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Assessing the impacts of cassava technology on poverty reduction in Africa

In Africa, there have been successes in cassava research in terms of the development of production technologies, particularly improved varieties with high yield potential. The study addresses the question of whether and to what extent adoption of improved cassava varieties has led to rural poverty reduction in four African countries, namely Tanzania, Democratic Republic of Congo, Sierra Leone and Zambia. Data for the study come from a household survey conducted in the above-mentioned countries through a multinational-CGIAR support to agricultural research for development of strategic crops (SARD-SC) project in Africa. Given the observational nature of the data, a parametric approach (endogenous switching regression model) is applied. The results indicate that the model detects selectivity bias. Accounting for the bias, we find that adoption of cassava technology has resulted in an approximately 10 percentage point reduction in the poverty rate. Given an adoption rate of 34 per cent and a 10 percentage point reduction in the poverty rate, an estimated 24,309 households (equivalent to 194,469 individuals) have managed to move out of poverty in these four countries as a result of adoption of the technology. We also find that adoption of the technology has benefitted non-poor and female-headed households, relative to poor and male-headed households. The results present important evidence in favour of promoting cassava technology in a targeted fashion as part of an effective poverty reduction and sustained agricultural growth strategy in Africa. Considering the large realised and even more pronounced potential impacts of the adoption of cassava technology on poverty reduction, it is vital that regional and global development organisations should continue supporting the existing cassava improvement programme to sustain the technology development efforts in the continent.

Keywords: cassava varieties, households, adoption, selectivity bias, endogenous switching regression

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Introduction

In Africa, there have been successes in agricultural research, particularly in cassava research in terms of the development of improved varieties with high yield potential. While agricultural research is arguably an effective driver of agricultural growth, Hazell and Haddad (2001) note that its benefits do not necessarily materialise for the poor nor do they all necessarily work in the same direction. This might be related to the fact that the poor assume non-exclusive roles in society at the same time (i.e. wage earners, consumers and producers). As wage earners, they may indirectly benefit from adoption due to labour market effects (an increase in wage rate and employment) as the technology becomes widely adopted, leading to an increase in market supply. They may also indirectly benefit from adoption as consumers due to product market or price effects as the increase in market supply leads to lower market prices. However, as the poor are also producers, the lower market prices may work against them, given that the demand for food in developing countries is price inelastic. The net impacts of agricultural research on the poor could thus be positive or negative depending on the circumstances under which they operate. However, in a study of the role of agricultural technology on world poverty using the computable general equilibrium (CGE) model, de Janvry and Sadoulet (2001) demonstrate that in Africa the direct effect of agricultural technology on poverty is the most important. This implies that agricultural research directly benefits the poor in Africa mainly if they are adopters. However, given that the poor are risk averse, constrained by lack of access to resources and information, they are less likely to adopt. Even when they are able to adopt, they do so late in the adoption life cycle in which case the benefits of the technology in terms of higher incomes may have already been erased because of the lower market prices. Therefore, assessing the actual impacts of adoption on the poor when they are able to do so, and the potential impacts of adoption on the current non-adopters should they be able to adopt is not trivial.

Seeking for evidence of the poverty impacts of the cassava research efforts, we address the question of whether and to what extent adoption of cassava technology has resulted in poverty reduction in four major cassava-producing African countries, namely Tanzania, Democratic Republic of Congo (DRC), Sierra Leone and Zambia. We also look into whether or not the impacts of adoption of the technology are more favourable towards poor versus non-poor, as well as male-headed versus female-headed households, or vice versa. Finally, we estimate the number of poor who have managed to move out of poverty as a result of adoption of the technology. The overall objective of the study is, therefore, to assess the causal effect of the adoption of cassava technology on poverty reduction. It is achieved by testing the null hypothesis that adoption of cassava technology in the study countries has not led to poverty reduction. Cassava technology in the present study refers to improved cassava varieties. Beyond establishing the causal link between adoption of cassava technology and poverty reduction, we estimate the number of poor lifted out of poverty due to adoption of the technology. To this end, we establish a procedure by which we assess the impacts

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of adoption of the cassava technology on poverty reduction based on the results of the simultaneous estimation of the ESR model (i.e. a system of equations for adoption of cassava technology and per capita household expenditure). As far as we know, no study has estimated the number of poor lifted out of poverty due to the adoption of cassava technology, although a number of studies have done so for maize varieties. In a study on the economic and poverty impacts of maize research in West and Central Africa, Alene *et al*. (2009) estimated that over one million poor moved out of poverty annually since the mid-1990s. Most recently, Zeng *et al*. (2015) estimated that adoption of maize varieties has led to a 0.8–1.3 per cent poverty reduction, implying that up to 104,000 households in rural Ethiopia have escaped poverty.

The role of cassava research and policy support in Africa

Historically, cassava was a marginalised crop in Africa in the sense that it had not received as much attention as cereals from various stakeholders including policy makers and researchers. In fact, since most cassava producers are poor smallholders, it was regarded as 'food of the poor' (Rosenthal and Ort, 2011). However, following the realisation of its role against hunger during recurrent droughts, particularly the severe drought of 1982-83, it has started receiving more attention from both policy makers and researchers. For example, in East and Southern Africa, farmers were encouraged to have a piece of land under cassava (Alene *et al*., 2013). In the meantime, cassava research has been strengthened, leading to the development of improved production and processing technologies. The International Institute of Tropical Agriculture (IITA), in partnership with the respective national cassava research programmes of various African countries, has developed a number of improved cassava varieties that combine multiple pest and disease resistances with superior post-harvest qualities and yield potential (Nweke, 2004). More than 40 improved cassava varieties have been developed over the last 45 years (IITA, 2013). Most of these varieties have successfully been promoted to cassava farmers by national extension services and non-governmental institutions under different collaborative project initiatives and programmes. Among such initiatives is the USAID/IITA multi-country project (unleashing the power of cassava) which has helped to disseminate the varieties in countries such as Ghana, Malawi, Mozambique, Nigeria, Sierra Leone, DRC and Tanzania. These efforts have led to higher yield, shorter maturity period and higher tolerance to diseases such as Cassava Mosaic Disease and Brown Streak Disease. In Malawi, for example, adoption of cassava technology has boosted cassava production, contributing to measurable gains in household calorie intake (Rusike *et al*., 2010). In DRC, it has enhanced household food adequacy (Rusike *et al*., 2014).

Given the policy and research support it has received over the past few decades, cassava is being transformed into one of the most important enterprises in Africa. A number of industrial products such as high quality flour and starch are currently produced from cassava. There have been on-going efforts to create strong linkages among cassava value chain actors and partnerships with the private sector, which has a vested interest in the quality of the cassava crop for industrial uses. Private companies multiply and distribute planting materials of improved varieties (FAO/IFAD, 2005). As the uses of industrial cassava continue to increase in Africa, the private sector demands not only more output but also higher quality, which will be dictated by the type of varieties to be cultivated, and production and post-harvest management practices to be applied. Demand for cassava is already on the rise, leading to increased production. Food and Agriculture Organization (FAO) data from 2000 to 2013 show that about 60 per cent of the increases in global cassava production occurred in Africa. There is now more cassava produced in Africa than the rest of the world combined, with the leading producers in the continent being Nigeria, DRC, Ghana, Tanzania and Mozambique. By 2020 over 60 per cent of the global cassava production is expected to be in Africa (FAO/IFAD, 2005). In terms of consumption, cassava is now the second most important crop after maize, contributing over 40 per cent of the food calories consumed in Africa and supporting over 200 million people in the continent as a major staple food crop (Enete, 2009; Yidana and Amadu, 2013). In the DRC, it accounts for more than half of the daily calorie consumption per capita, providing the cheapest and most readily available food when compared with other close substitutes such as maize. Its role is even more pronounced during dry seasons, serving as the last line of defence against hunger. Given its unique and significant contribution to the livelihoods of African farmers, and its potential for transforming the African economies, cassava is among the six commodities defined by the African Heads of States as strategic crops for Africa.

Methodology

Empirical model

As the sample households were not randomly assigned to treatment and control groups during the dissemination of the cassava technology, isolating the poverty impacts of adoption of the technology is challenging. In the absence of random assignment, the decision between adoption and non-adoption could be influenced by observed and unobserved household characteristics. That is, households would self-select themselves either *into* adoption or *out of* adoption depending on their observed and unobserved characteristics. Past empirical studies have attempted to address such a challenge using a number of parametric and non-parametric approaches (Asfaw *et al*., 2012; Khonje *et al*., 2014; Shiferaw *et al*., 2014). The most common ones include propensity score matching (PSM) and endogenous switching regression model (ESR). While the PSM approach creates a condition that mimics a randomised experiment based on the conditional independence assumption and allows the estimation of causal effects, it is limited by the fact that the experimental condition is created based on measured

characteristics. This leaves the analyst with no choice but to assume that no unmeasured characteristics exist that affect both the treatment and outcome variables. As a result, most analysts resort to parametric approaches such as the ESR model that takes into account both the measured and unmeasured attributes in estimation of treatment impacts. The present study applies the ESR approach in view of its capability in taking account of unobserved heterogeneities, thereby providing unbiased and consistent parameter estimates upon which the assessment of the causal effects is based.

The ESR model consists of one treatment selection equation and two separate outcome equations conditional on the selection criterion. In the present study, the treatment variable is adoption while the outcome variable is household expenditure. Thus, the selection equation refers to the adoption decision on cassava technology and there are two expenditure equations conditional on adoption.

The adoption equation can be specified as:

$$A_i^* = \gamma Z_i + u_i, i = 0, 1 \tag{1}$$

where A_i^* is the latent variable indexing the propensity of adoption with i taking 1 for the status of adoption and 0 for that of non-adoption; Z_i is a vector of exogenous variables influencing adoption; γ is a vector of parameters to be estimated; u_i is the error term associated with adoption.

Assuming that a given household decides adopting cassava technology if the expected utility from adoption outweighs that of non-adoption or decides against adoption, the adoption criterion can be given as:

$$\begin{cases} A_i = 1 \ \ if \ A_1^* > A_0^* \\ A_i = 0 \ \ otherwise \end{cases} \tag{2}$$

Also, assuming a standard normal distribution for the error term, equation 1 is cast as a probit model.

With regard to the household expenditure equation, we follow the modelling of the production and consumption behaviours of a rural household by Straus (1983) and specify household expenditure as a function of consumption-side and production-side variables within the framework of consumer demand and production theories. We assume separability between production and consumption decisions, which are recursive in the sense that production decisions are made first and subsequently used in allocating the full income for consumption of goods.

The two linear expenditure equations, conditional on the adoption criterion, can be specified as below where households face two regimes (1) adoption, and (2) non-adoption:

$$\begin{aligned} &\text{Regime 1} \ \ Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \ \ \ if \ \ A_i = 1 \\ &\text{Regime 2} \ \ Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \ \ \ if \ \ A_i = 0 \end{aligned} \tag{3}$$

where Y_{1i} and Y_{2i} are daily per capita expenditures observed for each household depending on the adoption criterion; X_i represents a vector of exogenous variables that affect expenditure; β is a vector of parameters to be estimated; ε_{1i} and ε_{2i} are the error terms associated with the two expenditure equations.

The error terms are assumed to have a tri-variate normal distribution with zero mean and non-singular covariance matrix (Maddala, 1983) given as:

$$\text{cov}(u, \varepsilon_1, \varepsilon_2) = \begin{bmatrix} \sigma_u^2 & \sigma_{u\varepsilon_1} & \sigma_{u\varepsilon_2} \\ \sigma_{\varepsilon_1 u} & \sigma_{\varepsilon_1}^2 & \cdot \\ \sigma_{\varepsilon_2 u} & \cdot & \sigma_{\varepsilon_2}^2 \end{bmatrix} \tag{4}$$

where σ_u^2 is variance of the error term in the adoption equation which is assumed to be 1; $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_2}^2$ are variances of the error terms in the expenditure equations; $\sigma_{u\varepsilon_1}$ and $\sigma_{u\varepsilon_2}$ are covariances of the error terms between the adoption equation and the expenditure equations.

The covariances between the error terms in the expenditure equations are undefined since the daily per capita expenditures Y_{1i} and Y_{2i} are not observed simultaneously. The expected values of the error terms, ε_1 and ε_2, conditional on the adoption criterion, are non-zero because of the possible correlation between the error term in the adoption equation and the error terms of the expenditure equations:

$$E(\varepsilon_{i1} | A_i = 1) = \sigma_{u\varepsilon_1} \frac{\phi(\hat{A})}{\Phi(\hat{A})} \tag{5a}$$

$$E(\varepsilon_{i2} | A_i = 0) = -\sigma_{u\varepsilon_2} \frac{\phi(\hat{A})}{1 - \Phi(\hat{A})} \tag{5b}$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative function; $\frac{\phi(\hat{A})}{\Phi(\hat{A})}$ and $\frac{\phi(\hat{A})}{1 - \Phi(\hat{A})}$ are the inverse Mill's ratio evaluated at $\hat{A} = Z_i\gamma$ in the adoption equation where $\hat{A}$ is the predicted probability of adoption, A_i.

As the ESR model addresses the issue of selection bias as a missing variable problem, the inverse Mills ratio terms from the probit adoption model are added into the expenditure equations to correct for the potential selection bias as:

$$Y_{1i} = \beta X_{1i} + \sigma_{u\varepsilon_1} \frac{\phi(\hat{A})}{\Phi(\hat{A})} + \epsilon_{1i} \ \ if \ A_i = 1 \tag{6a}$$

$$Y_{2i} = \beta X_{2i} + \sigma_{u\varepsilon_2} \frac{\phi(\hat{A})}{1 - \Phi(\hat{A})} + \epsilon_{2i} \ \ if \ A_i = 0 \tag{6b}$$

If the $\sigma_{u\varepsilon_1}$ and $\sigma_{u\varepsilon_2}$ are statistically significant, switching is endogenous. Otherwise, switching is exogenous. The above equations can be estimated in a two-stage procedure. However, the efficient way to estimate them is by full information maximum likelihood estimator (FIML) (Lokshin and Sajaia, 2004).

Assessing the impacts of adoption on poverty reduction

In this study, we assess both the actual and potential impacts of adoption of cassava technology on poverty reduction. Actual impacts refer to the actual gain in incomes (proxied by expenditure) and associated actual reduction of poverty among the current adopters while potential impacts refer to the potential gain in incomes and associated potential

reduction of poverty among the current non-adopters, considering them as potential adopters should they choose and be able to adopt cassava technology.

Both the actual and potential impacts of adoption on poverty reduction are assessed based on the parameter estimates of the ESR model that consists of the system of one adoption equation of cassava technology and two expenditure equations. For both the actual and potential impacts, we firstly estimate the ESR model using the FIML estimator, and then generate distributions of expected daily per capita expenditures under observed and counterfactual conditions. For adopters, we generate two distributions under observed (with adoption) and counterfactual (without adoption, i.e. had they not adopted) using equation 7a and equation 7b given, respectively, as:

$$E(Y_{1i}|A_i = 1) = X_{1i}\beta_1 + \sigma_{\varepsilon_1 u}\frac{\phi(\hat{A})}{\Phi(\hat{A})} \quad (7a)$$

$$E(Y_{2i}|A_i = 1) = X_{1i}\beta_2 + \sigma_{\varepsilon_2 u}\frac{\phi(\hat{A})}{\Phi(\hat{A})} \quad (7b)$$

Based on the two distributions generated using equations 7a and 7b, we compute the average daily per capita expenditure and the three indices of poverty (poverty headcount index, poverty gap index and poverty gap-squared index) separately for each distribution. The difference in the respective average daily per capita expenditure and indices of poverty between the observed (with adoption) and counterfactual (without adoption) distributions for adopters will provide the actual impacts of adoption in terms of the actual increase in average daily per capita expenditure and associated actual reduction in the indices of poverty.

Analogously, for non-adopters, we generate two distributions under observed (without adoption) and counterfactual (with adoption, i.e. had they adopted) using equation 7c and equation 7d given, respectively, as:

$$E(Y_{2i}|A_i = 0) = X_{2i}\beta_2 + \sigma_{\varepsilon_2 u}\frac{\phi(\hat{A})}{1 - \Phi(\hat{A})} \quad (7c)$$

$$E(Y_{1i}|A_i = 0) = X_{2i}\beta_1 + \sigma_{\varepsilon_1 u}\frac{\phi(\hat{A})}{1 - \Phi(\hat{A})} \quad (7d)$$

Based on the two distributions generated using equations 7c and 7d, we compute the average daily per capita expenditure and the three indices of poverty described above. The difference in the respective average daily per capita expenditure and indices of poverty between the observed (without adoption) and counterfactual (with adoption) distributions for non-adopters provides the potential impacts of adoption in terms of the potential increase in average daily per capita expenditure and associated potential reduction in the indices of poverty.

Data and measurement of model variables

The data for this study came from a formal household survey conducted in four major cassava-producing countries, namely Tanzania, DRC, Sierra Leone and Zambia. Both non-random and random sampling methods were applied in the selection of the sample households. The non-random selection was applied to identify districts that have high potential for cassava production. Once the districts were selected, a two-stage random sampling was applied. The first stage involved the selection of villages and the second stage involved the selection of sample households. The standardised questionnaire included sections on household demographic, biophysical, socio-economic and institutional characteristics. The study has one treatment variable, thirteen independent variables and four outcome variables (Table 1). The treatment variable is adoption, which was measured based on whether or not the household cultivated one or more improved cassava varieties in 2013. The independent variables are a set of demographic, biophysical, socioeconomic and institutional characteristics of the study households. The choice of these variables is driven by economic theory of the production and consumption behaviours of a rural household and knowledge of similar previous research. The four outcome variables are daily per capita expenditure, and the three Foster, Greer and Thorbecke (FGT) indices of poverty (headcount index, poverty gap index and poverty gap-squared index).

Although poverty has multiple dimensions, it was measured in this study based on its monetary dimension of consumption expenditure. As consumption is considered not only a better outcome indicator but also may be better measured than income, expenditure is chosen for measuring poverty based on FGT indices as presented in Haughton and Khandker (2009). The consumption expenditure is constituted from two components – food consumption expenditure and non-food consumption expenditure. Data on consumed quantities of the list of food items differentiated by source (own production, purchase, gifts, borrowing and food aids) over the past one week preceding the survey were collected. Both quantities and prices were obtained for each food item reported to have been purchased and consumed over the given period of time. Reported prices for purchased food were applied to compute the imputed value of home-produced food and food items acquired through gifts, borrowing and food aids. Data on non-food consumption were similarly collected by asking the list of non-food items with the respective quantities and prices over the past one month preceding the survey. The food and non-food expenditures over the two given periods were respectively adjusted to daily food and non-food expenditure level. They were then converted to USD by the purchasing power parity (PPP) exchange rate of the respective country and aggregated to daily household expenditure for each sample household. Finally, the daily per capita household expenditure adjusted for the PPP was used in the analysis. An individual is considered to live in extreme poverty if he or she subsists on an average of USD 1.25 or less a day adjusted for the PPP. This is the poverty line. The headcount index measures the poverty rate, which is the proportion of people living below the poverty line. The poverty gap index measures the depth of poverty, which is the extent of income shortfall from the poverty line. The poverty gap-squared index measures the severity of poverty that indicates the degree of income inequality among the poor themselves.

Table 1: Description of treatment, independent and outcome variables.

Variable	Code	Description
Treatment variable		
Adoption	Adoption	Adoption = 1 if the household cultivated one or more improved cassava varieties in 2013; otherwise Adoption = 0
Outcome variables		
Daily per capita expenditure	Daily per capita expenditure	Household expenditure measured in USD per capita per day adjusted for purchasing power parity
Poverty headcount index	Poverty head-count index	The poverty headcount index measures the poverty rate, which is the proportion of people living below the poverty line
Poverty gap index	Poverty gap index	The poverty gap index measures the depth of poverty, which is the extent of income shortfall from the poverty line
Poverty gap-squared index	Poverty gap-squared index	The poverty gap-squared index measures the severity of poverty that indicates the degree of income inequality among the poor themselves
Demographic independent variables		
Gender	Gender	Gender = 1 if the head of the household is male; otherwise Gender = 0
Age	Age	Age1 = 1 if age of the head of the household is below 30 years; otherwise Age1 = 0 Age2 = 1 if age of the head of the household is between 30 and 65 years; otherwise Age2 = 0 Age3 = 1 if age of the head of the household is 65 years and above; otherwise Age3 = 0
Education	Education	Education = 1 if the head of the household has some formal education; otherwise Education = 0
Primary occupation	Occupation	Occupation = 1 if the primary occupation of the household is crop and livestock production; otherwise Occupation = 0
Socioeconomic independent variables		
Cultivated cassava land	Cultivated	Number of acres dedicated to cassava production
Labour	Labour	Number of family members working on own farm, including the operator of the farm
Household type	Subsistent	Subsistent = 1 if more than 50 per cent of the household's cassava production is devoted for home consumption; otherwise Subsistent = 0
Biophysical independent variables		
Cassava cropping system	System	System = 1 if the household is practicing mono-cropping; System = 0 if the household is practicing cassava mixed cropping system with other crops
Institutional independent variables		
Access to planting materials in the vicinity	Seeds	Seeds = 1 if the household has access to planting materials in their villages; otherwise Seeds = 0
Access to extension	Extension	Extension = 1 if the household was visited by an extension agent in the past year; otherwise Extension = 0
Access to credit	Credit	Credit = 1 if the household received loan for purchase of cassava planting materials and fertilisers in the past year; otherwise Credit = 0
Membership to local associations	Membership	Membership = 1 if the household belongs to a local farm association; otherwise Membership = 0
Country	TZ	TZ = 1 if the household is from Tanzania; otherwise TZ = 0
	DRC	DRC = 1 if the household is from DRC; otherwise DRC = 0
	SL	SL = 1 if the household is from Sierra Leone; otherwise SL = 0
	ZA	ZA = 1 if the household is from Zambia; otherwise ZA = 0

Source: own composition

Results and discussion

The results from the descriptive analysis establish the empirical relationship between adoption and individual household characteristics and outcome variables. The results from the multivariate analysis include the estimates of the actual and differential income effects of the adoption of cassava technology on the poor *vis-a-vis* the non-poor, as well as on the female-headed *vis-a-vis* the male-headed households, the estimates of the number of poor lifted out of poverty due to adoption, the potential impacts on poverty reduction should the current non-adopters be able to adopt cassava technology, and the barriers to adoption of this technology.

Descriptive results

Table 2 presents the descriptive statistics of the treatment, outcome and explanatory variables included in the model. The rate of adoption as defined by the proportion of households who reported to have planted one or more improved cassava varieties in 2013 is 34 per cent. The majority of the household characteristics are significantly different between adopters and non-adopters. For example, a relatively larger proportion of adopters have access to extension, planting materials (denoted by seeds) and credit services. About 33 per cent of adopters are visited by extension agents, compared to only 22 per cent of non-adopters. Analogously, about 30 per cent of adopters reported to have access to planting materials, compared to only 17 per cent of non-adopters.

As for the relationship between adoption and outcome variables, a straightforward comparison between adopters and non-adopters shows that adopters have relatively higher daily per capita expenditure than non-adopters (Table 3). Further, the rate, depth and severity of poverty are lower among adopters than non-adopters. The headcount ratio for adopters is about 45 per cent, compared to about 50 per cent for non-adopters. Analogously, adopters have relatively smaller poverty gap (indicator of income shortfall from poverty line) and poverty gap-squared (indicator of degree of inequality

Table 2: Descriptive statistics of the treatment and independent variables.

Variable	Level	Non-adopters	Adopters	Pooled sample
Adoption	Number of obs.	1273	646	1919
Gender	Male=1	0.865	0.850	0.860
	Age1	0.086	0.082	0.085
Age	Age2	0.802	0.819	0.808
	Age3	0.111	0.099	0.107
Education	Formal=1	0.747	0.716	0.737
Occupation	Agriculture	0.948	0.920	0.939
Subsistent	Subsistent=1	0.456	0.356	0.422
Cultivated	Ha	1.7	2.9	2.1
Labour	Number	3.8	4.6	4.1
System	Mono cropping=1	0.374	0.371	0.373
Seeds	Yes=1	0.166	0.300	0.210
Extension	Yes=1	0.216	0.327	0.253
Credit	Yes=1	0.033	0.075	0.047
Membership	Yes=1	0.541	0.551	0.544
TZ	Yes=1	0.312	0.306	0.310
DRC	Yes=1	0.134	0.217	0.162
SL	Yes=1	0.235	0.367	0.279
ZA	Yes=1	0.319	0.110	0.249

For details of variables see Table 1
Source: own calculations

Table 3: Descriptive statistics of outcome variables.

Outcome variable	Non-adopters	Adopters	Pooled sample
Daily per capita expenditure (USD)	1.93 (2.85)	2.01 (2.90)	1.95 (2.62)
Poverty headcount index	0.504	0.446	0.485
Poverty gap index	0.220 (0.279)	0.171 (0.253)	0.204 (0.271)
Poverty gap-squared index	0.126 (0.203)	0.093 (0.177)	0.115 (0.195)

Figures in parenthesis are standard deviations
Source: own calculations

among the poor) than non-adopters. On average, adopters have a poverty gap of 17 per cent compared to 22 per cent for non-adopters. Since these results are generated without taking account of the effects of other observed and unobserved household characteristics, they have no causal interpretation. In such a situation, adopters and non-adopters will not be truly comparable with respect to the poverty outcome variables that we are intending to evaluate in this study. This is because the differences in the outcome variables between adopters and non-adopters might be not because of adoption but because of the difference in the uncontrolled observed characteristics and unobservables. The next section provides the results of the multivariate analysis conducted using the ESR model. Since the ESR model controls for observed characteristics and takes account of unobserved heterogeneities, the parameter estimates of the ESR model that are used in the estimation of causal effects of adoption are unbiased and consistent.

Results from multivariate analysis

Table 4 presents the results from the multivariate analysis (the ESR model) implemented in STATA using the *movestay* command (Lokshin and Sajaia, 2004). The likelihood ratio test rejects the null hypothesis of joint independence [$\chi 2$ (1) =786.5; p=0.000]. This provides evidence of appropriateness of the assumption that effects of covariates across the two groups – adopters and non-adopters – are significantly different. Hence, we have two distinct regression equations or regimes rather than one. In addition, the model detects selectivity bias. This implies that the decision into adoption and non-adoption of cassava technology is likely based on unobservables (e.g. risk-taking behaviour) that correlate with the outcome variable (i.e. expendi-

Table 4: FIML estimates of the ESR model of per capita expenditure.

Variable	Selection/adoption equation		Outcome/expenditure equations			
			Regime 1 (adoption)		Regime 2 (non-adoption)	
	Estimate	SE	Estimate	SE	Estimate	SE
Gender	-0.277**	0.115	-0.050	0.111	0.142*	0.080
Age2	-0.119	0.142	-0.152	0.136	-0.165*	0.100
Age3	-0.012	0.176	-0.259	0.169	-0.312***	0.122
Education	0.346***	0.120	-0.015	0.118	0.125	0.085
Subsistent	-0.183**	0.078	-0.033	0.076	-0.034	0.054
Cultivated	0.050**	0.021	-0.002	0.013	0.015	0.017
Labour	0.051***	0.019	-0.066***	0.020	-0.043	0.014
Occupation	-0.217	0.153				
System	0.294***	0.091				
Seeds	0.391***	0.097				
Credit	0.370**	0.167				
Membership	0.142*	0.086				
Extension	0.465***	0.092				
TZ	0.724***	0.114	0.388***	0.145	0.596***	0.073
DRC	1.211***	0.127	-0.411***	0.157	0.188*	0.099
SL	1.233***	0.173	0.315*	0.193	0.636***	0.146
Constant	-1.470***	0.275	0.989***	0.333	-0.058	0.144
Sigma(σ_j)			0.768***	0.040	0.778***	0.019
σ_j			-0.25		-0.08	
Rho(ρ_j)			-0.320*	0.175	-0.100	0.170

LR test of independent equations: $\chi^2(1)=786.5$; $p=0.000$; for details of variables see Table 1
*, ** and *** denote, respectively, significance level at 10%, 5%, and 1%
Source: own calculations

ture). With the covariances between the error terms of the adoption equation and the expenditure equations for both adopters and non-adopters being negative, we have a case of negative selection *into* and *out of* adoption. The current adopters are likely to have self-selected themselves *into* adoption precipitated by expected benefits from adoption of cassava technology in terms of increased consumption expenditure. Similarly, the current non-adopters are likely to have self-selected themselves *out of* adoption because they may not have expected to benefit from adoption. The current adopters had they not adopted would have done worse than the current non-adopters. In contrast, the current non-adopters had they adopted would have done better than the current adopters. These can be readily seen in the estimates of the expected daily per capita expenditure under observed and counterfactual conditions as suggested by Maddala (1986)[5]. The average daily per capita expenditure of the current adopters had they not adopted would have been USD 1.23, compared to USD 1.26 observed for the current non-adopters (Tables 5 and 6). That is, the current adopters had they not adopted would have an average daily per capita expenditure of USD 0.03 less than what the current non-adopters are actually observed to have. In the same Tables, it can also be seen that the average daily per capita expenditure of the current non-adopters had they adopted would have been USD 2.19, compared to USD 1.52 observed for the current adopters. That is, the current non-adopters had they adopted would have USD 0.67 more daily per capita expenditure than what the current adopters are currently having.

Actual impacts of adoption

The results indicate that adoption resulted in a USD 0.29 increase in daily per capita expenditure (USD 1.52 cf. USD 1.23, Table 5). About 44 per cent of adopters are below the poverty line but, had it not been for adoption, the poverty rate would have been about 54 per cent. This suggests that the USD 0.29 gain in average daily per capita expenditure due to adoption of cassava technology has led to an approximately 10 percentage point reduction in poverty (Table 5). It also yielded a 3 percentage point reduction in depth of poverty, translating into a per capita cost savings of USD 11 per year. Drawing on the estimates of the gain in average daily per capita income (as proxied by the average daily per capita expenditure) and associated reduction in the respective indices of poverty reported in Table 5, a 1 per cent increase in daily per capita expenditure due to adoption is associated with a 0.8, 1.03 and 1.56 per cent reduction in rate, depth and severity of poverty respectively. While the results are consistent that adoption of cassava technology has a poverty-reducing impact at the USD 1.25 per capita per day poverty line, there is no guarantee that they would hold at different poverty lines. The following section presents the sensitivity of the poverty-reducing impacts of the adoption of cassava technology to different poverty lines.

[5] In addition to the sign and magnitude of the covariances that depict the direction and degree of non-random selection, it is important to estimate the mean values of the dependent variables for the alternate choice because they shed light on the effects of self-selection (Maddala, 1986).

Table 5: Average effects on adopters.

Outcome variable	Decision stage		Average effect
	Adopt	Not to adopt	
Daily per capita expenditure (USD)	1.52	1.23	0.29 (0.015)***
Headcount index	0.443	0.547	-0.103 (0.034)***
Poverty gap index	0.093	0.123	-0.030 (0.006)***
Poverty gap squared index	0.024	0.038	-0.014 (0.003)***

*** denotes statistical significance at 1%; figures in parenthesis are standard errors
Source: own calculations

Table 6: Average effects on non-adopters.

Outcome variable	Decision stage		Average effects
	Adopt	Not to adopt	
Daily per capita expenditure (USD)	2.19	1.26	0.93 (0.014)***
Poverty headcount index	0.044	0.567	-0.523 (0.016)***
Poverty gap index	0.005	0.140	-0.135 (0.005)***
Poverty gap-squared index	0.001	0.043	-0.042 (0.002)***

*** denotes statistical significance at 1%; figures in parenthesis are standard errors

Source: own calculations

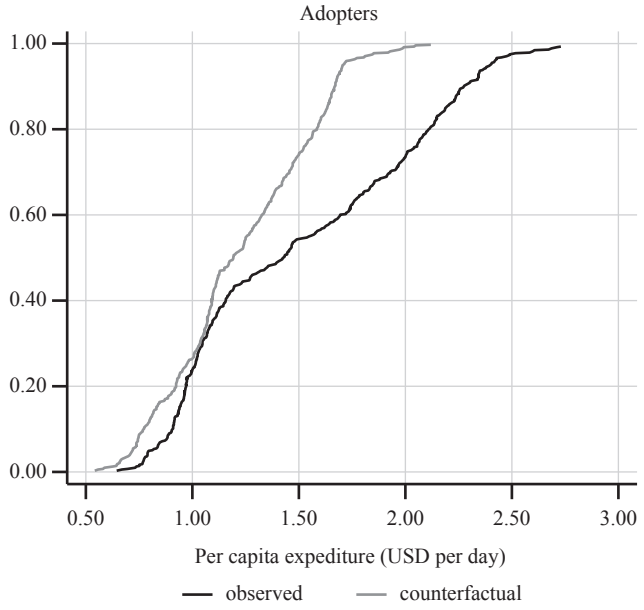

Figure 1: Observed and counterfactual cumulative distribution.
Source: own composition

Sensitivity of results to different poverty lines

To check the effect of different poverty lines on poverty, we look at the entire distribution using the theory of stochastic dominance. The distribution of the observed daily per capita expenditure for adopters lies predominantly to the right of the counterfactual as high as the USD 2.25 poverty line (Figure 1). Now, the question is whether the USD 2.25 per day poverty line is such that all conceivable poverty lines are below it. Given that almost all of the individuals are below the poverty line of USD 2.25 per capita per day, intersection of the two distributions is unlikely beyond USD 2.25 per day. This is confirmed using the Kolmogorov–Smirnov statistic for first degree stochastic dominance, rejecting the hypothesis that the two distributions are the same.

Impacts of adoption on female-headed vis-a-vis male-headed households

Table 7 reports the poverty-reducing impacts of adoption disaggregated by type of household, revealing that adoption has greater income effects and associated poverty-reducing impacts among female-headed households than among male-headed households. The former are observed to have an average daily per capita expenditure of USD 1.69. But, had they not adopted, they would have an average daily per capita expenditure of USD 1.08, implying that they gained USD 0.62 compared to USD 0.23 gained by the latter. As a result, the rate poverty among female-headed households is 15 percentage points lower than among male-headed households. The difference in both daily per capita expenditure and poverty rate between the two groups is statistically significant. The female-headed households have also performed better in terms of both the depth and severity of poverty. This is not unexpected given that female-headed households are more likely than male-headed households to adopt cassava technology. This implies that, controlling for the observable and unobservable heterogeneities in household characteristics, female-headed households are not disadvantaged relative to male-headed households when it comes to cassava technology.

Impacts of adoption on the poor vs. the non-poor

To assess the differential impacts of adoption on the poor *vis-à-vis* the non-poor, we decompose the overall increase in average daily per capita expenditure. The average observed daily per capita expenditure for adopters is USD 1.52, compared to USD 1.23 had they not adopted, yielding a 23 per cent gain which is decomposed as:

$$(G/E_c)\% = \beta(G_p/E_{c,p})\% + (1-\beta)(G_n/E_{c,n})\% \quad (8)$$

where $(G/E_c)\%$ is the overall average gain as a percentage of the counterfactual daily per capita expenditure (c) for the whole sample; β is the expenditure share of the poor in total expenditure; $(G_p/E_{c,p})\%$ is the average gain as a percentage of the counterfactual daily per capita expenditure (c) for the poor (p); $(G_n/E_{c,n})\%$ is the average gain as a percentage of the counterfactual daily per capita expenditure (c) for the non-poor (n). The first term on the right side of equation 8 provides the share of the gain that accrues to the poor while the second term provides the share of the gain that accrues to the non-poor.

In the light of equation 8, the 23 per cent overall average gain due to adoption is decomposed such that 5 per cent would accrue to the poor, compared to 18 per cent that would accrue to the non-poor (Table 8). In other words, of the USD 0.29 gain due to adoption, USD 0.23 accrues to the non-poor, and USD 0.06 accrues to the poor group.

Number of poor lifted out of poverty due to cassava technology

Beyond establishing causality between adoption and poverty, we have also estimated the number of households who have managed to overcome poverty as a result of the adoption of cassava technology. Firstly, we estimate the population of adopting households. Secondly, we apply the FGT headcount indices of poverty computed separately

Table 7: Poverty-reducing impacts of adoption disaggregated by type of household.

Outcome variable	Head of household (HH)	Decision stage		Average effects	Difference in average effects between male-headed and female-headed HH
		Adopt	Not to adopt		
Daily per capita expenditure (USD)	Female	1.69	1.08	0.600 (0.043)	0.37 (0.041) ***
	Male	1.49	1.26	0.230 (0.015)	
Poverty headcount index	Female	0.373	0.610	-0.237 (0.056)	-0.155 (0.046) ***
	Male	0.455	0.537	-0.082 (0.016)	
Poverty gap index	Female	0.052	0.181	-0.129 (0.021)	-0.114 (0.016) ***
	Male	0.100	0.114	-0.014 (0.005)	
Poverty gap-squared index	Female	0.010	0.069	-0.059 (0.011)	-0.053 (0.008)***
	Male	0.026	0.033	-0.007 (0.003)	

*** denotes significance at 1% level; numbers in parentheses are standard errors
Source: own calculations

Table 8: Differential impacts of adoption on the poor vs. non-poor in daily per capita expenditure (USD).

Group	Decision stage		Average gain as a percentage of the counterfactual	Expenditure share (%)	Share of overall average gain (%)
	Adopt	Not to adopt			
All	1.52	1.23	23.6		
Non-poor	2.05	1.56	31.4	57.0	17.9
Poor	1.09	0.97	12.4	43.0	5.3

Non-poor refers to the group of adopters who are above the poverty line with and without adoption; *poor* refers to those who are below the poverty line without adoption; some of them have moved out of poverty with adoption while some others remain poor despite adoption
Source: own calculations

from the observed and counterfactual distributions to the estimated population of adopting households and calculate the population of poor households (observed) as well as the population of households who would have been poor had it not been for adoption (counterfactual). Thirdly, we take the difference between the two estimated population figures, yielding the poverty impacts of adoption expressed in terms of the number of households who managed to overcome poverty.

Given an adoption rate of 34 per cent, 236,006 out of the total estimated 694,135 cassava-producing households in the study districts are considered to have adopted one or more improved cassava varieties in 2013. In the same year, 44.4 per cent of these households (equivalent to 104,787 households) are observed to be below the poverty line. Had it not been for adoption, the poverty rate would have ticked 10.3 percentage points, rising to 54.7 per cent. This means that there would be 129,095 poor households without adoption. This implies that an estimated 24,309 households (equivalent to 194,469 individuals estimated at eight persons per household) have managed to move out of poverty.

Potential impacts of adoption

Potential impacts refer to potential benefits that may accrue to the current non-adopters should they choose to adopt the cassava technology in the future. An approach similar to the one applied for the assessment of the actual impacts is applied, considering the current non-adopters as potential adopters. A comparison of the actual versus the potential impacts of adoption shows that the latter (Table 6) is greater than the former (Table 5). This is apparent in Figures 1 and 2 where the size of the gap between the observed and counterfactual curves in Figure 2 (potential impacts) is larger than the case in Figure 1 (actual impacts). Non-adopters are observed to have an average daily per capita expenditure of USD 1.26. But, had they adopted, they would have an average daily per capita expenditure of USD 2.19, yielding an additional gain of USD 0.93. Drawing on the potential gain in average daily per capita expenditure and associated potential reduction in the poverty rate reported in Table 6, it is established that a 1 per cent increase in daily per capita expenditure due to adoption is associated with a 1.25 per cent potential reduction in the poverty rate among current non-adopters, compared to 0.8 per cent actual reduction among current adopters. Current non-adopters would also potentially fare better than the current adopters in terms of depth of poverty. A 1 per cent increase in daily per capita expenditure due to adoption is associated with a 1.31 per cent potential reduction in depth of poverty among current non-adopters, compared to 1.03 per cent actual reduction among current adopters. These results suggest that it is important to address the barriers to adoption in order that the current non-adopters can take up the cassava technology.

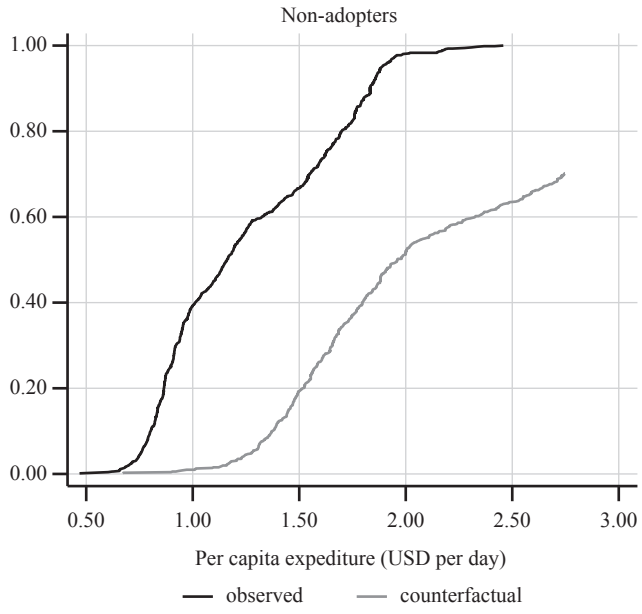

Figure 2: Observed and counterfactual cumulative distribution.
Source: own composition

Barriers to adoption

In order to identify the barriers to adoption, we rely on the parameter estimates of the selection or adoption equation of the ESR model in Table 4. The major barriers to adoption are identified as lack of access to extension, planting materials, credit, formal education and limited availability of resources (labour force and cassava farm area). Gender and education level of the head of the household are found to have statistically significant effects on adoption of improved cassava varieties. The probability of adopting cassava technology is lower for male-headed households than female-headed households. Consistent with expectation, education is positively related to adoption of cassava technology, indicating that households with a formal education are more likely to adopt cassava technology than those households without. Labour force and cassava farm area are also found to be statistically significant between adopters and non-adopters. In terms of biophysical characteristics, the type of cassava cropping system has a statistically significant relationship with adoption. Households who practice a mono cassava cropping system are more likely to adopt improved cassava varieties than those who practice a mixed cropping system. As regards the institutional characteristics, access to planting materials, access to extension services and credit services are found to significantly influence adoption. Households with access to planting materials, extension visits and credit are more likely to adopt improved cassava varieties.

Conclusion and implications

The study assesses the actual and potential impacts of adoption of cassava technology on poverty reduction in four African countries. Unlike many past impact assessment studies, it goes beyond establishing the causal link between adoption of technology and poverty reduction and estimates the number of poor lifted out of poverty. The study also assesses the differential impacts of adoption on the poor vs. the non-poor, as well as on female-headed

vs. male-headed households. To achieve these objectives, a parametric approach (endogenous switching regression model) is applied. The results indicate that the model detects selectivity bias. With the covariances between the error terms of the adoption equation and the expenditure equations for both adopters and non-adopters being negative, we conclude that they may have self-selected *into* and *out of* adoption. With the bias accounted for, adoption of cassava technology results in an approximately 10 percentage point reduction in the poverty rate. Given an adoption rate of 34 per cent and a 10 percentage point reduction in the poverty rate, an estimated 24,309 households (equivalent to 194,469 individuals) managed to move out of poverty as a result of adoption. This implies that cassava technology can be promoted as part of an effective poverty reduction and sustained agricultural growth strategy for Africa. Results disaggregated by type of household show that adoption of cassava technology has benefited female-headed households and the non-poor, relative to male-headed households and the poor. Targeted interventions will thus be more effective in terms of reducing costs, maximising average impacts and reducing poverty.

A comparison of the actual versus the potential impacts of adoption suggests that the non-adopters, had they adopted the technology, would have benefited more than what the actual adopters had, implying that continued dissemination efforts and reaching out to current non-adopters could increase the average impact of adoption on poverty reduction and is, therefore, worthy of investment. Currently, only 34 per cent of the cassava producers are adopters. Addressing the identified barriers to adoption (e.g. lack of access to extension, planting materials, credits and limited availability of resources) would allow exploiting the full potential of the cassava technology in poverty reduction. Considering the large realised and even more pronounced potential impacts of the adoption of cassava technology on poverty reduction, it is vital that regional and global development organisations working for the betterment of the African poor should continue to support the existing cassava improvement programme to sustain the technology development efforts in the continent.

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