					
North	North region (1=Yes; 0=No)	0.27	0.44	0	1
Southwest	Southwest region (1=Yes; 0=No)	0.34	0.47	0	1
Southeast	Southeast region (1=Yes; 0=No)	0.15	0.36	0	1
South-South	South-South region (1=Yes; 0=No)	0.25	0.43	0	1
Male	Head of household's Gender (1=Yes; 0=No)	0.92	0.28	0	1
Age	Head of household's age(years)	50.82	13.53	18.00	105.00
Edu	Year of head of household's Education	9.07	5.10	0.00	22
Size of Household	Size of household over 12 years old	4.65	2.36	1.00	16.00
Home Consumption	Ratio of Cassava used for home consumption in 10% scale (100 = sale+home consumption+others)	3.48	1.92	0	10
Price Difference	Price difference between improved and local varieties per 10lb in Naira	0.36	1.75	-5.13	33.92
Distance to Market	Distance to main market (per 10Mile)	1.11	1.61	0.00	14.96
Institutional and policy factors					
Extension Agency	A number of contacts with extension agencies in 2015	2.21	7.35	0	180
Association	Number of groups the household belongs to	2.41	1.42	0	7
Credit	Accessibility (1=Yes; 0=No)	0.44	0.50	0	1

Table 4. Tobit Estimation and Decomposed Results for Improved Cassava Variety Adoption

	Tobit	Marginal Effects Conditional on Being Uncensored
Explanatory Variables	Coefficient (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)
Socio-economic factors		
Southwest	19.873***	19.485***
	(2.520)	(2.459)
Southeast	8.669***	8.427***
	(3.237)	(3.151)
South-South	2.860	2.763
	(2.736)	(2.642)
Male	3.494	3.411
	(3.442)	(3.359)
Age	0.001	0.001
	(0.077)	(0.075)
Edu	0.093	0.091
	(0.198)	(0.193)
Size of Household	0.272	0.265
	(0.430)	(0.420)
Home Consumption	-2.456***	-2.398***
	(0.514)	(0.501)
Price Difference	0.815	0.796
	(0.540)	(0.527)
Distance to Market	0.071	0.069
	(0.578)	(0.564)
Institutional and policy factors		
Extension Agency	0.240*	0.235*
	(0.130)	(0.127)
Association	1.184	1.156
	(0.739)	(0.721)
Credit	-5.371***	-5.244***
	(2.038)	(1.988)
Intercept	57.238***	
	(5.858)	

Notes: N = 1087, The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table 5. Tobit Estimation Results for Aggregated Trait Adoptions

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Resilience Trait	**Marketability Trait**	**Cooking-quality Trait**	**Resilience Trait**	**Marketability Trait**	**Cooking-quality Trait**
Explanatory Variables (1)	Coefficient (Std. Err) (2)	Coefficient (Std. Err) (3)	Coefficient (Std. Err) (4)	dF/dx (Std. Err) (5)	dF/dx (Std. Err) (6)	dF/dx (Std. Err) (7)
Socio-economic factors						
Southwest	-57.167***	14.082***	17.953***	-16.985***	13.463***	17.128***
	(7.653)	(2.828)	(2.832)	(2.419)	(2.692)	(2.685)
Southeast	-55.999***	7.839**	6.605*	-16.782***	7.430**	6.195*
	(10.027)	(3.628)	(3.637)	(2.722)	(3.447)	(3.420)
South-South	-19.783***	1.184	2.276	-7.684***	1.110	2.117
	(7.516)	(3.069)	(3.076)	(2.907)	(2.876)	(2.861)
Male	9.099	3.421	1.325	2.567	3.256	1.255
	(10.000)	(3.863)	(3.868)	(2.823)	(3.676)	(3.664)
Age	0.398*	-0.003	-0.036	0.112*	-0.003	-0.034
	(0.224)	(0.086)	(0.086)	(0.063)	(0.082)	(0.082)
Edu	-0.248	0.027	0.043	-0.070	0.026	0.041
	(0.572)	(0.222)	(0.222)	(0.161)	(0.211)	(0.211)
Size of Household	-4.140***	0.196	-0.190	-1.168***	0.186	-0.180
	(1.268)	(0.483)	(0.485)	(0.359)	(0.460)	(0.460)
Home Consumption	-5.534***	-2.649***	-2.143***	-1.561***	-2.521***	-2.030***
	(1.595)	(0.578)	(0.580)	(0.453)	(0.548)	(0.548)
Price Difference	0.752	0.825	-0.276	0.212	0.786	-0.262
	(1.389)	(0.604)	(0.623)	(0.392)	(0.575)	(0.590)
Distance to Market	-0.662	0.103	0.264	-0.187	0.098	0.250
	(1.704)	(0.650)	(0.651)	(0.481)	(0.619)	(0.616)
Institutional and policy factors						
Extension Agency	0.088	0.266*	0.243*	0.025	0.253*	0.230*
	(0.327)	(0.146)	(0.146)	(0.092)	(0.139)	(0.138)
Association	4.920**	0.783	0.445	1.388**	0.746	0.421
	(2.152)	(0.828)	(0.831)	(0.608)	(0.788)	(0.787)
Credit	0.499	-3.140	-4.232*	0.141	-2.989	-4.009*
	(5.874)	(2.286)	(2.291)	(1.657)	(2.176)	(2.169)
Intercept	-9.996	56.131***	58.608***			
	(16.924)	(6.573)	(6.584)			

Notes: The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table 6. Tobit Estimation Results for Individual Resilience Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Pest	**Disease**	**Drought**	**Pest**	**Disease**	**Drought**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	-76.817***	-48.197***	-65.716***	-4.110***	-6.749***	-9.715***
	(18.011)	(11.211)	(11.884)	(1.067)	(1.691)	(1.902)
Southeast	-24.275	-50.658***	-68.632***	-2.097	-6.951***	-9.924***
	(17.865)	(14.685)	(16.036)	(1.448)	(1.862)	(2.062)
South-South	-23.456	-3.028	-48.247***	-2.043	-0.616	-8.155***
	(15.005)	(10.639)	(12.062)	(1.291)	(2.163)	(2.026)
Male	15.068	8.552	-10.637	0.924	1.215	-1.329
	(21.145)	(14.529)	(14.365)	(1.300)	(2.066)	(1.796)
Age	-0.279	0.470	0.171	-0.017	0.067	0.021
	(0.462)	(0.324)	(0.346)	(0.028)	(0.046)	(0.043)
Edu	0.261	-0.177	-0.620	0.016	-0.025	-0.077
	(1.155)	(0.827)	(0.881)	(0.071)	(0.118)	(0.110)
Size of Household	-0.345	-4.715**	-4.707**	-0.021	-0.670**	-0.588**
	(2.377)	(1.905)	(1.996)	(0.146)	(0.274)	(0.253)
Home Consumption	-3.393	-3.257	-7.672***	-0.208	-0.463	-0.958***
	(3.093)	(2.225)	(2.671)	(0.191)	(0.318)	(0.340)
Price Difference	2.151	-0.170	-1.985	0.132	-0.024	-0.248
	(2.009)	(2.343)	(2.722)	(0.124)	(0.333)	(0.340)
Distance to Market	-3.263	-1.918	1.125	-0.200	-0.273	0.141
	(3.646)	(2.623)	(2.555)	(0.225)	(0.373)	(0.319)
Institutional and policy factors						
Extension Agency	0.339	-0.643	0.256	0.021	-0.091	0.032
	(0.560)	(0.756)	(0.431)	(0.034)	(0.108)	(0.054)
Association	5.252	2.227	7.934**	0.322	0.316	0.991**
	(4.321)	(3.179)	(3.312)	(0.267)	(0.452)	(0.418)
Credit	-25.034**	5.691	2.956	-1.534**	0.809	0.369
	(12.233)	(8.442)	(9.179)	(0.769)	(1.201)	(1.147)
Intercept	-98.531***	-70.355***	-26.869			
	(36.482)	(25.286)	(25.614)			

Notes: The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table 7. Tobit Estimation Results for Individual Marketability Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	High yield	**Early maturity**	**Big tuber**	**High yield**	**Early maturity**	**Big tuber**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	8.432*	15.289***	5.955	5.350*	11.757***	3.716
	(4.420)	(4.012)	(4.387)	(2.791)	(3.058)	(2.727)
Southeast	23.994***	-4.898	22.244***	16.539***	-3.435	15.183***
	(5.560)	(5.240)	(5.530)	(3.931)	(3.650)	(3.870)
South-South	15.358***	-12.275***	6.976	10.130***	-8.270***	4.380
	(4.713)	(4.461)	(4.709)	(3.110)	(2.995)	(2.959)
Male	-4.999	3.284	12.296**	-3.384	2.371	8.033**
	(5.858)	(5.588)	(6.099)	(3.965)	(4.034)	(3.978)
Age	-0.047	-0.051	-0.035	-0.032	-0.037	-0.023
	(0.133)	(0.124)	(0.132)	(0.090)	(0.089)	(0.086)
Edu	0.007	0.173	0.087	0.005	0.125	0.057
	(0.344)	(0.318)	(0.339)	(0.233)	(0.230)	(0.221)
Size of Household	1.372*	0.818	0.706	0.929*	0.591	0.461
	(0.741)	(0.695)	(0.741)	(0.501)	(0.501)	(0.484)
Home Consumption	-1.686*	-3.702***	-1.435	-1.141*	-2.673***	-0.938
	(0.893)	(0.846)	(0.881)	(0.604)	(0.607)	(0.576)
Price Difference	0.954	0.527	0.195	0.646	0.380	0.127
	(0.898)	(0.845)	(0.938)	(0.608)	(0.610)	(0.613)
Distance to Market	-0.685	-1.165	-0.060	-0.464	-0.841	-0.039
	(1.022)	(0.977)	(0.988)	(0.692)	(0.705)	(0.646)
Institutional and policy factors						
Extension Agency	0.459**	0.151	0.254	0.311**	0.109	0.166
	(0.216)	(0.205)	(0.215)	(0.146)	(0.148)	(0.140)
Association	-1.916	0.392	2.847**	-1.297	0.283	1.860**
	(1.272)	(1.188)	(1.263)	(0.860)	(0.857)	(0.824)
Credit	3.781	-7.678**	2.466	2.559	-5.544**	1.611
	(3.527)	(3.297)	(3.507)	(2.386)	(2.377)	(2.291)
Intercept	21.971**	38.047***	-4.190			
	(10.129)	(9.468)	(10.199)			

Notes: The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

Table 8. Tobit Estimation Results for Individual Cooking Quality Trait Adoption

	Tobit			Marginal Effects Conditional on Being Uncensored		
	Poundability	**Taste of Fufu**	**Taste of Gari**	**Poundability**	**Taste of Fufu**	**Taste of Gari**
Explanatory Variables	Coefficient (Std. Err)	Coefficient (Std. Err)	Coefficient (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)	dF/dx (Std. Err)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Socio-economic factors						
Southwest	-33.754***	17.791***	14.205***	-6.818***	12.702***	13.010***
	(7.490)	(4.292)	(3.188)	(1.577)	(3.030)	(2.905)
Southeast	37.060***	8.650	-19.775***	14.225***	5.909	-16.328***
	(8.218)	(5.513)	(4.186)	(3.377)	(3.807)	(3.363)
South-South	-33.777***	5.036	1.077	-6.821***	3.376	0.957
	(8.213)	(4.678)	(3.465)	(1.648)	(3.138)	(3.077)
Male	-9.963	6.160	1.497	-2.270	4.374	1.325
	(9.455)	(5.921)	(4.378)	(2.155)	(4.204)	(3.875)
Age	-0.231	-0.202	-0.041	-0.053	-0.144	-0.037
	(0.227)	(0.130)	(0.098)	(0.052)	(0.092)	(0.086)
Edu	-0.228	-0.018	0.296	-0.052	-0.013	0.262
	(0.567)	(0.339)	(0.252)	(0.129)	(0.241)	(0.223)
Size of Household	1.268	0.285	-0.442	0.289	0.202	-0.391
	(1.230)	(0.730)	(0.549)	(0.280)	(0.518)	(0.486)
Home Consumption	0.226	-1.862**	-1.749***	0.052	-1.322**	-1.548***
	(1.451)	(0.883)	(0.660)	(0.331)	(0.626)	(0.583)
Price Difference	-1.080	-1.692	-0.462	-0.246	-1.202	-0.409
	(1.786)	(1.114)	(0.706)	(0.407)	(0.790)	(0.625)
Distance to Market	2.057	-2.169**	0.467	0.469	-1.540**	0.413
	(1.538)	(1.024)	(0.732)	(0.351)	(0.726)	(0.648)
Institutional and policy factors						
Extension Agency	-1.123*	0.282	0.286*	-0.256*	0.200	0.253*
	(0.638)	(0.216)	(0.164)	(0.146)	(0.153)	(0.145)
Association	-3.093	0.222	-0.319	-0.705	0.158	-0.282
	(2.192)	(1.260)	(0.941)	(0.500)	(0.895)	(0.833)
Credit	6.316	-7.631**	-5.783**	1.439	-5.420**	-5.119**
	(5.938)	(3.471)	(2.596)	(1.354)	(2.462)	(2.296)
Intercept	-16.646	34.778***	55.136***			
	(16.688)	(10.032)	(7.452)			

Notes: The p values are in parentheses (* p <0.1, ** p< 0.05, *** p <0.01). (IITA)

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