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Are farmers using cropping system intensification technologies experiencing poverty reduction in the Great Lakes Region of Africa?

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Abstract

This study evaluated the poverty reduction impact of the adoption of cropping system intensification (CSI) technologies using the endogenous switching regression (ESR) model in the Great Lakes region of Africa that comprises Burundi, eastern DR Congo, and Rwanda. The study data came from a household survey of 1,495 sample households interviewed between October and December 2014. Results indicated that the adoption of the CSI technologies had increased crop yield, crop income, and per capita consumption expenditure in the region, resulting in poverty reduction. Among the three countries, eastern DR Congo witnessed the highest poverty reduction (13% points) followed by Rwanda (6% points) and Burundi (2% points). Considering the adoption rate and size of the target population in each country at baseline, an estimated 180 thousand poor individuals had escaped poverty due to the adoption of the CSI technologies. This presents important evidence in favor of promoting CSI technologies as part of poverty reduction strategy. Given the large population size that remains poor even after adoption, we suggest that research-based poverty reduction strategies such as the CSI technologies should be complemented with development interventions.

KEYWORDS

adoption, Africa, cropping system intensification technologies, Great Lakes region, impact, poverty

1 | INTRODUCTION

In Africa, agriculture has long been placed at the center of poverty reduction strategy. This was evident in the "Maputo Declaration on Agriculture and Food Security in Africa." In July 2003, in Maputo, the African Heads of State and Government, including those of Burundi, DR Congo, and Rwanda, endorsed the Maputo Declaration that contained several provisions with greater bearing on agriculture. Prominent among the provisions was a commitment to allocate at least 10% of their respective national budgets to achieve 6% agricultural growth (AfDB, 2013; AU, 2003). While the commitments were fulfilled in most countries over five years, no meaningful resources were deployed in the Great Lakes region that consists of Burundi, eastern DR Congo, and Rwanda. This was due to decades of episodes of civil strikes, conflicts, wars, and political instability that devastated much of these countries' physical, social, and human capital since the 1990s until 2005 (Sanginga, 2006; Vanlauwe, Astern, & Blaume, 2014). As a result, agricultural productivity remained very low and poverty became prevalent (Kintché et al., 2017; Shackelford et al., 2018; USAID, 2015). As the region started to emerge out of the protracted conflicts that had disrupted the agricultural system, and the political instability in the region subsided in the mid-2000s, three independent CGIAR centers (International Institute of Tropical Agriculture (IITA), International Center for Tropical Agriculture (CIAT), and Bioversity International) came together to revive the agricultural system by establishing a research and development project called the Consortium for Improving Agricultural-based Livelihoods in Central Africa (CIALCA). The project primarily aimed at reducing poverty among smallholder farmers through increasing farm-level productivity and household income, and improving nutrition. Hence, through the CIALCA project, many CSI technologies were developed, validated, packaged, and introduced into the three countries to increase agricultural productivity and improve household income, thereby reducing poverty while maintaining the natural resource base. The CSI technologies include improved crop varieties (ICV), improved crop management (ICM) practices, integrated pest management (IPM) practices, and postharvest (PH) technologies. The introduction of such technologies was based on consistent research findings in neighboring countries such as Kenya and Central African Highlands that demonstrated the potential of such technologies to contribute to development outcomes and poverty reduction (Asfaw, Shiferaw, Simtowe, & Lipper, 2012; Marenya & Barrett, 2007; Pypers, Sanginga, Ksaereka, Walangululu, & Vanlauwe, 2011; Vanlauwe et al., 2010). For example, Marenya and Barrett (2007) demonstrated the high potential of ISFM practices in increasing food production in Kenya. Similarly, Pypers et al. (2011) demonstrated the high potential of cassava–legume systems in the Central African Highlands.

The CIALCA project had been actively going on in the Great Lakes region for over eight years since 2006 at the time of this study. Yet, little was known about the poverty impacts of the CSI technologies disseminated by the project in the region. This study thus aimed to assess the poverty reduction impacts of the adoption of the CSI technologies introduced into the region through the project. Beyond establishing the causal effect of the adoption of the CSI technologies on crop yield, crop income, and per capita consumption expenditure, the study estimated the number of poor adopters that escaped poverty in the region, more specifically the CIALCA areas of Burundi, eastern DR Congo, and Rwanda. To our knowledge, this is the first paper inclusive of major agricultural technologies to establish a causal link between agricultural research products and poverty reduction in the Great Lakes region of Africa using a more rigorous approach that controls for both measured and unmeasured heterogeneities in household characteristics. Most of the past impact studies have considered only crop varieties, ignoring complementary innovations and technologies (Ogundari and Bolarinwa, 2018). Further, while some of the past studies (e.g., Asfaw et al., 2012; Dontsop, Okoruwa, Adeoti, & Adenegan, 2012, Kassie, Teklewold, Marenya, Jaleta, & Erenstein, 2014; Khonje, Manda, Alene, & Kassie, 2015; Mathenge, Smale, & Olwande, 2014; Rusike et al., 2014; Shiferaw, Kassie, Jaleta, & Yirga, 2014) have established the causal link between adoption of improved agricultural technologies and consumption expenditure, they have not estimated the actual number of poor lifted out of poverty. Furthermore, some of the past studies which have estimated the poverty reduction effects have, however, not evaluated the distribution impacts of the technologies on different groups of households such as male-headed vis-à-vis female-headed households (e.g., Khonje et al., 2015).

To fill in these gaps and move beyond the impact of genetic improvement (use of ICVs), our study considered ICM and IPM practices along with ICVs. Further, we extended the poverty analysis methodology beyond identifying the causal effect of the adoption of the CSI technologies, making it possible to estimate the actual number of poor lifted out of poverty as a result of the adoption of the CSI technologies. We also extended the poverty analysis to examine the distributional impacts of the CSI technologies on male-headed vis-à-vis female-headed households. Furthermore, as an improvement over some of the previous studies which used the propensity score matching method that only controls for measured characteristics, our study applied a more rigorous analytical approach, the instrumental variable-based approach, particularly the ESR which controls for both unobserved heterogeneity and endogeneity in the covariates. The advantage of the ESR model is that it deals with self-selection bias caused by heterogeneities in observed and unobserved household characteristics, resulting in robust estimates of the impact of the intervention on individual adopters' outcomes (Maddala, 1986). Only a few studies have recently addressed the issue of unobservable heterogeneities (Manda et al., 2019; Wossen et al., 2019).

The rest of the paper is organized as follows: Section 2 describes how the CIALCA project was implemented and provides an overview of the different CSI technologies introduced into the region. Section 3 discusses the survey design and describes the data used in the analysis. Section 4 presents the theoretical framework, highlighting the adoption decision, while Section 5 presents and discusses the empirical model estimation of adoption decision and outcome variables. This section will highlight the challenges in impact assessment and discuss the empirical model (ESR) used in the study to address the challenges and assess the poverty impacts of the CSI technologies. Section six presents the results and discusses the poverty impacts of the adoption of the CSI technologies. The last section concludes and draws some implications.

2 | DESCRIPTION OF THE CIALCA PROJECT

The operational domain of CIALCA was the Great Lakes region, including Burundi, eastern DR Congo, and Rwanda. The project was led by the three CGIAR institutions mentioned above (Ouma et al., 2011). Given the fact that the proposed activities were expected to complement each other, the three CGIAR institutes agreed to operate as a consortium to create synergy and ensure efficient resource utilization at the national level (Macharia et al., 2012; Ouma et al., 2011). In this joint initiative, IITA was mandated for developing and disseminating CSI technologies, addressing the ecological and economic dimensions of the sustainability of banana-based farming systems in the region. In particular, IITA focused on market access as a driving force for improving the banana-based farming systems. The mandate of Bioversity International was also related to enhancing the contribution of the banana-based farming systems to rural well-being. However, its focus was on enhancing the capacity of the national and regional institutions to mobilize investments toward research for development. The mandate also included enhancing the capacity of national research institutions to conserve local Musa germplasm. This was aimed at introducing and evaluating new MUSA cultivars, which would lead to the selection of best-performing cultivars that would later be multiplied and disseminated to the smallholder banana producers. CIAT was mandated with developing and disseminating stress-tolerant and biofortified crop varieties for market-driven diversification and intensification as well as natural resource management (NRM) systems, which are adapted to the local conditions of the project areas. As in Bioversity International, CIAT was also mandated with revitalizing the capacity of national and regional in research for development.

In addition to low genetic potential of the local cultivars, the project targeted addressing declining soil fertility by introducing multipurpose legumes through integrated (strategic, adaptive and applied) research approach that involved a strong partnership with various organizations such KU Leuven and UCL, which backed the strategic research

TABLE 1 List of CSI technologies introduced into the Great Lakes region through the CIALCA project

Improved Crop Varieties(ICV)
Improved bean varieties
Improved soybean varieties
Improved groundnut varieties
Improved pigeon pea varieties
Improved cowpea pea varieties
Improved banana varieties
Improved crop management (ICM) practices
Improved maize–legume intercropping (planted in lines)
Use of fresh and decomposed manure
Rotation of maize with new high-biomass climbing bean or soybean varieties
Debudding, uprooting, and destroying of sick banana plants, and use of clean suckers
Fertilizer use on maize, cassava, or grain legumes, applied in the planting hole/line
Combined manure/compost and fertilizer application in the planting hole plans
Cassava planted at about 2 m × 0.5 m intercropped with legumes
Locally produced banana plantlets (Banana macropropagation)
Integrated pest management (IPM)practices
Uprooting and destroying infected plants (BBTV control)
Planting of beans in mulched bananas using sticks, not hoes.
Banana coffee intercropping
Banana plantation management.
Mucuna fallows
Applying Chromolaena or Tithonia.
PH technologies
Soybean processing into milk and cake.
Preparation of business plan
Collective marketing/bulking of produce

Source: www.cialca.org.

on sustainable use of the natural resource. Capacity building was also a big part of the project, involving the National Agricultural Research System (NARS), universities, nongovernmental organizations (NGO), community-based organizations, and the private sector.

Table 1 presents the list of over 30 technologies developed, validated, and disseminated by CIALCA in different locations in Burundi, eastern DR Congo, and Rwanda. These technologies broadly included ICVs of banana, maize, cassava, soybean, and beans among other crops; ICM practices such as recommended crop spacing, intercropping, and use of fertility enhancement practices; IPM practices used especially for control of banana diseases such as *banana Xanthomonas wilt* (BXW) and banana bunchy top virus (BBTV); and PH technologies including business plans and collective marketing and processing of soybean into soy milk. In addition to the development, validation, and dissemination of various technologies, market opportunities were identified for banana and banana products such as banana juice and wine.

While the development and validation of the technologies were implemented in action sites using on-farm trials and farmer participatory approaches in partnership with NARS, the dissemination was carried out in satellite sites in partnership with development partners. An increase in farm-level productivity, extra protein intake, and household income by at least 20% constitute the milestones of the project (Macharia et al., 2012).

3 | SURVEY DESIGN AND DATA DESCRIPTION

The data for this study came from a household survey conducted in three countries (Burundi, eastern DR Congo, and Rwanda) between October and December 2014. The sample was proportional across the three countries, with each country constituting one-third of the total sample (501 in Burundi, 503 in eastern DR Congo, and 491 in Rwanda). The sampling strategy involved the identification of action sites, which are made up of several villages, followed by a random selection of households. Action sites are administrative units known by different names in different countries. For example, in DRC, an action site is called "Localité," while in Burundi and Rwanda, it is called "Cellules" and "Secteurs," respectively. In this study, we defined a household as a group of people residing in the same household for at least half of the year and regularly sharing meals. The selection of the sample households proceeded in two stages. First, five villages were selected from the list of villages in the action sites where the consortium of the three CG centers, in partnership with the national programs, developed, validated, and disseminated the CSI technologies. Then, 20 households were randomly selected from each of the selected villages. In total, 1,495 households were randomly selected from 130 villages in the three countries. The female-headed households accounted for 30% of the total sample.

Data were collected on the household composition and characteristics, assets, expenditure, food security, technology adoption (ICVs, ICM practices, IPM practices, and PH practices that include preparation of business plans, soybean processing into milk and other products, and improved marketing), land use and management, livestock ownership, livestock products, access to institutional support services (extension, training, and credit), communal property resources, and multistakeholder platform and intervention landscape. Besides, data were collected on the adoption of more than 30 agricultural technologies that were disseminated in various locations of the three target countries (Table 1). The adoption study considered over 30 technologies that included ICVs (e.g., banana, maize, cassava, soybean, and beans), ICM practices (e.g., crop spacing, intercropping, and use of fertility enhancement), IPM practices (e.g., BXW control), and PH technologies (e.g., business plans and collective marketing and processing of soy milk, banana juice, and wine). In addition to the development, validation, and dissemination of various technologies, market opportunities were identified for banana and banana products.

4 | THEORETICAL FRAMEWORK

Following Singh, Squire, and Strauss (1986), we relied on the standard economic model that combines the production and consumption behaviors of an agricultural household to assess the impact of the adoption of the CSI technologies on outcome variables of interest such as consumption expenditure.

An agricultural household is assumed to maximize the utility of consumption subject to a combined set of budget, production, and time constraints. The household optimal choice problem is generically set as follows:

$$\max_{x \in S(z)} U(x,z) \tag{1}$$

where $U(\cdot)$ is the household utility function; x is the full set of choice variables including consumption and production; z is the set of nonchoice variables that may affect the utility function U; and $S(z)$ is a set of constraints.

The maximization of the household utility subject to the combined constraint (budget, production, and time) shows that the household can choose the level of consumption and inputs used in the agricultural production.

$$\max_{c,x_1,\ldots x_J} \left\{ U'(c,z_u): s.t.\, p_c \cdot c = p_r * \left(\sum_{j=1}^{J} f(x_j,z_j) \right) - \sum_{k=1}^{K} p_k \sum_{j=1}^{J} x_{jk} \right\} \tag{2}$$

where c denotes the vector of consumption goods with the corresponding price vector p_c; $x_j = (x_{jk})_{k=1,\ldots,K}$ vector of inputs with the corresponding price vector, p_k; z_u is a vector of household characteristics affecting household utility; z_j is a vector of different environmental characteristics affecting production; f is a production function; and p_{ri} is the price of good i.

The optimal choices can be solved recursively in two stages. The first stage involves solving for the optimal choices of the inputs of production and generating the maximized value of profits, which will then be substituted into the combined constraint set ("full" income). The second stage involves solving for the optimal choices of consumption by maximizing the household utility function subject to the "full income" constraint that contains the maximized value of profits.

In assessing the impact of adoption of CSI technologies on the outcomes of interest (e.g., consumption expenditure), the model is recursive. That is, the production decision is made first followed by consumption decision conditional on production decisions but not vice versa. That is, the household first chooses the optimal set of production inputs that result in higher income and maximize the utility of consumption of food and nonfood items subject to the maximized income.

The above theoretical exposition clearly shows that the solution to the household utility maximization first resulted in the optimal choice of production inputs that maximized profit. This captures the production behavior of the household. In the second stage, the household maximizes utility subject to the income constraint that contains the maximized value of profit. The solution to this utility optimization resulted in the optimal choice of consumption goods, capturing the consumption behavior of the household. The combination of the production and consumption behavior would capture the economic behaviors of the household, leading to poverty analysis. An individual consuming $1.25/capita/day or less worth of goods and services adjusted for PPP is considered poor.

We now show how farmers decide to adopt a CSI technology using the random utility framework. Adoption was defined in terms of the number of different technological components. Farmers who used at least two of the ICVs disseminated combined with at least four ICM and IPM practices were considered as adopters. Different criteria were applied to ensure that the CSI technologies in questions were developed, validated, and disseminated as part of the implementation of the CIALCA project (Dontsop, Diagne, Okoruwa, Ojehomon, & Manyong, 2013). In particular, we asked a series of questions that include the year of first awareness and first use, as well as the source of the technology. This allowed us to retain only the one that fell within the dissemination framework of CIALCA.

A rational household is assumed to adopt a technology if the utility of adoption is greater than that of nonadoption. However, since we cannot observe the utilities, we define the adoption criteria as follows:

$$C_i^* = Z_i\alpha + \varepsilon_i \text{ with } C_i = \begin{cases} 1 & \text{if } C_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where C^* denotes the difference between the utility of adoption and that of nonadoption for household i; C_i represents the observed adoption status where $C_i = 1$ if the farmer reported to have used the CIS as defined above, and $C_i = 0$, otherwise; α denotes a vector of parameters to be estimated; Z represents household- and farm-level characteristics; and ε_i is the random error term.

5 | EMPIRICAL MODEL

If observational data are used to assess the impact of the adoption of a given intervention, the difference in mean values of the outcome variables of interest between adopters and nonadopters may result in biased estimates, even if measured characteristics of sampled households are controlled. This is because adopters and nonadopters can be different based on unmeasured characteristics as they were not randomly assigned to the technologies. In the presence of self-selection on unobservables, it will not be possible to identify the causal effect of the adoption of the CSI technologies. In this study, the sample households were not randomly assigned to the CSI technologies. As a result, it was likely that the sample farmers had selected themselves into adoption and out of adoption based on both observables and unobservable (Diagne, Midingoyi, & Kinkingninhoun-Medagbe, 2009; Dontsop et al., 2012; Imbens & Wooldridge, 2009). To address the self-selection bias, we used an instrumental variable (IV)-based estimator (Abadie, 2003; Imbens, 2004; Manski & Pepper, 2000). In particular, we applied the ESR model in this study to account for the potential self-selection bias in adoption (Maddala & Nelson, 1975). Several have used this model in their studies in recent time (see Asfaw et al., 2012; Kassie et al., 2015; Khonje et al., 2015; Manda et al., 2019; Tufa et al., 2019; Shiferaw et al., 2014).

In this study, we assessed the impact of the CSI technologies on three outcome variables—crop yield, crop income, and per capita consumption expenditure using the ESR model. The impact assessment proceeded in two stages. The first stage involved estimating a probit model of adoption. The second stage involved estimating a linear model of each of the three outcome variables with selectivity correction. The linear consumption expenditure equations, conditional on adoption decision, were given as follows:

$$\text{Regime 1 (Adopters):} \quad y_{1i} = x_{1i}\beta_1 + w_{1i} \text{ if } C = 1 \tag{4a}$$

$$\text{Regime 2 (Nonadopters):} \quad y_{2i} = x_{2i}\beta_2 + w_{2i} \text{ if } C = 0 \tag{4b}$$

where y_{1i} and y_{2i} represent the consumption expenditure for adopters and nonadopters; x_{1i} and x_{2i} are vectors of exogenous covariates; β_1 and β_2 are vectors of parameters to be estimated; and w_{1i} and w_{2i} are random disturbance terms.

Although the nonlinearity in the probit model of adoption makes identification possible during the simultaneous estimation of the adoption and outcome equations, it is usually advisable to include a valid instrumental variable in the adoption equation (Shiferaw et al., 2014). The validity of an instrumental variable can be verified using a simple falsification test (Di Falco, Veronesi, & Yesuf, 2011). A valid

TABLE 2 Descriptive statistics of the outcome and independent variables by adoption status

Variables	Burundi			DR Congo		
	Adopters ($N = 351$)	Nonadopters ($N = 150$)	Full sample ($N = 501$)	Adopters ($N = 298$)	Nonadopters ($N = 205$)	Full sample ($N = 503$)
Consumption expenditure ($/capita/day)	0.62	0.56	0.58	0.86	0.73	0.81
Poverty indices						
Poverty headcount index	0.61	0.63	0.62	0.61	0.68	0.64
Poverty gap index	0.28	0.26	0.28	0.27	0.4	0.29
Poverty gap squared index	0.16	0.14	0.16	0.16	0.27	0.17
Membership to associations (Yes = 1)	0.72	0.62	0.65	0.77	0.41	0.63
Access to credit (Yes = 1)	0.30	0.35	0.34	0.11	0.06	0.09
Farm occupation (Yes = 1)	0.63	0.64	0.64	0.64	0.62	0.63
Gender of the household head (Male = 1)	0.78	0.77	0.77	0.76	0.79	0.77
Farming experience (years)	35	35	35	32	31	32
Education of the household head (years)	4.25	3.88	4.10	3.83	3.71	3.75
Age of household head (years)	51.19	50.09	50.42	52.33	50.22	51.47
Household size (number)	6.01	6.16	6.11	6.66	6.15	6.45
Farm size (ha)	1.09	1.04	1.05	1.15	0.80	1.00
Livestock ownership (TLU)	0.73	0.73	0.73	0.71	0.60	0.66
Value of assets ($)	87.35	69.73	75.00	88.09	65.98	79.08
Number of improved technologies known by the household (#)	12.19	11.46	11.68	17.11	12.40	15.19
Access to extension (Yes = 1)	1	1	1	1	1	1

Note: The exchange rates at the time of the survey were 700 Rwanda Franc, 920 Congolese Franc, and 1,500 Burundian Franc to a US dollar for Rwanda, DR Congo, and Burundi, respectively. $ is the United States dollar.

Abbreviation: TLU, Tropical Livestock Units.

***Significant at 1% level.

Source: Author's calculations using CIALCA survey data, 2014.

instrument is directly associated with the selection equation, which, in our case, is the adoption equation, but not directly associated with outcome variables (e.g., consumption expenditure). Ordinary least square estimation may lead to biased parameter estimates since the expected values of the error terms (w_1 and w_2) conditional on the selection criterion given in Equation (3) are nonzero (Shiferaw et al., 2014). We assume that the error terms in the selection equation (Equation 3) and outcome equations (Equations 4a and 4b) to have a trivariate normal distribution with mean zero and covariance matrix given in Equation (5).

$$\Omega = \mathrm{cov}(\varepsilon, w_1, w_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_1^2 & \cdot \\ \sigma_{2\varepsilon} & \cdot & \sigma_2^2 \end{bmatrix} \tag{5}$$

where $\sigma_\varepsilon^2 = \mathrm{var}(\varepsilon)$, $\sigma_1^2 = \mathrm{var}(w_1)$, $\sigma_2^2 = \mathrm{var}(w_2)$, $\sigma_{\varepsilon 1} = \mathrm{cov}(\varepsilon, w_1)$, and $\sigma_{\varepsilon 2} = \mathrm{cov}(\varepsilon, w_2)$.

We also assume that the variance of the selection equation (σ_ε^2) to be equal to 1. This is because the α parameter estimates in the selection model (Equation 3) are estimable up to a scale factor. Note that the covariance between the error terms of the outcome equations (w_1 and w_2) are not defined because y_1 and y_2 are never observed simultaneously (De Janvry, Dunstan, & Sadoulet, 2011; Maddala, 1983). It is also important to note that since the error term of the selection equation (ε_i) can be correlated with that of the outcome equations (w_1 and w_2), the expected values of w_1 and w_2 conditional on the selection criterion are nonzero (Asfaw et al., 2012) as given in Equations (6) and (7).

$$E(w_{1i}|C = 1 = \sigma_{\varepsilon 1} \frac{\phi\left(Z_i \alpha\right)}{\Phi\left(Z_i \alpha\right)} \equiv \sigma_{\varepsilon 1} \lambda_1 \tag{6}$$

$$E(w_{2i}|C = 0 = \sigma_{\varepsilon 2} \frac{\phi\left(Z_i \alpha\right)}{1 - \Phi\left(Z_i \alpha\right)} \equiv \sigma_{\varepsilon 2} \lambda_2 \tag{7}$$

where ϕ is the standard normal probability density function and Φ the standard normal cumulative density function.

Rwanda			The Great Lakes region			
Adopters (N = 282)	Nonadopters (N = 209)	Full sample (N = 491)	Adopters (N = 730)	Nonadopters (N = 765)	Pool sample (N = 1,495)	Difference test
0.60	0.61	0.60	0. 68	0.45	0.56	−3.26***
0.65	0.64	0.65	0.63	0.65	0.64	0.74
0.28	0.32	0.29	0.29	0.34	0.29	
0.16	0.21	0.16	0.17	0.21	0.17	
0.41	0.40	0.41	0.68	0.45	0.56	−5.36***
0.41	0.43	0.42	0.28	0.27	0.29	−1.05
0.59	0.62	0.61	0.61	0.63	0.63	1.10
0.79	0.74	0.77	0.76	0.78	0.77	1.28
31	30	31	32	32	32	0.17
4.37	4.92	4.61	4.47	3.84	4.15	−2.85***
51.27	50.44	50.92	51.95	50.0	50.95	−2. 85***
5.78	6.25	5.98	6.41	5.97	6.18	−3.39***
0.94	0.95	0.94	1.21	0.82	1.05	−3.17***
0.79	0.92	0.84	0.92	0.73	0.82	−3.48***
56.62	69.93	62.28	83.80	62.00	72.61	−5.55***
11.47	11.47	11.47	14.35	10.88	12.57	−12.72***
1	1	1	1	0.99	0.99	−0.39

To correct the selection bias, we can use a two-stage procedure where in the first stage, we compute the inverse Mills ratio ($\lambda_{1i}=\phi(Z_i\alpha)/\Phi(Z_i\alpha)$ and $\lambda_{2i}=\phi(Z_i\alpha)/1-\Phi(Z_i\alpha)$) at the predicted probability of adoption (Equation 3). In the second stage, we estimate the outcome equations (Equations 4a and 4b) after including the inverse Mills ratios computed in the first stage.

However, the efficient method is simultaneous estimation using the full information maximum likelihood estimator (FIML; Maddala, 1983). Following the FIML estimation, we use the parameter estimates and associated covariates of regime 1 and regime 2 to compute the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU).

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

Adopters under observed condition

$$E(y_{i1}|C=1;x)=x_{i1}\beta_1+\sigma_{\varepsilon 1}\lambda_{i1} \tag{8a}$$

Nonadopters under observed condition

$$E(y_{i2}|C=0;x)=x_{i2}\beta_2+\sigma_{\varepsilon 2}\lambda_{i2} \tag{8b}$$

Adopters under counterfactual condition

$$E(y_{i2}|C=1;x)=x_{i1}\beta_2+\sigma_{\varepsilon 2}\lambda_{i1} \tag{8c}$$

Nonadopters under counterfactual condition

$$E(y_{i1}|C=0;x)=x_{i2}\beta_1+\sigma_{\varepsilon 1}\lambda_{i2} \tag{8d}$$

The difference between Equations (8a) and (8c) gives the estimate of ATT.

$$\mathrm{ATT}=\left(y_{i1}|C=1;x\right)-\left(y_{i2}|C=1;x\right),=x_{i1}\left(\beta_1-\beta_2\right)+\lambda_{i1}\left(\sigma_{\varepsilon 1}-\sigma_{\varepsilon 2}\right) \tag{9}$$

The difference between Equations (8d) and (8b) gives the estimate of ATU.

$$\mathrm{ATU}=\left(y_{i1}|C=0;x\right)-\left(y_{i2}|C=0;x\right),=x_{i2}\left(\beta_1-\beta_2\right)+\lambda_{i2}\left(\sigma_{\varepsilon 1}-\sigma_{\varepsilon 2}\right) \tag{10}$$

The first term on the right of Equation (9) measures the predicted mean value of outcome variable for adopters, had they have the same returns to their characteristics as nonadopters. Similarly, the first term on the right of Equation (10) measures the predicted mean value of consumption expenditure for nonadopters, had they have the same returns to their characteristics as adopters. The parameter estimates (λ) measure the potential effects of unmeasured characteristics.

5.1 | Measuring poverty impacts using the ESR model

The procedure employed in measuring the poverty reduction impacts of the adoption of CSI technologies is described as follows. First, the ESR model of consumption expenditure was estimated as described in the previous section. Then, to assess the impacts of the adoption of the CSI technologies on poverty reduction measured by the FGT indices of poverty, we first generated the distributions of the expected consumption expenditure for adopters under observed and counterfactual conditions using Equation (8a) and Equation (8c), respectively. Then, we computed the FGT indices of poverty for both distributions of expected consumption expenditure and took the difference in the FGT indices of poverty between the two distributions. The differences would provide the estimates of the poverty reduction impacts of adoption in average terms.

A similar procedure was applied for nonadopters. That is, first we generated the distributions of the expected consumption expenditure for nonadopters under observed and counterfactual conditions using Equation (8b) and Equation (8d), respectively. Then, we computed the FGT indices of poverty for both distributions and calculated the difference in the FGT indices of poverty between the two distributions. The differences would provide the estimates of the poverty reduction impacts of potential adoption in average terms.

The rate of poverty was determined based on the poverty line of \$1.25/capita/day at PPP (purchasing power parity exchange rates)[1] (Sen, 1999). That is, individuals whose per capita consumption expenditures were at or below \$1.25/capita/day evaluated at PPP were considered poor. The poverty line was computed using data on per capita expenditure data because in developing countries data on expenditure are considered more reliable than income data in developing countries (Christiaensen, Scott, & Wodon, 2002). Based on the distributions of per capita consumption expenditure under observed and counterfactual conditions, the poverty rate was calculated under observed and counterfactual conditions, with the difference providing an estimate of the poverty reduction impacts of the adoption of the CSI technologies. The actual number of individuals lifted out of poverty (₦) because of adopting CSI technologies was estimated as follows:

$$₦ = \frac{(p_{rr} * C_A * P_{ssa^-})}{p_{sf}} * H_s$$

where p_{rr} denotes poverty reduction rate based on ESR estimates; C_A is the number of farm households who adopted CSI technologies; $\overline{H_s}$ is the average household size; p_{sf} is population of sampled households or individuals; and P_{ssa} is the population size of sample area.

6 | RESULTS AND DISCUSSION

6.1 | Descriptive statistics

Table 2 presents the descriptive statistics of the independent and outcome variables for the Great Lakes region by adoption status. Across the three countries in the region, the poverty rate as measured by the poverty headcount index stood at 64%. The depth of poverty as measured by the poverty gap index was 29%, indicating that the poor, on average, had an income shortfall of 29% (or \$0.36) below the poverty line. The severity of poverty as measured by the poverty gap squared index suggested income inequality among poor households.

Without holding other factors constant, adopters and nonadopters were significantly different with respect to several variables such as access to credit services, age, household size, consumption expenditure, farm size, livestock ownership, and value of assets. For example, we found that about 27% of adopters had access to credit services compared to 29% of nonadopters. Given that there were systematic differences in most of the household characteristics, we cannot identify the causal effect of the adoption on the outcome variables such as crop yield, crop income, and consumption expenditure based on simple mean differences. This is because the causal effect of the adoption of the CSI technologies on the outcome variables could be due to the statistically significant differences in the household characteristics. For example, adopters had a consumption expenditure of \$0.68/capita/day compared to \$0.45/capita/day for nonadopters. The poverty rate among adopters was 2% lower than nonadopters. The depth of poverty and the severity of poverty were also lower among adopters than nonadopters. These differences may not necessarily be due to adoption alone. Since the difference in the outcome variables such as poverty between adopters and nonadopters could be due to differences in the measured and unmeasured household characteristics, we opted to use the ESR model that takes account of the heterogeneities in both the measured and unmeasured household characteristics.

TABLE 3 FIML parameter estimates of the ESR model for crop income in the Great Lakes region

	Burundi		DR Congo		Rwanda	
	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters	Adopters
Variables	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Membership to associations (#)	0.31 (0.66)	0.29 (0.13)**	1.02 (0.68)	0.06 (0.08)	−0.23 (0.34)	0.11 (0.11)
Access to credit (Yes = 1)	0.18 (0.51)	0.05 (0.13)		−0.63 (0.27)**	0.78 (0.28)***	−0.13 (0.16)
Farm occupation (Yes = 1)	0.39 (0.47)	−0.31 (0.14)**	−1.11 (1.27)	−0.00 (0.16)	0.16 (0.23)	−0.04 (0.16)
Gender of the household head (Male = 1)	0.09 (0.65)	−0.07 (0.16)	−9.65 (5.47)*	0.68 (0.19)***		
Farming experience (years)			0.07 (0.03)**	0.00 (0.00)	0.09 (0.11)	0.12 (0.12)
Education of the household head (years)	0.18 (0.31)	0.16 (0.08)**	9.80 (5.59)*	−0.16 (0.13)	0.03 (0.16)	−0.02 (0.10)
Age of household head (years)	0.27 (1.00)	−0.22 (0.26)	−1.51 (1.50)	−0.87 (0.48)*		
Household size (number)			2.70 (1.38)*	0.07 (0.17)	−0.48 (0.29)*	−0.37 (0.18)**
Farm size (ha)	0.23 (0.21)	0.24 (0.05)***	0.27 (0.27)	0.11 (0.05)**	−0.67 (0.30)**	−0.02 (0.09)
Livestock ownership (TLU)	0.26 (0.29)	0.15 (0.06)**				
Value of assets (US$)	0.20 (0.28)	0.08 (0.08)	−0.29 (0.21)	0.17 (0.07)**		
Distance to market (walking minutes)	−0.03 (0.36)	−0.12 (0.08)			0.01 (0.00)***	0.00 (0.00)
Native of the village	0.00 (0.68)	0.24 (0.16)	−9.22 (5.52)*	−0.17 (0.21)		
Contribution of own farm labor	−0.05 (0.18)	0.05 (0.06)	−0.00 (0.01)	0.01 (0.00)***		
Constant	2.07 (4.97)***	5.75 (1.22)***	14.75 (6.14)**	5.71 (1.76)***	4.13 (0.57)***	5.00 (0.60)***
sigma0	1.39 (1.76)*		−0.09 (0.09)		0.57 (3.02)***	
sigma1	1.15 (2.44)**		1.21 (4.07)***		1.34 (6.40)***	
rho0	−0.34 (0.57)		0.35 (0.50)		−0.70 (2.03)**	
rho1	−0.70 (2.51)**		−0.86 (3.01)***		−0.49 (1.65)*	
Model diagnoses						
Wald chi-square	18.02**		11.70*		50.68***	
Log likelihood	−690.69		−513.52		−576.07	
Number of observations	372		299		320	

*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

6.2 | Adoption of CSI technologies

Figure A1 shows that adoption rates of the disseminated CSI technologies varied greatly across the three countries, ranging from 30% in Burundi to 59% in eastern DR Congo. The average adoption rate for the region stood at 49%. The adoption rates of ICVs of beans and cassava were the highest in eastern DR Congo. As in eastern DR Congo, a relatively large percentage of households adopted improved bean varieties followed by improved maize varieties in Rwanda. In general, the adoption of ICM practices is the highest in Rwanda where two out of three households in the sample adopted ICM practices. IPM practices focused mainly on reducing the effects of BXW and BBTV that had led many households to uproot infected banana plants to avoid contamination. Despite the worsening effects of these diseases, the adoption rate of IPM practices was lower in eastern DR Congo, compared to the case in Burundi and Rwanda. The adoption rate of IPM practices in Burundi and Rwanda was 43% and 54%, respectively. The adoption of PH technologies was the lowest among the CSI technologies. These technologies included largely business plans and collective marketing in eastern DR Congo and Rwanda, while in Burundi, in addition

TABLE 4 ESR-based ATT and ATU of the adoption of CSI technologies on crop income

Country	Farm households' type and treatment effect	Decision stage: To adopt	Decision stage: Not to adopt	Average treatment effects
Burundi	Households who adopted—ATT	62.2	12.6	49.7*** ($t = 37.4$)
	Households who did not adopt—ATU	58.6	8.3	50.3*** ($t = 20.2$)
DR Congo	Households who adopted—ATT	18.9	6.4	12.6*** ($t = 3.6$)
	Households who did not adopt—ATU	76.0	16.3	59.7*** ($t = 9.5$)
Rwanda	Households who adopted—ATT	23.3	15.5	7.9*** ($t = 7.6$)
	Households who did not adopt—ATU	28.8	8.3	20.6*** ($t = 5.0$)

***Significant at 1% level.

TABLE 5 ESR-based ATT of the adoption of CSI technologies on beans and maize yield

Country	Decision stage: To adopt	Decision stage: Not to adopt	Average treatment effects
Beans			
Burundi	492.7	403.4	89.3*** (8.4)
Eastern DR Congo	298.9	121.5	177.4*** (31.9)
Rwanda	627.0	583.3	43.0*** (7.1)
Maize			
Burundi	601.8	365.0	236.8*** (5.6)
Eastern DR Congo	1,286.8	650.5	636.3** (2.2)
Rwanda	665.1	221.4	443.7*** (40.7)

**Significant at 5% level.

***Significant at 1% level.

to these, the processing of agricultural products was included. A maximum of 17% of the sample households adopted these technologies. The plausible explanation was the limited level of education of households, capital, technical know-how, and delay in the implementation of the latter, all of which were essential for the successful adoption of PH technologies (Doss, Mwangi, Verkuijl, & Groote, 2003; Kamdem, 2018). Also, the high rate of adoption in Burundi and Rwanda was due to better organization of the extension services in the two countries compared to the case in DR Congo, which experienced years of civil instabilities.

6.3 | The impact of CSI technologies on crop yield and income based on the ESR model

Table 3 presents the parameter estimates of the ESR model of crop income. The correlation coefficients between the error term of the adoption equation and that of the crop income equation for adopters (rho1) were negative and statistically significant for all the three countries, suggesting self-selection in adoption. Households who had below-average crop income tended to adopt the CSI technologies. These results are in line with several past studies (Lokshin & Sajaia, 2004; Manda et al., 2019; Tufa et al., 2019; Wossen et al., 2019).

The result of the likelihood ratio test also indicated that covariates had statistically significant differential effects between adopters and nonadopters. For example, the number of memberships to associations, farm occupation, education, farm size, and livestock ownership significantly affected the crop income of adopters in Burundi. However, none of these variables affected the crop income of nonadopters in the same country. Similarly, in eastern DR Congo farm size and value of assets were important determinants of the crop income of adopters. But, none of these variables were determinants of crop income of nonadopters in the same country. In Rwanda, household size was inversely related to crop income. Similar patterns of variations could be observed for Rwanda. These results suggest the existence of two regimes consistent with the assumption. These results are in agreement with previous studies (Kassie et al., 2015; Khonje et al., 2015).

Table 4 presents the ATT and ATU of adopting/not adopting CSI technologies on crop income in the three countries of the Great Lakes region. The estimation of the ATT and ATU was based on parameter estimates of the ESR model of crop income. Results revealed that both the ATT and ATU for crop income were all statistically significant ($p > .01$). For example, in Burundi, the adoption of CSI technologies resulted in $49.7 worth of additional crop income. In contrast, nonadopters would have earned about $50 more, had they adopted the same technologies. Similarly, in DR Congo, adopters of the CSI technologies gained $12.6 crop income. In contrast, nonadopters would have gained $59.7, had they adopted the same. Among the three countries, Rwanda gained the least from adoption ($7.9). However, nonadopters would have gained $20.6, had they adopted. Generally, results showed that the adoption of CSI technologies was positively and significantly associated with crop income in all targeted countries in the Great Lakes region. These results are in line with that of Manda et al. (2019) who found a positive and statistically significant association between adoption of improved cowpea varieties and household income in Nigeria. Results also showed that the benefit to nonadopters

TABLE 6 FIML parameter estimates of the ESR for consumption expenditure in the Great Lakes region

	Burundi		DR Congo		Rwanda		Great Lakes region	
	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Variables	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Number of associations	0.01 (0.79)	0.02 (0.74)	0.02 (1.17)	0.00 (−0.01)	0.01 (0.37)	−0.01 (0.21)	0.01 (1.61)	0.01 (0.41)
Access to credit (Yes = 1)	0.02 (1.16)	0.01 (0.41)	0.13 (2.20)**	−0.02 (−0.04)	−0.03 (1.51)	−0.09 (1.41)	0.01 (0.58)	0.02 (0.34)
Farm occupation (Yes = 1)	−0.03 (1.55)	−0.05 (1.31)	0.01 (0.24)	0.13 (1.28)	−0.08 (3.47)***	−0.17 (2.77)***	−0.04 (−2.72)***	0.02 (0.51)
Gender of the household head (Male = 1)	−0.02 (0.78)	−0.00 (1.42)	0.00 (1.44)	0.01 (0.94)	−0.02 (0.81)	−0.13 (1.43)	−0.04 (−2.33)**	0.06 (1.02)
Farming experience (years)	0.00 (2.14)**	0.08 (0.65)	0.08 (0.81)	−0.40 (1.37)	−0.00 (0.22)	0.01 (1.98)**	0.00 (−0.59)	0.00 (−0.41)
Education of the household head (years)	0.01 (0.56)	0.06 (1.31)	−0.09 (2.26)**	0.01 (0.04)	0.04 (2.65)***	0.06 (1.63)	0.01 (1.41)	0.04 (1.56)
Age of household head (years)	−0.14 (2.07)**	0.01 (0.61)	0.01 (0.59)	0.06 (1.10)	0.02 (0.34)	0.19 (1.46)	0.00 (−0.09)	−0.07 (−0.58)
Household size (number)	−0.02 (4.26)***	−0.03 (4.31)***	−0.05 (8.23)***	−0.09 (4.02)***	−0.03 (4.77)***	−0.03 (2.41)**	−0.03 (−10.35)***	−0.05 (−5.61)***
Farm size (ha)	0.02 (2.84)***	0.01 (0.27)	0.01 (1.16)	0.00 (0.08)	0.07 (5.10)***	0.11 (1.95)**	0.02 (3.80)***	0.01 (0.47)
Livestock ownership (TLU)	0.04 (2.30)**	0.04 (1.28)	0.04 (2.85)***	0.08 (0.88)			0.04 (5.03)***	0.04 (1.11)
Value of assets (US$)	0.06 (5.24)***	0.04 (1.94)*	0.09 (5.76)***	0.15 (3.55)	0.05 (5.12)***	0.02 (0.60)	0.06 (8.93)***	0.08 (3.97)***
Access to extension (Yes = 1)			−0.17 (0.53)	−0.40 (1.12)	0.10 (0.78)		0.05 (0.38)	−0.54 (−2.14)**
Distance to market (walking minutes)	−0.00 (0.06)	0.02 (0.88)	0.02 (0.99)	0.03 (0.49)	−0.01 (0.44)	0.05 (1.63)	0.01 (0.76)	0.01 (0.51)
Burundi							−0.19 (−9.87)***	−0.14 (−2.68)***
Rwanda							−0.10 (−5.25)***	−0.07 (−1.28)
Constant	0.69 (2.89)***	−0.01 (0.02)	0.40 (0.85)	1.98 (1.91)*	0.23 (0.79)	−0.44 (0.98)	0.47 (2.23)**	1.09 (2.33)**
sigma0	0.12 (23.84)***		0.31 (−12.17)***		0.19 (10.27)***		0.24 (24.0)***	
sigma1	0.20 (40.48)***		0.32 (32.97)***		0.23 (44.68)***		0.26 (66.4)***	
rho0	−0.05 (0.09)		−0.01 (0.98)		−0.87 (2.80)***		−0.08 (0.32)	
rho1	−0.28 (1.13)		−0.21 (1.65)*		0.01 (0.97)		−0.25 (3.0)***	
Model diagnostics								
Wald chi-square	26.54***		46.87***		25.78***		78.56***	
Log likelihood	−40.06		−276.87		−40.97		−521.99	
Number of observations	501		503		491		1,495	

*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

TABLE 7 (a) ESR-based ATT and ATU of the adoption of CSI technologies on consumption expenditure. (b) Gender-disaggregated ESR-based ATT and ATU of the adoption of CSI technologies on consumption expenditure ($/capita/day)

	Farm households' type and treatment effect	Decision stage		Average treatment effects
		To adopt	Not to adopt	
(a)				
Country				
Great Lakes region	Households who adopted—ATT	0.47	0.12	0.35*** ($t = 28.12$)
	Households who did not adopt—ATU	0.51	0.44	0.06*** ($t = 21.02$)
Burundi	Households who adopted—ATT	0.45	0.42	0.03*** ($t = 7.50$)
	Households who did not adopt—ATU	0.60	0.41	0.19*** ($t = 12.57$)
DR Congo	Households who adopted—ATT	0.56	0.11	0.45*** ($t = 21.64$)
	Households who did not adopt—ATU	0.61	0.53	0.30*** ($t = 12.18$)
Rwanda	Households who adopted—ATT	0.43	0.16	0.27*** ($t = 52.54$)
	Households who did not adopt—ATU	0.49	0.44	0.05*** ($t = 5.08$)
(b)				
Group by gender				
ALL	Households who adopted—ATT	0.46	0.39	0.07*** ($t = 28.12$)
	Households who did not adopt—ATU	0.53	0.40	0.13*** ($t = 19.31$)
Male-headed households	Households who adopted—ATT	0.44	0.41	0.04*** ($t = 16.03$)
	Households who did not adopt—ATU	0.51	0.40	0.10*** ($t = 17.40$)
Female-headed households	Households who adopted—ATT	0.45	0.14	0.32*** ($t = 75.85$)
	Households who did not adopt—ATU	0.54	0.37	0.17*** ($t = 15.12$)

***Significant at 1% level.

would have been higher in DR Congo and Rwanda, had they adopted the same technologies.

The positive income effect of the adoption of the CSI technologies was expected to have resulted from the increase in crop yields. Though the focus of the paper was largely on income, we estimated the impact of CSI technologies on selected crops (beans and maize). Table 5 presents the ATT of adopting/not adopting CSI technologies on the two crops in the three countries of the Great Lakes region. The ATT for yield of beans and maize were statistically different from zero at 1% for both crops. For beans, the yield gain at the plot level varied from 43 kg in Rwanda to 89.3 kg in Burundi to 117.4 kg in DR Congo. For maize, the gain was higher than that of beans, ranging from 236.8 kg in Burundi to 443.7 in Rwanda to 636.3 kg in eastern DRC.

6.4 | The impact of CSI technologies on consumption expenditure

Table 6 presents the parameter estimates of the ESR model of consumption expenditure. While the ESR model is theoretically identifiable even when the same independent variables are in all the three equations, it is often suggested that instruments be used based on substantive arguments for better identification (Manda et al., 2019; Tufa et al., 2019). In this study, the number of neighboring farmers that were using the technology in the area was used as an instrument after performing a simple falsification test for its validity. Results suggested that the selected instrument could be considered as valid, as it was related to the probability of adoption of CSI technologies ($z = 5.12$; $p = .000$) but not directly associated with the outcome variable (consumption expenditure) at less than 5% probability level ($t = 1.67$; $p = .095$).[2] This suggests that if neighboring households are already using some of the CSI technologies, it is easier for the sample households to follow suit given their knowledge of the inherent characteristics of promoted technologies. This is in agreement with the findings of Adegbola and Gardebroek (2007). Results also showed that the correlation coefficient between the error term of the adoption equation and that of the consumption expenditure equation for adopters (rho1) was negative and statistically significant. This suggests that adopters have self-selected themselves into adoption. The results also revealed differences in the parameter estimates of the effects of covariates between adopters and nonadopters. This is consistent with the assumption of the existence of two regimes. For example, farm size and livestock ownership significantly affected the consumption expenditure of adopters in Burundi. However, none of these variables affected the consumption expenditure of nonadopters in the same country. Similarly, in eastern DR Congo livestock ownership and value of assets were important determinants of the

TABLE 8 Impact of the adoption of CSI technologies on poverty

No	Variable	Country Burundi	DR Congo	Rwanda	CIALCA Region
1	Sample for each country (1)	501	503	491	1,495
2	Adoption rate (%) (2)	29.7	59.2	57.4	89
3	Poverty rate in the actual adopting group (3)	60	61	47	
4	Poverty rate in the counterfactual group (4)	62	74	53	
5	Poverty reduction rate (% point) (5 = 4–3)	0.02	0.13	0.06	
6	Adopting households (number) (6 = 1*2/100)	432	447	451	1,330
7	Population in sampled households (7)	2,956	3,320	2,946	9,269
8	Average household size (8 = 10/1)	5.90	6.60	6.00	6.20
9	People out of poverty from sample (number) (9 = 5*6*8)	76.44	295.15	568.55	940.14
10	Population size of sampled area (10)	733,709	1,294,866	2,205,933	4,234,508
11	Poor lifted out of poverty (number) (11 = 9/7*10)	4,358	99,653	75,972	179.983

Note: (1) = Total sample collected from each country. (2) = The CIALCA adoption rate in each country, meaning a household that has adopted at least one CIALCA technologies. (3) = The poverty reduction rate was computed from the endogenous switching regression estimates. (4) = The poverty reduction rate was computed from the endogenous switching regression estimates. (7) = This is the total number of individual in the entire household sampled. (10) = Total population in 2014 of study districts: 7 in Burundi, 3 in DR Congo South Kivu, and 8 in Rwanda. The population data of the CIALCA mandate area were obtained from different sources: Plan Quinquennal de Croissance et de l'Emploi/Province du Sud-Kivu (2011–2015), World Development Indicators (2014), National Institute of Statistics of Rwanda (2012). National Institute of Statistics of Burundi (2010).

Source: Author's calculations using CIALCA survey data 2014 (The calculation procedure of figures in this table is given in the Appendix 1).

consumption expenditure of adopters. But, none of these variables were determinants of the consumption expenditure of nonadopters in the same country. In Rwanda, value of assets significantly affected the consumption expenditure of adopters but not that of nonadopters.

Table 7a presents the ATT and ATU of adopting CSI technologies on consumption expenditure in the Great Lakes region. Results showed that the adoption of CSI technologies was positively and significantly associated with consumption expenditure in the Great Lakes region. For example, the gain for adopters in the Great Lakes region was \$0.35/capita/day, with households in eastern DR Congo gaining the most (\$0.45) followed by Rwanda (\$0.27) and Burundi (\$0.03). These impacts are displayed graphically in Figure A2(a–c) (see Appendix 1). Similarly, had the current nonadopters adopted the same technologies, they would have benefited. On average, nonadopters in the Great Lakes region would have gained \$0.06 per capita per day, had they adopted. Under such a scenario, nonadopters in eastern DR Congo would have benefited the most followed by those in Burundi and Rwanda. The potential impacts under the scenario of adoption are displayed in Figure A3(a–c) (see Appendix 1).

Comparing the ATT with ATU, nonadopters in Burundi, had they adopted, would have benefited more than adopters. The average gain in consumption expenditure for nonadopters in Burundi would have been \$0.19/capita/day, compared to \$0.03/capita/day for adopters in the same country (Table 6). This means that nonadopters in Burundi would have gained \$0.16/capita/day more than what the current adopters had gained.

Comparison of the ATT between female-headed and male-headed households showed that the former had benefited from adoption ($0.32/capita/day) compared to the latter ($0.04/capita/day). The ATT and ATU for household consumption expenditure were all statistically different from zero at 1% (Table 7b). These results are consistent with those reported by Dontsop et al. (2012) for the impact of New Rice for Africa (NERICA) adoption in Nigeria.

6.5 | Estimation of the total number of poor households lifted out of poverty

Table 8 presents the estimates of the total number of poor individuals who managed to overcome poverty through the adoption of the CSI technologies in the Great Lakes region (see Appendix 1 for estimation steps). The estimation procedure is similar to the case in Manda et al. (2019), Zeng et al. (2015), and Wossen et al. (2017). Results showed that the gain in crop income and hence consumption expenditure due to the adoption of CSI technologies led to poverty reduction, with eastern DR Congo experiencing the most reduction (13% point) followed by Rwanda (6% point) and Burundi (2%). In terms of the actual number of poor who managed to overcome poverty, an estimated 99,653, 75,972, and 4,358 poor individuals managed to escape poverty in eastern Congo, Rwanda, and Burundi, respectively. This gives a total of 179,983 poor individuals that moved out of poverty in the three countries of the Great Lakes region. This conforms to the findings in several studies which demonstrated that the adoption of agricultural technologies, particularly improved crop varieties, helped to reduce poverty levels in Tanzania, Nigeria, Zambia, and Ethiopia (Asfaw et al., 2012; Khonje et al., 2015; Manda et al., 2019; Wossen et al., 2017, 2019; Zeng et al., 2015).

7 | CONCLUSION AND POLICY IMPLICATION

This article assessed the poverty reduction impacts of the adoption of CSI technologies using the ESR model in the Great Lakes region of Africa. The study data came from a household survey conducted in 2014 with a sample of 1,495 households in three countries of the Great Lakes region (Burundi, eastern DR Congo, and Rwanda). Each country had one-third of the sample (501 in Burundi, 503 in DR Congo, and 491 in Rwanda). Results indicated that adoption has increased crop yield (e.g., beans and maize) and crop income, which in turn led to increased consumption in the region, resulting in poverty reduction in the region. Among the three target countries, eastern DR Congo witnessed the most reduction (13% points) followed by Rwanda (6% points) and Burundi (2% points). These translated into an estimated 180,000 poor in the Great Lakes region escaping poverty through the adoption of the CSI technologies. Comparing results by household type, we found that the female-headed households had benefited more from the adoption of CSI technologies than male-headed households.

The results present important evidence in favor of policy interventions geared toward promoting CSI technologies for poverty reduction and improving rural household welfare. Besides, the dissemination should target and reach out to the current nonadopters for effective poverty reduction in the region. For example, the current nonadopters in Burundi, had they decided to adopt the CSI technologies, would have increased their consumption and reduced the poverty level to a larger extent than had the current adopters. Nonetheless, given the large population size that remains poor even after adoption, adoption of CSI technologies alone cannot be sufficient to lift the poor out of poverty, suggesting that research-based poverty reduction strategy should be complemented with development interventions.

CONFLICT OF INTEREST

None declared.

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ENDNOTES

[1] The poverty line of US$1.25/capita/day was converted to purchasing power parity.

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

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APPENDIX 1

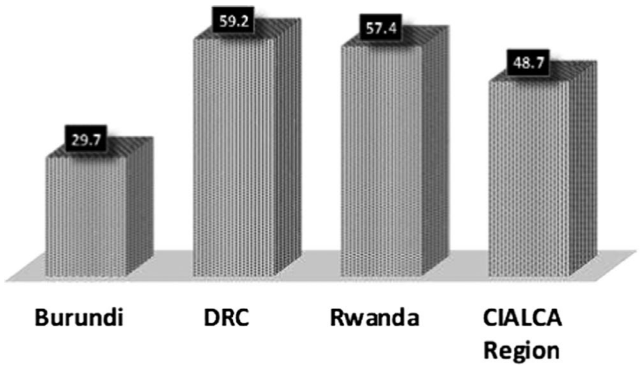

FIGURE A1 Adoption of CSI technologies in the Great Lakes region. Source: Author's calculations using CIALCA survey data 2014

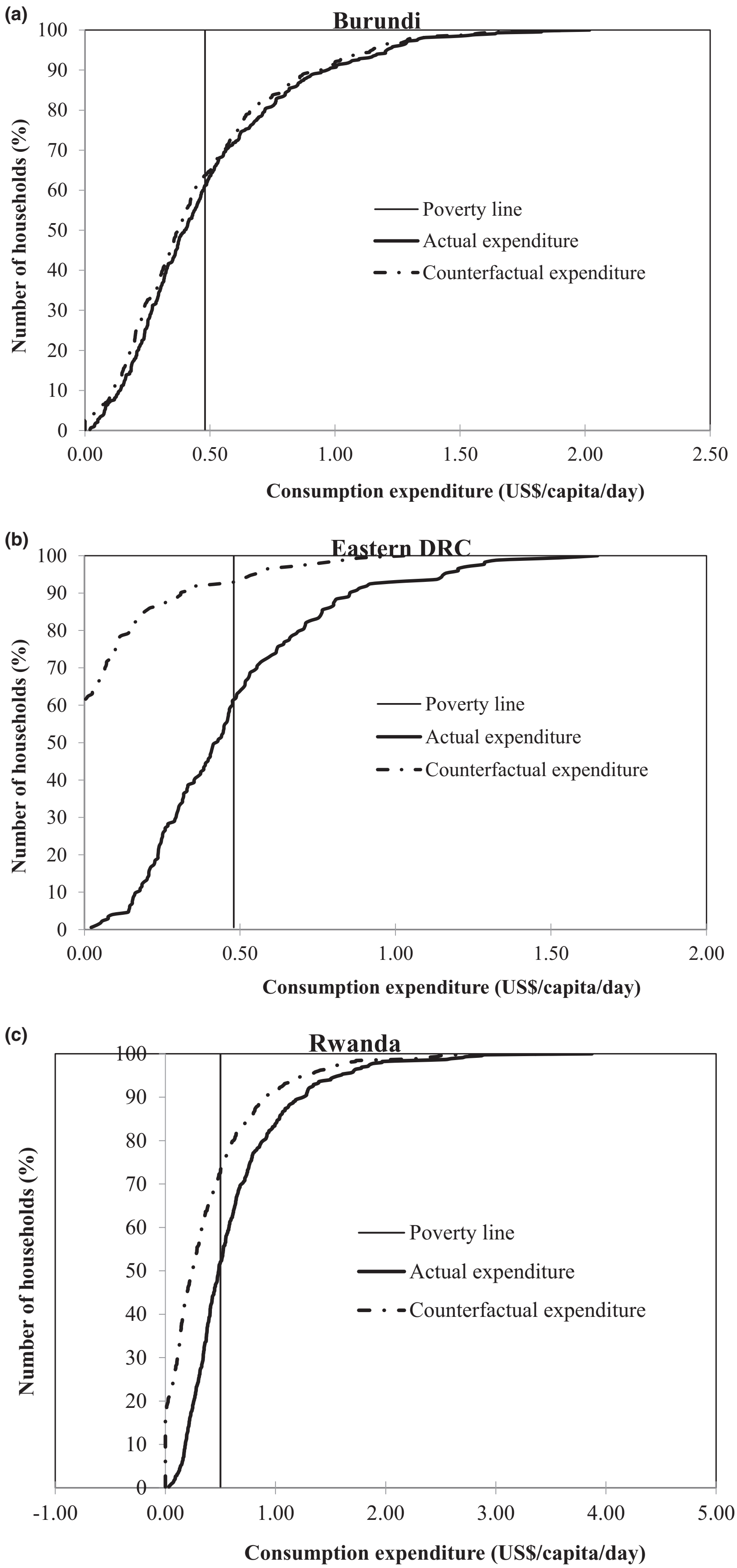

FIGURE A2 (a) Actual and counterfactual consumption expenditure distribution for adopters in Burundi. (b) Actual and counterfactual consumption expenditure distribution for adopters in DR Congo. (c) Actual and counterfactual consumption expenditure distribution for adopters in Rwanda

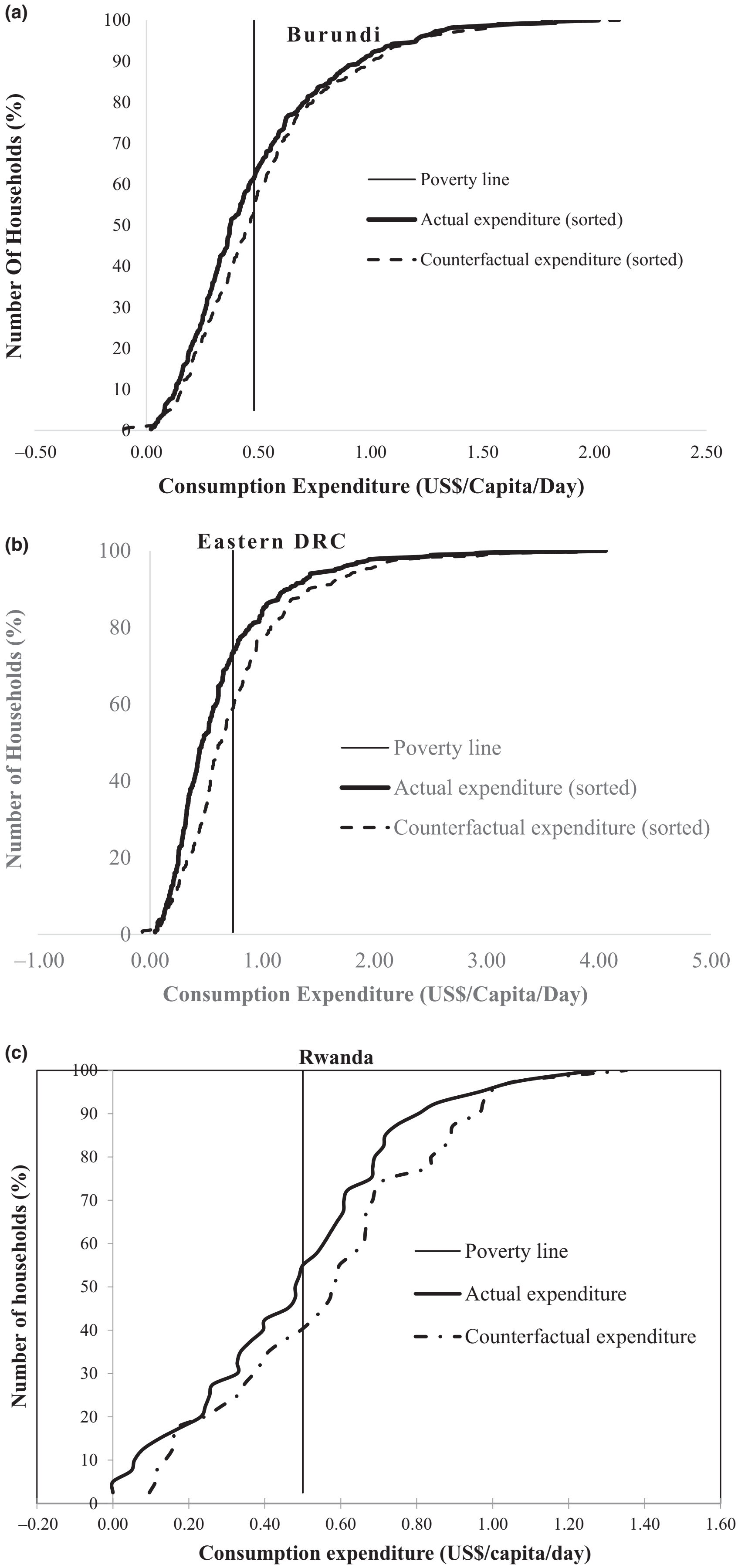

FIGURE A3 (a) Actual and counterfactual consumption expenditure distribution for nonadopters in Burundi. (b) Actual and counterfactual consumption expenditure distribution for nonadopters in DR Congo. (c) Actual and counterfactual consumption expenditure distribution for nonadopters in Rwanda