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Assessing the extent and determinants of adoption of improved cassava varieties in south-western Nigeria

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This paper investigates the determinants of adoption of improved cassava varieties in south- western Nigeria. The data come from a farm household survey of 841 households selected using a three-stage stratified random sampling procedure. The data collection was conducted in 2011 by the International Institute of Tropical Agriculture (IITA), Ibadan, Nigeria. Empirical estimates of a Double-Hurdle model revealed that adoption increases with the age of the household head and is influenced by the gender of the household head, hired labour, cultivated land, and access to credit. The results further showed that the intensity of adoption is influenced by hired labour and farm size; access to information about the improved cassava varieties is determined by the age, gender, and level of education of the household head, and by off-farm income.

Key words: Adoption, improved cassava, double-hurdle, Nigeria.

INTRODUCTION

Cassava plays key roles in African development as a famine-reserve crop, rural food staple, cash crop for urban consumption, and raw material for livestock and industry (Nweke et al., 2002). Cassava is a staple food for over 200 million people in sub-Saharan Africa and an important food and cash crop in several tropical African countries, especially Nigeria where it plays a principal role in the food economy (Agwu and Anyaeche, 2007). Approximately hundred million Nigerians eat cassava-based foods at least once a day and the per capita consumption exceeds 200 kg/year in the north central, southwest, southeast, and south-south parts of the country (Africa Agriculture News, 2013). Cassava is the most important source of carbohydrates for human consumption in the tropics after maize. The high level of carbohydrates is an advantage in Africa because it makes cassava the cheapest source of food calories (Nweke et al., 2002).In most countries, cassava is becoming an important cash crop that has a high potential for use as an industrial raw material in the manufacture of starch, flour, and many other important products.

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For decades, Nigerian farmers relied solely on the traditional varieties and this reliance generated concern.The limitations of these varieties included a low yield,long maturity period, and high susceptibility to diseases such as Cassava Mosaic Disease(CMD) and brown streak Disease (CBSD). Achieving a substantial increase in cassava productivity which has been one of the major goals of successive Nigerian Governments over several decade require ability to overcome the above limitations.

To accomplish this objective, the government initiated modern research into cassava in 1954. This research led to the development of some improved cassava varieties. Subsequently, the severe attack of the Cassava Bacterial Blight (CBB) the years that followed necessitated a collaboration between the International Institute of Tropical Agriculture (IITA) and its partners that let to the development of resistant improved cassava varities to the CBB (Akoroda et al.,1985). IITA releases the first two IITA clones in 1976, namely TMS 30211 and TMS 30395, which were rapidly followed by TMS 30572, TMS 30001, TMS 300017, TMS 30110, TMS 30337, TMS 30555, TMS 4(2)1425 and others (IITA 1984). Since then, efforts to improve cassava have continually increased such that IITA working with national partners has developed more than forty ICVs in the last forty five years (Eke-Okoro and Njoku, 2012).

In a recent study conducted by Abdoulaye et al (2014) ICVs adopters were observed to have a higher yield of about 16 tons/ha compared with 10 tons/ha for non-adopters. The implication is that the desired increase in productivity due to the ICVs and the subsequent impact on poverty reduction will not be achieved unless the ICVs are widely adopted by the Nigerian farmers. However, evidence from the literature shows that the adoption of ICVs is not yet universal in Nigeria. This implies that some farmers cultivate the improved cassava varieties (adopters) and some do not (non-adopters). Also, the level of adoption among the adopters also varies. This implies that there are some farmers among the adopters that utilized all their available farmland for ICVs whereas others only plant ICVs on a share of their farmland. This raises two pertinent questions: first, why are some cassava farmers adopting ICVs and others are not. Second, why does the intensity or the size of the area of farmland devoted to the cultivation of ICVs vary among the adopters?, third, what is the role of access to information on ICVs adoption in Southwestern Nigeria.

Studies that have attempted to provide answers to the above questions which are needed for future agricultural planning is still very scanty and in particular no recent information on ICVs adoption in the southwest is available. The most recent studies on ICVs adoption was conducted in the 1980s (Ay et al., 1983; Ikpi et al., 1986; Keyser, 1984). Thus, leaving a gap in the literature that this study intends to fill. Therefore, the broad objective of this study is to examine the determinants and intensity of adoption of ICVs in Southwestern Nigeria. Specifically, the study assess the influence of the farmers' socio-economic/demographic characteristics on the decision to adopt the ICVs and also examine the effect of access to information on the adoption of ICVs in Southwestern Nigeria .

Most importantly, in contrast to most adoption studies in Nigeria that adopted either logit, probit or tobit models (Igodan et al., 1988; Saka et al., 2005; Eze et al., 2006; Saka and Lawal, 2009; Junge et al., 2009; Okoedo-Okojie and Onomolease, 2009; Odoemenen and Obinne, 2010; Kudi et al., 2011), we employ a Double-Hurdle model to deal with the two-stage decision process involved in improved agricultural technology adoption and assess the effect of access to information using the Heckman Probit selection model. In order to achieve the stated objectives of this study, we therefore tested the following hypotheses: The extent and determinants of ICVs do not depend on the farmers' socio-economic characteristics and access to information has no significant effect on the adoption of improved cassava varieties in South western Nigeria.

CONCEPTUAL, ANALYTICAL FRAMEWORK AND ESTIMATION TECHNIQUES

Modeling the intensity and determinants of improved cassava varieties adoption

Rogers and Shoemaker (1971) defined adoption as the decision to apply an innovation and to continue using it. According to Wale and Yallew (2007), farmers' decisions about adoption are either discrete (whether or not to take up the technology) or continuous (the intensity of use of the technology). The theory of utility maximization is generally used to explain farmers' responses to new technology (Adesina and Seidi, 1995; Adesina and Baldu-forson, 1995).

According to this theory, a farmer will adopt a given technology such as ICVs if the utility obtained from it exceeds that of the traditional varieties. For instance, if U_{i0} is the utility derived from the use of the traditional cassava variety while U_{i1} is the expected utility from the adoption of ICVs; although not observed directly, the utility that farmer i will derive from adopting a given measure of the ICVs (j) can be expressed as:

$$U_{ij} = X_i \beta_j + \tau_{ij} \qquad j = 1, 0; \quad i = 1, ..., n \tag{1}$$

Where X_i is a farm–specific function, β_j is a parameter to be estimated, τ_{ij} is a disturbance term with mean zero and constant variance. In addition, adoption of any agricultural technology may also be measured by both the timing and extent of utilization by individuals (Sunding and Zilberman, 2001). In this study, a farmer is defined as an adopter if he or she is found to be growing at least one ICV. This implies that an adopter could still be growing the traditional cassava varieties alongside the improved varieties. We defined the adoption variable as a dummy with 1 indicating adoption and 0 otherwise. A farmer would adopt an ICV, that is., j=1 if $U_{i1} > U_{i0}$.

The intensity of adoption is measured by the proportion of farmland devoted to the production of ICVs.The literature suggests several theoretical or conceptual models on farmers' decisions to adopt new technology (Feder and Slade, 1984; Abadi and Panned, 1999; Negatu and Parikh, 1999; Isham, 2002). Many of the numerous studies that assessed the determinants of adoption of improved agricultural technology have utilized the Logit, Probit, or Linear probability models.

The objective of this study goes beyond the determinants of adoption to analyze the intensity of ICV adoption in Nigeria. The Tobit model has been employed by many authors to assess the intensity of agricultural technology adoption (Adesina and Baldu-Forson, 1995; Roos et al., 2000; Alene et al., 2000; Abadi-Ghadim et al., 2005; Jensen et al., 2007). One of the major drawbacks of the Tobit model is the fact that the decisions on whether or not to adopt ICVs and how much to adopt are assumed to be made jointly and hence the factors affecting the two decisions are assumed to be the same. However, it is believed that the adoption process is in two stages; the first stage involves the decision to adopt and the second stage involves the decision on the proportion of the area to be devoted to ICVs. Hence, the explanatory variables in the two stages may differ. Against this backdrop, the use of a single model may be erroneous, since the factors influencing the two-stage decisions will be difficult to analyze using just one model. In this study, we believe that it is likely the decisions on adoption and intensity of adoption of ICVs in southwestern Nigeria may not be made jointly, and the factors affecting each decision may not be the same. Thus we used the double-hurdle model proposed by Cragg (1971) in which the event of a farmer being a potential adopter and the intensity of adoption are treated separately. Furthermore, empirical results by both Moffatt (2003) and Martínez-Espiñeira (2006) reveal that the double-hurdle model gives results superior to those obtained from Tobit and P-Tobit models.

According to Cameron and Trivedi (2009), a double-hurdle model has the interpretation that it reflects a two-stage decision-making process, each part being a model of one decision. The two parts are functionally independent. The double-hurdle model is a parametric generalization of the Tobit model, in which two separate stochastic processes determine the decision to adopt and the level of adoption of the technology (Green, 2000; Martínez-Espiñeira, 2006). In addition, the double–hurdle model allows for the possibility of zero observations in both outcomes (Wooldridge, 2001; Cameron and Trivedi, 2005). The model has an adoption (D) equation presented below:

$$D_i = 1 \quad \text{if} \quad D_{i^*} > 0 \text{ , and } D_i = 0 \text{ otherwise} \qquad (2)$$

$$D_{i^*} = \lambda Z_i + \pi_i$$

Where D^* is a latent variable that takes the value 1 if the farmer adopts ICVs and 0 otherwise, Z is a vector of household characteristics and λ is a vector of parameters. The level of adoption (Y) has an equation of the following:

$$Y_i = Y_{i^*} = \gamma' X_i + \tau_i \text{ if } Y_{i^*} > 0 \text{ and } D_{i^*} > 0 \text{, 05 otherwise} \qquad (3)$$

Where: Y_i is the observed answer to the proportion of area planted with improved cassava varieties. X is a vector of the individual's characteristics and γ is a vector of parameters. The error terms, π_i and τ_i are distributed as follows:

$$\left.\begin{array}{l} \pi_i \sim N(0,1) \\ \tau_i \sim N(0,1) \end{array}\right\} \qquad (4)$$

The log-likelihood function for the double-hurdle model is:

$$LogL = \sum_0 \ln\left[1 - \Phi(\lambda_i Z_i^{1})\left(\frac{\gamma X_i^{'}}{\theta}\right)\right] + \sum \ln\left[\Phi(\lambda Z_i^{'})\frac{1}{\theta}\phi\left(\frac{Y_i - \gamma X_i^{'}}{\theta}\right)\right] \qquad (5)$$

The independent double hurdle model assumes that the two error terms from the two hurdles are normally distributed and uncorrelated. This suggests that the two stage ICVs adoption decision and the intensity of use/adoption are done independently by the farmers. Under the assumption of independency between the error terms π_i and τ_i the model as originally proposed by Cragg (1997) is equivalent to a combination of a truncated regression model and a univariate probit model.

The double-hurdle and the closely related two-part model have been used extensively to assess agricultural technologies adoption by Cooper and Keim (1996), Uri (1998), Teklewold et al. (2006), Shiferaw et al. (2008), Langyintuo and Mungoma (2008), Legese et al. (2009), Kassie et al. (2009), Gebregziabher and Holden (2011), Smith et al. (2011) and Alamerie et al. (2013) among many others. Empirically, the double model contains logit and Tobit model estimnated as a single equation in STATA and the estimated equations are presented implicitly below:

D = f(age, age2, educ, hlab, ownland, extconta, gender, moccup, fasize, error term)
Y = f(age, age2, educ, hlab, ownland, extconta, gender, moccup, fasize, error term)

Where D and Y are the adoption status and the proportion of area devoted to ICVs production, respectively.

Access to information and adoption

Awareness or exposure to improvred agricultural technologies through information either from the extension agents, mass media or mobile phone has been identified as one of the vital eterminants of technology adoption (Diagne and Demont, 2007; Dontsop-Nguezet et al., 2011). In addition, information source have been reported as important stimulus to individuals in the adoption process (Rogers, 1995). Certainly, the adoption of ICVs is not likely to be possible if the farmers are not aware of or exposed to ICVs through access to information. Hence, the adoption of ICVs can be described as a two-stage process (Cragg, 1971).

The first involves obtaining all the available relevant information about ICVs and the second involves taking a critical decision whether to adopt ICVs or not. This leads to a sample selectivity problem, since only those who obtain information about the varieties are in a better position to adopt it, whereas it is mandatory to make an inference about ICV adoption among the rural population as a whole. Thus, we adopt Heckman Sample Selectivity model (Maddison, 2006). The Probit model for sample selection assumes that an underlying relationship exists between the independent (socio-economic and demographic characteristics of the farmers) and the dependent variables (access to information) (Deressa et al., 2008), the latent equation being given by:

$$y_j^* = x_j \alpha + \tau_{1j} \qquad (6)$$

Such that we observed only the binary outcome given by the probit

Table 1. Description of the variables included in the analysis.

Variables	Description	Expected sign
Dependent variable		
Adoption status(binary)	1 if farmer adopt at least one ICV, 0 otherwise	
Proparea	The share of ICVs area to total farmland (%)	
Independent variables		
Age	Age of household head in years	-/+
Age2	Square of age of household head	-/+
Gender	Dummy (1=male)	-/+
Offinc	Off-farm income. Dummy (1=yes)	+
Educ	Years of formal education of household head (years)	+
Extconta	Contact with extension agents. Dummy (1=yes)	+
amtcredit	Total amount of credit obtained in Naira	+
Fasize	Total farmland cultivated (ha)	+
Reland	Rented land. Dummy (1=yes)	+
Patecheva	Participation in technology evaluation. Dummy (1=yes)	+
Moccup	Main occuipation. Dummy (1= farming, 0 otherwise)	+
Ownland	Ownership of farmland . Dummy (1=yes)	+
Hlab	Hired labour. Dummy (1 if cost of hired labor is greater than mean of the group and 0 otherwise)	+/-

model as:

$$y_j^{probit} = (y_j^* > 0) \tag{7}$$

The dependent variable is observed only if j is observed in the selection equation

$$y_j^{select} = (w_j\varphi + \tau_{2j} > 0) \tag{8}$$

$$\tau_1 \sim N(0,1)$$
$$\tau_2 \sim N(0,1)$$
$$Corr(\tau_1, \tau_2) = \rho$$

The selection equation is (6), while (8) is the outcome equation. Where: x is a k-vector regressor, w is a m vector of repressors. τ_1 and τ_2 are the error terms. In cases where $\rho \neq 0$, standard probit techniques applied to Equation (6) will generate biased estimates. However, the Heckman Probit (heckprob) provides consistent, asymptotically efficient estimates for all parameters in such models (Statacorp, 2003).

Therefore, in thus study, the Heckman Probit selection model is employed to analyze the effect of access to information on the adoption of ICVs in southwestern Nigeria. The first part of model is the probit model, estimating the determinants of access to information. In the second part, we estimate the determinants of adoption of ICVs with access to information as one of the explanatory variables. The description and definition of the variables used in the models are presented in Table 1.

Data and descriptive statistics

The study area is Southwestern Nigeria. The data for this study originated from a survey conducted by IITA. Five (Ekiti, Osun, Ogun, Ondo and Oyo) out of the six States that comprise the Southwestern geopolitical zone were selected for the study. A three-stage stratified random sampling procedure was employed, whereby States were used as strata to improve sampling efficiency and account for possible major differences in the adoption of ICVs across States. Rural Local Government Areas (LGAs) were used as primary sampling units (PSUs). Enumeration areas (Eas), defined as a cluster of housing units, were used as secondary sampling units (SSUs) and households were the final sampling units.

LGAs were selected from each State based on probability proportional to size, where size is measured in terms of the number of Eas. The Eas that formed the sampling frame were obtained from the Nigerian Bureau of Statistics which uses the 2003/2004 master sampling frame of the National Integrated Survey of Households. The advantage of using Eas as sampling units is that each EA is approximately the same size. This ensured that all farmers had an equal probability of being selected. Within each LGA, four Eas were selected at random from a sampling frame classified as rural or semi-urban, giving a total of 80 Eas.

Finally, a list of households was developed for selected Eas and a sample of at least 10 farming households was selected randomly in each of the sampled Eas, giving a total of at least 841 households (Table 2). The survey was carried out over three months from August to October 2011. Community and household questionnaires were administered by trained enumerators with a senior agricultural economist in the field and the general supervision of IITA's economist. Data collection involved Focus Group Discussion (FGD), farmers' interviews, field observation of varieties, and plot area measurements.

Socio-economic characteristics of the respondents

The percentage distribution of adopters and non-adopters of ICVs by State (Table 3) shows that Ogun has the highest number of adopters (94%) followed by Osun (87%), Ondo (86%), Ekiti (81%)

Table 2. Distribution of the sampling households across the selected states.

Characteristics	State					
	Ekiti	Ogun	Ondo	Osun	Oyo	All
All enumeration areas (EAs)	11561	12754	19213	25910	31137	100575
All local government areas (LGAs)	16	20	18	30	33	117
Sample LGAs	2	3	4	5	6	20
Sample EAs or communities	8	12	16	20	24	80
Sample households	88	125	175	209	244	841

Source: IITA/DIIVA Adoption and Impact Survey (2011).

Table 3. Percentage distribution of adopters and non-adopters of ICVs by State.

State	Adopters (N=670)	Non-adopters (N=155)
	Percentage	Percentage
Ogun	94.35	5.65
Osun	87.44	12.56
Ondo	86.39	13.61
Ekiti	81.40	18.60
Oyo	65.27	34.73

Source: IITA/DIIVA Adoption and Impact Survey (2011).

and Oyo (65%). Table 4 shows the main socio-economic characteristics of the farmers by adoption status. As revealed by the t-test there is no significant difference between the adopters and non- adopters in age, total area of farmland cultivated, share of cassava in the farmland cultivated, and amount of credit obtained for cassava planting material and fertilizer. More importantly, there is no significant difference in the cost of planting material.

This shows that the average cost is the same for ICVs and traditional varieties and has a negative implication for the seed sector. However, the adopters and non-adopters of ICVs are statistically significantly different in the number of years of education, number of mobile phones, and cost of hired labor, herbicide, and fertilizer.

RESULTS AND DISCUSSION

Determinants and intensity of improved cassava varieties adoption

The result of the double-hurdle model is presented in Table 5. A positive significant coefficient in the first Hurdle-Logit model signifies that the corresponding regressor increases the probability of a positive observation in the adoption process. Similarly, in the second part, a positive coefficient means that, conditional on a positive count, the corresponding variable increases the value of the count (Cameron and Trivedi, 2009). The results of the first part of the model show that the log-likelihood of -77.83 and the LR chi^2 (10) 481.25 (significant at 1% level), imply that the model is fitted and the explanatory variables used in the model are collectively able to explain the extent and determinants of ICV adoption in southwestern Nigeria.

The results of the first part of the double-hurdle model are basically the Logit model of determinants of ICVs adoption and show that the coefficient of the gender of the household head is negative and statistically significant. This implies that adoption of ICVs is higher among female-headed than male-headed households. Labor is one of the main inputs in cassava production. Improved practices are labor intensive, hence availability (both hired and farm labor) is necessary for improved technology adoption.The coefficient of hired labor is positive and statistically significant. This shows that those farmers that have access to labor are more likely than not to adopt ICVs.

This finding is consistent with that of Hailu (2008) for the adoption of improved technologies for teff and wheat production in Ethiopia, Land is an important variable in agricultural production. The size of the land available for farming is usually a major factor in explaining technology adoption (Just and Zilberman, 1983). If farmers are land constrained, the probability of adoption would be very low. Owned farmland is more important than rented farmland in crop production. Hence, farmers producing crops on their own farmland are expected to have a higher probability of adopting ICVs. The result shows that

Table 4. Socio-economic/demographic characteristics of adopters and non-adopters.

Characteristics	Adopter (A) (N=670)	Non-adopter (NA) (N=155)	Mean difference (A-NA)	T-test statistics	P- value
Age (years)	50.00	49.00	0.82	0.56	0.57
Years of formal education	6.00	5.00	0.96	2.08**	0.04
Farmland (ha)					
Total farmland cultivated	3.16	2.85	0.31	0.72	0.47
Own land cultivated	2.43	2.34	0.08	0.19	0.85
Rented land cultivated	1.85	1.76	0.09	0.19	0.85
Sharecropped land cultivated	0.16	0.21	0.05	0.50	0.62
Cassava share of farm land cultivated (%)					
Cassava share of total farm land cultivated	64.55	63.61	0.94	0.38	0.70
Cassava share of owned land cultivated	46.45	47.98	1.53	0.39	0.69
Cassava share of rented land cultivated	38.29	39.59	1.29	0.28	0.78
Cassava share of sharecropped farm land cultivated	8.10	12.56	4.47	1.18	0.24
Household asset endowment					
Number of radios	2.00	2.00	0.04	0.39	0.09
Number of television sets	1.00	1.00	0.09	1.05	0.01
Number of mobile phones	2.00	1.00	0.23	3.59***	0.00
Access to credit					
Amount of credit borrowed for planting material	2113.32	2018.07	95.25	0.11	0.55
Amount of credit borrowed for fertilizer	1316.92	387.09	929.82	1.45	0.35
Estimated cost of cassava production (₦)					
Hired labor for land preparation	17918.06	22425.47	4507.41	1.66*	0.06
Hired labor for planting	6645.68	8202.02	1556.33	1.01	0.85
Hired labor for weeding	13346.46	15951.26	2604.79	1.48	0.82
Hired labor for harvesting	6526.78	6806.92	280.14	0.22	0.98
Cost of cassava planting material	6355.51	2473.08	3882.45	1.43	0.35
Cost of herbicide/pesticide	3328.91	2557.69	771.22	2.87***	0.002

*,**,*** implies significant at 10%, 5% and 1%, respectively, Source: IITA/DIIVA Adoption and Impact Survey (2011).

the coefficient of owned farmland is positive and statistically significant. This reveals that farmer-owners are more likely to adopt than those that practice farming on rented farmland.

The age of the household head, regarded as a primary variable in technology adoption, is negative and statistically significant thus indicating that younger farmers are more likely than older farmers to adopt ICVs (Rämö et al., 2009; Jensen et al., 2007). This is in line with the general literature on technology adoption and has been explained by the fact that older farmers are usually more reluctant to change. In addition, the young farmers are less risk-averse (Rogers, 1983; Alavalapati et al., 1995). This finding is similar to those of Jensen et al. (2007) and Rämö et al. (2009), but in contrast to the findings of Teklewold et al. (2006) and Hailu (2008).

However, the positive coefficient of age-square reveals that age shows a quadratic pattern in the adoption of ICVs. This implies that the adoption of ICVs among the younger farmers would increase to a certain level and then start to decrease as age increases in line with the life cycle hypothesis. Access to credit and specifically the amount of credit obtained are very important in agricultural production as credit allows farmers to invest in new technology or acquire other productivity enhancing inputs such as agro-chemicals and fertilizer. Thus, the amount of credit obtained is expected to increase the probability of adoption. The result shows that the amount of credit obtained by the farmers significantly increases the adoption of ICVs in the study area.

Table 5. Determinants and intensity of adoption of improved cassava varieties: Double-hurdle.

Variables	First-Hurdle		Second-Hurdle	
	Coefficient	Std. Error	Coefficient	Std. Error
Amount of credit	0.000*	0.000	9.35E-07	1.36E-06
Age2	0.002**	0.001	-0.0001	8.44E-05
Age	-0.257**	0.116	0.005	0.009
Education	0.023	0.055	-0.005	0.006
Hired labor	1.009*	0.521	0.136*	0.055
Own farmland	8.943***	1.309	-0.309	0.376
Extension	0.023	0.47	-0.005	0.053
Gender	-3.187**	1.393	-0.024	0.079
Main occupation	0.652	0.691	-0.045	0.094
Total farmland	0.001	0.096	-0.069***	0.011
Constant	2.446	3.008	4.539	0.461
LR Chi2(10)	481.25***		46.96***	
Pseudo R2	0.76		0.012	
Log likelihood	-77.83		2009.5594	
lnalpha			-1.33	0.076
Alpha			0.264	0.019

***, **, and *, implies significant at 1, 5, and 10% respectively, Source: IITA/DIIVA Adoption and Impact Survey (2011).

This implies that adoption would increase as farmers gained more access to credits related to agricultural production. A significant positive effect of access to credit on the adoption of improved maize varieties was reported by Feleke and Zegeye (2006) and Paudel and Matsuoka (2008). Similar effects on the adoption of fish enterprises were observed by Matiya et al. (2005). In the same vein Beshir et al. (2012) also obtain a positive effect of credit on determinants of chemical fertilizer technology adoption in North eastern highlands of Ethiopia. Beke (2011) found that the coefficient for predicted probability of being credit constrained has a negative and significant effect on the adoption and use intensity of improved rice varieties in Ivory Coast. This suggests that credit constraints tend to reduce the adoption of improved agricultural technologies. The implication is that farmers should also be granted access to adequate credit to achieve increased adoption of ICVs.

The result of the second part of the double-hurdle shows that the coefficient of hired labor has a positive and significant effect on the probability of increasing the proportion of total farmland devoted to cassava production in the study area. However, a negative and significant coefficient was observed for total farmland. This could be due to the fact that as the area of available farmland increases, there is a tendency for the farmers to go into multiple cropping, thereby reducing the land for cassava production. This is in agreement with the findings of Roos et al. (2000), Villami et al. (2008), Breen et al. (2009) and Rämö et al. (2009) on perennial energy crop adoption, but contrary to the findings of Doss and Morris (2001) for the adoption of inorganic fertilizer.

The effect of information on adoption of ICVs

Information is an essential component of agricultural technologies adoption. A farmer that is not aware of the existence of ICVs will not be likely to adopt. In this paper we empirically examine the effect of access to information on the adoption of ICVs in Nigeria using the Heckman Probit Selection model. To justify the use of this model we evaluate its appropriateness over the standard probit model by examining the presence of any sample selection. This is done by checking if there is any correlation between the error terms of the outcome (regression)and selection (Probit) models. The result shows that the rho is significantly different from zero (Wald χ^2 =24.66, with ρ =0.003), thus justifying the use of this model to assess the effect of information on ICV adoption in the study area.

The results of the Heckman Probit selection model are presented in Table 6. The first stage is referred to as the selection model and takes into account whether or not the farmer has access to information about ICVs. The second stage, known as the outcome model, examines whether the farmer adopted any ICV, conditional on whether any information was obtained about the ICV. The dependent variable of the first stage model (access to information) is specified as binary, which is equal to one if the farmer has access to information about the ICVs and

Table 6. The results of the heckman probit selection model.

Variables	Selection model		Outcome equation	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Age	-0.016***	0.004	0.013**	0.006
Gender	0.333**	0.161	-0.257	0.243
Years of formal education	0.067***	0.015	0.025	0.018
Rented farmland	-0.287*	0.147	0.531*	0.317
Own farmland	-0.034	0.158	0.045	0.157
Off-farm income	0.577**	0.233	-0.308**	0.156
Participate in technology evaluation	0.219	0.231	0.241	0.172
Hired labor	0.600***	0.124	0.353	0.236
Contact with extension agents	0.072	0.180	-0.036	0.175
Constant	0.617	0.405	-0.094	0.555
Wald(X^2)	24.66***	ρ =0.003		

***, **, and *, implies significant at 1, 5, and 10% respectively, Source: International Institute of Tropical Agriculture (IITA)/DIIVA Adoption and Impact Survey (2011).

0 otherwise. The dependent variable of the adoption model is also binary, equal to one and if the farmer planted at least one ICV and 0 otherwise. The results of the first stage show that the factors that tend to significantly affect farmers' access to information are age, gender, years of formal education, rented farmland, and off-farm income. The coefficients of gender, education, off-farm income, and hired-labor variables are positive and statistically significant. Since, gender is one if the household head is male and 0 otherwise.

Therefore, the positive significance of gender implies that the male-headed households have a higher probability of having access to information than female-headed households. The significance of education at 1% suggests that education is a very important determinant of access to information. The implication is that the educated household head, the primary decision-maker, is more capable of obtaining and assimilating information about the advantages of the adoption of an ICV and the negative effects that could result from not adopting it. Participation in off-farm activities could further predispose the farmers to getting access to information.

The coefficients of age and rented farmland are both negative and statistically significant in determining farmers' access to information. This implies that younger farmers are more likely than older farmers to have access to information. Those farmers that operate on rented farmland are likely to experience limited access to information. The result of the outcome model reveals that the adoption of ICVs based on access to information is positively and significantly determined by the age of the household head and use of rented farmland; off-farm income has a negative and statistically significant effect on the decision of farmers to adopt ICVs in the study area.

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

The collaboration between IITA and its partners has resulted into the development of ICVs and their subsequent dissemination to farmers in Nigeria.This study provides empirical information concerning the factors that determine the adoption of ICVs and the intensity of adoption in southwestern Nigeria, using sub-nationally representative data collected by IITA from about eight hundred and fourty one households for the study.

The results of the Double-Hurdle model reveal that the adoption of ICVs is higher among female-headed than male-headed households. Those farmers that have access to labor are more likely to adopt ICVs than those who are labor-constrained. In addition, farmers that own their farmland are more likely to adopt than those that practice farming on rented farmland. Younger farmers are more likely than older farmers to adopt ICVs. Access to credit increases ICV adoption tremendously and access to abundant hired labor is important in the study area. As the area of available farmland increases, there is a tendency for the farmers to go into multiple cropping, thereby reducing the area for cassava production.This suggests that an increase in area could have the tendency to encourage multiple cropping and thus reduce the intensity of ICV adoption.

The Heckman Probit selection model is employed to analyze the two-stage process of access to information and adoption of ICVs-having access to information, which creates awareness about the ICVs, in the first stage and then in the second stage adopting the IVCs, based on the information about the attributes and benefits inherent in adoption. The results further indicate that age of the household head, gender, education, and off-farm income are the variables that are positive and statistically significant in determining access to information on ICV adoption. Factors determining adoption are age, rented farmland, and off-farm income.

Finallay, this study has been able to empirically establish that cassava farmers in southwestern Nigeria are capable of intensively adopting ICVs if they have access to credit and hired labor, and own their farmland. Therefore, we recommend that access to credit should be improved and the present land tenure system in the rural areas should be re-examined to ensure that farmers have adequate access to land for agricultural production.

Conflict of Interest

The authors have not declared any conflict of interest.

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