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Analysis of adoption and impacts of improved cassava varieties in Zambia

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Abstract

This paper analyzes the adoption and welfare impacts of improved cassava varieties in Zambia using data from a sample of 500 farm households. Using different treatment effect estimators—endogenous switching regression, propensity score matching, and inverse probability weighting, the paper shows that adoption of improved cassava varieties leads to significant gains in crop yields, household income, and food security. Results further show that improved cassava varieties have significant poverty-reducing impacts in Zambia. Stimulating agricultural growth largely depends on policies that stimulate adoption of improved cassava varieties.

JEL classifications: C31, I3, O33, Q16

Keywords: Adoption; Africa, Improved cassava varieties; Treatment effect estimators; Welfare, Zambia.

1. Introduction

In Zambia, agriculture is important for achieving the development goals of alleviating poverty and improving food security. Stimulating agricultural growth, and thus reducing poverty and improving food security, primarily depends on the adoption of improved agricultural technologies, including improved cassava varieties (ICV).

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Cassava is the second main staple food crop grown in Zambia and it is a vital crop for food security as well as poverty reduction through rural income. It is estimated that over 15% of the daily calorie intake is derived from cassava (Dorosh et al., 2007). The crop is commonly grown in Luapula, Northern, North-Western, Copperbelt, and Western provinces where it is considered as a staple food crop (Soenarjo, 1992). Cassava generates many benefits to farmers unlike other staple food crops like sweet potatoes, millets, and sorghum. It is used as famine reserve crop, cash crop for urban consumption, industrial raw materials, and earner of foreign exchange (Dixon et al., 2003). The importance of the crop is increasing such that in the recent years cassava production has expanded to the Southern and Eastern parts of the country (Chitundu, 1999). The expansion of cassava production in Africa is largely attributed to sustained investments in research and extension aimed at addressing a wide range of biotic and abiotic constraints (Nweke et al., 2002).

One of the major biotic constraints to cassava production is cassava mosaic virus disease (CMD) and is transmitted by the whiteflies and infected cuttings. Besides CMD, cassava brown streak virus disease (CBSD) has also become a threat to the crop. In response to disease threats, the International Institute of Tropical Agriculture (IITA) initiated cassava research in the early 1970s with a focus on developing varieties with resistance to major diseases. Cassava breeding was initiated using breeding materials from Moor plantation near Ibadan and a limited number of east African landraces with resistance to CMD were developed through interspecific hybridization in the 1930s (Haggblade and Zulu, 2003). This work resulted in several elite genotypes that had resistance to CMD as well as high yields and good consumer acceptability. The development of these resistant varieties, and their delivery to national programs for testing under specific local conditions during the late 1970s and 1980s, led to the successful deployment of CMD-resistant cassava in Sub-Saharan Africa (Nweke et al., 2002). In addition to their resistance to CMD and other diseases and pests, the ICV had superior postharvest qualities, wide agro-ecological adaptation, and improved yield gains of 50–100% without the use of chemical fertilizers—this offered a good prospect for improving household food security in Zambia.

In Zambia, the national cassava improvement programs developed and released varieties that outperform the local varieties using breeding materials received from IITA such as Tropical Manihot Selections (TMS). Over the period 1990–2011, IITA and the national programs in Zambia released a total of eight improved varieties. The increased availability of ICV opened up

a range of profitable commercial opportunities for production of cassava-based foods, feeds, and industrial products.

Although there has been increased availability of ICV, production and yields continue to dwindle i.e. yield has been declining for the last three years (see Fig. 1). Moreover farmers are not realizing potential yield gains of over 22 tonnes per hectare (tons/ha) from ICV (see Table 1).

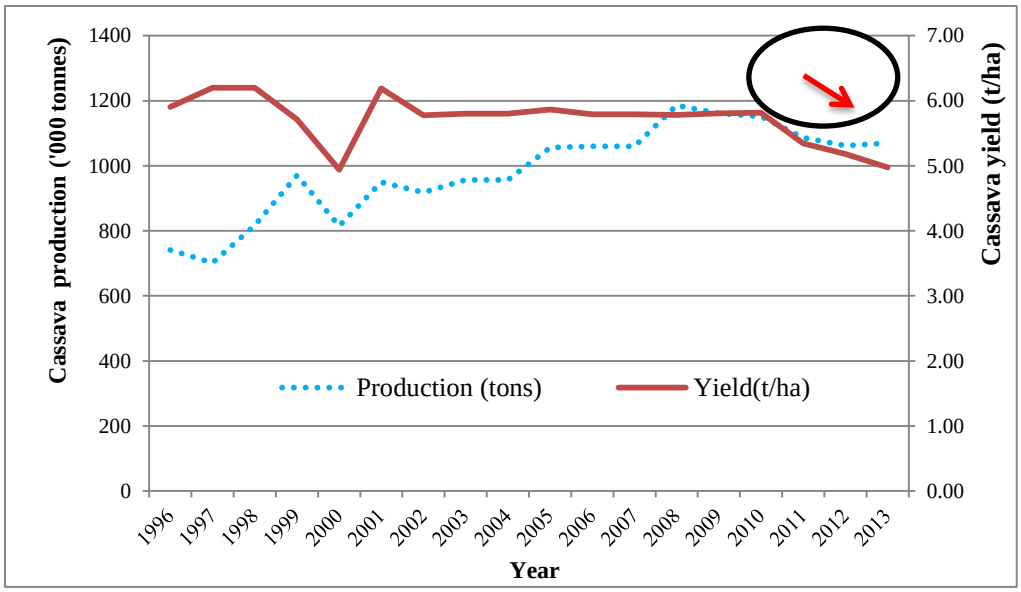

Fig.1. Cassava production and yield in Zambia 1996-2013. Data source: FAOSTATS

Table 1

Characteristics of common improved cassava varieties and their adoption rates (% of households) in Zambia

Varieties	Attributes for major improved cassava varieties					Adoption rate (% of households)					
						District					All
	IITA material	Year of release	Yield (t/ha)	Maturity	Taste	Serenje	Samfya	Mansa	Kasama	Kaoma	
All improved cassava varieties						5	58	24	10	53	30
Bangweulu	None	1993	31	12 to 16	Bitter	4	15	8	2	28	11
Nalumino	None	1993	29	16 to 24	Bitter	0	1	0	2	27	6
Mweru	IITA X Nalumino	2000	41	16	Sweet	0	5	7	0	0	2
Chila	IITA X Nalumino	2000	35	16	Bitter	0	3	1	0	1	1
Kariba						0	0	0	3	0	1
Tanganyika	IITA X Nalumino	2000	36	16	Sweet	0	0	0	3	0	1
Kampolombo	IITA X Nalumino	2000	39	16	Sweet	1	0	1	0	0	0
Kapumba	None	1993	22	16 to 24	Sweet	0	1	0	0	0	0
Other[a]						0	0	2	3	0	0

Note: Adoption rates were computed by authors using survey data and major attributes were drawn from Haggblade and Nyembe (2008).
[a] Others included improved varieties such as FAO, Agriculture, Research, and Mwansamfungo

Instead farmers are obtaining average yields of 5.2 tons/ha which is very low as compared to maximum potential. The current adoption rate of 30% (Table 1) for ICV is still very low and as such farmers cannot realize maximize returns from cassava production. This implies that most farmers still plant local varieties that have been cultivated by their grandparents across generations. Continuous use of recycled varieties has triggered low cassava productivity. The adoption of new varieties has also been low and slow in Malawi and Zambia largely due to the fact that most of these varieties lack the consumption attributes highly valued by farmers (Alene et al., 2013). Therefore, efforts aimed at enhancing the impact of cassava technologies on smallholder agricultural productivity and incomes require understanding and identifying the constraints and incentives which influence the adoption of improved cassava varieties.

There is limited empirical evidence on the impacts of modern technologies such as ICV in Africa especially in Sub-Sahara Africa. Several studies on the impacts of improved varieties (e.g., Alene et al., 2013; Amare et al., 2012; Becerril and Abdulai, 2010; Carletto et al., 2011; Crost et al., 2007; Hossain et al., 2006; Kassie et al., 2011; Maredia and Raitzer, 2010; Mathenge et al., 2014; Mendola, 2007; Smale and Mason, 2014) have assumed that the characteristics and resources of adopters and non-adopters have the same impact on outcome variables (i.e., homogenous returns to their characteristics and resources). Many of these studies have looked at crops such as maize, rice, groundnuts, pigeon peas, and wheat (Asfaw et al., 2012; Crost et al., 2007; Kassie et al., 2011; Shiferaw et al., 2014) unlike cassava.

Most of these previous studies used single econometric models in estimating adoption impacts. Alene et al. (2013) estimated the economic impacts of cassava research in Malawi and Zambia using economic surplus approach. They found that multiplication and distribution of clean cassava planting materials generated a modest rate of return of 24%. In Zambia, Khonje et al. (2015) used propensity score matching and endogenous regression models to assess the impacts of adoption of improved maize varieties. They established that adoption of improved maize varieties leads to significant gains in crop income, consumption expenditure and food security. Smale and Mason (2014) applied panel data regression methods to assess the impact of the adoption of hybrid maize on the income and equality status of maize-growing smallholder farmers, using panel data for the 2002–03 and 2006–07 growing seasons. They established that growing hybrids increased gross nominal income of smallholder maize growers by an average of 29%. Using double hurdle model estimation, Langyintuo and Mungoma (2008) found that

factors influencing the adoption and use intensity of high yielding maize (IHYM) differ between the poorly-and well-endowed households. In East Africa i.e. Kenya, recent analysis on the impact of the adoption of hybrid seed on Kenyan smallholders found that adoption had positive influence on income and assets (Mathenge et al., 2014). Kassie et al. (2011) and Kijima et al. (2008) found that adoption of improved groundnut varieties and new rice variety for Africa (NERICA) reduced poverty significantly through increased farm income respectively in Uganda. In Tanzania, Asfaw et al. (2012) and Amare et al. (2012) found that the adoption of improved pigeonpea and maize varieties increased household welfare through consumption expenditure. In Ethiopia, Shiferaw et al. (2014) established that adoption of improved wheat varieties increased household food security and non-adopters would have benefited more had they adopted new varieties. In West Africa, some studies established that adoption of improved maize varieties is associated with improved household welfare (Alene et al., 2009). In the Democratic Republic of Congo, Rusike et al. (2014) found that the cassava research-for-development (R4D) programs had positive effects on cassava markets participation, adoption of improved varieties, crop management practices, and household food adequacy. While in Malawi R4D has contributed to measurable gains in area planted to cassava, cassava yields, and household caloric intake (Rusike et al., 2010). Elsewhere, studies have also proved that adoption of improved agricultural technologies led to higher crop yields, lower food prices, high incomes, improved food security and reduced poverty levels (Becerril and Abdulai, 2010; Carletto et al., 2011; Crost et al., 2007; Hossain et al., 2006; Maredia and Raitzer, 2010; Mendola, 2007; Minten and Barrett, 2007).

The major objective of this study is to explore the impacts of adopting improved cassava varieties on household income, asset, poverty, and food security using different treatment effect estimators—endogenous switching regression (ESR), propensity score matching (PSM), and inverse probability weighting (IPW) models. We used tobit model in estimating adoption intensity of ICV. Different treatment effect estimators were used to isolate the adoption impacts on various outcome indicators such as food security and poverty. Unlike most previous studies, this paper is unique because firstly, none of previous studies have looked at adoption analysis of ICV and its associated impacts as far as our knowledge base is concerned. Secondly, we used more recent data (2013) and applied different treatment effect estimators to validate econometric results. Therefore, this will help us to provide robust empirical evidence on the adoption of ICV and its economic impacts.

2. Cassava research in Zambia

The breeding program by the Zambia Root and Tuber Improvement Program led to two waves of varietal releases, the first was in 1993 and the second in 2000. In 1993, three varieties, namely *Bangweulu*, *Kapumba*, and *Nalumino* were released. These varieties have higher yield ability and possess superior attributes compared to other traditional cassava varieties (Table 1).

Starting from 1988/89 growing season there were a series of multiplication and distribution of cassava planting materials to respond to the increased demand for cassava materials in the country. Through efforts of improvement program and a consortium under Program against Malnutrition (PAM) 552,000 cuttings were distributed in three consecutive seasons (1989–1992) to individual farmers (Soenarjo, 1992). Most of the cassava materials were susceptible to CMD, but a local clone called *Nalumino* was identified as resistant and was used in breeding program. The conventional breeding program also started in 1988/89 growing season in Mansa with 15,077 seedlings from 12 different crosses (Soenarjo, 1992). By 1992, preliminary evaluation identified 15 clones as being tolerant to CMD and further evaluations led to the release of four new varieties—*Mweru*, *Chila*, *Tanganyika*, and *Kampolombo* in 2000 (Table 1).

On adoption[2], overall 30% of farm households in Zambia have adopted ICV. Higher adoption rates are observed in Samfya (58%) and Kaoma (53%) as compared to other districts such as Serenje which had the lowest adoption rate of 5% (see Table 1). This confirms that in Luapula and Western provinces, cassava is a major staple food crop and extensively produced. Although a total of eight ICV were released in 1993 and 2000, only two varieties—*Bangweulu* (11%) and *Nalumino* (6%) are the most common improved varieties in Zambia (Table 1).

The rest of the paper is organized as follows: the next section discusses survey design and data collection in five districts in Zambia; the econometric framework and estimation technique are presented in Section 4; Section 5 presents and discusses the empirical results and Section 6 draws conclusion and implications.

[2] Adoption was measured by percentage of households who planted improved cassava varieties in 2012/2013 growing season. However this could be further improved if we had panel data so that adoption rate is defined for more than two growing seasons. Adoption intensity was measured as total land in hectares under cultivation allocated to ICV by each household. We used both variables in econometric analysis.

3. Survey design and data collection

The data used in this paper come from a survey of 500 sample households conducted between July and September 2013 in Zambia. This was a baseline survey conducted by IITA in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled Support to Agricultural Research and Development for Strategic Crops (SARD-SC) in Zambia. A survey questionnaire was prepared and administered by trained enumerators who collected data from households through personal interviews. The survey was conducted in the same SARD-SC project districts in Central province (Serenje district); Luapula province (Samfya and Mansa districts); Northern province (Kasama district) and Western province (Kaoma district) in Zambia (see Fig. 2).

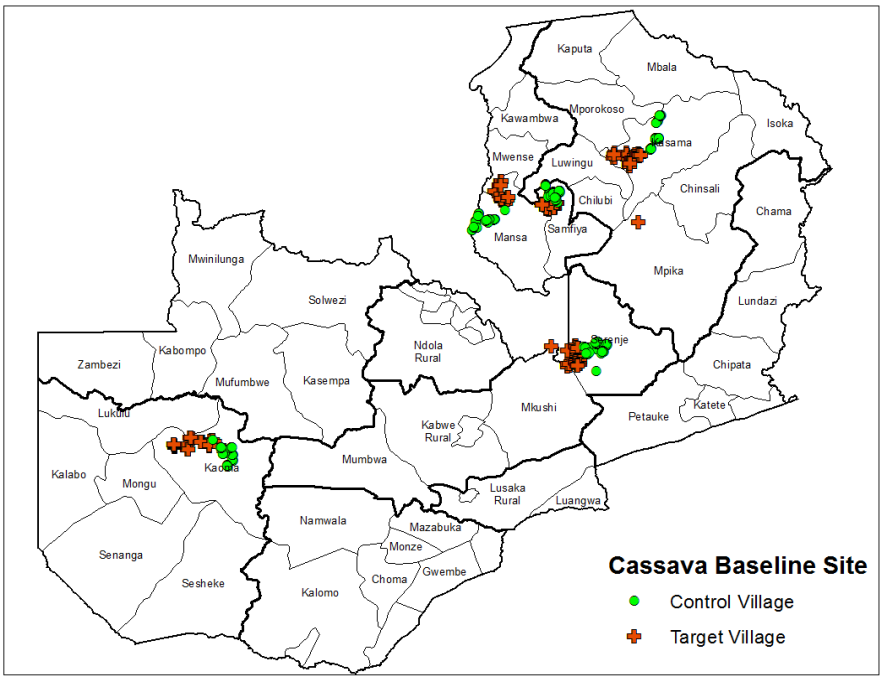

Fig.2. Villages where cassava baseline survey was conducted in Zambia

These were targeted by the project as the major cassava growing areas. In the first stage, each district was stratified into agricultural blocks and two blocks were purposively selected as primary sampling units—one control and one target. In the second stage, five agricultural camp [3] were randomly selected from each sampled block, with the camps allocated proportionally to the

[3] Agricultural camp is a catchment area made up of eight different zones comprising villages and is headed by an agricultural camp officer.

selected block and the camps selected with probability of selection proportional to size. In the third stage, two villages were randomly selected from each camp. Overall, ten camps were selected in each of five districts—Serenje, Samfya, Mansa, Kasama, and Kaoma. The distribution of the sample households by province, district, and gender is presented in Table 2.

Table 2

The distribution of the sample households by district and gender

District	Province	Gender of household head		All
		Female	Male	
Serenje	Central	22	78	100
Samfya	Luapula	14	86	100
Mansa	Luapula	12	88	100
Kasama	Northern	10	90	100
Kaoma	Western	20	80	100
All		78	422	500

Source: Author's calculations using the survey data

A total sample of 500 farm households was selected randomly from the five districts with the number of households from each selected camp (and village) being proportional to the size of the camp (and village). The survey collected valuable information on several issues at household level. Data were collected on the farmers' resource use patterns, production practices, technology choices and preferences, constraints to market participation, socioeconomic profiles, input markets, access to services and markets for cassava and cassava processing.

4. Econometric framework and estimation technique

4.1. Estimation of technology adoption and use intensity

Several econometric models have been used to study adoption behavior of farm households and to identify determinants of technology adoption. Following Becerril and Abdulai (2010) and Crost et al. (2007), the decision to adopt technology is modeled in a random utility framework. Let T^* denote the difference between the utility from adoption (U_{iA}) and the utility from non-adoption (U_{iN}) of improved cassava varieties (ICV), such that a household i will choose to adopt the technology if $T^*=U_{iA} - U_{iN}>0$. The fact is that the two utilities are unobservable; they can be expressed as a function of observable components in the latent variable model below:

$$T_i^* = Z_i\alpha + \varepsilon_i \quad \text{with } T_i=\begin{cases}1 & if\ T_i^*>0 \\ 0 & otherwise\end{cases} \tag{1}$$

where T is a binary 0 or 1 dummy variable for the use of the new technology; T= 1 if the technology is adopted and T= 0 otherwise. α is a vector of parameters to be estimated, Z is a vector that represents household-and farm-level characteristics, and ε is the random error term.

We used the tobit model proposed by Tobin (1958) for a corner solution to estimate factors that affect use intensity of ICV (for more details see Cameron and Trivedi, 2010; Davidson and MacKinnon, 2004; Long, 1997; Maddala and Lahiri, 2006; Wooldridge, 2013). Tobit is fairly restrictive because it requires that the decision to adopt ICV and use intensity be determined by the same process. The double hurdle (DH) proposed by Cragg (1971) to address corner solution models is more flexible than the Tobit because it accounts for the possibility that factors influencing adoption process and factors influencing use intensity may be different. However, we could not use DH because adoption of ICV is not constrained by factors like availability of planting materials. DH is mainly used where there is constrained adoption.

4.2. Impact evaluation of technology adoption

Estimation of the impact of technology adoption on household welfare outcome variables based on non-experimental observations is not trivial. What we cannot observe is the outcome variable for adopters, in the case that they did not adopt. That is, we do not observe the outcome variables of households that adopt, had they not adopted (or the converse). In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of households (as adopters and non-adopters), but rather to the household itself deciding to adopt given the information it has, therefore the two group may be systematically different (Amare et al., 2012).

Most studies (e.g., Alene et al., 2013; Hamazakaza et al., 2013; Langyintuo and Mungoma, 2008; Mason et al., 2013; Rusike et al., 2014; Rusike et al., 2010; Smale and Mason, 2014) have utilized single econometric models such as correlated random effects (CRE), fixed-effect models, tobit, propensity score matching, economic surplus, double hurdle, and endogenous switching regression. The disadvantage of using a single model is that the estimates are not robust enough because each model has its own limitations which cannot be individually corrected. Unlike most previous studies, this paper is novel as we used the most recent (2013)

data and three different econometric approaches—(1) endogenous switching regression (ESR), (2) propensity score matching (PSM) and (3) inverse probability weighting (IPW) models in impact analysis.

4.2.1. Endogenous switching regression

The average treatment effect on the treated (ATT) computes the average difference in outcomes of adopters category with and without a technology. Most commonly used methods to calculate ATT such as PSM ignore unobservable factors that affect the adoption process, and also assumes the return (coefficient) to characteristics to be same for adopters and non-adopters, which is not the case in many recent empirical studies (e.g. Asfaw et al., 2012; Di Falco et al., 2011; Shiferaw et al., 2014; Teklewold et al., 2013). The ESR framework proceeds in two stages: the first stage is the decision to adopt an ICV (Eqn. 1), and this is estimated using a probit model; in the second stage an Ordinary Least Squares (OLS) regression with selectivity correction is used to examine the relationship between the outcome variable and a set of explanatory variables conditional on the adoption decision. The two outcome regression equations, conditional on adoption can be expressed as:

Regime 1 (Adopters): $y_{1i} = x_{1i}\beta_1 + w_{1i}$ if $T = 1$ (2a)

Regime 2 (Non-adopters): $y_{2i} = x_{2i}\beta_2 + w_{2i}$ if $T = 0$ (2b)

Where y_{1i} and y_{2i} represents welfare outcome variables such as yield, asset value, household income [4], food security, and poverty, x_{1i} and x_{2i} are vectors of exogenous covariates, β_1 and β_2 are vectors of parameters; and w_{1i} and w_{2i} are random disturbance terms. According to Shiferaw et al. (2014), it is important for the Z variables in the adoption model (Eqn.1) to contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption, for the ESR model to be identified. The selection instruments we used included the following: access to extension (yes=1) and longevity in variety uses (years). Following Di Falco et al. (2011) selection instruments were selected by performing a simple falsification test—if a variable is a valid selection instrument, it will affect the technology adoption decision but it will not affect the welfare outcome variable. Results show that the selected instruments can be considered as valid, as they are jointly statistically significant in

[4] We used consumption expenditure as proxy for household income in this study.

explaining adoption decision [LR χ^2= 119 (p= 0.000)] but are not statistically significant in explaining the outcome equation [F= 1.60 (p= 0.07)] [5].

The estimation of β_1 and β_2 using OLS may lead to biased estimates, because the expected values of the error terms (w_1 and w_2) conditional on the selection criterion are non-zero (Shiferaw et al., 2014). The error terms in Eqns. 1 and 2 are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \text{cov}\,(\varepsilon, w_1, w_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{bmatrix} \tag{3}$$

where σ_ε^2 =var (ε), σ_1^2 = var (w_1) , σ_2^2 = var (w_2) $\sigma_{\varepsilon 1} = cov(\varepsilon, w_1)$, and $\sigma_{\varepsilon 2} = cov(\varepsilon, w_2)$. We can assume that σ_ε^2 equals to 1 since the β coefficients in the selection model are estimable up to a scale factor. The covariance between w_1 and w_2 is not defined since y_1 and y_2 are never observed simultaneously (Maddala, 1983). An important implication of the error structure is that because the error term of the selection Eqn. 1 ε_i is correlated with the error terms of the welfare outcome functions (2) (w_1 and w_2), the expected values of w_1 and w_2 conditional on the sample selection are non-zero (Asfaw et al., 2012);

$$E(w_{1i}|T = 1) = \sigma_{\varepsilon 1} \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 1}\lambda_1 \tag{4}$$

$$E(w_{2i}|T = 0) = \sigma_{\varepsilon 2} \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 2}\lambda_2 \tag{5}$$

where ϕ is the standard normal probability density function, Φ the standard normal cumulative density function, $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi((Z_i\alpha)}$ and $\lambda_{2i} = \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$ where λ_1 and λ_2 are the inverse mills ratio [6] calculated from the selection equation and will be included in 2a and 2b to correct for selection bias in a two-step estimation procedure i.e., ESR model. The above ESR framework can be used to estimate the average treatment effect of the treated (ATT), and of the untreated (ATU), by comparing the expected values of the outcomes of adopters and non-adopters in actual and

[5] Detailed results for falsification test are not presented in the paper. But they can be provided to the individuals upon request.

[6] We acknowledge that generation of inverse mill ratio could result in heteroscedasticity problem. However this was not accounted for because bootstrap estimators do not provide reliable standard errors for the estimator implemented by *teffects psmatch* as matching estimators are not differentiable (for more see Abadie and Imbens 2012).

counterfactual scenarios. Following Di Falco et al. (2011) and Shiferaw et al. (2014), we calculate the ATT and ATU as follows:

Adopters with adoption (observed in the sample)

$$E(y_{i1}|T = 1; x) = x_{i1}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i1} \quad (6a)$$

Non-adopters without adoption (observed in the sample)

$$E(y_{i2}|T = 0; x) = x_{i2}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i2} \quad (6b)$$

Adopters had they decided not to adopt (counterfactual)

$$E(y_{i2}|T = 1; x) = x_{i1}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i1} \quad (6c)$$

Non-adopters had they decided to adopt (counterfactual)

$$E(y_{i1}|T = 0; x) = x_{i2}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i2} \quad (6d)$$

The average treatment effect on the treated (ATT) is computed as the difference between (6a) and (6c);

$$ATT = (y_{i1}|T = 1; x) - (y_{i2}|T = 1; x) = x_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \quad (7)$$

The average treatment effect on the untreated (ATU) is given by the difference between (6d) and (6b);

$$ATU = (y_{i1}|T = 0; x) - (y_{i2}|T = 0; x) = x_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \quad (8)$$

The expected change in the mean outcome of adopters if adopters or non-adopters had similar characteristics to non-adopters or adopters is captured by the first term on the right of Eqns. (7) and (8). The second term (λ) is the selection term that captures all potential effects of the difference in unobserved variables. The model was estimated in Stata 13 by *movestay* and *switch_probit* commands for continuous and binary outcome variables respectively.

4.2.2. Propensity score matching

Since results from ESR may be sensitive to its model assumption i.e., selection of instrumental variables, we also used PSM and IPW approaches to check robustness of the estimated treatment effect results from ESR. Following Heckman et al. (1997), let Y_1 be the value of welfare outcome variable when the household *i* is subject to treatment ($T = 1$) and Y_0 the same variable when the household does not adopt ICV ($T = 0$). Then following Takahashi and Barrett (2013), the ATT can be defined as:

$$ATT = E\{Y_1 - Y_0|T = 1\} = E(Y_1|T = 1) - E(Y_0|T = 1 \quad (9)$$

We can observe the outcome variable of adopters $E\ (Y_1 |\ T = 1)$, but we cannot observe the outcome of those adopters had they not adopted $E\ (Y_0\ |\ T = 1)$, and estimating the ATT using Eqn. (9) may therefore lead to biased [7] estimates. PSM relies on an assumption of conditional independence—it is conditional on the probability of adoption given observable covariates, an outcome of interest in the absence of treatment, Y_1 and adoption status (T) are statistically independent (Takahashi and Barrett, 2013). Rosenbaum and Rubin (1983) define the propensity score or probability of receiving treatment as:

$$p(X) = pr(T = 1)\ \perp X \tag{10}$$

Another important assumption of PSM is the common support condition, which requires substantial overlap in covariates between adopters and non-adopters, so that households being compared have a common probability of being both an adopter and a non-adopter, such that $0 < p(X) < 1$ (Takahashi and Barrett, 2013). If the two assumptions are met, then the PSM estimator for ATT can be specified as the mean difference of the adopters matched with non-adopters who are balanced on the propensity scores and fall within the region of common support, expressed as:

$$ATT = E(\ Y_1 | T = 1, p(X)) - E(Y_0 | T = 1, p(X)) \tag{11}$$

PSM technique is a two-step procedure: firstly, a probability (logit or probit) model for adoption of ICV is estimated to calculate the propensity score for each observation; secondly, each adopter is matched to a non-adopter with similar propensity score values, in order to estimate the ATT. Despite the fact that PSM tries to compare the difference between the outcome variables of adopters and non-adopters with similar characteristics in terms of quantity [8], it cannot correct unobservable bias because it only controls for observed variables (to the extent that they are perfectly measured). We estimated PSM using *teffects psmatch* command in Stata 13 which implements nearest-neighbor matching in the estimation process. The standard errors implemented in *teffects psmatch* were derived by Abadie and Imbens (2012).

[7] The use of ESR models helped to eliminate the bias and as such results were more robust.

[8] Adopters and non-adopters can have same average education but this does not necessarily mean education has same return (coefficient) on outcome variable for both groups of households as the quality of education may vary across the group.

4.2.3. Inverse probability weighting

Inverse probability weighting (IPW) estimates the effect of parameters using means of the observed outcomes weighted by the inverse probability of treatment. There is no outcome model. The IPW estimators use quasi-maximum likelihood (QML) to estimate the parameters of the conditional probability model. The vector of estimating functions is the concatenation of the estimating functions for the effect parameters with the estimating functions for the conditional-probability parameters (Cattaneo et al., 2013). The sample estimating functions used by the IPW estimators are

$$s_{ipw,i}(x_i, \hat{\theta})' = s_{ipw,e,i}(x_i, \hat{\theta}, \hat{\gamma})', s_{tm,i}(z_i, 1, \hat{\gamma})' \quad (12)$$

The estimating functions $s_{ipw,e,i}(z_i, \hat{\theta}, \hat{\gamma})'$ vary over the effect parameter. All the IPW estimators use normalized inverse-probability weights. The functional form for the normalized inverse-probability weights varies over the effect parameters potential-outcome means (POM), average treatment effects (ATE), and average treatment effects on the treated (ATT) (for more details see Cattaneo et al., 2013). We used *teffects ipw* command in Stata 13 in the estimation process.

PSM assigns greater weight to comparison group subjects with estimated probabilities that more closely resemble those of the participants. IPW, on the other hand, assigns greater weight to comparison-group members with higher estimated probabilities of participation. IPW approach is also more appealing intuitively (Handouyahia et al., 2013).

5. Results and discussion

5.1. Socioeconomic characteristics of the sample households

Table 3 present socioeconomic attributes of selected variables by district and adoption category. The results show that the level of education of the household head is significantly high for farmers in Samfya (7.42 years) district than other districts (Table 3). The results show that adopters are distinguishable in terms of household characteristics such as age, education, and household size. Adopters have higher level of education of 7.31 years than non-adopters who have average of 6.78 years (Table 3). This makes farmers better to understand the importance of adopting modern agricultural technologies. Education is hypothesized to have a positive impact on technology adoption (Huffman, 2001). This is consistent with the expectation that the probability of adopting new agricultural technologies such as ICV increases with the level of

education of the household head due to greater awareness of the availability and benefits of new agricultural technologies. Education not only facilitates adoption but also enhances productivity, especially among adopters of improved technology. Alene and Manyong (2007) found that education had a greater impact on cowpea yields among adopters of improved varieties relative to its effect on yields among non-adopters. Adopters are also relatively younger than non-adopters. On average, farm households in Kasama (19.80 hectares) and Kaoma (19.10 hectares) had more land [9] than those in other districts (Table 3). Results also reveal that adopters owned more land (21.45 hectares) and they allocated about 1.08 hectares to ICV as compared to non-adopters who owned less land of 15.70 hectares and only 0.73 hectares was allocated to local varieties (see Table 3).

Table 3

Socioeconomic characteristics of the sample households by district and adoption category

Variable	District					Adoption category		All
	Serenje (N=100)	Samfya (N=100)	Mansa (N=100)	Kasama (N=100)	Kaoma (N=100)	Non-adopters (N=350)	Adopters (N=150)	(N=500)
Household income (ZMW/capita)	2.55	2.84	2.09	2.54	2.56	2.37	2.85	2.52
Yield (kg/ha)	5362	5976	4582	5634	4643	4826	6204	5240
Value of cassava production (ZMW/ha)	6662	6754	6220	8114	5498	6815	6262	6649
Asset value (ZMW/capita[a])	40	51	25	30	113	49	59	52
Poverty headcount (%)	71	75	79	76	73	75	73	75
Food security (self-assessment) (%)	52	62	68	81	62	66	63	65
Gender of household head (1= Male)	0.78	0.86	0.88	0.90	0.80	0.85	0.82	0.84
Age of household head (years)	54	46	47	50	51	50	49	50
Education in years (number)	6.01	7.42	7.31	7.19	6.78	6.78	7.31	6.94
Total household size (number)	7.60	7.66	7.05	7.49	7.59	7.53	7.35	7.48
Farmer's group association (1=yes)	0.85	0.7	0.76	0.8	0.68	0.76	0.75	0.76
Tropical livestock units (TLU)	0.19	0.41	0.06	0.03	1.25	0.32	0.54	0.39
Hoe ownership (1=yes)	1.00	1.00	0.97	0.98	1.00	0.99	1.00	0.99
Bicycle ownership (1=yes)	0.79	0.81	0.85	0.81	0.61	0.79	0.75	0.77
Amount of land owned (ha)	17.4	14.5	16.3	19.8	19.1	15.7	21.45	17.4
Access to extension (1=yes)	0.29	0.27	0.2	0.24	0.24	0.22	0.31	0.25
Access to credit (1=yes)	0.00	0.04	0.01	0.01	0.01	0.01	0.03	0.01
Number of bundles planted	54	78	42	21	58	44	65	51
Variety experience (years)	11.7	13.2	12.8	12.9	11.6	12.8	11.6	12.4

Source: Author's calculations using the survey data. [a]ZMW denotes Zambian Kwacha and US$1= ZMW5.47 at the time of survey

[9] In Zambia, on average most farmers own large farm size (17 hectares) but only 5% of the total was under cassava.

Farmers can only allocate more land to improved varieties if they have enough land, and therefore those who own more land are expected to have a comparative advantage when it comes to adopting ICV. As noted by Smale and Mason (2014), farm size has an increasingly positive effect on the probability that maize-growing households plant hybrids.

Farmers in Kaoma district had highest asset value per capita (ZMW113) and tropical livestock units (1.25) as compared to other districts (Table 3). Adopters are also distinct in terms of asset holdings—asset value per capita (ZMW59 *vs*. ZMW49) and tropical livestock units (0.54 *vs*. 0.32) and have more assets than non-adopters (Table 3). This suggests that farmers with broader resource base (assets) are more likely to experiment with new technology options as they can ably hedge against the associated risks of the technology. They can also use asset based income to finance inputs such as planting materials for ICV. The results also show that more cassava bundles were planted in Samfya district as compared to other four districts where the survey was done. On average, adopters had used more cassava bundles of planting materials than non-adopters. The average cassava yields [10] is 5240 kilograms per hectare (kg/ha) in the study area. Farmers in Samfya had highest cassava yields of 5976 kg/ha as compared to other districts (Table 3). Adopters had higher yields of 6204 kg/ha as opposed to 4826 kg/ha for non-adopters (Table 3). However, the average yields are far from maximum potential of over 22000 kg/ha for improved cassava varieties (Table 1).

Farmers in Serenje and Samfya districts had more access to institutional support services such as extension services and credit respectively as compared to those in other districts. Similarly, adopters had more access to both extension services and credit than non-adopters. As noted by Abdulai and Huffman (2014), institutional support services such as access to extension services are important in the dissemination of new technologies and consequently affect their impact on household welfare. Farmers can only adopt modern technologies if they know their inherent characteristics (Adegbola and Gardebroek, 2007). On the other hand, credit provides the much needed capital to address challenges that come with adoption of new technologies—in

[10] Cassava yields or production are mostly under estimated because farmers rarely keep records and as such they report the crop that was harvested and used. It is difficult for farmers to provide precise production or yield because majority of the crop is kept in the field and they only harvest a small portion for immediate use. No wonder the reported yields in the study are quite low.

most cases adoption of new technologies is associated with high input costs that can hardly be financed by farmer's own resources.

Farmers in Samfya district had highest household income per capita of ZMW2.84 compared to other districts. Adopters had higher household income per capita of ZMW2.85 compared to ZMW2.37 for non-adopters (Table 3). This indicates that adopters were better off or less poor than non-adopters. Consumption expenditure as proxy for household income is considered as a better measurement for household well-being than real income because real incomes are seasonal, difficult to measure for several reasons and are more likely to be under-reported in household surveys (Christiaensen et al., 2002 ; Deaton, 1997).

On poverty [11], more people were poor in Mansa district (79%) than other districts and also adopters (73%) are less poor than non-adopters (75%). Results for food security show that farmers in Kasama district are more food secure (81%) than those in other districts. Contrary to the expectation, results reveal that adopters were more food insure that non-adopters. This could be attributed to the way food security was measured—it was farmer's self-assessment of whether they have enough food or not and in most cases it is not objective.

5.2. Determinants of adoption and use intensity of improved cassava varieties

Table 4 present the estimates of the factors influencing adoption and use intensity of ICV in Zambia. Adoption was defined as the percentage of households who reported growing any of the ICV in 2012/2013 growing season while intensity of adoption was defined as quantity of land in hectares allocated to ICV by each household [12].

Tobit estimates measure factors that affect adoption intensity of improved cassava varieties. The tobit estimate results indicate that once the decision to adopt ICV has been made, factors that affect amount of land allocated to ICV might be different or the same. Results show that access to extension services positively and significantly affects amount of land allocated to ICV. Farmers who are regularly visited by extension workers and those who attend field days or host demonstration/trials or get media extension messages are likely to adopt modern agricultural

[11] Poverty was generated based on international poverty line of US$1.25/capita/day at purchasing power exchange rate of ZMW2.735 using consumption expenditure (proxy for household income in this study) data.

[12] However the definition of adoption could be further improved if we had panel data set so that adoption rate is applicable for more than two growing seasons or years.

technologies and increase amount of land allocated to ICV due to their increased exposure and awareness. Farmers can only adopt modern agricultural technologies if they are aware of the availability and benefits of these technologies and their inherent characteristics (Adegbola and Gardebroek, 2007). Similar results were also found for adoption of improved maize and pigeon peas in Tanzania (Amare et al. 2012) and for sorghum in Ethiopia (Geberessiliese and Sanders, 2006).

Table 4

Tobit estimates results for adoption and use intensity of improved cassava varieties in Zambia

Variable	One-stage tobit with decomposition						
			Average marginal effects	Marginal effects		Marginal effects for adopters	
	Coefficient	Standard error	Coefficient	Coefficient	t-statistic	Coefficient	z-value
Value of assets per capita (ZMW)	-0.000	0.001	-0.000	-0.000	0.27	0.000	0.49
Land ownership (ha)	0.002	0.002	0.001	0.002	1.21	-0.001	0.98
Tropical livestock units (TLU)	0.059	0.080	0.017	0.059	0.74	0.214	2.78**
Farmer's group membership (1=yes)	0.182	0.213	0.053	0.182	0.85	0.108	0.59
Access to credit (1=yes)	1.185	0.616	0.348	1.185	1.92*	0.322	0.78
Gender of household head (1=Male)	-0.081	0.259	-0.024	-0.081	0.31	0.274	1.35
Age of household head (years)	0.008	0.007	0.002	0.008	1.14	0.006	0.97
Education of household head (years)	-0.011	0.034	-0.003	-0.011	0.33	-0.028	0.98
Total household size (number)	-0.094	0.046	-0.028	-0.094	2.03**	-0.001	0.04
Extension contact	0.131	0.043	0.038	0.131	3.02***	0.036	1.17
Longevity in variety use (years)	-0.013	0.010	-0.004	-0.013	1.25	0.007	0.79
Male members > 15 years (number)	0.101	0.097	0.030	0.101	1.04	-0.035	0.42
Female members > 15 years (number)	0.025	0.104	0.007	0.025	0.25	-0.117	1.32
Household members working on farm (number)	0.115	0.058	0.034	0.115	1.99**	0.082	1.70*
Household members working off farm (number)	0.022	0.163	0.006	0.022	0.14	-0.069	0.39
Household members working as causal laborers (number)	-0.161	0.073	-0.047	-0.161	2.19**	-0.044	0.72
Province dummy (Central as reference)						-0.057	0.14
Luapula	2.238	0.366	0.6567037	2.238	6.11***	-0.379	0.77
Northern	0.585	0.414	0.172	0.585	1.41	-0.110	0.25
Western	2.662	0.395	0.781	2.662	6.74***		
Constant	-2.861	0.620			4.61***		
Number of observation	500					150	

Notes: *Significant at 10%; ** Significant at 5%; and ***Significant at 1%.
Source: Author's calculations using the survey data.

Access to credit was found to be significant and positively influenced the amount of land under ICV. Access to credit for various inputs enables farmers to easily adopt modern agricultural technologies unlike where it is a constraint. Therefore, increased access to institutional support services such as extension, credit, and input supply should thus be a major part of efforts aimed at promoting adoption of modern technologies. Province dummies control to some extent for intra-regional differences in agro-ecology, institutional support services such as extension and credit, and infrastructure development i.e., market access and road networks. Results also show that there is a positive and significant relationship between Tropical livestock units (TLU) and amount of land allocated to ICV for adopters. For adopters livestock enable them to have additional resources that can be used in financing farming activities.

Cassava production can be labour intensive and in circumstances where farmers are resource constrained, they can hardly hire out labour for cassava production. This is the reason family labour becomes important. Total household size was found to negatively affect amount of land allocated to ICV. This implies that as the number of household size increases either less land becomes available for cassava production or the family tends to be resource constrained for them to adopt and allocated more land to ICV.

We found that number of household members working as causal labourers negatively and significantly influenced the quantity of land a farmer allocates to ICV. This result makes sense because having more household members working as casual labourers deprives the household of the much needed labour resource required in cassava production. On the contrary, number of household members working on farm positively and significantly influenced the amount of land allocated to ICV. This may suggest that households with relatively more labour working on the farms have higher probability of allocating more land to ICV than labour constrained households.

5.3. Impacts of improved cassava varieties on outcome variables

The correlation between adoption of improved farm technology and household welfare outcome variables is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem (Amare et al., 2012). We estimated the impact of improved cassava varieties (ICV) on yield (kg/ha), asset value (ZMW/capita), household income (ZMW/capita), food security (%), and poverty status (%) using three treatment effect estimators—endogenous

switching regression (ESR), propensity score matching (PSM), and inverse probability weight (IPW).

Before discussing the causal effects of cassava technology adoption on the welfare of farmers, we want to investigate the overlap assumption—it is one of the assumptions required to use the *teffects* estimators, which states that each individual has a positive probability of receiving each treatment level. After estimating the propensity scores for the adopters and non-adopters we checked the overlap assumption. A visual inspection of the density distribution of the estimated propensity scores for the two groups indicates that the overlap assumption is satisfied. There is substantial overlap in the distribution of the propensity scores for the two groups and the density does have too much mass around 0 or 1 (see Fig. 3). The overlap assumption is violated when an estimated density has too much mass around 0 or 1 (for details see Busso et al., 2011).

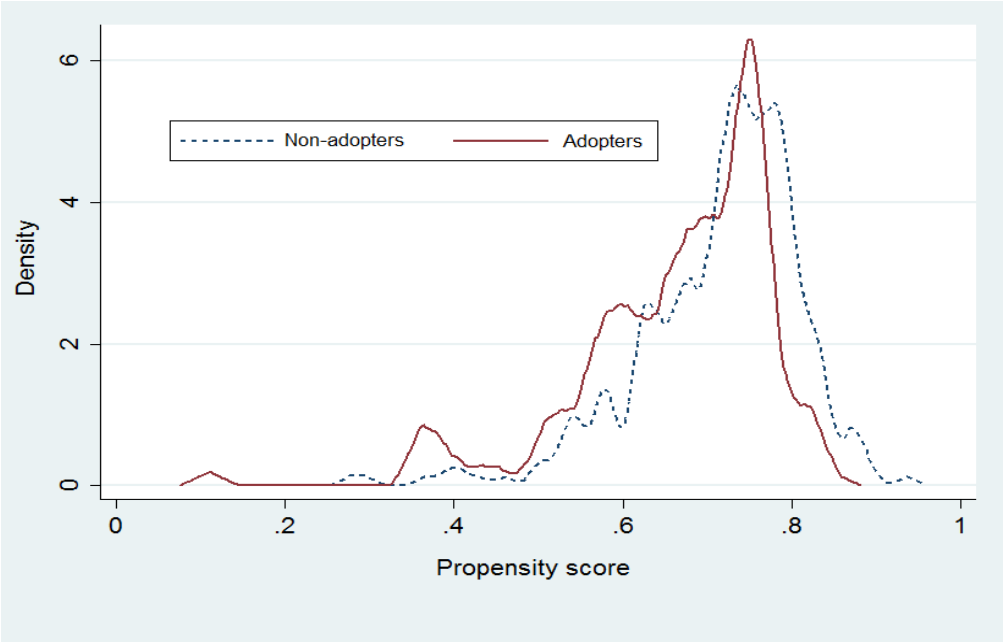

Fig.3. Propensity score distribution for overlap assumption.

5.3.1 Endogenous switching regression estimation results

Table 5 presents the ESR-based average treatment effects of adoption of ICV on outcome variables—yield (kg/ha), asset value (ZMW/capita), household income (ZMW/capita), food security, and poverty status—under actual and counterfactual conditions. Key continuous outcome variables such as yield, asset value, and household income were transformed to natural

logarithm with the purpose of normalizing distribution of the data. The detailed determinants of ESR model are not discussed due to space limitations, but it is worth noting that the estimated coefficients on the selection terms were significantly different from zero, suggesting that there was self-selection in the adoption of ICV in Zambia.

As we see from last column in Table 5, both adopters and non-adopters would significantly benefit from adoption of ICV. On productivity, households who actually adopted would have yield loss of 2101kg/ha had they not adopted. Households that did not adopt would have yield gains of 740kg/ha had they adopted. Since most ICV are high yielding, resistant to pests and diseases, drought tolerant and many more advantages, adopters of such varieties are likely to get higher yields [13]. On asset value, households who actually adopted would have per capita asset value of ZMW9.69 (US$1.77) less had they not adopted (Table 5).

Table 5

ESR-based average treatment effects of adoption of improved cassava varieties on welfare outcome variables

Means of outcome variable	Farm households type and treatment effects	Decision stage		Average treatment effects (ATE)
		To adopt	Not to adopt	
Yield (kg/ha)	Farm households that adopted (ATT)	3737	1636	2101***(23.72)
	Farm households that did not adopt (ATU)	2473	1733	740***(9.99)
Asset value (ZMW/capita)	Farm households that adopted (ATT)	19.39	9.70	9.69***(18.61)
	Farm households that did not adopt (ATU)	18.20	29.13	-10.93***(18.28)
Household income (ZMW/capita)	Farm households that adopted (ATT)	1.94	1.49	0.46***(10.86)
	Farm households that did not adopt (ATU)	1.84	0.30	1.54***(63.86)
Food security (%)	Farm households that adopted (ATT)	29.01	14.46	14.55***(3.98)
	Farm households that did not adopt (ATU)	31.10	26.71	4.39(1.20)
Poverty status (%)	Farm households that adopted (ATT)	-10.28	-0.90	-9.37***(3.35)
	Farm households that did not adopt (ATU)	35.43	20.82	14.61***(7.70)

Notes: Absolute values of *t*-statistics in parentheses;***Significant at 1%
Source: Author's calculations using the survey data.

On the contrary, households that did not adopt would have per capita asset value of about ZMW10.93 (US$2) less had they adopted. This could be attributed to the computation of asset value which includes livestock such as browsers i.e., goats that heavily destroy the cassava crop. This implies that if you are non-adopter and you want to adopt you need to reduce number of livestock or invest significantly in hedgerows. Adopters of ICV would lose per capita household

[13] We only accounted for additional benefits due to increased yield from adoption of ICV.

income of ZMW0.46 (US$0.08) had they not adopted (see Table 5). Similarly, households that did not adopt would have per capita household income of ZMW1.54 (US$0.28) more had they adopted ICV (Table 5).

ESR results also show that adoption of ICV reduced probability of poverty by 9.37% points for adopters had they not adopted. ESR results further show that adoption of ICV would also increase probability of food security for adopters by 14.55% points had they not adopted ICV. Higher adoption rate of ICV is associated with increased household food security if most farm households get food from own production rather than other sources i.e. food purchase. Overall ESR results show that adoption of ICV increase yields, per capita asset value, per capita household income, food security, and poverty reduction for adopters and households that did not adopt would also have benefited significantly had they adopted ICV. Khonje et al. (2015) also established that adoption of improved maize varieties led to significant gains in crop income, consumption expenditure, and food security and it is also noted that adoption process had significant poverty-reducing impacts in Eastern Zambia. Langyintuo and Mungoma (2008) also noted that the increase in the adoption rate and use intensity of improved maize varieties had subsequent impacts on food security and general livelihoods of households in Zambia. Shiferaw et al. (2014) also found that adoption of improved wheat varieties in Ethiopia increased food security.

5.3.2 Propensity score matching estimation results

Since results from ESR may be sensitive to its model assumption i.e., selection of instrumental variables, we also used IPW and PSM approaches to check robustness of estimated treatment effects from ESR. The PSM estimates Table 6, column 4 clearly isolate the impacts of adoption on yield (kg/ha) and household income (ZMW/capita). PSM average treatment effects on the treated (ATT) show that adoption of ICV positively and significantly increases yield and per capita household income. Farmers who adopted ICV had higher yields of 1970kgs/ha and per capita household income of ZMW0.69 (US$0.13) than non-adopters. Adoption of agricultural technologies helps increase crop productivity and income. Thus technologies that boost crop productivity and address production and marketing constraints are crucial in reducing poverty and attaining food security.

Table 6

Treatment effect estimates of the impact of cassava variety adoption on welfare outcome variables

Outcome variable	Treatment effect type	Treatment effect estimator	
		Inverse probability weight (IPW)	Propensity score matching (PSM)
Yield (kg/ha)	ATEs on the treated (ATT)	2184***(3.48)	1970**(2.81)
Asset value (ZMW/capita)	ATEs on the treated (ATT)	-16.89(0.81)	8.91(0.39)
Household income (ZMW/capita)	ATEs on the treated (ATT)	0.43(1.53)	0.69**(2.11)
Food security (%)	ATEs on the treated (ATT)	-6.45(1.22)	-8.60(1.35)
Poverty (%)	ATEs on the treated (ATT)	-1.04(0.21)	3.30(0.52)

Notes: Absolute values of Z-statistics in parentheses. ** Significant at 5% and ***Significant at 1%.
Source: Author's calculations using the survey data

Other studies also established a significant link between adoption of new agricultural technologies and poverty reduction and improved food security in Tanzania, Mexico, Kenya, Zambia, Bangladesh, Ethiopia (e.g., Amare et al., 2012; Becerril and Abdulai, 2010; Khonje et al., 2015; Mathenge et al., 2014; Mendola, 2007; Shiferaw et al., 2014).

5.3.3 Inverse probability weighting estimation results

The IPW estimates average treatment effects on the treated (ATT) presented in Table 6, column 3, show that adoption of ICV has a positive and significant effect on yield (kg/ha). Thus ATT shows that farmers who adopted ICV had higher yields of 2184kg/ha. Though not statistically significant under IPW, adoption of ICV led to increased household income and reduced probability of high poverty levels.

6. Conclusion

This paper analyzes adoption of improved cassava varieties (ICV) and its impacts in Zambia using data obtained from a sample of 500 farm households. The tobit model estimates showed that adoption is significantly affected by access to extension advice and credit, household size, number of household members working as casual laborers and those who work on farm.

Easy access to institutional supports services i.e., extension and credit market play a major role for farmers to adopt and intensively use ICV. However, access to reliable and competitive credit markets and extension remains a challenge, possibly due to poor infrastructure and institutional support services. Since markets are imperfect, there are emerging institutional

innovations such as social capital (farmer's group associations) for collective marketing that reduces transaction costs. Therefore, increased access to institutional support services such as extension, credit, and input supply should thus be a major part of efforts aimed at promoting adoption of modern technologies.

Using endogenous switching regression, inverse probability weight, and propensity score matching models, the paper further shows that adoption of ICV leads to significant gains in yield, household income, and improving food security. The results further show that ICV had significant poverty-reducing impacts in Zambia. Although the magnitude of the estimated effects varies across the three econometric methods, the quantitative results are consistent with descriptive statistics and similar. On average adoption of improved cassava varieties (ICV) increased yield in the range of 1,970–2184kg/ha and per capita household income from ZMW0.46 to ZMW0.69. The adoption process also reduced probability of poverty by 9% points and increased household food security by a probability of 9% points and about 15% points respectively. Higher adoption rate of ICV is associated with increased income, poverty reduction and household food security if most farmers get food from own production rather than food purchase. Adopters would lose significantly had they not adopted ICV while non-adopters would benefit more had they adopted ICV. Therefore stimulating agricultural growth (thus reducing poverty and improving food security) primarily depends on the adoption of improved agricultural technologies like ICV. This also points to the need for policies aimed at enhancing adoption of improved varieties among non-adopters through more efficient extension, credit, and input supply systems.

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