ASSESSING THE CROP PRODUCTIVITY AND HOUSEHOLD WELFARE EFFECTS OF ADOPTING CERTIFIED SEEDS OF IMPROVED CASSAVA VARIETIES IN UGANDA[1]

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ABSTRACT

This article identifies the determinants, crop productivity, and household welfare impacts of adopting certified seeds of improved cassava varieties (c-ICVs) in Uganda. The determinants were identified using the two-part model while the crop productivity and household welfare impacts were assessed using the endogenous switching regression model. The data came from 609 farm households in Uganda's three major cassava-growing regions (Eastern, Northern, and mid-Western). The results showed that adopters of c-ICVs experienced a considerable increase in productivity (stem and root yields) and improvement in welfare outcomes (cash income and consumption expenditure). The results provide evidence of the effectiveness of the country's seed certification and genetic improvement efforts over recent years and justify increased investments in genetic improvement and seed certification. However, it is essential to note that farmers' widespread adoption of the high-yielding uniform c-ICVs could come at the cost of the diverse landraces, reducing cassava varietal diversity. Replacing the landraces could increase the crop's

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genetic vulnerability to biotic and abiotic stresses. It is also important to be cautious that farmers' widespread adoption of the c-ICVs could come at the cost of biodiversity loss as adoption of c-ICVs is often accompanied by increased application of agrochemicals (pesticides for disease control) that negatively impact the environment.

Keywords: Cassava varieties, adoption incidence and intensity, seed certification, productivity and household welfare, Uganda

1. INTRODUCTION

Crop yields have stagnated across most parts of Africa (Tian and Yu, 2019), preventing agriculture from supporting a structural transformation (de Janvry et al. 2016). The lack of quality seeds of improved varieties is considered a key limiting factor for increasing agricultural productivity on smallholder farms in Africa (World Bank, 2016). The seed quality problem is particularly significant with vegetatively reproduced crops (VRCs). The private sector generally ignored the seed system of VRCs in Africa due to complex seed multiplication and distribution requirements and low perceived commercial value (Tadesse et al. 2013).

In Uganda, low seed quality is a significant problem for cassava-producing smallholder farmers. Most cassava farmers in the country use recycled planting materials from their farms, neighbors, and local markets. Planting materials accessed through these informal channels are often infected with diseases. The quality of cassava planting materials in Uganda is affected by cassava mosaic disease (CMD) and cassava brown streak disease (CBSD). CMD and CBSD represent the country's most critical biotic constraints to cassava production, causing up to 100% yield loss (Pariyo et al. 2015). Cassava yield on farmers' fields ranges from 8.0 t/ha to 12 t/ha (Fermont et al. 2009). However, it can reach as high as 25t/ha on research stations (NARO, 2011). The yield gap between farmers' fields and research stations can be attributed to the difference in seed quality. Hence, improving cassava seed quality can benefit smallholder farmers in Uganda because cassava is the second most important staple food crop after plantains, with a daily per capita caloric intake of 300 Kcal, accounting for 13% of the total caloric intake (FAO, 2015). Research efforts to improve the quality of cassava planting materials are hampered by the crop's unique biological characteristics (e.g., bulkiness, perishability, low multiplication rate). Further, cassava's vegetative propagation makes it easier for farmers to use recycled planting materials but more difficult for regulators to enforce property rights of new seed technologies, resulting in low returns to investment in quality/certified planting materials (Wossen et al. 2020). Addressing these biological and economic constraints entails instituting a formal seed production and distribution system.

The National Agricultural Research Organization of Uganda (NARO) adopted the agricultural innovation system (AIS) in the early 2000s. The AIS[2] stimulated interactive learning and knowledge exchange among cassava stakeholders in the value chain, developing and disseminating 19 improved cassava varieties over 13 years from 2000 to 2013 (NARO, 2011; NARO, 2014). The approach led to the development of suitable improved cassava varieties (ICVs) and the establishment of a community-based network of cassava seed entrepreneurs (CSEs) (Wellard et al. 2015). Governmental institutions [e.g., NARO, National Agricultural Advisory Services (NAADS)], non-governmental development organizations, and the private sector (e.g., CSEs certified by the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF)) facilitated the rapid multiplication and distribution of certified seeds of improved cassava varieties (c-ICVs) (NARO, 2014). However, empirical evidence lacks on determinants, crop productivity, and household welfare effects of adopting c-ICVs. The lack of evidence on the impacts of seed certification is not limited to Uganda. A review of the literature shows a growing list of impact studies related to improved varieties of different crops, including cassava (Asfaw et al. 2012a; Asfaw et al. 2012b; Kassie et al. 2011; Kuntashula and Mungatana, 2013; Khonje et al. 2015; Magrini and Vigani, 2016; Feleke et al. 2016; Abdoulaye et al. 2018; Manda et al. 2019; Tufa et al. 2019; Wossen et al. 2019). However, no study has accounted for seed quality differences of adopted improved varieties. Previous impact studies defined the adoption of improved varieties of different crops without considering the seed quality (i.e., whether the seed is certified or not) (Khonje et al. 2015; Feleke et al. 2016; Wossen et al. 2019; Manda et al. 2019; Tufa et al. 2021). As a result, it can be argued that the measured impacts of improved varieties in those studies could be underestimated as some of the adopted varieties could be of lower seed quality. This study differentiates the improved varieties into certified and uncertified seeds.

[2] AIS is the participatory generation, dissemination, and utilization of agricultural-related knowledge or technology by a spectrum of actors including scientists, farmers, input suppliers, traders, food stockists, extension workers, the private sector, and other interested stakeholders (Spielman, 2006).

Further, no study has analyzed the determinants of the intensity of adoption of the c-ICVs. Previous studies have generally focused on adoption incidence and ignored adoption intensity. Adoption incidence is different from adoption intensity. Adoption incidence is about a farmer's decision to use a given variety regardless of the area of land allocated to the variety. In contrast, adoption intensity is defined in the present study as the area of land allocated to the adopted varieties. Hence, adoption incidence and adoption intensity could be determined by different factors

Regarding indicators, previous studies related to cassava considered only the root yield as a productivity indicator (Feleke et al. 2016; Afolami et al. 2015) and per capita income or per capita consumption as welfare indicators (Feleke et al. 2016). This study considered the root yield (used as food) and the stem (used as planting material) as productivity indicators and per capita cash income and consumption as welfare outcome indicators. When measuring cassava productivity, it is important to consider the root and stem yields. Cassava stem, used as a planting material, constitutes a source of income. Similarly, it is important to consider both consumption expenditure and household income when measuring household welfare. In the context of developing countries, consumption expenditure is preferable because farmers can better recall their expenditures than their income. Farmers earn income from selling crops and livestock over several months, which is challenging to recall.

Further, some of the previous studies are fraught with methodological inadequacies. For example, in Uganda, the few available impact studies on cassava technologies (Bua, 1998; Wellard et al., 2015) were conducted based on mean yields, income, and food security comparisons. Others applied the ordinary least squares (OLS) and the matching methods, such as propensity scoring matching (PSM). However, given the endogeneity problem resulting from a potential correlation between the treatment variable and the error term, OLS regression could lead to spurious impact estimates due to the potential correlation between the error term and treatment variable (Greene, 2003). Further, OLS regression fails to account for pre-existing differences between adopters and non-adopters, leading to biased impact estimates (Caliendo and Kopeing, 2005). Similarly, since the PSM only controls for the observed covariates, the impact estimates could be biased due to unobserved heterogeneity. The failure to control for unobserved heterogeneity between adopters and non-adopters could lead to biased impact estimates (Kuntashula and Mungatana, 2013).

This study aims to fill in the above knowledge gaps and addresses two policy research questions:

(i) Which factors influence the decision to use certified seeds (adoption incidence) and subsequently allocate land (adoption intensity) and

(ii) whether or not adopting c-ICVs would lead to productivity gains and welfare improvement.

The study addressed the two research questions using a nationally representative dataset. The first research question related to adoption incidence and intensity was addressed using the two-part model. The first part dealt with identifying the factors influencing the decision to adopt seeds of c-ICVs (adoption incidence). The second part dealt with identifying the factors influencing the decision on how much land to allocate to the varieties conditional on adoption (adoption intensity). The second research question was addressed using the endogenous switching regression (ESR) model.

The paper contributes to the literature by generating new knowledge on the determinants of smallholder farmers' c-ICV adoption incidence and intensity and the joint impacts of seed certification and genetic improvement. The research evidence generated from this study is essential to address barriers to adopting improved technologies and designing effective interventions. In particular, it enables policymakers to design better seed policies and extension interventions to help smallholder farmers adopt c-ICVs. It also allows justifying research funding for cassava breeding and seed certification.

The paper is divided into five sections. The following section presents the methodology. Section 3 provides an overview of the study area and the sampling strategy. Section 4 presents the results, focusing on the adoption incidence and intensity determinants, crop productivity, and household welfare effects. The final section concludes and draws implications.

2. METHODOLOGY

2.1. Two-part model

A new variety adoption is often a sequential process involving two different decisions over time: the decision of whether to adopt a new variety followed by the decision of how many acres of land to allocate (or intensity of adoption) (Afolami et al. 2015; Mercer and Pattanayak, 2003).

Following Mwesigye and Matsumoto (2016), we used the two-part model to identify the determinants of c-ICV adoption incidence and intensity. The two-part model has two chronologically sequenced decisions. The first decision pertains to whether or not to adopt c-ICVs (adoption incidence). In contrast, the second decision pertains to how many acres of land should be allocated to the new c-ICVs, conditional on the first decision (adoption intensity). The first part consists of a discrete choice variable, while the second consists of a continuous variable as a dependent variable.

The first part uses the probit model to estimate the adoption incidence. The probit model of adoption incidence can be motivated as a latent variable model given as:

$$T_i^* = H'\gamma + u \;, \tag{1}$$

where T_i^* is a latent continuous real-valued index variable for observation i, representing the difference between the utility of adopting and not adopting the c-ICVs; γ is a vector of parameters to be estimated; H is a set of independent variables hypothesized to explain c-ICV adoption; u is the error term.

Since T^* in Eq. (1) is unobserved, the observable adoption outcome can be defined by a binary indicator T_i where $T_i = 1 \; if \; T_i^* > 0$; $T_i = 0$ if $if \; T_i^* \leq 0$ (i.e., taking on 1 if the household adopted c-ICVs and 0 otherwise)

The probit model of adoption can then be given as

$$Pr(T_i = 1|H) = H'\gamma + u = \Phi(H'\gamma), \tag{2}$$

where Φ is the cumulative standard normal distribution; Pr is the probability of c-ICV adoption**;** H and γ are as defined above.

The estimation of the probit model of adoption incidence (i.e., the first part of the two-part model) described above was followed by the estimation of adoption intensity (i.e., the second part) on the sub-sample of positive observations (i.e., adopters) using the generalized linear model (GLM) fitted using the OLS.

2.1. ESR model

The ESR model consists of a selection equation (Eq. 2) and two separate regimes of an outcome equation (Eq. 3a and Eq. 3b) conditional on the selection criterion.

$$\text{Regime 1} \quad Y_{i1} = \beta_1 X_{i1} + e_{i1} \quad if \; T_i = 1 \tag{3a}$$

Regime 2 $\quad Y_{i2} = \beta_2 X_{i2} + e_{i2} \quad if\ T_i = 0$ (3b)

Where Y_{i1} and Y_{i2} are outcome variables (i.e., yield per acre for productivity outcome or per capita cash income and per capita consumption expenditure for household welfare outcomes) observed for each household depending on the selection criteria; X_i represents a vector of exogenous variables that influence the outcome variables; β is a vector of parameters to be estimated in the outcome equations; e_{i1} and e_{i2} are the error terms associated with the outcome equations.

The above equations (Eq. 2, Eq. 3a, and Eq. 3b) were estimated simultaneously using the Full Information Maximum Likelihood (FIML) (Lokshin and Sajaia 2004).

Following Lokshin and Sajaia (2004), the expected outcomes for adopters under observed conditions were computed using Eq. (4) as

$$E(Y_{i1}|T_i = 1) = X_{i1}\beta_1 + \sigma_{e_1u}\lambda_{i1} \tag{4}$$

Where σ_{e_1u} is the covariance of the error terms between the selection equation and the outcome equation for regime 1; $\lambda_{i1} = \frac{\phi(\hat{\boldsymbol{T}})}{\Phi(\hat{\boldsymbol{T}})}$ is the inverse Mill's ratio evaluated at $\hat{\boldsymbol{T}} = \gamma Z_i$ in the selection equation with $\hat{\boldsymbol{T}}$ being the predicted probability of c-ICV adoption; $\phi(\hat{\boldsymbol{T}})$ and $\Phi(\hat{\boldsymbol{T}})$ are the standard normal probability density function and the standard normal cumulative function, respectively.

Continuing to follow Lokshin and Sajaia (2004), the expected outcomes for adopters under counterfactual conditions (i.e., had adopters not adopted the c-ICVs) were computed using Eq. (5) given as

$$E(Y_{i2}|T_i = 1) = X_{i1}\beta_2 + \sigma_{e_2u}\lambda_{i1} \tag{5}$$

Where σ_{e_2u} is the covariance of the error terms between the selection equation and the outcome equations for regime 2. The other terms are as defined above.

The difference between Eq. (4) and Eq. (5), referred to as the average treatment effect on the treated (ATT), constitutes the productivity and welfare outcomes of c-ICV adoption. It was computed in Eq. (6) given as:

$$ATT = E(Y_{i1}|T_i = 1) - E(Y_{i2}|T_i = 1) = X_{i1}(\beta_1 - \beta_2) + (\sigma_{e_1u} - \sigma_{e_2u})\lambda_{i1} \tag{6}$$

3. STUDY AREA, SAMPLING STRATEGY, AND VARIABLE MEASUREMENT

3.1. Study area

Uganda has three major cassava-growing regions. These are the Eastern, with 342,387 ha followed by the Northern, 269,886 ha, and the mid-Western, with 131,328 ha (MAAIF, 2010). This study was conducted in 12 districts in the three regions, with four districts purposively selected from each region (Figure 1). Districts were purposively selected and stratified into most and least active based on cassava production levels, the importance of cassava, and community participation levels in cassava initiatives. This information came from a baseline study (NARO, 2014) and Key Informant Interviews (KIIs) of District Agricultural Officers (DAOs). Figure 1 shows that the most active districts were Serere and Ngora (Eastern), Apac and Amoratar (Northern), and Masindi and Kiryandongo (mid-Western).

Similarly, the least active districts were Kaliro and Kamuli (Eastern), Lira and Oyam (Northern), and Kyenjonjo and Hoima (mid-Western). The most active districts were the primary sites of the AIS interventions that included the dissemination of c-ICVs. The least active districts were not targeted with the AIS interventions. Hence, there could be more c-ICV adopters in the most active districts than in the least active districts and vice versa. The stratification of the districts based on cassava production was done to guarantee the representation of the two groups of farmers - the most active and least active farmers. District vibrancy in cassava production was not used to separate the target population into treatment and control groups or adopters and non-adopters. The classification of the households into treatment (adopters) and comparison groups (non-adopters) of the certified seeds and improved varieties was based on sample farmers' responses to specific questions on seed quality (certified, uncertified) and variety type (improved, local) in the survey questionnaire.

3.2. Sampling strategy

The target population is defined as a group of cassava-growing households from both the most active and least active districts. The target population (N=1800) was determined from 12 districts with 150 farmers per district (=150×12). A sampling frame, consisting of the 1800 cassava-growing households, was then constructed based on the National Crops Resources Research Institute (NaCRRI) databases obtained from District Agricultural Officers (DAOs), NARO Zonal

Agricultural Research and Development Institutes (ZARDIs) and local agricultural extension offices (NARO, 2011, 2014).

The sample size (591 households) was determined using Yamane's formula given as $n = [N/(1+Ne^2)](100/r)$ where n is sample size; N is target population size; e is the margin of error (taken at 3.5%), and r is the response rate at 95% (Yamane, 1967). To make up for households that may not be available for the interview, we added 12 households, raising the sample size to 612. Hence, data were collected from 612 households using a pre-tested standardized questionnaire. However, three questionnaires were discarded during data processing for lack of consistency, leaving us with a sample size of 609 households. As some households operated multiple cassava plots, the number of observations used in the data analysis could exceed the number of sample households.

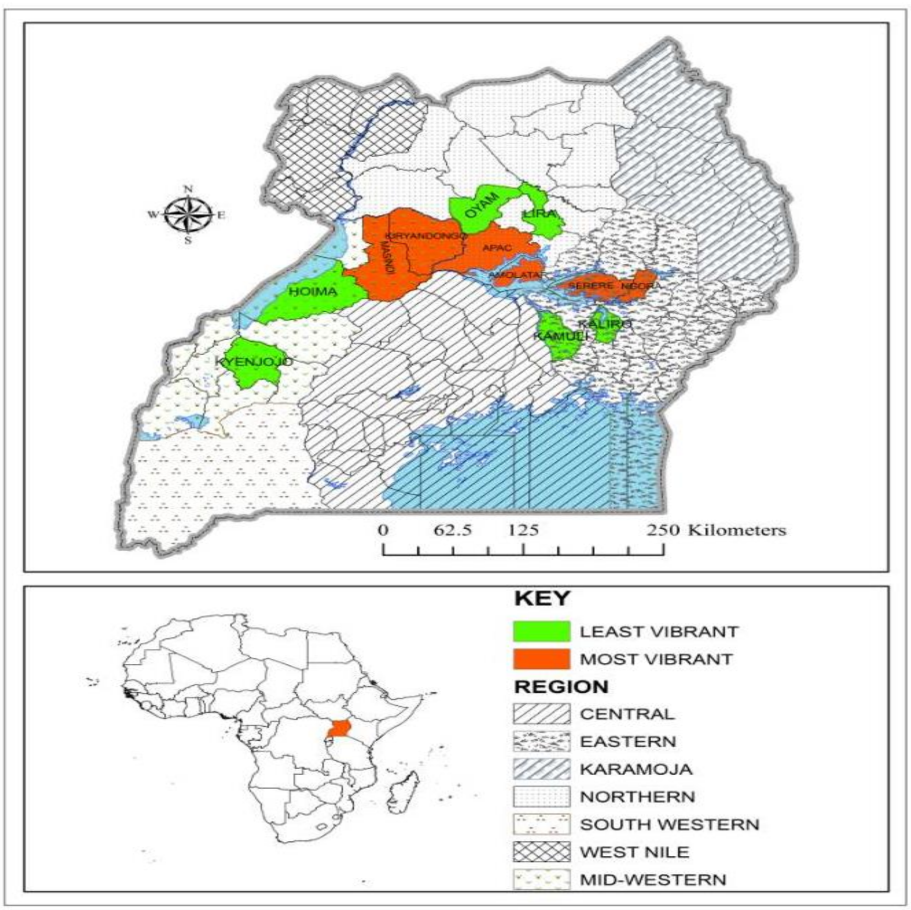

Figure 1: Map of the study region

3.3. Variable measurement

In the two-part model, adoption incidence was measured using dummy variables. In particular, adoption incidence was measured by five dummy variables such that (a) *ICVs* = 1 if a farmer used improved varieties (seeds could be certified or uncertified) and 0 if they used seeds of local varieties (*ICVs vs. LCVs*); (b) *c-ICVs* = 1 if a farmer used certified seeds of improved varieties and 0 if a farmer used uncertified seeds of both improved and local varieties (*c-ICVs vs. u-ICVs +LCVs*); (c) *c-ICVs* = 1 if a farmer used certified seeds of improved varieties and 0 if a farmer used uncertified seeds of improved varieties (*c-ICVs vs. u-ICVs*); d) *ICVs* = 1 if a farmer used certified seeds of improved varieties and 0 if a farmer used seeds of local varieties (*c-ICVs vs. LCVs*); e) *u-ICVs* =1 if a farmer used uncertified seeds of improved varieties and 0 if a farmer used seeds of local varieties (*u-ICVs vs. LCVs*). Adoption intensity was measured by the land area allocated to the different seed types.

In the ESR model, the study has one treatment variable (adoption of c-ICVs compared to u-ICVs and LCVs) and two outcome variables – productivity and household welfare. We considered cassava stem and cassava root productivity measured in bags per acre and t/acre, respectively. Cassava stem is used as a planting material and firewood. Cassava roots can be consumed in fresh and processed form. It can also be processed into various industrial products such as starch and ethanol.

Household welfare was measured by household cash income per capita and household consumption expenditure per capita in UGX. Household cash income per capita was measured based on the sales of cassava stems, fresh cassava roots, and processed cassava products. Consumption expenditure was measured based on food expenditure for the preceding year covering 12 months consistent with the World Bank's LSMS-ISA standard module. The independent variables (farm and household characteristics) fall under four categories: institutional, socio-demographics, shocks, and regional dummies. We hypothesize that the adoption incidence and intensity of c-ICVs are correlated with institutional, socioeconomic, demographic, shocks and regions (Table 1).

Institutional characteristics: Four institutional characteristics are hypothesized to influence the farmers' decision to adopt c-ICVs. These are access to extension services, credit services, all-weather roads, and household membership in Agricultural Innovation Platforms (AIPs). Barriers to agricultural technology adoption primarily include external constraints like credit, inputs, and output market imperfections and information inefficiencies (Cordaro and Desdoigts, 2016). Social networks can facilitate information transfer about agricultural innovations and complement traditional extension services (Carter et al. 2019). Hence, farmers with access to extension services and credit services and who belong to an AIP are more likely to adopt c-ICVs because the access and platform membership can create an enabling environment for adoption through information transfer and capital availability (Khonje et al., 2015; Magrini and Vigani, 2016). Information transfer about new technologies is a necessary, if not sufficient, condition for adoption (de Janvry et al. 2016). Access to tarmac all-weather roads can facilitate adoption by reducing transaction costs.

Socio-demographic characteristics: Seven socio-demographic characteristics are hypothesized to influence the farmers' decision to adopt c-ICVs. These are the educational level of household members, the age and sex of the household head, household size, livestock holdings, asset value, and total land operated. Young, educated, and men farmers respond to new technologies differently than senior, less educated, and women farmers. Young, educated, and men farmers are less resistant to adopting new technologies than senior, less educated, and women farmers, who are considered risk avers to adopt new technologies such as c-ICVs. Educated farmers can seek, gather, process new information, and adopt new technologies (Kassie et al. 2011; Asfaw et al. 2012b; Ghimire et al. 2015). The sex of the household head is a proxy for gender roles. Women farmers tend to have institutional and cultural limitations in decision-making power. Household size is a proxy for labour availability. As improved technologies entail intensive management, we hypothesize that households with large sizes tend to adopt c-ICVs. Livestock holdings, as measured in Tropical Livestock Units (TLU), asset value (UGX), and total land operated in acres, are indicators of resource availability. Households with a significant resource availability tend to adopt new technologies such c-ICVs.

*Shocks***:** Input price increase is used as an indicator of a household's vulnerability to shocks. High input price may significantly influence a household's ability to adopt new agricultural technology, especially c-ICVs, which are related to input access.

Regional dummies: Regional dummies are included to assess the influence of geographical location on a household's c-ICV adoption.

Table 1: Definition of variables

Variable	Definition
Institutional	
Access to extension	Access to extension = 1 if the household received extension services; 0 otherwise
Access to credit services	Access to credit =1 if the household received credit; 0 otherwise
Access to all-weather roads (tarmac)	Access to all-weather roads =1 if the household had access to tarmac road in proximity; 0 otherwise
Agricultural Innovation Platforms (AIPs) membership	AIP membership = 1 if the household was a member of AIP; 0 otherwise
Socio-demographics	
Average education of a household	Measured as the total number of formal education years of all household members divided by the household size
Household head age	Measured in years
Household head sex	1 if the household head is female and 0 if male
Household size	Measured as the total number of people in the household
Livestock size	Number of own livestock measured in Tropical Livestock Units (TLUs)
Asset value	Measured in UGX
Landholdings	Measured in Acres
Shocks	
High input price shock	Input price = 1 if a household experienced a high input price increase and 0 otherwise
Regional dummies	Mid-Western Region = 1 if a household domiciled in the mid-Western Region; Northern Region = 1 if a household domiciled in the Northern Region

4. RESULTS AND DISCUSSIONS

4.1. Descriptive summaries of outcome variables

Table 2 compares cassava productivity, household cash income per capita, and household consumption expenditure per capita outcomes between adopters of three groups of cassava varieties (c-ICVs, u-ICVs, and LCVs). The results showed that adopters of c-ICVs were more productive than adopters of u-ICVs. From each acre of cassava land, adopters of c-ICVs harvested 11 bags more stems and 317 kgs more roots than adopters of u-ICVs had harvested, suggesting that seed certification contributed to productivity gains. Similarly, adopters of c-ICVs were more productive than adopters of LCVs. From each acre of cassava land, adopters of c-ICVs harvested ten bags more stems, and 637 kg more roots than adopters of LCVs had harvested, suggesting that genetic improvement combined with seed certification contributed to productivity gains.

The welfare measures (household cash income per capita and household consumption expenditure per capita) indicated that adopters of c-ICVs were better off than adopters of u-ICVs and LCVs (Table 2). These differences appear to be translated into differences in household food security and poverty status. A relatively smaller proportion of adopters of c-ICVs were food insecure and poor than adopters of u-ICVs and LCVs. About 27% of adopters of c-ICVs had reported being food-deprived in 2015, compared to 38% of adopters of u-ICVs and 34% of adopters of LCVs. Similarly, about 51% of adopters of c-ICVs had reported being poor, compared to 68% of adopters of u-ICVs and 74% of adopters of LCVs.

Table 2: Descriptive summary statistics of the outcome variables

Variable	**c-ICVs**	**u-ICVs**	**LCVs**	**c-ICVs vs. u-ICVs**	**c-ICVs vs. LCVs**
Parcel stem yield (bags/acre)	47.91 (43.60)	36.70 (37.91)	37.30 (112.29)	11.21***	10.60
Parcel root yield (kg/acre)	3153.79 (2687.35)	2836.91 (2380.73)	2518.17 (1935.59)	316.88	635.616
Household consumption expenditure per capita) ('000 UGX)	1451.24 (1952.59)	1112.27 (941.18)	977.40 (611.19)	338.96**	473.836***
Household cash income per capita) ('000 UGX)	1927.63 (5261.34)	999.26 (6734.61)	383.080 (2389.57)	928.37	1544.55***
Food deprivation (=1 if food-deprived in 2015 and 0 otherwise)	0.273 (0.448)	0.379 (0.486)	0.344 (0.476)	-0.107**	-0.072*
Household food expenditure per capita) ('000 UGX)	801.419 (483.953)	698.629 (436.475)	675.351 (398.619)	102.790**	126.068***
Headcount index (% poor)	51.3	68.1	74.3	-16.8	
Poverty gap index	0.179	0.284	0.301	-0.105	
Poverty severity index	0.081	0.148	0.151	-0.067	
N	97	200	305		

Note: Figures in parentheses are standard deviations; * p<0.1 is significance at 10%; ** p<0.05 is significance at 5%; *** p<0.01 is significance at 1%

4.2.Descriptive summaries of household characteristics

Table 3 presents mean comparisons in household characteristics between adopters of c-ICVs, u-ICVs, and LCVs. The results showed that a relatively higher proportion of adopters of c-ICVs were members of AIPs, belonged to other farmer groups, and reported receiving extension services than adopters of u-ICVs and LCVs. For example, nearly 55% of adopters of c-ICVs were members of AIPs compared to about 30% of adopters of u-ICVs and 13% of adopters of LCVs. Further, a relatively higher proportion of adopters of c-ICVs had access to extension services than adopters of u-ICVs and LCVs. Specifically, about 33% of the adopters of c-ICVs had access to extension services compared to about 15% of adopters of u-ICVs and 8% of adopters of LCVs. Adopters of c-ICVs were more educated, older, and wealthier (measured by asset value and TLU) than non-adopters of u-ICVs and LCVs.

Table 3: Descriptive summary statistics of household characteristics

Variable	c-ICVs	u-ICVs	LCVs	c-ICVs vs. u-ICVs	c-ICVs vs. LCVs
AIP (Agricultural Innovation Platform) membership (1=yes; 0=no)	0.545 (0.500)	0.296 (0.457)	0.131 (0.338)	0.250***	0.414***
Group membership (1=yes; 0=no)	0.879 (0.328)	0.759 (0.429)	0.738 (0.441)	0.120***	0.141***
Access to extension (1=yes; 0=no)	0.333 (0.474)	0.153 (0.361)	0.085 (0.280)	0.181***	0.248***
Education (years)	9.847 (4.627)	8.45 (4.35)	7.483 (4.399)	1.397***	2.364***
Age of household head (years)	48.48 (13.962)	46.68 (14.479)	44.317 (13.717)	1.800	4.163***
Family size (#)	7.071 (2.600)	7.744 (3.651)	6.941 (2.662)	-0.673*	0.13
Total land operated (acres)	22.53 (77.013)	36.266 (280.438)	7.335 (23.283)	-13.736	15.195***
Livestock size (TLU)	4.566 (6.299)	3.561 (5.708)	1.995 (2.384)	1.005	2.571***

Asset value (UGX'000,000)	14.700 (38.600)	8.975 (24.600)	5.233 (11.100)	5.7247	9.467***
N	99	203	305		

Note: Figures in brackets are standard deviations; * p<0.1 is significance at 10%; ** p<0.05 is significance at 5%; *** p<0.01 is significance at 1%

4.3.Determinants of technology adoption and adoption intensity

Table 4 presents the determinants of adoption incidence and intensity of the three groups of cassava varieties (c-ICVs, u-ICVs, and LCVs), estimated using the two-part model. The two-part model estimated the adoption incidence and adoption intensity models independently.

We estimated ten models to identify the determinants of the adoption incidence and intensity of all groups of varieties. The estimation results of all ten models are presented in Table A-1 in the annex. Of the ten models, six (i.e., 3-8) are linked to c-ICVs, the seeds of interest. Model 3 and model 4 present results on the determinants of the adoption incidence and intensity of c-ICVs relative to u-ICVs and LCVs combined, respectively. Model 5 and model 6 present results on the determinants of c-ICVs relative u-ICVs, respectively. Lastly, model 7 and model 8 present results on the determinants of c-ICVs relative to LCVs, respectively.

The results consistently showed that AIP membership was positively associated with the adoption incidence of c-ICVs (models 3 and 7). The plausible explanation is that AIP membership facilitates knowledge acquisition through training and extension services, experience sharing among farmers, and expert guidance from the AIP actors, such as researchers and seed certification regulators (Mapila et al. 2012).

The results also consistently showed that educational level was positively and significantly associated with the adoption incidence and intensity of c-ICVs (models 3, 4, 6, 7, and 8). Similarly, the results showed that households who received extension services were more likely to adopt c-ICVs and allocate more land to the adopted c-ICVs (models 3, 5, and 7). Livestock size was also positively and significantly associated with adopting c-ICVs (models 3 and 7). Household size was negatively associated with the incidence and intensity of adoption (models 3-6 and 8).

Table 4: Determinants of the adoption incidence and intensity of c-ICVs compared to u-ICVs and LCVs

Variable	**[c-ICVs vs. (u-ICVs + LCVs)]**		**[c-ICVs vs. u-ICVs]**		**[c-ICVs vs. LCVs]**	
	Incidence	**Intensity**	**Incidence**	**Intensity**	**Incidence**	**Intensity**
	Probit	**GLM**	**Probit**	**GLM**	**Probit**	**GLM**
Specification	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
AIP membership)	0.481***	0.961	0.303	0.961	0.707***	0.961
	(3.003)	(1.539)	(1.616)	(1.539)	(3.698)	(1.539)
All-weather road	0.244	0.885	0.215	0.885	0.386*	0.885
	(1.558)	(1.490)	(1.168)	(1.490)	(1.958)	(1.490)
Education	0.0501**	0.202**	0.0158	0.202**	0.110***	0.202**
	(1.999)	(2.185)	(0.552)	(2.185)	(3.360)	(2.185)
Access to extension	0.509***	0.250	0.458**	0.250	0.593***	0.250
	(2.982)	(0.382)	(2.276)	(0.382)	(2.855)	(0.382)
Access to training	-0.0973	1.078	-0.159	1.078	0.0465	1.078
	(-0.460)	(1.374)	(-0.654)	(1.374)	(0.175)	(1.374)
Access to credit	-0.0846	0.394	-0.138	0.394	-0.0452	0.394
	(-0.669)	(0.778)	(-0.924)	(0.778)	(-0.298)	(0.778)
Farm size	-0.00362*	0.034***	-0.004	0.034***	-0.004	0.0340***
	(-1.647)	(2.834)	(-1.576)	(2.834)	(-1.208)	(2.834)
Asset value	0.0264	0.0768	0.00807	0.0768	0.0219	0.0768
	(0.457)	(0.344)	(0.124)	(0.344)	(0.308)	(0.344)
Livestock size	0.0290*	-0.0338	0.0222	-0.0338	0.0953***	-0.0338
	(1.695)	(-0.482)	(1.173)	(-0.482)	(3.362)	(-0.482)
H.H. head sex	-0.0537	-0.853	0.0130	-0.853	-0.0343	-0.853
	(-0.300)	(-1.132)	(0.0586)	(-1.132)	(-0.166)	(-1.132)
H.H. head age	0.00427	-0.0351*	0.00428	-0.0351*	0.00382	-0.0351*
	(0.876)	(-1.799)	(0.730)	(-1.799)	(0.651)	(-1.799)
Family size	-0.0374*	-0.223**	-0.0481*	-0.223**	-0.0452	-0.223**
	(-1.649)	(-2.331)	(-1.903)	(-2.331)	(-1.523)	(-2.331)
Input cost shock	0.311*	0.0794	0.265	0.0794	0.398*	0.0794
	(1.723)	(0.116)	(1.247)	(0.116)	(1.800)	(0.116)
Mid-Western	0.168	-0.612	0.308	-0.612	0.143	-0.612
	(0.893)	(-0.708)	(1.419)	(-0.708)	(0.611)	(-0.708)
Northern	0.610***	-1.275*	0.739***	-1.275*	0.663***	-1.275*
	(3.899)	(-1.924)	(3.969)	(-1.924)	(3.494)	(-1.924)
Constant	-2.187***	2.771	-1.196*	2.771	-2.428***	2.771
	(-3.946)	(1.261)	(-1.907)	(1.261)	(-3.488)	(1.261)
n	712	712	367	367	462	462

Note: Figures in brackets are standard errors; * p<0.1 is significance at 10%; ** p<0.05 is significance at 5%; *** p<0.01 is significance at 1%

4.4. Impact results based on the ESR model

Table 5 reports the ESR model results on the expected productivity and welfare outcomes under observed (to adopt) and counterfactual conditions (not to adopt). The ESR ATT in column 4 of Table 5 is interpreted as the mean difference between the predicted outcomes under observed conditions where adopters adopted the c-ICVs and counterfactual conditions in which they decided not to adopt. The ATT stem productivity results indicate that adopters of c-ICVs harvested 17.68 bags per acre (43.67 bags/ha) more than they would have harvested had they used u-ICVs or LCVs.

Similarly, the ATT root productivity results indicate that adopters of c-ICVs were observed to have harvested 7.52 t/acre (18.6 t/ha). However, had they not adopted the c-ICVs, they would have harvested only 3.31 t/acre (8.2 t/ha). This result suggests that adopting c-ICVs led to a 4.21 t/acre (10.40 t/ha) gain in root harvests. The productivity gains in the present study are greater than those of previous studies that demonstrated improved cassava varieties' positive genetic improvement effects on productivity (Feleke et al. 2016; Wossen et al. 2019). The higher productivity gains might be explained by the marginal effects of seed certification, which were not considered in previous studies. The yield of the c-ICVs under observed conditions (18.6 t/ha) in the present study is closer to the yield in research stations (25 t/ha) than in the farmers' fields (8-15 t/ha) (NARO, 2011) because seed certification has narrowed the yield gap between on-farm and on-station yields of ICVs.

Regarding welfare outcomes, adopters of c-ICVs spent 32.3% more on household consumption goods than they would have spent had they used u-ICVs or LCVs. The difference is statistically significant at the 1% level. They also earned 87% more cash income from cassava sales than they would have earned had they used u-ICVs or LCVs. The difference is statistically significant at a 1% level, suggesting that seed certification and genetic improvement enhanced household welfare outcomes through increased productivity. Our findings are consistent with several studies that demonstrated the positive effects on household welfare of improved varieties of different crops, including cassava (Feleke et al. 2016; Tufa et al. 2019; Shiferaw et al. 2014; Khonje et al. 2015; Magrini and Vigani, 2016).

The productivity gains and household welfare improvement induced by adopting c-ICVs could prompt farmers to disadopt the landraces, potentially reducing cassava varietal diversity and increasing the crop's potential genetic vulnerability to biotic and abiotic stresses. It might also lead to biodiversity loss as c-ICVs are often accompanied by increased application of agrochemicals that negatively impact the environment.

Table 5: Impact of c-ICV adoption on cassava productivity and household welfare based on the ESR model

Outcome variable	**Adoption decision**		**Treatment effects**	
	To adopt	**Not to adopt**	**ATT**	**t-test**
Cassava stem yield (bags/acre)	66.68	49.00	17.68 ***	7.33
Cassava root yield (t/acre)	7.52	3.31	4.21***	13.09
Household consumption expenditure per capita ('000 UGX)	7.42	7.10	0.32***	5.47
Houseold income per capita ('000 UGX)	6.13	5.26	0.87***	5.36

Note: Standard errors are computed using bootstrapping. * $p<0.1$ is significance at 10%; ** $p<0.05$ is significance at 5%; and *** $p<0.01$ is significance at 1%; Since 1 hectare =2.47 acres, then 17.68 stem bags/acre=43.67 stem bags/ha while 4.21 t/acre = 10.40 t/ha

5. CONCLUSIONS AND IMPLICATIONS

We applied the two-part model to identify the factors associated with the adoption incidence and intensity of c-ICVs. We also applied the ESR model to assess the cassava productivity and household welfare impacts of adopting c-ICVs based on data collected from 609 cassava-growing households in three regions of Uganda. We generated impact evidence of the adoption of c-ICVs. Further, unlike most previous adoption and impact studies, we circumscribed four significant limitations of previous impact evaluations. In particular, we did the following: (1) unlike previous impact studies that ignored seed certification, we distinguished the improved cassava varieties into certified and uncertified and assessed the impact of seed certification; (2) unlike previous impact studies that considered only a single indicator of productivity (usually root yield) and household welfare (per capita crop income or per capita consumption expenditure), we used multiple measures (root yield and stem yield for productivity; per capita crop income and per capita consumption expenditure for household welfare); (3) unlike most previous studies that used less rigorous impact estimation methods such as the PSM, we applied the ESR model that is considered a rigorous impact estimation technique and (4) unlike most previous studies that used sub-national, district-level or regional level datasets, we used a nationally representative data set collected from three major cassava growing regions.

The results showed that AIP membership, education, livestock size, and access to extension services were significant determinants of the adoption of c-ICVs. The results support continued efforts and development programs in promoting AIP membership, access to extension services, education, and asset creation measured by livestock ownership.

The results also showed that adopters of c-ICVs experienced a considerable increase in productivity (stem and root yields) and improvement in welfare outcomes (cassava cash income and consumption expenditure). The findings indicated the effectiveness of the seed certification and genetic improvement efforts over recent years and justified sustained investments in these two areas. While the results provide significant evidence in favor of intensifying the genetic improvement and seed certification efforts, they also suggested that adopting c-ICVs alone was insufficient to close the yield gap between on-farm and on-research stations. The observed yield of c-ICVs in the present study was 18.6 t/ha compared to 8-15 t/ha in the farmers' fields and 25 t/ha in research stations (NARO, 2011). Thus, further efforts are warranted to improve the adoption of complementary agronomic practices to close the remaining yield gap.

Finally, it is vital to be cautious with the implications of farmers' widespread adoption of the uniform improved varieties influenced by the productivity advantages of the improved varieties over the landraces. Famers may replace the diverse landraces with high-yielding improved varieties, reducing cassava varietal diversity. The replacement could increase the cassava's genetic vulnerability to biotic and abiotic stresses. Farmers who adopt the improved varieties may also increase the application of agrochemicals (e.g., pesticides for disease control), potentially causing biodiversity loss.

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Table A-1: Determinants of adoption incidence and intensity of improved cassava varieties

Variable	ICVs vs. LCVs		c-ICVs vs. u-ICVs + LCVs		c-ICVs vs. u-ICVs		c-ICVs vs. LCVs		u-ICVs vs. LCVs	
	Adoption Incidence	Adoption intensity	Adoption Incidence	Adoption intensity	Adoption Incidence	Adoption intensity	Adoption Incidence	Adoption intensity	Adoption Incidence	Adoption intensity
	Probit	GLM	Probit	GLM	Probit	GLM	Probit	GLM	Probit	GLM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AIP membership)	0.463*** (3.233)	0.838*** (2.932)	0.481*** (3.003)	0.961 (1.539)	0.303 (1.616)	0.961 (1.539)	0.707*** (3.698)	0.961 (1.539)	0.409** (2.516)	0.379 (1.470)
All-weather road	0.167 (1.214)	0.321 (1.139)	0.244 (1.558)	0.885 (1.490)	0.215 (1.168)	0.885 (1.490)	0.386* (1.958)	0.885 (1.490)	0.0811 (0.524)	0.0955 (0.361)
Education	0.0591*** (2.654)	0.0850* (1.916)	0.0501** (1.999)	0.202** (2.185)	0.0158 (0.552)	0.202** (2.185)	0.110*** (3.360)	0.202** (2.185)	0.0488* (1.957)	0.0136 (0.328)
Access to extension	0.208 (1.364)	0.715** (2.310)	0.509*** (2.982)	0.250 (0.382)	0.458** (2.276)	0.250 (0.382)	0.593*** (2.855)	0.250 (0.382)	0.00687 (0.0398)	0.612** (2.135)
Access to training	0.0191 (0.0930)	-0.0652 (-0.169)	-0.0973 (-0.460)	1.078 (1.374)	-0.159 (-0.654)	1.078 (1.374)	0.0465 (0.175)	1.078 (1.374)	0.0257 (0.108)	-0.275 (-0.732)
Access to credit	0.0319 (0.318)	-0.256 (-1.165)	-0.0846 (-0.669)	0.394 (0.778)	-0.138 (-0.924)	0.394 (0.778)	-0.0452 (-0.298)	0.394 (0.778)	0.0690 (0.634)	-0.474** (-2.508)
Farm size	-0.003** (-1.993)	-0.0006 (-0.183)	-0.00362* (-1.647)	0.034*** (2.834)	-0.004 (-1.576)	0.034*** (2.834)	-0.004 (-1.208)	0.0340*** (2.834)	-0.0026 (-1.436)	-0.00459 (-1.620)
Asset value	0.0537	0.218**	0.0264	0.0768	0.00807	0.0768	0.0219	0.0768	0.0603	0.192**
	(1.156)	(2.226)	(0.457)	(0.344)	(0.124)	(0.344)	(0.308)	(0.344)	(1.166)	(2.189)
Livestock size	0.0515*** (3.145)	0.0345 (1.100)	0.0290* (1.695)	-0.0338 (-0.482)	0.0222 (1.173)	-0.0338 (-0.482)	0.0953*** (3.362)	-0.0338 (-0.482)	0.046*** (2.685)	0.0703** (2.507)
H.H. head sex	-0.157 (-1.160)	-0.291 (-0.905)	-0.0537 (-0.300)	-0.853 (-1.132)	0.0130 (0.0586)	-0.853 (-1.132)	-0.0343 (-0.166)	-0.853 (-1.132)	-0.205 (-1.374)	0.163 (0.587)
H.H. head age	0.00243 (0.628)	-0.00622 (-0.721)	0.00427 (0.876)	-0.0351* (-1.799)	0.00428 (0.730)	-0.0351* (-1.799)	0.00382 (0.651)	-0.0351* (-1.799)	0.00144 (0.342)	0.00670 (0.875)
Family size	0.00496 (0.282)	-0.0293 (-0.801)	-0.0374* (-1.649)	-0.223** (-2.331)	-0.0481* (-1.903)	-0.223** (-2.331)	-0.0452 (-1.523)	-0.223** (-2.331)	0.0174 (0.918)	0.0358 (1.173)
Input cost shock	0.212 (1.348)	-0.0995 (-0.314)	0.311* (1.723)	0.0794 (0.116)	0.265 (1.247)	0.0794 (0.116)	0.398* (1.800)	0.0794 (0.116)	0.0978 (0.556)	0.107 (0.370)
Mid-Western	-0.154 (-1.126)	0.208 (0.663)	0.168 (0.893)	-0.612 (-0.708)	0.308 (1.419)	-0.612 (-0.708)	0.143 (0.611)	-0.612 (-0.708)	-0.198 (-1.374)	0.167 (0.650)

Northern	-0.0653 (-0.521)	-0.349 (-1.254)	0.610*** (3.899)	-1.275* (-1.924)	0.739*** (3.969)	-1.275* (-1.924)	0.663*** (3.494)	-1.275* (-1.924)	-0.339** (-2.402)	0.445* (1.705)
Constant	-1.234*** (-2.814)	-1.029 (-1.123)	-2.187*** (-3.946)	2.771 (1.261)	-1.196* (-1.907)	2.771 (1.261)	-2.428*** (-3.488)	2.771 (1.261)	-1.318*** (-2.720)	-1.655** (-2.065)
n	712	712	712	712	367	367	462	462	595	595