Are agricultural technologies pro-poor? The case of improved cassava varieties in sub-Saharan Africa

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Abstract:

The paper assesses whether, and if so, to what extent, the adoption of improved cassava varieties are more favourable towards the food insecure (pro-poor) as measured by the share of overall benefits. Data for this study came from a household survey conducted in Tanzania, DR Congo, Sierra Leone and Zambia through multinational-CGIAR support to agricultural research for development of strategic crops project in Africa. Given the observational nature of the data, a parametric approach (endogenous switching and Poisson regression model) was applied, accounting for potential self-selection bias that may arise from unobserved heterogeneities. Results provided consistent findings that adoption of cassava varieties decreased the rate, depth and severity of food insecurity. Decomposition of the overall average gains in calories due to adoption resulted in over four-fifths accruing to food insecure, compared to only one-fifth accruing to the food secure group. This implies that the impacts of cassava varieties are more favourable towards the food insecure than the food secure and thus present important evidence on the effectiveness of the adoption of cassava technology for reducing the rate and depth of food insecurity in sub-Saharan Africa.

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Introduction

More than half a century passed since international agricultural research was launched in developing countries. The near consensus view is that in Asia and Latin America agricultural research avoided widespread food shortages that would cause particular hardship on the poor, suggesting that without agricultural research, food supply would have been smaller, pushing food prices up, and making it difficult for the poor to have access to food. In essence, agricultural research has been one of the best investments ever made to help the poor in Asia and Latin America. However, when it comes to Africa, the success of agricultural research is contentious in that more than half a century later Africa still faces widespread food shortages, currently spending USD 35b yr^{-1} on food imports, and poverty remains deep and widespread in many countries. For example, over the last 2 decades, Africa made the least progress toward poverty reduction (MDGs report, 2015). Today, Africa has the highest percentage of poor (41%). As a result, some have even questioned if Africa should rely on agriculture and invest in agricultural research for growth and poverty reduction, prompting policy makers and donors to demand for definitive answers on the societal impacts of agricultural research. This study addresses the question of whether and to what extent agricultural technologies are pro-poor in terms of improving food security[1], focusing on the adoption of cassava varieties. To address this research question, we tested two hypotheses: (i) causal relationship between adoption of improved cassava varieties and household food security (as measured by daily calorie consumption per capita, food insecurity headcount index, calorie deficit index and duration of food shortage); (ii) favourability of the food security benefits of the adoption of improved cassava varieties towards the food insecure (pro-poor) as measured by the share of overall benefits accruing to the poor *vis-à-vis* the non-poor. Data for this study came from a household survey conducted in Tanzania, DRC, Sierra Leone and Zambia in 2013 through multinational-CGIAR support to agricultural research for development of strategic crops (SARD-SC) project in Africa.

[1] According to the Food and Agriculture Organization (FAO) Household food security is achieved when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life

Given the observational nature of the data and associated self-selection problem, we apply the instrument variable (IV) approach. Our measures of food insecurity are based on a continuous variable (calorie consumption) and count variable (number of months of food shortage). Therefore, we addressed the identification challenge by estimating linear and count models with endogenous switching that take account of the potential self-selection problem indicated above. More specifically, we applied the ESR model to first establish the causal relationship between adoption and consumption, and the Endogenous Switching Poisson Regression (ESPR) model to estimate the impact of adoption on duration of food shortage. The advantage of these models is that they allow for both unobserved heterogeneity and endogeneity in the covariates (Simar, et al. 2015). Standard methods of decomposition are applied to the overall average gains of adoption to assess if the impacts of cassava varieties are pro-poor or more favourable towards the food insecure than the food secure. Beyond determining the bias towards or against the poor, we estimated the number of food insecure who managed to become food secure as a result of the adoption of cassava varieties. To this end, we established a procedure for assessing the impacts of adoption on food security.

The next section presents the impact identification challenges and strategies. Section 3 presents the econometric models (ESR and ESPR) that are applied to assess the causal effect of adoption on consumption and duration of food shortage. It will also present the procedure applied for determining the impact of adoption on the rate and depth of food insecurity. Section 4 describes the data and measurement of outcome, treatment and independent variables. Section seven presents descriptive results, highlighting the differences in outcome and independent variables between adopters and non-adopters. Section 5 presents and discusses the empirical results from the ESR. The results from the ESR will focus on the actual and potential impacts of adoption on calorie consumption, rate and depth of food insecurity as well as the distribution of the overall average gains in calorie consumption among three different household groups. The presentation of the actual impacts will also be disaggregated by gender. Section 6 presents and discusses the empirical results from the ESPR and highlights the main findings in terms of the impact of adoption on duration of food shortage. The final section concludes by summarizing the key findings and drawing policy implications in terms of the effectiveness of the adoption of cassava technology for reducing food insecurity in SSA.

1. **Ex post impact identification strategy**

Given the non-random allocation of households to treatment (adopters) and control (non-adopters) groups in the present study, identifying the causal effect of adoption on outcome variable such as consumption is challenging. In addressing the research question of the present study, the identification challenge arises from the fact that the decision into adoption and non-adoption of cassava technology could be based on unobservables that correlate with both consumption and observable predictors. Unobservables in the consumption equation may be correlated with the unobservables in the adoption equation. Household characteristics that are unobservable to the researcher may determine both the selection into adoption and consumption. Thus, a parameter estimating the relationship between adoption and consumption can be confounded with the selection process into adoption. For example, adopters may be risk-takers who thrive on innovations and expect to benefit from adoption in terms of increased consumption. In contrast, non-adopters may be risk-averse who stay away from innovations and may not expect to benefit from adoption. Thus, the measures of consumption between adopters and non-adopters would differ even in the absence of adoption. With adopters and non-adopters potentially being fundamentally different, it will be difficult to determine if the difference in consumption between these two groups is due to adoption or the underlying difference in their risk-taking behaviour or other factors that already exist between the two groups. When an unobserved characteristic such as risk-taking behaviour is omitted from the model, its effects are pooled into the error term, which will correlate with adoption and induce endogeneity. The failure to account for the potential self-selection to adoption in the consumption equation may therefore result in biased and inconsistent estimators. Past empirical studies have attempted to address such challenges using a number of parametric and non-parametric identification strategies (Shiferaw et al. 2014; Khonje et al. 2014; Asfaw et al. 2012). The most common ones include propensity matching score (PSM) and instrumental variable (IV) approaches. The PSM approach is, however, limited by the fact that it is based on the assumption that no unmeasured characteristics exist that affect both the treatment (adoption) and outcome (consumption) variables. As a result, most analysts resort to parametric approaches such as the IV approaches, particularly the ESR approach that takes into account both the measured and unmeasured attributes. Given that our measures of food insecurity in the present study are based on a continuous variable (calorie consumption) and a count variable (duration of food shortage as measured by number of months), we, respectively, address the identification challenge by estimating linear and count models with endogenous switching that takes account of the potential self-selection problem indicated above. More specifically, we apply the ESR model to first establish the causal relationship between adoption and consumption and then asses the impacts on the rate and depth of food insecurity. We apply the ESPR model to estimate the impact of adoption on duration of food shortage. The advantage of these models is that they allow for both unobserved heterogeneity and endogeneity in the covariates.

2. Model

The effect of the treatment defined by adoption of cassava technology on the outcome variable defined by calorie consumption can be estimated using a linear regression given as

$$Y_i = X_i'\beta + \vartheta A_i + \varepsilon_i \ldots\ldots \quad (1)$$

where Y_i is daily consumption per capita; X_i is a vector of covariates used to model daily consumption per capita; β represent a vector of parameters to be estimated; A_i represents adoption of cassava technology; ϑ is the coefficient associated with adoption A_i; ε_i is the error term.

Eq. (1) can be consistently and efficiently estimated using the Ordinary Least squares (OLS) estimator provided that adoption is randomly assigned. But, if adoption is endogenous, which is likely so, given the possibility that the study households may self-select into adoption and non-adoption, the dummy variable that denotes adoption A_i may be correlated with the error term ε_i in which case the OLS estimator would be inappropriate and lead to biased and inconsistent estimates. If adoption were continuous, one way to address this issue would be making use of the standard IV approach. But, since adoption is a discrete variable in the present study, the most appropriate means to deal with this issue is to apply a latent variable approach given as

$$A_i^* = Z_i'\gamma + u_i \ ; A_i = \begin{cases} 1 & \text{if} A_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \ldots\ldots \quad (2)$$

where A_i^* represents a latent continuous variable representing adoption; Z_i is a vector of covariates used to model adoption; γ represent a vector of parameters to be estimated; u_i is the error term.

If the error term is assumed to have standard normal distribution, Eq. (2) becomes a probit model. Allowing for endogenous switching where the effect of adoption involves differences in parameter estimates of the covariates, we will apply the ESR model.

3.1.The ESR model

The ESR consists of one adoption equation and two consumption equations conditional on the adoption equation. The two consumption equations, conditional on A_i, can be specified as below where households face two regimes (1) adoption, and (2) non-adoption

Regime 1 $\quad Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad \text{if} \quad A_{1i} = 1 \ldots\ldots$ (3a)

Regime 2 $Y_{2i} = \beta_{2i}X_{2i} + \varepsilon_{2i}$ if $A_{1i} = 0$…………………………………… (3b)

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

The expected values of the error terms, ε_1 and ε_2, conditional on the adoption equation are non-zero because of the possible correlation between the error term in the adoption equation and the error terms of the consumption equations.

$$E(\varepsilon_{i1}|A_i = 1) = \sigma_{u\varepsilon_1}\frac{\phi(\hat{A})}{\Phi(\hat{A})} \quad \text{(4a)}$$

$$E(\varepsilon_{i2}|A_i = 0) = \sigma_{u\varepsilon_2}\frac{\phi(\hat{A})}{1-\Phi(\hat{A})} \quad \text{(4b)}$$

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 selection (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 Mill's ratio terms from the probit model are added into the consumption equations to correct for the potential selection bias as

$$Y_{1i} = \beta_1 X_{1i} + \sigma_{u\varepsilon_1}\frac{\phi(\hat{A})}{\Phi(\hat{A})} + \varepsilon_{1i}, \text{ if } A_i = 1 \quad \text{(5a)}$$

$$Y_{2i} = \beta X_{2i} + \sigma_{u\varepsilon_2}\frac{\phi(\hat{A})}{1-\Phi(\hat{A})} + \varepsilon_{2i}, \text{ if } A_i = 0 \quad \text{(5b)}$$

If the $\sigma_{u\varepsilon_1}$ and $\sigma_{u\varepsilon_2}$ are statistically significant, we will have endogenous switching. Otherwise, we will have exogenous switching. The above equations can be estimated in a two-stage procedure. However, the efficient way to them is by Full Information Maximum Likelihood (FIML) (Lokshin and Sajaia 2004).

3.2.Procedure for assessing the impacts of adoption on the reduction of food insecurity

In the present study, we assess both the actual and potential impacts of adoption of cassava technology on the reduction of food insecurity. Actual impacts refer to the reduction of food insecurity or calorie deficit among the actual or current adopters while potential impacts refer to the reduction in food insecurity 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 the reduction of food insecurity will be assessed based on the parameter estimates of the ESR model that consists of the system of one adoption equation of cassava technology and two consumption equations. For both the actual and potential impacts, we will first estimate the ESR model using the FIML estimator, and then generate four distributions of expected daily consumption per capita under observed and counterfactual conditions. For adopters, we generate two distribution under observed (with adoption) and counterfactual (without adoption i.e., had they not adopted) using Eq. (6a) and Eq. (6b), respectively given as

$$E(Y_{1i}|A_i = 1) = X_{1i}\beta_1 + \sigma_{\varepsilon_1 u}\frac{\phi(\hat{A})}{\Phi(\hat{A})} \quad \text{……… (6a)}$$

$$E(Y_{2i}|A_i = 1) = X_{1i}\beta_2 + \sigma_{\varepsilon_2 u}\frac{\phi(\hat{A})}{\Phi(\hat{A})} \quad \text{……… (6b)}$$

Based on the two distributions, we will compute the indices of food insecurity (food insecurity headcount index and food insecurity gap index) separately for each distribution. The difference in the respective indices of food insecurity between the observed (with adoption) and counterfactual (without adoption) distributions for adopters will provide the actual impacts of adoption on the rate and depth of food insecurity.

Similarly, for non-adopters, we generate two distribution under observed (without adoption) and counterfactual (with adoption i.e., had they adopted) using Eq. (6c) and Eq. (6d), respectively given as

$$E(Y_{2i}|A_i = 0) = X_{2i}\beta_2 + \sigma_{\varepsilon_2 u}\frac{\phi(\hat{A})}{1-\Phi(\hat{A})} \quad \text{……… (6c)}$$

$$E(Y_{1i}|A_i = 0) = X_{2i}\beta_1 + \sigma_{\varepsilon_1 u}\frac{\phi(\hat{A})}{1-\Phi(\hat{A})} \quad \text{……… (6d)}$$

Based on the two distributions, we will compute the indices of food insecurity described above. The difference in the respective indices of food insecurity between the observed (without adoption) and counterfactual (with adoption) distributions for non-adopters will provide the potential impacts of adoption on the rate and depth of food insecurity.

3.3.The ESPR model

The ESPR model will be estimated to assess the impacts of adoption of cassava technology on the duration of food shortage. Following Miranda (2004), the conditional probability density function of the duration of food shortage as measured by number of months is assumed to follow a standard Poisson distribution given by

$$f(y_i; \lambda_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

where $\lambda_i = \exp(X'\beta + \gamma A_i + v_i)$ is the mean value.

The mean value depends on a vector of explanatory variables X_i, a binary switching variable $(A_i = 0{,}1)$ which indicates adoption status, a random component v_i that accounts for unobserved heterogeneity.

The adoption status A_i is characterised by an index process that contains a vector of explanatory variables Z_i which may contain some or all the elements of X_i given in Eq. (2). The joint distribution of v_i and u_i is assumed to be normal with mean vector 0 and covariance matrix given as $\Sigma = \begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$ where σ^2 is the variance of v_i; ρ is the correlation between the duration of food shortage and the adoption indicator; the variance of u_i is normalized to 1 for identification.

If ρ is zero, v_i and u_i are independent such that A_i can be treated as an exogenous process, that is, there is no self-selection under this formulation. Thus, the parameter estimates are unbiased and consistent.

4. Data, description and measurement of variables

The data used in the study came from a formal survey conducted by administering standardized questionnaire to selected households. Both non-random and random sampling methods were applied in the selection of the 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 random sampling involved the selection of villages while the second-stage random sampling involved the selection of sample households. A total of 1445 households have been used in this study. The standardized questionnaire included sections on household demographic characteristics, land ownership, cassava production systems, access to inputs, awareness/knowledge and use of agricultural technologies, cassava consumption/processing/marketing and other utilization, sources of information about farming and processing, food security, institutional settings, cost of production, as well as problems associated with cassava production, processing and marketing.

4.1.Description and measurement of independent variables

The description and measurement of independent variables is presented in Table 1a. The independent variables came from four groups of household characteristics - demographic, socioeconomic, biophysical and institutional characteristics.

Table 1a: Description and measurement of independent variables

Variables	Code	Description
Demographic		
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 a formal education; otherwise education=0
Occupation - primary	Occupation	Occupation=1 if the primary occupation of the household is crop and livestock production; otherwise Occupation=0
Socioeconomic		
Cassava farm	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 the household is subsistent with more than 50% of its cassava production devoted for home consumption; otherwise Subsistent=0
Biophysical		
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		
Access to planting materials in 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
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 study country is Tanzania; otherwise TZ=1
	DRC	DRC=1 if the study country is DRC; otherwise DRC=0
	SL	SL=1 if the study country is Sierra Leone; otherwise SL=1
	ZA	ZA=1 if the study country is Zambia; otherwise ZA=1

4.2.Description and measurement of treatment variable

The treatment variable is adoption of cassava technology measured based on whether the household has cultivated one or more improved cassava varieties in 2013 (Table 1b). These varieties were developed by the International Institute of Tropical Agriculture (IITA) in collaboration with the national research programs in the respective countries.

Table 2 presents the outcome variables - daily consumption per capita, food insecurity headcount index and food insecurity gap index and duration of food shortage. The two indices of food insecurity are developed based on the daily consumption per capita. The indices are adapted from the FGT indices of poverty as presented in Haughton and Khandker (2009). The food insecurity headcount index measures the food insecurity rate, which is the share of the population consuming less than the threshold level of calories (2100 Kcal per capita per day) established by FAO. Households whose members consume 2100 Kcal per capita per day are considered food insecure and those who consume above the threshold level are considered food secure. The food insecurity gap index measures the depth of food insecurity that indicates the average calorie deficit from the threshold level. This index helps to understand the number of kilocalories missing from the diets of food insecure individuals.

Table 2: Description and measurement of outcome variables

Variables	Code	Description
Outcome variables		
Daily consumption per capita	Daily consumption per capita	Per capita calorie consumption measured in KCAL per day
Food insecurity head count index	Food insecurity head count index	The food insecurity headcount index measures the rate of food insecurity, which is the proportion of people living below the 2100 Kcal per capita per day.
Food insecurity gap index	Food insecurity gap index	The food insecurity gap index measures the depth of food insecurity, which is the calorie deficit from the 2100 Kcal per capita per day level
Duration of food shortage	Duration of food shortage	The duration of food shortage measures the number of months in the past year the household run short of food

5. Differences between adopters and non-adopters: Results from descriptive analysis

Table 3 provides the descriptive statistics of the independent variables hypothesized to influence the treatment and outcome variables (adoption, calorie consumption and duration of food shortage). Without controlling for the effect of other household characteristics, demographic characteristics do not seem to have a systematic association with adoption.

However, some socioeconomic characteristics such as cassava farm and institutional characteristics such as access to planting materials and extension seem to be systematically associated with adoption. A relatively larger proportion of adopters have access to planting materials, extension services than non-adopters. For example, about 28% of adopters have access to planting materials through dealers in their vicinity compared to only about 15% of non-adopters. Similarly, 33% of adopters were visited by extension agents compared to only about 22% of non-adopters.

Table 3: Descriptive statistics of independent variables

Variables	Levels	Non-adopters	Adopters	Pooled sample
Adoption		32.5	67.5	-
Gender	Male=1	86.5	86.2	86.4
Age	Age1	8.0	7.9	7.9
	Age2	80.3	81.5	80.7
	Age3	11.7	10.6	11.3
Education	Formal=1	80.5	80.0	80.3
Labour	Number	3.50	3.90	3.60
Membership	Yes=1	54.8	56.6	55.4
Occupation - primary	Agriculture	95.2	91.9	94.1
Subsistent	Subsistent=1	48.2	39.6	45.4
Cassava farm	Ha	0.60	0.90	0.70
System	Mono cropping=1	34.1	30.0	32.8
Seeds	Yes=1	14.9	28.1	19.2
Extension	Yes=1	21.8	33.2	25.5
TZ	Yes=1	33.1	35.1	33.8
DRC	Yes=1	17.5	29.8	21.5
SL	Yes=1	11.5	21.1	14.6
ZA	Yes=1	37.8	14.0	30.1

As for the relationship between adoption and outcome variables, a straightforward comparison between adopters and non-adopters shows no statistically significant difference in daily consumption per capita and duration of food shortage (Table 4). Since these findings do not take account of unobserved heterogeneities and also do not hold constant the effects of observed household characteristics, they have no causal interpretation. The next section provides the results of two multivariate analyses that take account of observed and unobserved heterogeneities, thus allowing for assessment of the causal effect of adoption of cassava technology. The first multivariate analysis is done using the ESR model with daily consumption per capita as an outcome variable, while the second multivariate analysis is done using the ESPR model with number of months of food shortage as an outcome variable.

Table 4: Descriptive statistics of outcome variables

Outcome variables	Non-adopters	Adopters	Pooled sample
Daily consumption per capita (Kcal)	2349	2330	2342
Food insecurity headcount index (%)	62.5	59.6	61.5
Food insecurity gap index (%)	27.7	26.6	27.3
Duration of food shortage (number of months in the past year)	1.34	1.38	1.35

6. Impact of adoption: Results from the ESR

The ESR model of daily consumption per capita as outcome variable conditional on adoption as treatment variable was estimated using full information maximum likelihood (FIML). The details of the parameter estimates are not discussed here because of space limitation but it is worth noting that the likelihood ratio test rejects the null hypothesis of joint independence [$\chi 2$ (1) = 799.98; p=0.000]. This provides evidence of appropriateness of the assumption that effects of covariates vary across the two groups – adopters and non-adopters.

6.1.Impacts of adoption on levels of calorie consumption and food insecurity

Table 5 shows that the mean daily consumption per capita of adopters is 1747 Kcal compared to 1577 Kcal had they not adopted. This implies that adopters would have 160 Kcal less, had they not adopted, implying that adoption yielded a 10.1% gain in overall average daily consumption per capita. In terms of its impact on reduction of food security, about 76% of adopters were observed to have a daily consumption per capita of below 2100 Kcal per day (food insecure). Had it not been for adoption of cassava technology, the rate of food insecurity would have been about 90%, suggesting that adoption of cassava technology led to about 14% point reduction in food insecurity. Drawing on the estimates of the reduction in the rate of food insecurity and the average gain in daily consumption per capita reported in Table 5, a 1% gain in daily consumption per capita due to adoption is associated with a 1.6% reduction of the rate of food insecurity.

Table 5: Average effects on adopters

Outcome variables	Decision stage		Average effects
	Adopt	Not to adopt	
Daily consumption per capita (Kcal)	1747	1587	160 (12.797) †††
Food insecurity headcount index (%)	75.9	90.0	14.1(5.728) †††
Food insecurity gap index (%)	20.5	25.7	5.2(11.343) †††

Note. †††denote statistical significance at 1%; numbers in parenthesis are t-statistics

Table 5 also shows that adoption of cassava technology yielded a 5.2% point reduction in depth of food insecurity as measured by the food insecurity gap index. The observed depth of food insecurity for adopters is 20.5%, which amounts to 430 Kcal. Were it not for adoption, the depth of food insecurity would have increased to 25.7%, which amounts to a calorie deficit of 540 Kcal. This implies that adoption resulted in cutting the calorie deficit by 110 Kcal per capita among the food insecure group of households.

The results in the present study are consistent with the finding in many studies which have demonstrated the positive effect of agricultural technologies on food security (Rusike et al. 2014; Rusike et al. 2010; Kambewa, 2010). In Zambia, Malawi and Mozambique, for example, adoption of improved cassava varieties has boosted cassava production allowing farmers to have more harvest for food with some surplus for sale to get cash (Kambewa, 2010). A study on the evaluation of the cassava research for development (R4D) program on household food adequacy in DRC demonstrated statistically significant positive effects on household food adequacy (Rusike et al. 2014). A similar study conducted in Malawi demonstrated that the R4D approach has contributed to measurable gains in household calorie intake (Rusike et al. 2010).

6.2.Gender-disaggregated impacts

Table 6 reports gender-disaggregated impacts of adoption, revealing that adoption had a higher food insecurity-reducing impact among female-headed households than among male-headed households. Female-headed households were observed to have an average daily consumption per capita of 1755 Kcal. But, had they not adopted, they would have daily consumption per capita of 1524 Kcal, implying that they did gain a daily consumption per capita of 231 Kcal compared to 148 Kcal gained by male-headed households. Female-headed households had gained 83 Kcal more than what the male-headed households had. This implies that controlling for most of the observable and unobservable heterogeneities in household characteristics female-headed households are no disadvantaged than male-headed households when it comes to cassava technology.

Table 6: Gender-disaggregated average effects on adopters

Outcome variables	Groups	Decision stage		Average effects
		Adopt	Not to adopt	
Daily consumption per capita (Kcal)	MHH	1745	1597	148 (10.910) †††
	FHH	1755	1524	231(7.696) †††
Food insecurity headcount index (%)	MHH	75.5	89.6	-14.1(5.282) †††
	FHH	78.4	92.3	-13.9(2.234) ††
Food insecurity gap index (%)	MHH	20.8	25.3	-4.5(9.353) †††
	FHH	19.0	27.9	-8.9(7.602) †††

Note: FHH refers to female-headed households; MHHs refers to male-headed households; ††† significant at 1% level; †† significant at 5% level; numbers in parentheses are t-statistics

6.3.Distribution of gains among different household groups

This section addresses the question of what proportion of the overall average gains in calories due to adoption of cassava technology accrued to the different household groups. Based on the effect of the adoption in terms of calorie gains, we have classified the sample households into three groups. The first group consists of households who were food insecure without adoption but have gained enough calories with adoption and managed to overcome food insecurity. We refer to this group as *uplifted*. The second group consists of those households who were food insecure without adoption but unlike the first group have not gained enough calories with adoption to overcome food insecurity. They remain food insecure. We refer to this group as *insecure*. Although this group of households remains food insecure after adoption, it does not mean that they did not benefit from adoption. But rather it means that the gain in calories was not large enough to help them overcome food insecurity. They have, however, minimized their calorie deficits. The third group consists of food secure households without adoption and remain so with adoption. We refer to this group as *secure*. While this group was food secure without adoption, they have gained more calories with adoption and strengthened their food security status.

The distribution of gains in calories due to adoption among these three groups of households (i.e., the *uplifted*, *insecure* and *secure*) can be implemented using

$$(ATT/C_c)\% = \beta_u(G_u/C_{c,u})\% + \beta_i(G_i/C_{c,i})\% + (1-\beta_u-\beta_i)(G_s/C_{c,s})\%, \ldots\ldots\ldots.. (8)$$

where $(ATT/C_c)\%$ is the average treatment effect on adopters in daily consumption per captia (i.e., overall average calorie gains) as a percentage of the counterfactual (without adoption) daily consumption per capita (c) for the whole sample; β_u is the calorie share of the *uplifted* group in total caloric consumption without adoption; G_u is the average gain in daily consumption per capita for the *uplifted* group with adoption; $C_{c,u}$ is the counterfactual (without adoption) daily consumption per capita for the *uplifted* group; β_i is the calorie share of the *insecure* group in total caloric consumption without adoption; G_i is the average gain in daily consumption per capita for the *insecure* group with adoption; $C_{c,i}$ is the counterfactual (without adoption) daily consumption per capita for the *insecure* group; G_s is the average gain in daily consumption per capita for the *secure* group with adoption; $C_{c,s}$ is the counterfactual (without adoption) daily consumption per capita for the *secure* group.

The first term on the right side of Eq. (8) provides the share of the overall average calorie gains that accrue to the *uplifted* group and constitutes the food insecurity *rate-reducing* effects; the second term provides the share of the overall average calorie gains that accrue to the *insecure* group and constitutes the food insecurity *depth-reducing* (calorie *deficit-reducing*) effects of adoption; and the third term constitutes the share of the overall average calorie gains that accrue to the *secure* group. It constitutes the food security *status-strengthening* effect.

Now, using eq. (8), the 10.1% overall average calorie gains due to adoption reported in the previous section were decomposed such that 4.0% would accrue to the *uplifted* group; 5.0% to the *insecure* group and 1.1% to the *secure* group. Expressed in actual calorie terms, out of the 160 Kcal gain with adoption, 61 Kcal per day that is equivalent to 38% accrued to the uplifted group; 76 Kcal (48%) to the insecure group and 23 Kcal accrued to the secure group, amounting to 14.0%. This shows that more than four-fifths (86%) of the overall average gains in calories accrued to the households who were food insecure without adoption. Only 14% accrued to the food secure households without adoption. This implies that the food insecurity rate-reducing and the food insecurity depth-reducing effects were larger than the food security status-strengthening effects. Stated in a different way, the effects of cassava technology were more favourable towards the food insecure than the food secure households. This presents important evidence in support of policy for promoting adoption of cassava technology as an effective strategy for addressing food insecurity in SSA.

6.4.Potential impacts of adoption

The potential impacts of adoption on the rate and depth of food insecurity were assessed considering the current non-adopters as potential adopters. Non-adopters were observed to have an average daily consumption per capita of 1631 Kcal. But, had they adopted, they would have a daily consumption per capita of 1950 Kcal, yielding an additional gain of 319 Kcal. The gain in calories would have translated into a 29.5% point reduction in rate of food insecurity.

Drawing on the estimated percentage changes in rate of food insecurity and daily consumption per capita reported in Table 7, a 1% gain in daily consumption per capita due to adoption is associated with a 1.6% potential reduction of the rate of food insecurity among the current non-adopters should they choose and be able to adopt cassava technology.

Table 7: Average effects on non-adopters

Outcome variables	Decision stage		Average effects
	Adopt	Not to adopt	
Daily consumption per capita (Kcal)	1951	1632	319†††(30.672)
Food insecurity headcount index (%)	63.3	92.8	-29.5†††(5.757)
Food insecurity gap index (%)	13.9	23.0	-9.1†††(28.502))

Note. Numbers in parenthesis are t-statistics; ††† denotes statistical significance at 1%

A comparison of the actual and. potential impacts of adoption shows that the former is smaller than the latter, suggesting that adopters would have done worse than the current non-adopters had they reversed roles. In other words, if the actual adopters had been placed in the position of the current non-adopters, they would have done worse than the current non-adopters. The fact that the current adopters had actually adopted was in their best interest. This is because, without adoption, they would have been in a worse position in terms of the rate and depth of food insecurity compared to the position where the current non-adopters actually are. These can be readily seen in the estimates of the expected daily consumption per capita under observed and counterfactual conditions. It can be seen in Tables 5 and 7 that the mean daily consumption per capita of the actual adopters had they not adopted would have been 1587 Kcal compared to 1632 Kcal observed for the current non-adopters. That is, the actual adopters had they not adopted would have consumed 45 less Kcal than what the current non-adopters actually consumed. This implies that the actual adopters had they not adopted would have done worse than the current non-adopters.

Conversely, if the current non-adopters (i.e., potential adopters) had been placed in the position of the actual adopters, they would have done better than the actual adopters. These can be readily seen in Tables 5 and 7 that the observed mean daily consumption per capita of the current non-adopters had they adopted would have been 1951 Kcal compared to 1747 Kcal observed for the actual adopters. That is, the current non-adopters had they adopted would have consumed 204 more kilo calories than what the actual adopters are currently consuming. This implies that the current non-adopters had they adopted would have done better than the actual adopters. This suggests that addressing the barriers to adoption so that the current non-adopters will be able to take up the cassava technology is worthwhile. The difference between the actual and potential impacts is apparent in Figure 1 and 2 where the size of the gap between the observed and counterfactual curves in Figure 2 (potential impacts) is greater as the case in Figure 1 (actual impacts).

Figure 1: Observed and counterfactual cummulative distribution

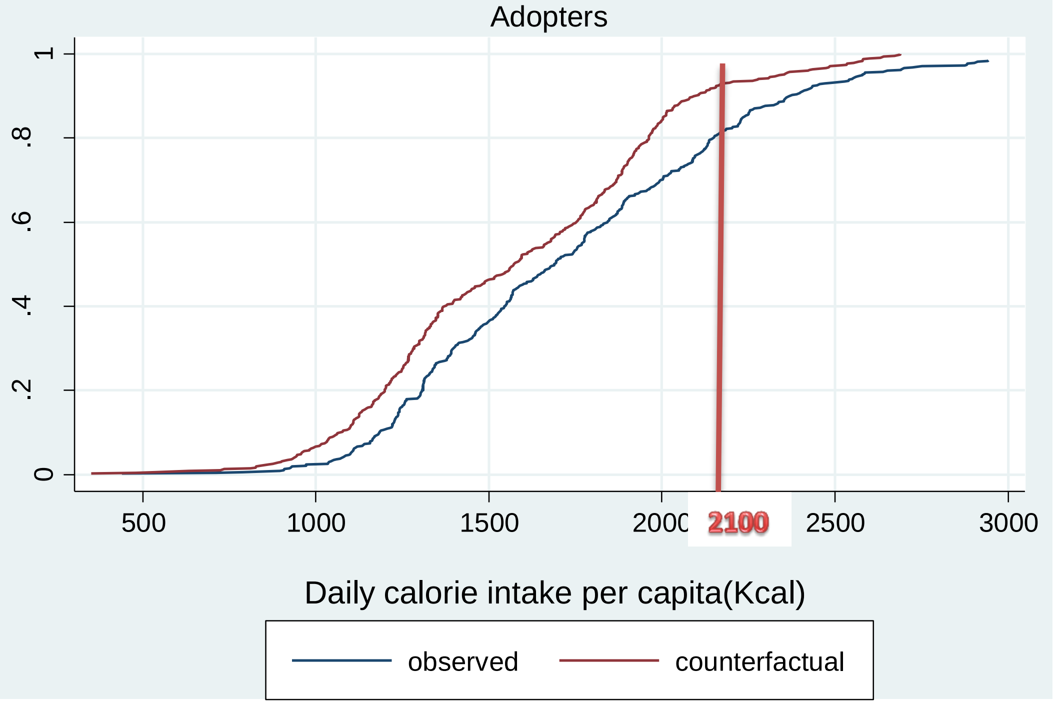
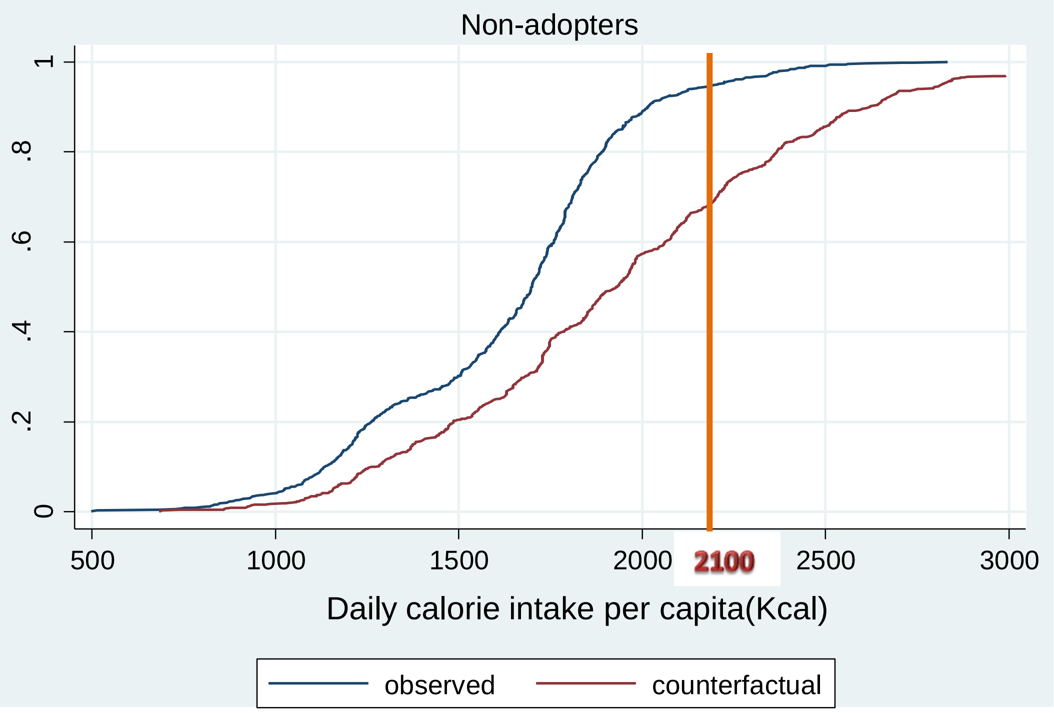


Figure 2: Observed and counterfactual cummulative distribution



7. Impact of adoption on duration of food shortage: Evidence from ESPR model

Although food security is a function of both physical availability and economic accessibility, it is sometimes difficult to distinguish between physical availability and economic accessibility at the household level in rural regions where local markets are not functioning well. This is because rural households generally depend on own food production as a means to have access to food in which case physical availability and accessibility access strongly overlap (Pieters et al. 2013). In this section, the assessment of the impacts of adoption on duration of food shortage was based on the lack of physical availability from own food production. The model was estimated by Maximum Likelihood (ML) estimator using adaptive quadrature. The model consists of two equations - the switch and the outcome model. The switch model is a probit model that predicts the probability of adoption. The outcome model is a Poisson model that estimates the causal effect of adoption on duration of food shortage. The models were identified through both nonlinear functional forms and some exclusion restrictions. The parameter estimates of the duration of food shortage based on the ESPR model are presented in Table 8. One of the most relevant characteristics in the model is the correlation coefficient between unobserved factors that affect the duration of food shortage and adoption. The coefficient is statistically significant, thus indicating self-selection. This implies that ignoring the endogeneity would have resulted in biased and inconsistent parameter estimates. If the endogeneity were ignored, adoption would have decreased the duration of food shortage by only 11% compared to 67% when the potential self-selection is allowed. The estimated correlation coefficient is 0.78 and statistically significant, implying that a longer period of food shortage is associated a lower probability of adoption.

Table 8 shows that adoption has a statistically significant effect on duration of food shortage, implying that adopters of cassava technology would have faced more months of food shortage were it not for adoption. Adoption would cut the duration of food shortage by 67% [=exp. (-1.104)-1]. This finding is consistent with that of Rusike et al. (2010) who demonstrated that adoption of cassava technologies increased the number of months households can meet minimum caloric requirements from home-produced staples and therefore improvement in food security.

Even though the focus of the study is on the causal effect of adoption, important relationships have also been established between a number of demographic and socioeconomic characteristics and the duration of physical shortage. For example, controlling for other household characteristics female-headed households face fewer months of food shortage than male-headed households. This is consistent with the finding presented in the previous section that adoption had a higher food insecurity reducing impacts among female-headed households than among male-headed households.

Table 8: ML estimates of the Endogenous switching Poisson model for duration of food shortage

Variables	Selection equation/adoption		Outcome variable/number of months of food shortage	
	Estimate	SE	Estimates	SE
Adoption			-1.104†††	0.248
Gender	-0.244††	0.107	-0.364†††	0.097
Age2	-0.078ns	0.136	.0382ns	0.125
Age3	0.045ns	0.170	0.002 ns	0.156
Education	0.275††	0.108	0.055 ns	0.097
Labour	0.042††	0.017	0.043†††	0.015
Membership	0.138†	0.079	0.187†††	0.075
Occupation	-0.181ns	0.146	-0.086 ns	0.146
Subsistent	-0.194††	0.075	-0.224†††	0.071
Cultivated	-0003ns	0.002	-0.010†††	0.002
System	0.168††	0.084	0.153††	0.078
Seeds	0.321†††	0.092	-	-
Extension	0.488†††	0.098	-	-
Tanzania	-0.459†††	0.142	-0.091 ns	0.123
DRC	0.065ns	0.145	-0.639†††	0.137
Zambia	-1.075†††	0.156	-1.246†††	0.166
Constant	-0.191ns	0.242	1.081†††	0.246
Sigma(σ_j)	0.817†††	0.086		
Rho(ρ_j)	0.781†††	0.186		

LR test of independent equations: $\chi 2$ (1) =256.61; *p*=0.000; ††† denotes statistical significance at 1%; †† denotes statistical significance at 5%; † denotes statistical significance at 10%; *ns* denotes no statistical significance at less than 10%

8. Conclusion and implications

The study established the causal relationship between adoption of cassava technology with calorie consumption, food insecurity and duration of food shortage in four major cassava-producing countries of SSA, namely Tanzania, DRC, Zambia and Sierra Leone. The food security indicators used in this study are based on households' daily consumption per capita that came from both food availability through own production and accessibility through purchases. Data for this study came from a household survey conducted in Tanzania, DRC, Sierra Leone and Zambia through 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 was applied, accounting for potential selection bias that may arise from unobserved heterogeneities. Results provided consistent findings that adoption of cassava technology would decrease the rate and depth of food insecurity as well as the duration of food shortage. Overall, adoption resulted in increasing the average daily calorie consumption per capita by 160 Kcal, yielding a 14% point reduction in rate of food insecurity. Adoption had also resulted in decreasing the per capita calorie deficit or depth of food insecurity by 110 Kcal among the food insecure households. Further, adoption of cassava technology had cut the duration of food shortage by 67%. Decomposition of the overall average gains in calories due to adoption resulted in over four-fifths accruing to the group of households who were food insecure without adoption compared to only one-fifth accruing to the food secure without adoption. This implies that the impacts of cassava technology were more favourable towards the food insecure than the food secure. This implies that addressing the barriers to adoption so that the current non-adopters will be able to take up the cassava technology is worthwhile. These results present important evidence to draw policy implications in favour of the effectiveness of the adoption of cassava technology for reducing the rate and depth of food insecurity in SSA.

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Table 1b: Improved cassava varieties released in the study countries (2000-2013)

Tanzania		DRC		Sierra Leone		Zambia	
Variety	Year	Variety	Year	Variety	Year	Variety	Year
NDL 90/034	2003	Butamu	2005	SLICASS 1	2002	mweru	2000
hombolo 95	2004	Disanka	2005	SLICASS 2	2002	chila	2000
kiroba	2004	Mvuazi	2005	SLICASS 3	2002	tanganyika	2000
MM96/4684	2006	Nsansi	2005	SLICASS 4	2002	kampolombo	2000
MM96/3075B	2006	Zizila	2005	SLICASS 5	2002	Bangweulu	2001
MM96/8450	2006	Mbankana (I96/0067)	2008	80/40	2003	Kapumba	2001
MM96/4619	2006	94/0330	2008	80/32	2003	Nalumino	2001
MM96/5725	2006	01/1661	2008	83/15	2003	manyopola	NA
MM96/8233	2006	01/1229	2008	86/1	2003	kariba	NA
TMS I91/00063	2006	Obama je t'aime (TME419)	2008	87/29	2003		
TMS I92/0057	2006	Liyayi	2008	TMS 92/0057 (SLICASS 6)	2006		
TMS I92/0067	2006	Namale	2008				
TME 14	2006	Mayombe	2008				
KBH 2002/482	2006	MUTIENE	2013				
KBH 2002/494	2006	BOMENGO	2013				
KBH 2002/517	2006	LITOY	2013				
pwani	2012	MUZURI	2013				
mkumba	2012	KANSAKAKO	2013				
makutupora	2012	ILONA	2013				
dodoma	2012						
kizimbani-zanzibar	2012						
mahonda-zanzibar	2012						
kamba-zanzibar	2012						
machui-zanzibar	2012						