Received: 14 April 2020 | Revised: 13 May 2020 | Accepted: 5 June 2020
DOI: 10.1002/fes3.225

ORIGINAL RESEARCH

Food and Energy Security — Open Access
WILEY

# Household welfare impacts of an agricultural innovation platform in Uganda

**Beine Peter Ahimbisibwe**[1] | **John F. Morton**[2] | **Shiferaw Feleke**[3] | **Arega Alene**[4] | **Tahirou Abdoulaye**[5] | **Kate Wellard**[2] | **Eric Mungatana**[6] | **Anton Bua**[7] | **Solomon Asfaw**[8] | **Victor Manyong**[3]

[1]Ministry of Agriculture, Animal Industry and Fisheries (MAAIF), Entebbe, Uganda
[2]University of Greenwich, London, UK
[3]International Institute of Tropical Agriculture, Dar es Salaam, Tanzania
[4]International Institute of Tropical Agriculture, Lilongwe, Malawi
[5]International Institute of Tropical Agriculture, Bamako, Mali
[6]University of Pretoria, Pretoria, South Africa
[7]National Agricultural Research Organization, Entebbe, Uganda
[8]Food and Agricultural Organization (FAO), Rome, Italy

**Correspondence**
Shiferaw Feleke, International Institute of Tropical Agriculture, Dar es Salaam, Tanzania.
Email: s.feleke@cgiar.org

**Abstract**

Technical approaches to food production are important to the food security of growing populations in developing countries. However, strategic investments in research and farm-level adoption require greater coherence in agricultural, societal, and local policies. The Agricultural Innovation System (AIS) and formation of the Cassava Innovation Platform (CIP) in Uganda were designed to stimulate interactions between researchers and farmers, leading to the development of improved cassava varieties through participatory plant breeding (PPB) and participatory variety selection (PVS). Moreover, the establishment of a community-based commercialized seed system called Cassava Seed Entrepreneurship (CSE) has made an important contribution to the rapid multiplication and dissemination of clean planting materials in Uganda. The impact of CIP participation on rural household welfare was measured by household consumption expenditure per capita. The Endogenous Switching Regression (ESR) model was applied to data from a formal household survey conducted in the eastern, northern, and mid-western regions of Uganda. The education, farm size, livestock size, access to credit, cost of cassava planting materials, access to extension service, access to training, and social group membership are significantly associated with CIP participation. CIP participation resulted in a 47.4% increase in household consumption expenditure. This important evidence highlights the need to promote agricultural innovation platform for improving rural livelihoods. Moreover, CIP participation has impact heterogeneity within the participant group that is conditional on household characteristics such as the gender of the household head, pointing to the need to tailor specific interventions and target specific groups within farm households.

**KEYWORDS**
agricultural innovation systems, innovation platform, participation, rural household welfare, Uganda

## 1 | INTRODUCTION

Agricultural research in sub-Saharan Africa (SSA) has long been dominated by a top-down approach in which technical innovations such as improved crop varieties were first developed in experimental stations and then transferred to the farming communities for validation and adaptation (Pound & Conroy, 2017). However, such an approach has not generally led to widespread adoption of innovations (Pamuk, Bulte, Adekunle, & Diagne, 2015), prompting many agricultural research organizations in the region to look for alternative approaches. In the early 2000s, the National Agricultural Research Organization of Uganda (NARO) embraced the concepts of agricultural innovation system (AIS) and initiated Agricultural Innovation Platforms (AIPs) as a mechanism to operationalize the AIS concepts at a local level and make its national research programs for various commodities more relevant. NARO's adoption of CIP was mainly precipitated by the need to develop and disseminate most appropriate cassava disease management innovations to address the cassava mosaic disease (CMD) and cassava brown streak disease (CBSD). The formation of CIP stimulated interactive learning and exchange of knowledge among different stakeholders in the cassava value chain, leading to a better understanding of smallholder farmers' needs and conditions, and hence the development of most preferred cassava varieties through participatory plant breeding (PPB) and participatory variety selection (PVS). Drawing on the experiences from the implementation of this national initiative, the Eastern Africa Agricultural Productivity Project (EAAPP) launched a regional cassava research initiative in 2010 involving national and regional actors under the framework of the Cassava Regional Center of Excellence (CRCoE). The initiative led to the development of new improved cassava varieties most preferred by smallholder farmers (Wellard, Chancellor, Okecho, Ndagire, & Mugarura, 2015) and establishment of a community-based, commercialized seed system (the Cassava Seed Entrepreneurship-CSE), which contributed to the rapid multiplication, distribution, and uptake of disease-free planting materials.

NARO's application of the AIS concepts and smallholder farmers' participation in CIP (first under its national initiative and then as part of the regional CRCoE initiative) has been going on for nearly two decades now. However, empirical evidence is lacking on the effectiveness of CIP in improving the livelihoods of the participating households in Uganda. Empirical evidence on the effectiveness of AIPs in African agriculture is generally lacking, leading to little or no allocation of resources for promoting their use in agriculture (Spielman, 2006). The lack of such evidence is partly due to the lack of better indicators for measuring the complexities of agricultural innovation interactions and performance (Martin, 2009) and partly due to the limited availability of appropriate quantitative methods and tools (Cadilhon, 2013). Rajalahti, Janssen, & Pehu, (2008) suggest that with AIS being a recent development phenomenon, farmers' participation in agricultural innovation platforms (AIPs) can be used as an indicator for probing their effectiveness in welfare improvement. In light of this, a growing number of studies have used AIP participation as an indicator to examine the role of AIPs in food security and nutrition improvement and poverty reduction (Pamuk et al., 2015; Wellard, Rafanomezana, Nyirenda, Okotel, & Subbey, 2013; Mapila, Kirsten, & Meyer, 2012; Magreta Zingore, & Magombo, 2010; Kaaria, Njuki, Abenakyo, Delve, & Sanginga, 2008). For example, recently, Tambo and Wünscher (2017) applied the endogenous switching regression and maximum simulated likelihood techniques to assess the impact of farmer-led innovations on household income and consumption expenditure per adult equivalent.

Similarly, Pamuk et al. (2015) assessed the impact of innovation platforms (IPs) on food consumption and alleviation of rural poverty in central Africa. Similarly, Mapila et al. (2012) evaluated the impact of AIS interventions on rural livelihoods in Malawi. Magreta et al. (2010) also evaluated how linking farmers to markets using AIS concepts in agricultural research would lead to improvements in farmers' livelihoods in the rice-based farming systems of Southern Malawi. Further, Kaaria et al. (2008) assessed the performance of the Enabling Rural Innovation (ERI) initiative in linking smallholder farmers to markets and in improving livelihood outcomes in Uganda and Malawi. However, except for Tambo and Wünscher (2017) and Pamuk et al. (2015), most of these studies, while embracing Kaaria et al.'s suggestion of AIP participation as an indicator of the adoption of IS concepts, have not applied rigorous analytical tools that could address causal effect estimation issues such as endogenous selection bias in AIP participation. The failure to account for such a bias makes it difficult to distill the impact of AIPs on farming livelihoods. To address this issue, Tambo and Wünscher (2017) and Pamuk et al. (2015) have aimed to control for potential selection bias by estimating Double Difference (DD) models and panel models, while acknowledging the possibility of some estimation bias due to unobservable and time-varying factors. Other studies (e.g., Mapila et al., 2012) applied a less rigorous approach, such as the propensity score matching method (PSM). While the PSM approach helps to mitigate the selection bias by creating a condition that mimics a randomized experiment, it is, however, limited by the fact that the experimental condition is created based on measured characteristics only. As an improvement over the majority of the previous studies, this study applies a rigorous analytical approach, particularly the Endogenous Switching Regression (ESR), which controls both unobserved heterogeneity and endogeneity in the covariates (Lee, 1978; Maddala, 1986; Tambo & Wünscher, 2017). Nevertheless, as the estimated effects from the ESR model may be sensitive to the assumption of the model, we use the PSM approach as a robustness check (Shiferaw, Kassie, Jaleta, & Yirga, 2014). The assumption in the ESR is that the latent state variable (i.e., CIP participation) controlling regime change is endogenous. Our analysis also uses nationally representative household data from all significant cassava growing regions of Uganda.

Further, this study is based on consumption expenditure data, which is considered to be less prone to measurement errors and better measured in the context of developing countries. Consumption expenditure data are often preferred to income data because they are less prone to seasonal fluctuations and underreporting bias (Meyer & Sullivan, 2003). Consumption expenditure data also reflect a household's decision on nutrition and health (Atkinson, 1992). This article assesses the impact of CIP participation on household welfare in Uganda as well as the distribution of the welfare effects of CIP participation over the levels of specific household characteristics using the ESR model. To the extent that such a rigorous approach has not been previously applied to study the impact of cassava innovation platforms in Uganda, we note that our study represents an original contribution to the existing body of organized knowledge on agricultural innovation platforms in the country.

## 2 | CONCEPTUAL FRAMEWORK

We adapt the concepts of the structure—conduct—performance (S-C-P) model of markets to the context of innovation platforms, as in Cadilhon (2013). We define the structure of the cassava platforms as a network of the AIS actors involved in variety development and seed system initiatives (Figure 1). The structure of the variety development initiative initially consisted of farmers, national researchers, and other relevant stakeholders in Uganda, and later included regional actors from Tanzania, Kenya, and Ethiopia under the framework of the Cassava Regional Center of Excellence (CRCoE). Similarly, the structure of the CSE AIS initiative consisted of researchers, farmers, input suppliers (seed multipliers), inspectors, and regulators (seed certifiers), NGOs. In particular, the CSE comprises cassava researchers from NaCRRI who, together with cassava farmers, develop popular cassava varieties through the PPB and PPS; NaCRRI agronomists that train CSEs in cassava agronomic practices; cassava farmers that serve as CSEs; cassava seed multipliers that operate through tissue culture (TC) mass production and farmer field seed bulking (BioCrops and NARO-ZARDIs (Zonal Agricultural Research and Development Institutes)); NGOs that provide capacity building in business and market linkage dynamics (MEDA, Afrii, and CHAIN); the National Seed Certification Services (NSCS) agency of the Agriculture Ministry that provides seed inspection and certification services; and finally farmers who buy and use certified cassava seed.

The structure of the variety development initiative within the framework of national cassava research program of NARO, and CRCoE created an opportunity for interaction and exchange of knowledge in the context of the AIS concepts, leading to the conduct of participatory development of improved cassava varieties that met specific farmer needs (Wellard et al., 2015). Similarly, the structure of CSE initiative created an opportunity for knowledge exchange, and interactive learning, leading to the conduct of a functional commercialized cassava seed system in Uganda. The conduct of the CSE AIS initiative can also be expressed in terms of building the skills and knowledge of communities,

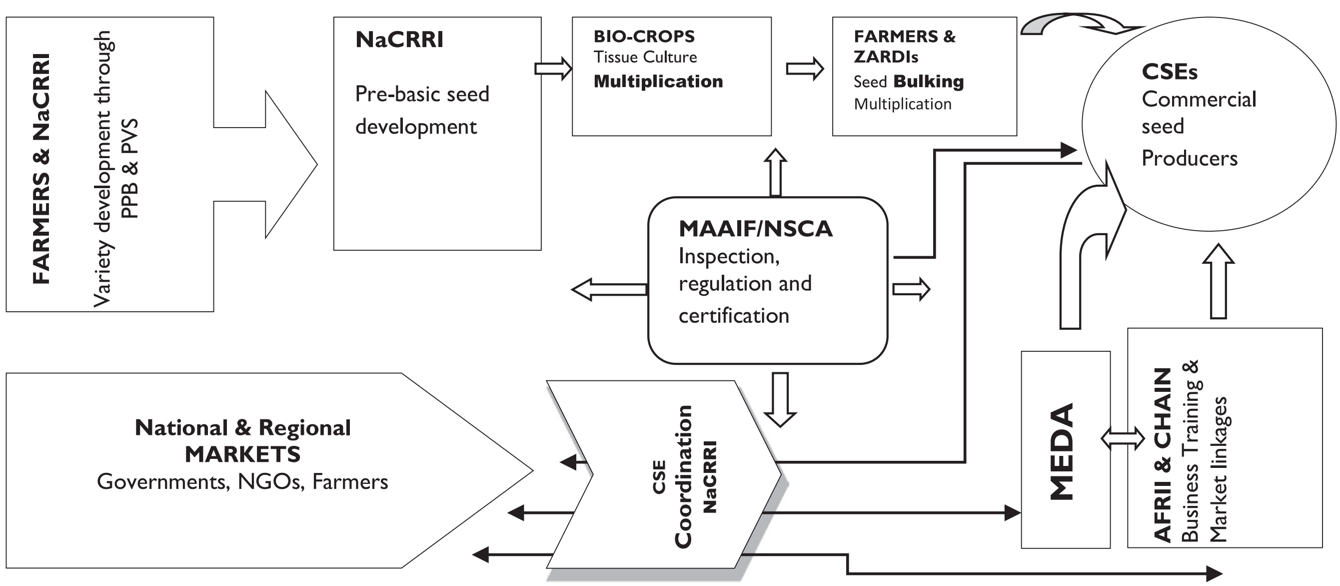


**FIGURE 1** Graphical representation of the CSE AIS Initiative (Source: Authors' compilation)

local service providers (finance, input supply, agricultural extension), local and central government agricultural inspectors, individual farmers, and farmer groups to engage effectively in markets (Fatunbi, Youdeowei, Ohiomoba, & Adekunle, 2016).

The performance of the platform is described in terms of the adoption of cassava innovations, leading to productivity and income gains that would finally translate into improved household welfare. As such, we conceptualize the welfare impact of farmers' participation in the platform in the context of how the conduct of the platform influences farmers to perceive a benefit in terms of improved household welfare. This is in tandem with the random expected utility theory framework where a given household is assumed to participate in the platform if the expected utility from participation outweighs that of nonparticipation. However, as the utilities of participation and nonparticipation are nonobservable, we assume that the household who is observed to participate in the platform has perceived to receive benefit from participation while the household observed to be nonparticipant has not perceived net benefit.

## 3 | EMPIRICAL MODEL

Following Fernandez-Cornejo, Hendricks, and Mishra (2005), the Kuhn-Tucker first-order conditions of constrained utility maximization (i.e., household utility maximized subject to production and income constraints) can be first solved to yield reduced-form equations for input use and output produced (production-side decision). Then, they can be solved for reduced-form equations for consumption demand following the determination of the "full income" through an optimal choice of input use and the output produced (consumption-side decision). The production-side and consumption-side equations give us a complete picture of the economic behavior of the farm household.

Our outcome equation links CIP participation to other control variables to the outcome variable of consumption expenditure, which can be expressed as:

$$Y_i = \psi H_i + \omega P_i + \upsilon_i \tag{1}$$

where $Y_i$ denotes consumption expenditure; $H_i$ is a vector of control variables with the associated parameters $\psi$; $P_i$ is a dummy variable denoting CIP participation, and the associated parameter $\omega$ measures the effect of CIP participation on consumption expenditure.

In the absence of a nonrandom assignment of households to treatment (CIP participants) and control (nonparticipants) groups, CIP participation denoted by $P_i$ is potentially endogenous, making it difficult to identify its effects on outcome variables. The identification challenge arises from the fact that the decision to participate in CIP could be based on unobservables that are correlated with both outcomes and observable predictors. The failure to account for the potential endogenous selection bias in the outcome equations may, therefore, result in biased and inconsistent estimators. Past studies have applied both semi-parametric and parametric approaches that take account of the potential self-selection problem (Abdoulaye, Wossen, & Awotide, ; Ainembabazi et al., 2018; Ali & Abdulai, 2010; Asfaw, Kassie, Simtowe, & Lipper, 2012; Becerril & Abdulai, 2010; Feleke, Manyong, Abdoulaye, & Alene, 2016; Khonje, Manda, Alene, & Kassie, 2015; Manda et al., 2019; Shiferaw et al., 2014; Tufa et al., 2019; Wossen et al., 2017). In this study, we use the parametric approach (endogenous switching regression model), and semi-parametric (propensity score matching) approaches, with the latter being used as a robustness check to the results of the former.

### 3.1 | The endogenous switching regression model

A given endogenous switching regression (ESR) model consists of one treatment selection equation and two separate outcome equations for the outcome variable of interest that are conditional on the selection criterion. The treatment selection equation is defined by a probit model, and the two outcome equations are linear. In the context of our study, the ESR model consists of a probit model of CIP participation and linear models of consumption expenditure.

The CIP participation equation can be specified as:

$$P_i^* = \gamma Z_i + u_i, \tag{2}$$

where $P_i^*$ is the latent variable indexing the probability of CIP participation; $Z_i$ is nonstochastic vectors of exogenous variables influencing the decision to participate; $\gamma$ is a vector of parameters to be estimated, and $u_i$ is random disturbances associated with CIP participation.

A given household is assumed to decide to participate if the expected utility from participation outweighs that of nonparticipation given as:

$$\begin{cases} P_i = 1 & \text{if } P_1^* > P_0^* \\ P_i = 0 & \text{otherwise} \end{cases} \tag{3}$$

The two outcome equations, conditional on $P_i$, can be specified as below where households face two regimes (1) participation, and (2) nonparticipation given as:

$$\begin{aligned} &\text{Regime 1} \quad Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad \text{if } P_i = 1 \\ &\text{Regime 2} \quad Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \quad \text{if } P_i = 0 \end{aligned} \tag{4}$$

 

where $Y_{1i}$ and $Y_{2i}$ are consumption expenditure observed for each household depending on the selection equation; $X_i$ represents a vector of exogenous variables that influence the outcome variables; $\beta$ is a vector of parameters to be estimated; $\varepsilon_{1i}$ and $\varepsilon_{2i}$ are the error terms associated with the outcome equations.

The error terms $u, \varepsilon_1$, and$\varepsilon_2$ are assumed to have a tri-variate normal distribution with zero mean and nonsingular covariance matrix (Maddala, 1983) given as:

$$cov\left(u, \varepsilon_1, \varepsilon_2\right) = \begin{bmatrix} \sigma_u^2 & \sigma_{u\varepsilon_1} & \sigma_{u\varepsilon_2} \\ \sigma_{u\varepsilon_1} & \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1\varepsilon_2} \\ \sigma_{u\varepsilon_2} & \sigma_{\varepsilon_2\varepsilon_1} & \sigma_{\varepsilon_2}^2 \end{bmatrix} \tag{5}$$

where $\sigma_u^2$ is variance of the error term in the selection equation which is assumed to be 1; $\sigma_{\varepsilon_1}^2$ and $\sigma_{e_2}^2$ are variances of the error terms in the outcome equations; $\sigma_{u\varepsilon_1}$ and $\sigma_{u\varepsilon_2}$ are covariances of the error terms between the selection equation and that of the outcome equations, measuring the direction and degree of nonrandom selection.

The covariances between the error terms in the outcome equations $\sigma_{\varepsilon_1\varepsilon_2}$ and $\sigma_{\varepsilon_2\varepsilon_1}$ are undefined since the outcome variables $Y_{1i}$ and $Y_{2i}$ cannot be observed simultaneously (Maddala, 1983).

The expected values of the error terms, $\varepsilon_1$ and $\varepsilon_2$, conditional on the participation criterion is nonzero because of the possible correlation between the error term in the participation equation and the error terms of the outcome equations.

$$E(\varepsilon_{i1}|P_i = 1) = \sigma_{u\varepsilon_1}\left[\frac{\phi(\hat{P})}{\Phi(\hat{P})}\right] \tag{6a}$$

$$E(\varepsilon_{i2}|P_i = 0) = -\sigma_{u\varepsilon_2}\left[\frac{\phi(\hat{P})}{1-\Phi(\hat{P})}\right] \tag{6b}$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative function; $-\frac{\phi(\hat{P})}{\Phi(\hat{P})}$ and $\frac{\phi(\hat{P})}{1-\Phi(\hat{P})}$ are the endogenous selection terms or inverse Mill's ratio evaluated at $\hat{P} = Z_i\gamma$ in the participation equation where $\hat{P}$ is the predicted probability of CIP participation, $P_i$.

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 linear outcome equations to correct for the potential selection bias given as:

$$Y_{1i} = \beta_1 X_{1i} + \sigma_{u\varepsilon_1}\left[\frac{\phi(\hat{P})}{\Phi(P)}\right] + \in_{1i}, \text{ if } P_i = 1 \tag{7a}$$

$$Y_{2i} = \beta X_{2i} - \sigma_{u\varepsilon_2}\left[\frac{\phi(\hat{P})}{1-\Phi(\hat{P})}\right] + \in_{2i}, \text{ if } P_i = 0 \tag{7b}$$

While the above equations can be estimated in a two-stage procedure, simultaneous estimation of the participation and outcome equations using the full information maximum likelihood (FIML) method is considered an efficient way (Lokshin & Sajaia, 2004). The FIML can be implemented in Stata® using the movestay command. A statistically significant estimate of $\sigma_{u\varepsilon_1}$ and $\sigma_{u\varepsilon_2}$ indicate endogenous switching.

Of particular interest in this study is the impact of CIP participation on rural welfare measured in terms of consumption expenditure. The expected outcomes for CIP participants under observed conditions and counterfactual conditions (i.e., had they not participated) will be computed using Equation (8a) and Equation (8b), respectively given as:

$$E(Y_{1i}|P_i = 1) = X_{1i}\beta_1 + \sigma_{u\varepsilon_1}\left[\frac{\phi(\hat{\boldsymbol{P}})}{\Phi(\hat{\boldsymbol{P}})}\right] \tag{8a}$$

$$E(Y_{2i}|P_i = 1) = X_{1i}\beta_2 + \sigma_{u\varepsilon_2}\left[\frac{\phi(\hat{\boldsymbol{P}})}{\Phi(\hat{\boldsymbol{P}})}\right] \tag{8b}$$

The difference in the expected outcomes from Equation (8a) and Equation (8b), referred to as the average treatment effect on treated (ATT), constitute the impact of CIP participation on consumption expenditure of participants.

Similarly, the expected outcomes for non-CIP participants under observed conditions and counterfactual conditions (i.e., had they participated) will be computed using Equation (9a) and Equation (9b), respectively given as:

$$E(Y_{2i}|P_i = 0) = X_{2i}\beta_2 - \sigma_{u\varepsilon_2}\left[\frac{\phi(\hat{\boldsymbol{P}})}{1-\Phi(\hat{\boldsymbol{P}})}\right] \tag{9a}$$

$$E(Y_{1i}|P_i = 0) = X_{2i}\beta_1 - \sigma_{u\varepsilon_1}\left[\frac{\phi(\hat{\boldsymbol{P}})}{1-\Phi(\hat{\boldsymbol{P}})}\right] \tag{9b}$$

The difference in the expected outcomes from Equation (9a) and Equation (9b), referred to as the average treatment effect on the untreated (ATU), constitutes the potential impact of CIP participation on consumption expenditure of nonparticipants.

## 3.2 | Propensity score matching method

We use the propensity score matching (PSM) method as a robustness check for the results from the ESR model. The main steps involved in the application of the PSM in the present study are (a) estimating the propensity scores of CIP participation using the logit model, (b) imposing a common support region, (c) matching the propensity scores between the CIP participant group and nonparticipant group in the common support region using different algorithms such as nearest neighbor (NN), kernel matching (KM), and radius matching (RM) options, (d) assessing the quality of the matches, and (e) estimating the impact.

Following Rosenbaum and Rubin (2011), the propensity score of CIP participation given a vector of observed covariates can be given as:

$$P(X_i) = P(P_i = 1 | X_i) = \beta' X_i + u_i \tag{10}$$

where $P(X_i)$ is the propensity score (conditional probability) of CIP participation; $P_i$ is the vector of observed households' participation decision with a value of 1 for the household who reported participating in CIP and 0 otherwise, $\beta$ is a vector of parameters to be estimated; $X_i$ represents the vector of preparticipating control variables which explain CIP participation, and $u_i$ is the error term that is independent of $X_i$ and is symmetrically distributed about zero.

In step 1, we estimate the propensity scores $P(X_i)$ using the logistic model (see Rosenbaum and Rubin, 1983). The propensity score is the probability that a farmer in the full sample participates or does not participate in the cassava platform, given a set of observed variables.

In step 2, we impose a common support region, which implies that the probability of participating and not participating for each possible value of the observable covariates is strictly within the unit interval. This ensures that there is sufficient overlap in the characteristics of CIP participants and nonparticipants to find adequate matches.

In step 3, we select a participant and nonparticipant with the same probability of participation so that we can think of them as if they were randomly selected. However, since it is difficult to find two households with precisely the same probability of participation, we look for a suitable matching estimator. While there are many such methods in the literature, the most commonly used ones are the NN, KM, and RM options. Using the three options, we establish matched pairs.

In step 4, we assess the quality of the matches using different criteria. After conditioning on the propensity scores using the above three matching algorithms, we implement a test of balance in measured covariates between participants and matched nonparticipants based on three indicators (i.e., pseudo-$R^2$ and $p$-values of the likelihood ratio test of the joint significance before and after matching and the mean standard bias).

Finally, we evaluate the CIP participation impact on the outcome of our interest, which is consumption expenditure using the average treatment effect on the treated (ATT) given as:

$$\mathrm{ATT} = E(Y_1 - Y_0 | P = 1) \tag{11}$$

## 4 | DATA

This study was conducted in a total of 12 districts in the Eastern, Northern, and Mid-Western Uganda, with four districts purposively selected from each region (Figure 2). The selection of the districts was made in consultation with key informants. Two of the four districts selected from each region are intervention districts, and the other two are nonintervention districts. It is important to note that both CIP participants and non-CIP members could be found in both intervention and nonintervention districts, even though the number of CIP participants was higher in the former districts than in the latter.

The sampling frame consists of cassava growing households from both intervention and nonintervention districts. It was constructed based on the NaCRRI's database consisting of coded cassava growing households who participated in several previous surveys (NARO, 2011, 2014) as well as the lists of registered and active cassava farmers in both the intervention and nonintervention districts obtained from District Agricultural Officers (DAOs), NARO Zonal Agricultural Research & Development Institutes (ZARDIs), and local agricultural extension offices.

The sampling framework was constructed from three regions, and four districts per region, and 150 households per district, providing a total of 1,800 eligible households under CIP evaluation. Following Yamane (1967), we calculated the sample size to be 591 households, considering a margin error of 3.5% and aiming for a response rate of 95%. To cater for attrition, the enumerators interviewed 20 more households, resulting in a total of 612 households. However, three questionnaires were discarded for lack of consistency leaving us with only a total of 609 households (i.e., participants and nonparticipants in cassava AIS initiatives). The participants account for a quarter of the total sample. The data were collected using a pretested structured questionnaire administered by trained and experienced enumerators. To mitigate the challenges of reverse causality in impact estimation, the questionnaire was designed in such a way as to capture preparticipation data on selected variables such as access to extension, and access to training. The selection of preparticipation control variables is based on knowledge of the intervention under evaluation as well as the social, economic, and institutional characteristics that might potentially influence their participation in the platform. The vector of preparticipation control variables ensures that they are not confounded with outcomes or the anticipation of participation.

The study has one treatment variable—CIP participation (measured by asking the selected households whether or not they participated in CIP in 2015), and one outcome

 

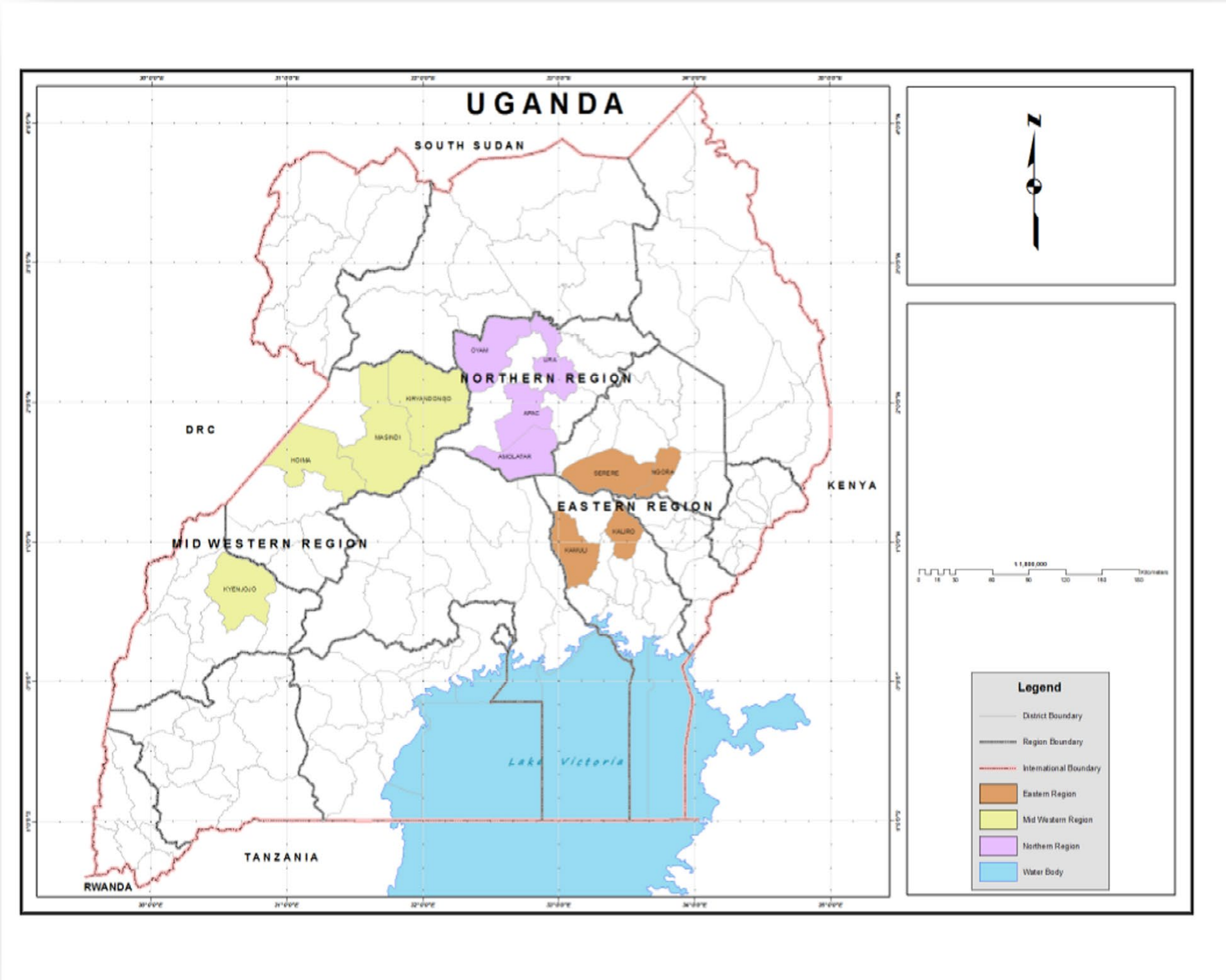


**FIGURE 2** Map of the study region

variable—food consumption expenditure per capita. The consumption expenditure was measured by asking the sample households on food expenditure for the preceding year covering 12 months consistent with the World Bank's LSMS-ISA standard module. The study has several independent variables (farm and household characteristics), falling under three categories: demographic, socioeconomic, and institutional. Under the demographic category, gender, age of the household head, educational level, and family size were included. Educational level is defined by a dummy variable, whether the head of the household attended a formal education as well as by a continuous variable that captures the total number of formal education years of all household members divided by the household size. The age of the household head is also a continuous variable measured in years. The gender of the household head is included as a dummy categorical variable that takes on the value of 1 if the household head is female and 0 if male. The socioeconomic category includes the cost of planting materials, ownership of cassava farm, total operated farm size, and livestock size as measured by Tropical Livestock Units (TLUs[1]). Similarly, the institutional category includes access to extension, training, and social group membership. These expose households to more information and learning opportunities, thereby increasing their chances of learning about the importance of agricultural innovation platform. In deciding whether or not to participate in AIS initiatives, households need information on the exact benefits accruable from joining CIP. Access to extension and access to training on the use of improved practices in the preintervention year (2010) are included and defined by dummy variables that take on the value of 1 if the household received extension services and training in 2010, and 0 if otherwise. These are used to instrument farmers' participation in the cassava platforms. Finally, regional dynamics are included to assess the effect of geographical location on the decision to participate in the AIS initiatives. The Eastern region is the most populated region followed by the Western region and, lastly, the Northern region. In terms of cassava production, the Eastern region is the largest producer, followed by the Northern region and, lastly, the Western region (UBOS, 2015). The regions are defined by dummy variables taking on the value of 1 if a household resides in the Midwestern or Northern regions, and 0 for the Eastern region.

# 5 | RESULTS

## 5.1 | Descriptive analysis

About a quarter of the sample households reported as being CIP participants, while the remaining are nonparticipants. Figure 3 compares the density estimates of the consumption expenditure used as an indicator for household welfare between CIP participants and nonparticipants, showing higher estimates for CIP participants. The consumption expenditure is 1.28 times higher among CIP participants compared with nonparticipants. While CIP participation might have contributed to the observed mean differences in the consumption expenditure, it will be misleading to attribute the entire difference to CIP participation without controlling for all the differences in household characteristics as well as any unmeasured heterogeneity.

Table 1 compares the descriptive statistics for the household characteristics between CIP participants and nonparticipants. The results indicate statistically significant differences in most of the household characteristics between CIP and non-CIP participants. The CIP participants are relatively older, better educated, and wealthier. They also have more access to institutions such as credit, extension, training programs, and nonfarm jobs compared with non-CIP participants. For example, nearly 60% of the CIP participants have access to credit compared with just over 40% of nonparticipants. Similarly, about 56% of the CIP participants have access to extension services compared with 10% of non-CIP participants.

Further, about 36% of the CIP participants received training on cassava agronomy compared with just 5% of non-CIP participants. These results suggest that CIP and non-CIP participants are systematically different. In the face of such systematic differences, it will be difficult to causally attribute the observed difference in consumption expenditure shown in Figure 3 above to CIP participation. The difference in consumption expenditure between them could well be due to the difference in the observed characteristics such as wealth, education, access to credit, and extension services presented in Table 1 below. The next section presents the results of a multivariate analysis based on the ESR model, controlling for all the differences in measured household characteristics and unmeasured heterogeneity.

## 5.2 | Multivariate analysis

The multivariate analysis is based on the ESR model, which can be identified due to the nonlinearity of the selection bias control terms (Maddala, 1986). However, it is usually advised that exclusion restrictions be imposed to improve identification. Hence, following Di Falco, Veronesi, and Yesuf (2011), who used information sources as instruments, we included two information-related instruments in the selection equation. These are (a) training and (b) extension services on the use of improved agricultural practices. Knowledge acquisition about improved agricultural practices through training and extension services before the introduction of the platforms could form the basis for farmers to decide in favor or against participation in the platform. Hence, we hypothesize that these variables tend to influence farmers' decision to participate in the platform (relevance criterion) but are unlikely to have a direct effect on consumption expenditure (exogeneity criterion). The validity of these instruments can be tested using a simple falsification test following Di Falco et al. (2011). Results show that the instruments are jointly statistically significant in the selection equation ($\chi^2 = 75.23$; $p = .000$) but not in the outcome equation for participants ($F = 0.35$; $p = .7045$) and for nonparticipants ($F = 2.09$; $p = .1256$). This can be further verified by examining the

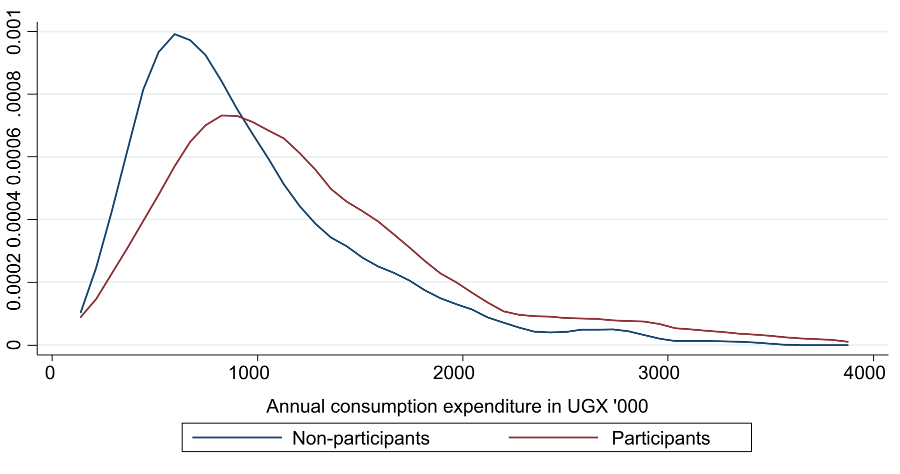


**FIGURE 3** Kernel density estimates of consumption expenditure

**TABLE 1** Descriptive statistics of control variables by CIP participation

| Variable | All | CIP participants | Non-CIP participants | Mean difference |
|---|---|---|---|---|
| Gender of HH head (1 = female) | 0.176 | 0.110 | 0.198 | −0.088** |
| Age of HH head (years) | 45.8 | 48.5 | 44.8 | 3.7*** |
| Age-squared | 2,292.9 | 2,536.1 | 2,210.4 | 325.7** |
| Education of HH head (1 = yes) | 0.928 | 0.987 | 0.908 | 0.079*** |
| Education of HH members (years) | 5.5 | 6.6 | 5.0 | 1.6*** |
| Family size (#) | 7.2 | 7.7 | 7.1 | 0.6** |
| Dependence ratio | 1.3 | 1.0 | 1.4 | −0.4*** |
| Farm ratio (cassava to total land) | 0.231 | 0.236 | 0.230 | 0.006 |
| Livestock size (TLU) | 2.941 | 4.987 | 2.248 | 2.739*** |
| Type of houseroof (1 = ironroof) | 0.644 | 0.675 | 0.633 | 0.042 |
| Cost of cassava seed (000 UGX/bag) | 13.132 | 15.700 | 12.259 | 3.441*** |
| Have nonfarm job(1 = yes) | 0.667 | 0.727 | 0.648 | 0.079* |
| Own radio (1 = yes) | 0.658 | 0.742 | 0.645 | 0.097** |
| Own bicycle (1 = yes) | 0.714 | 0.848 | 0.694 | 0.154*** |
| Own phone (1 = yes) | 0.653 | 0.757 | 0.616 | 0.141*** |
| HH main occupation (1 = farming) | 0.788 | 0.812 | 0.780 | 0.032 |
| Group membership (1 = yes) | 0.767 | 0.941 | 0.708 | 0.233*** |
| Cassava experience (years) | 8.3 | 7.6 | 8.5 | −0.9 |
| Farm distance (KM) | 0.52 | 0.75 | 0.44 | 0.31*** |
| Access to tarmac road(1 = yes) | 0.202 | 0.240 | 0.189 | 0.051 |
| Access to credit (1 = yes) | 0.456 | 0.597 | 0.409 | 0.188*** |
| Access to extension (1 = yes) | 0.220 | 0.558 | 0.105 | 0.453*** |
| Access to training (1 = yes) | 0.131 | 0.364 | 0.053 | 0.311*** |
| Northern region | 0.332 | 0.286 | 0.347 | −0.061 |
| Mid-western region | 0.323 | 0.344 | 0.316 | 0.028 |
| Household consumption expenditure per capita (UGX) | 1,036,615 | 1,237,627 | 968,560 | 269,067*** |

* Significant at 10%;
** Significant at 5%;
*** Significance at 1%.

statistical significance of the instruments in the selection equation, also known as the first-stage equation of the ESR model. Results indicate that the parameter estimates of these two instruments are both statistically significant in the selection equation (Table 2), suggesting that the assumption of the relevance of the instruments hold. The exogeneity hypothesis states that the instruments will only indirectly affect the consumption expenditure through its effect on the probability of CIP participation. While this hypothesis cannot generally be tested, we can argue that the selected instruments can be considered as exogenous to the current level of consumption expenditure since the farmers' responses to the questions on the instruments were solicited by asking the respondents if they had access to training and extension services in 2010 just before the introduction of the platforms, thus mitigating the risk of endogeneity stemming from reverse causality.

## 5.3 | Model diagnostics and parameter estimates

Results of the model diagnostics show that the correlation between the error terms of the outcome (consumption expenditure) equation for nonparticipants and the selection equation is statistically different from zero. This finding means that unobservable characteristics affecting the outcome of consumption expenditure are correlated with those affecting CIP participation. The statistically significant negative correlation

**TABLE 2** FIML estimates of the ESR model of CIP participation and consumption expenditure

| Variables | Selection Eq. of CIP participation | Outcome Eq. of consumption expenditure | |
|---|---|---|---|
| | | CIP-participants | CIP-participants |
| Gender of HH head (1 = female) | −0.3810 | −0.0399 | 0.0667 |
| | (0.2430) | (0.1120) | (0.0634) |
| Age of HH head (years) | −0.0341 | −0.0238* | −0.0044 |
| | (0.0250) | (0.0131) | (0.0095) |
| Age-squared | 0.0002 | 0.0002 | 0.0001 |
| | (0.0002) | (0.0001) | (0.0001) |
| Education of HH head (1 = yes) | 1.0990** | 0.1830 | −0.0048 |
| | (0.4310) | (0.1510) | (0.0883) |
| Education (years) | 0.0859* | 0.0350* | 0.0295** |
| | (0.0452) | (0.0193) | (0.0150) |
| Family size (#) | 0.0328 | −0.0753*** | −0.0713*** |
| | (0.0266) | (0.0157) | (0.0094) |
| Dependence ratio | −0.2270** | −0.0363 | −0.0403 |
| | (0.1140) | (0.0514) | (0.0307) |
| Access to credit (1 = yes) | 0.3860** | −0.0101 | −0.0100 |
| | (0.1540) | (0.0816) | (0.0495) |
| Land ratio (casssva to total) | 0.5580* | −0.2910* | 0.0289 |
| | (0.3110) | (0.1550) | (0.1460) |
| Livestock size (TLU) | 0.0566** | 0.0039 | 0.0135 |
| | (0.0248) | (0.0067) | (0.0098) |
| Type of houseroof (1 = ironroof) | −0.0314 | 0.1460 | 0.0422 |
| | (0.1710) | (0.0940) | (0.0510) |
| Cost of cassava seed (000 UGX) | 0.0304*** | 0.0009 | −0.0000 |
| | (0.0094) | (0.0051) | (0.0035) |
| Have nonfarm job(1 = yes) | −0.0022 | 0.2790*** | 0.1050** |
| | (0.1690) | (0.0944) | (0.0522) |
| Own radio (1 = yes) | −0.1830 | 0.0912 | 0.0725 |
| | (0.1570) | (0.0830) | (0.0520) |
| Own bicycle (1 = yes) | 0.2580 | 0.1320 | 0.0689 |
| | (0.1770) | (0.1040) | (0.0554) |
| Own phone (1 = yes) | 0.0196 | 0.0659 | 0.0560 |
| | (0.1710) | (0.0946) | (0.0511) |
| HH main occupation (1 = farming) | 0.3050 | 0.0419 | −0.1110* |
| | (0.1980) | (0.0966) | (0.0600) |
| Group membership (1 = yes) | 0.4420* | 0.1190 | −0.0023 |
| | (0.2290) | (0.2080) | (0.0529) |
| Cassava experience (years) | 0.0155 | 0.00161 | −0.0022 |
| | (0.0099) | (0.0056) | (0.0030) |
| Farm distance (KM) | 0.1960*** | 0.0342 | 0.0128 |
| | (0.0537) | (0.0220) | (0.0300) |

(Continues)

**TABLE 2** (Continued)

| | | Outcome Eq. of consumption expenditure | |
|---|---|---|---|
| **Variables** | **Selection Eq. of CIP participation** | **CIP-participants** | **CIP-participants** |
| Access to tarmac road(1 = yes) | 0.1120 | 0.1490 | 0.1000$^{*}$ |
| | (0.2020) | (0.0958) | (0.0602) |
| Northern region | 0.0399 | −0.0216 | 0.1260$^{**}$ |
| | (0.2300) | (0.1050) | (0.0629) |
| Mid-western region | 0.1500 | 0.1400 | 0.0501 |
| | (0.1870) | (0.0992) | (0.0605) |
| Access to training (1 = yes) | 0.5260$^{**}$ | | |
| | (0.2500) | | |
| Access to extension (1 = yes) | 1.2580$^{***}$ | | |
| | (0.2170) | | |
| Constant | −3.4690$^{***}$ | 7.0780$^{***}$ | 6.9100$^{***}$ |
| | (0.8160) | (0.5020) | (0.2710) |
| Rho1 | | −0.0524 | |
| | | (0.2139) | |
| Rho2 | | | −0.5394$^{*}$ |
| | | | (0.2300) |

*Note:* Wald test of indep. Equations $X^2(1) = 14.05$***.

Robust standard errors in parentheses.

* $p < .1$;

** $p < .05$;

*** $p < .01$

coefficient of the error terms of the CIP participation and that of consumption expenditure equation for nonparticipants suggests the exercise of self-selection among nonparticipants. Nonparticipants were likely to have self-selected themselves *out of* participation because they may not have perceived to benefit from participation. This result implies that nonparticipants have higher consumption expenditure than it would have been the case for a population of households who are assigned at random to nonparticipation status.

The Wald test of independent equations rejects the null hypothesis of joint independence, suggesting joint dependence between the selection and consumption expenditure equations for participants and nonparticipants. Consistent with our specification, we have two distinct regimes rather than one, justifying the use of the ESR model by providing evidence of the appropriateness of the assumption that the effects of covariates between the two regimes (with and without participation) are significantly different. This is apparent in the variation in the second-stage parameter estimates of the control variables in the outcome equations of the ESR model between CIP participants and nonparticipants presented in the third and fourth columns of Table 2. The results show noticeable differences in some of the parameter estimates of the consumption expenditure equations between the CIP participants and nonparticipants, suggesting the presence of some heterogeneity in the sample. For example, the age of the household head, and land ratio (cassava farm to total farm size) are significantly associated with consumption expenditure for participants but not for nonparticipants.

In contrast, the main occupation of the household head, access to the tarmac road, and region are significantly associated with consumption expenditure for nonparticipants, but not for participants. The differential returns might be explained by the variation in the quality of experience, soil, occupation, and infrastructure. However, variables such as family size, education, and access to nonfarm jobs are significantly associated with the outcomes of both participants and nonparticipants. For example, family size is negatively associated with the consumption expenditure of both participants and nonparticipants, with a slightly higher effect on participants. This is in line with the result in Tambo and Wünscher (2017), who find that household size significantly reduces consumption expenditure of both innovators and noninnovators, with a more pronounced effect on innovators compared to noninnovators.

Similarly, results from the first-stage estimation of the ESR model presented in the second column of Table 2 indicate that education of the household head, education level

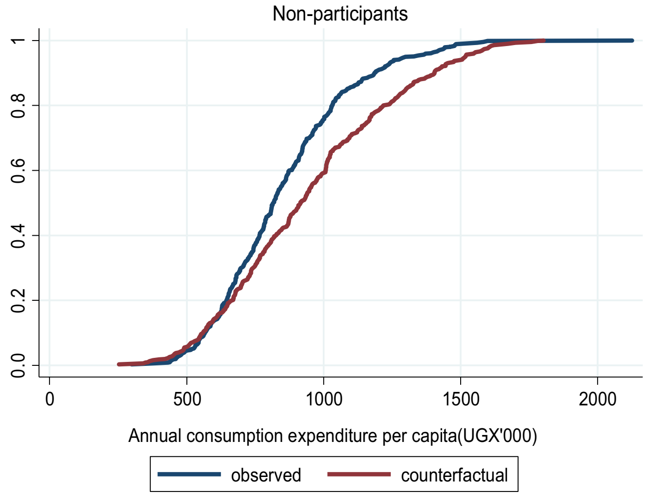


**FIGURE 5** Observed and counterfactual cummulative distribution non-participants

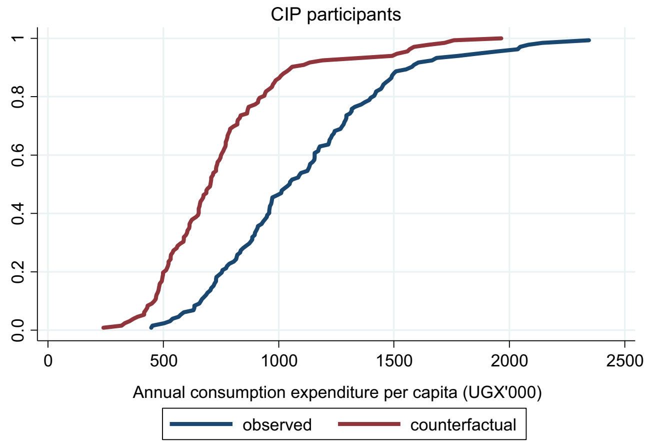


**FIGURE 4** Observed and counterfactual cummulative distribution CIP participants

of family members, land ratio (relative size of cassava land to total land), access to credit, dependence ratio (number of dependents to working members), social group membership, farm distance, access to training, access to extension, and cost of cassava planting materials are significantly associated with CIP participation. Specifically, farmers who have access to financial and social capital resources (land, capital, credit, membership) are more likely to participate in cassava platforms.

## 5.4 | Distribution of treatment effects

Figures (4–5) display that the observed (with participation) and the counterfactual (without participation) distributions of the consumption expenditure for participants and nonparticipants. With the observed distribution generally lying predominantly to the right of the counterfactual distribution, participants are likely to have generally benefited from their participation in terms of higher consumption expenditure (Figure 4). For example, the probability that consumption expenditure under observed conditions is greater than or equal to UGX 1,000,000 is about 0.50, compared with about 0.15 under counterfactual conditions, suggesting a higher probability of the current participants benefiting from CIP participation. Similarly, as the counterfactual distribution lies predominantly to the right of the observed distribution, nonparticipants would likely have generally benefited from participation in terms of higher improved household welfare (Figure 5). For example, the probability that consumption expenditure under observed conditions is greater than or equal to UGX 1,000,000 is nearly 0.2, compared with about 0.4 under counterfactual conditions, suggesting a higher probability of the current nonparticipants potentially benefiting from CIP participation. A visual comparison of the size of the gap between the observed and counterfactual curves in Figure 4 and Figure 5 shows that the former has a more significant gap than the latter, suggesting that the current participants have benefited more than the nonparticipants would have. In the next section, the point-by-point vertical differences between the observed and counterfactual consumption expenditure are averaged over the sample of participants to determine if the participants have overall benefited from participation.

## 5.5 | Average treatment effects

Table 3 presents the average treatment effects on the treated (ATT) and the untreated (ATU). In the context of this study,

**TABLE 3** Average consumption expenditure (UGX) effects on CIP participants and nonparticipants

| | Decision stage | | | |
|---|---|---|---|---|
| Group | Participate | Not to participate | Average treatment effect (ATT, ATU) | Percent change |
| CIP participants | 1,114,762 | 756,011 | 358,751*** | 47.4% |
| Non-CIP participants | 963,296 | 853,464 | −109,832*** | 12.8% |
| Heterogeneity effects | 151,466 | −97,453 | 248,919 | |

*** Statistical significance at 1% level; figures in parenthesis are standard errors.

*Source:* Own calculations.

**TABLE 4** OLS and quantile regression parameter estimates of consumption expenditure effects

| Variables | Quantile parameter estiamtes Lower (q25) | Median (q50) | Upper (q75) | OLS estimates |
|---|---|---|---|---|
| Gender of HH head (1 = female) | −0.2050** | −0.2140 | −0.0996 | −0.1080 |
| | (0.0967) | (0.1570) | (0.1790) | (0.0729) |
| Age of HH head (years) | −0.0526*** | −0.0563*** | −0.0423*** | −0.0480*** |
| | (0.0122) | (0.0159) | (0.0146) | (0.00992) |
| Age-squared | 0.0004*** | 0.0004*** | 0.0003** | 0.0003*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Education of HH head (1 = yes) | 0.7650*** | 0.7740*** | 1.0990*** | 0.8370*** |
| | (0.1280) | (0.1690) | (0.1830) | (0.2660) |
| Education (years) | 0.0157 | 0.0253 | 0.0174 | 0.0145 |
| | (0.0142) | (0.0171) | (0.0180) | (0.0121) |
| Family size (#) | −0.0889*** | −0.0765*** | −0.0781*** | −0.0971*** |
| | (0.0204) | (0.0152) | (0.0174) | (0.0090) |
| Dependence ratio | 0.0435 | 0.0154 | −0.0295 | 0.0343 |
| | (0.0459) | (0.0434) | (0.0620) | (0.0358) |
| Access to credit (1 = yes) | −0.0289 | −0.0069 | −0.0962 | −0.0838* |
| | (0.0706) | (0.0658) | (0.0596) | (0.0476) |
| Land ratio (casssva to total) | −1.0570*** | −0.7310** | −0.7650** | −1.0760*** |
| | (0.2880) | (0.3130) | (0.3590) | (0.1890) |
| Livestock size (TLU) | −0.0446*** | −0.0293*** | −0.0250*** | −0.0341*** |
| | (0.0108) | (0.0068) | (0.0090) | (0.0056) |
| Type of house roof (1 = iron roof) | 0.3440*** | 0.3140*** | 0.3280*** | 0.3440*** |
| | (0.0812) | (0.0743) | (0.0986) | (0.0543) |
| Cost of cassava seed (000 UGX) | −0.0002 | 0.0014 | 0.0005 | 0.0011 |
| | (0.0042) | (0.0032) | (0.0033) | (0.0029) |
| Have nonfarm job(1 = yes) | 0.6130*** | 0.6630*** | 0.5700*** | 0.6550*** |
| | (0.0637) | (0.0930) | (0.1120) | (0.0579) |
| Own radio (1 = yes) | 0.2020** | 0.0769 | 0.1600* | 0.1540*** |
| | (0.0944) | (0.0951) | (0.0829) | (0.0546) |

(Continues)

**TABLE 4** (Continued)

| Variables | Quantile parameter estiamtes Lower (q25) | Median (q50) | Upper (q75) | OLS estimates |
|---|---|---|---|---|
| Own bicycle (1 = yes) | 0.2310*** | 0.2330** | 0.2700** | 0.2590*** |
| | (0.0659) | (0.1110) | (0.1070) | (0.0666) |
| Own phone (1 = yes) | 0.1440*** | 0.0609 | 0.1080 | 0.0721 |
| | (0.0536) | (0.0577) | (0.0925) | (0.0554) |
| HH main occupation (1 = farming) | 0.3390*** | 0.3630*** | 0.2760* | 0.2860*** |
| | (0.0710) | (0.0962) | (0.1470) | (0.0706) |
| Group membership (1 = yes) | 0.1480 | 0.1890 | 0.1190 | 0.1270 |
| | (0.1450) | (0.1220) | (0.1540) | (0.1010) |
| Cassava experience (years) | 0.0147** | 0.0110* | 0.0118* | 0.0170*** |
| | (0.0061) | (0.00614) | (0.0063) | (0.0036) |
| Farm distance (KM) | 0.0690*** | 0.0531** | 0.0432 | 0.0638*** |
| | (0.0230) | (0.0214) | (0.0283) | (0.0138) |
| Access to tarmac road(1 = yes) | 0.1110 | 0.187* | 0.1450 | 0.2020*** |
| | (0.1130) | (0.1070) | (0.1050) | (0.0640) |
| Northern region | −0.2600 | −0.227 | −0.1300 | −0.3270*** |
| | (0.1610) | (0.1630) | (0.1320) | (0.0692) |
| Mid-western region | 0.377*** | 0.311*** | 0.3740*** | 0.3510*** |
| | (0.0739) | (0.0937) | (0.1090) | (0.0593) |
| Constant | −3.4690*** | 7.0780*** | 6.9100*** | −0.9030*** |
| | (0.8160) | (0.5020) | (0.2710) | (0.1480) |

*Note:* The dependent variable is the treatment effects ($TE_i$) of the outcome variable. Standard errors in parentheses.

* $p < .1$;

** $p < .05$;

*** $p < .01$.

**TABLE 5** The quality test of the propensity scores under different matching methods

| Status | Matching method | Pseudo $R^2$ | LR $\chi^2$ ($p$-value) | Mean standard bias | Total % mean bias reduction |
|---|---|---|---|---|---|
| Before matching | | 0.141 | 90.94 (.000) | 23.3 | |
| After matching | NN | 0.021 | 7.91 (.894) | 4.8 | 79.4% |
| | KM | 0.004 | 1.46 (.999) | 2.7 | 88.4% |
| | RM | 0.003 | 1.25 (.999) | 2.6 | 88.8% |

the ATT refers to the average effect of CIP participation on the CIP participants in terms of consumption expenditure, while ATU refers to the potential benefits that could have accrued to the current nonparticipants had they chosen to participate in the cassava platforms. Results indicate that CIP participation is associated with higher consumption expenditure. CIP participants are observed to have UGX 1,114,762, compared with UGX 756,011, had they not participated, indicating that CIP participation resulted in increasing consumption expenditure by about 47.4% (Table 3).

Similarly, nonparticipants are observed to have UGX 853,464. However, if they had participated in the cassava platforms, they would have 12.8% more consumption expenditure. The findings are in agreement with the results of Tambo and Wünscher (2017), and Pamuk et al. (2015). For example, applying the ESR model, Tambo and Wünscher (2017) found that farmer-led innovations significantly increased household income and consumption expenditure. Similarly, Pamuk et al. (2015) found that innovation platforms are more effective than conventional extension approaches in reducing poverty. While our results indicate that both participants and nonparticipants would benefit from participation, it is essential to note that the effects of participation are relatively higher on the current participants. This is apparent in the last row of Table 3, where the transitional heterogeneity effect is positive (UGX 248,919).

## 5.6 | Treatment effects over household characteristics

In the previous section, we showed that CIP participation led to increased consumption. In this section, applying the OLS and quantile regression, we assess the heterogeneous effects of the household characteristics at the mean and specific points of the distribution, such as the 25th, median or 75th percentile. Table 4 shows that the OLS and quantile parameter estimates show the effects of equal magnitude for most of the household characteristics. However, some characteristics that exhibit statistically significant effects at the 25th percentile level are found to have no such effects at other points of the distribution, such as the mean (as determined by OLS parameter estimates) or median or 75th percentile levels (as determined by quantile parameter estimates). For example, the parameter estimate of the gender of the household head and phone ownership is found to be statistically significant at the 25th percentile level. That is, there is a significant difference between male-headed and female-headed participants in terms of consumption expenditure as well as between participants who phone owners and nonowners. Specifically, at the 25th percentile, female-headed participants have 18.5% [$\approx$exp. $(-0.2050) - 1] \times 100\%$ less consumption expenditure than male-headed participants. Similarly, at the 25th percentile, CIP participants who own phones have 15.5% more consumption expenditure than participants who do not own phones. These results show that even though they are all participants in the platform, the effects of participation vary depending on such household characteristics as gender and phone ownership status of the participating household head. Other variables that have statistically significant effects at one level but no such effects at other points of the distribution include farm distance, access to the tarmac road, and region.

## 5.7 | Robustness check

As the results from the ESR may be sensitive to its assumptions (Shiferaw et al., 2014), we use the PSM as a robustness check. Since the reliability of the PSM results of treatment effects depends on the quality of the propensity matches (balance in covariates and common support) and adequacy of the PSM model specification, we checked for the extent of overall covariate balancing and overlap over the common support. Covariate balancing ensures whether the estimated propensity score adequately balances observed covariates between the participants and the comparison group (Austin, 2009).

After conditioning on the propensity scores using three conditioning methods (NN, KM, and RM), the test of balance in measured covariates between participants and matched nonparticipants was implemented based on three indicators (pseudo-$R^2$, $p$-values of LR test, and mean standard bias). Table 5 presents the results of the balance test based on the three indicators. The pseudo $R^2$ dropped significantly from 14.1% before matching to 2.1%, 0.4%, and 0.3% after matching with NN, KM, and RM, respectively. This suggests that matching led to a substantial reduction of systematic differences or bias in the distribution of the covariates between the participants and that of matched nonparticipants. Further, the

LR test for the joint significance of the covariates shows statistically significant differences in measured covariates before matching but showed no such differences after matching. Therefore, we fail to reject the hypothesis that the distributions of covariates after matching are approximately the same between the participant and comparison group. This suggests that there is no systematic difference in the distribution of covariates between CIP participants and nonparticipants after matching. The mean standard bias is also significantly reduced, ranging from about 79.4% with the NN to 88.4% with the KM, to 88.8% with RM, with the mean bias for overall covariates decreasing from 23.3 to 4.8, 2.7 and 2.6, respectively. Given the consistent test results across the three matching algorithms, it can be concluded that the quality of the match is satisfactory, indirectly satisfying adequacy in model specification and the requirement of the conditional independence assumption which implies that after controlling for observable covariates, the assignment of farmers to CIP participation is "as good as random" such that the potential outcomes are independent of participation status.

The common support or overlap condition was checked based on a visual inspection of the graphical displays of the distribution of the propensity scores (0.025, 0.943) depicted in Figure 6 below, showing a substantial overlap in the distribution of the propensity scores of participants and nonparticipants. This ensures the availability of observations in the pool of nonparticipants that may match the group of participants.

Table 6 presents the estimates of the average participation effects estimated using the PSM based on the NN, KM, and RM matching algorithms where the NN method is applied with a caliper (0.01) and single neighbor and replacement, the KM with normal kernel bandwidth (0.01), as well as the RM with calipers of width equal to 0.01.

The PSM results compare favorably with that of the ESR model in qualitative terms, generally showing positive rural welfare effects of CIP participation. In particular, CIP participation has a positive and statistically significant impact on consumption expenditure. For example, results from the ESR model show that CIP participation increases consumption expenditure by UGX 358,751, compared to UGX 244,694, UGX 136,746, and UGX 185,910 in the PSM results based on the NN, KM, and RM algorithms, respectively. Recall from the descriptive results (Table 1) that the mean difference in consumption expenditure between participants and nonparticipants was UGX 269,067. These quantitative differences could be because the effects of the unobserved heterogeneity were not accounted for in the PSM method.

## 6 | CONCLUSION

Using the ESR model, the study has sought to test if CIP participation has led to improved rural household welfare (measured by consumption expenditure) in Uganda. Data came from a formal household survey conducted in the Eastern, Northern, and Mid-Western parts of the country. Results indicate that better education, wealth (measured by livestock size and farm size), access to extension service, access to training, access to credit service, and social group membership tend to positively and significantly influence CIP participation. Similarly, education, family size, and access to nonfarm jobs are significantly associated with the consumption expenditure outcome of both participants and nonparticipants. In terms of impact, results indicate positive welfare effects of CIP participation. Specifically, CIP participation has increased consumption expenditure by 47.4% in Uganda.

Further, our results indicate that the current nonparticipants would have gained nearly 11% more consumption expenditure had they participated. This result suggests the potential of innovation platforms to achieve better livelihood outcomes, pointing to the need for reaching the current nonparticipants. The result also points to the need for advancing the AIS concepts such as participatory cassava technology development, seed inspection, and certification services, and cassava seed entrepreneurship that were applied in the cassava platform, leading to improved welfare.

The study has also examined the distribution of the welfare effects of CIP participation over the levels of specific household characteristics. Using OLS and quantile regression, the study has shown that the welfare effects of CIP

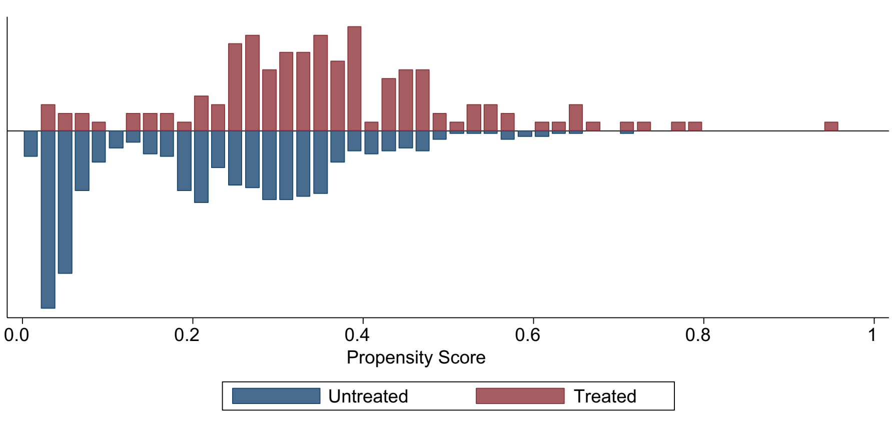


**FIGURE 6** Propensity score distribution displaying common support condition

**TABLE 6** ATT (UGX) from PSM under three different algorithms

| Matching algorithms | ATT | *SE* |
|---|---|---|
| NM | 244,694*** | 91,007 |
| KM | 136,746** | 68,840 |
| RM | 185,910*** | 68,761 |

*Note:* *** and ** denotes statistical significance at 1% and 5% level; figures in parenthesis are standard errors.

participation vary with household characteristics. Some characteristics, such as the gender of the household head, education, phone ownership, and access to credit and region, are found to exhibit statistically significant effects at different points of the distribution. This suggests the presence of heterogeneous effects conditional on household characteristics, pointing to the need for tailoring specific interventions and targeting specific groups of farm households. Finally, the lack of differential welfare effects of CIP participation across the three regions of Uganda suggests the potential of CIP as a mechanism to operationalize AIS concepts nationally.

## CONFLICT OF INTEREST

None declared.

## ORCID

*Shiferaw Feleke* https://orcid.org/0000-0002-0759-4070

## ENDNOTE

[1] TLUs are livestock numbers converted to a common unit. Conversion factors are: cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chicken = 0.01 (Harvest Choice, 2011).

## REFERENCES

Abdoulaye, T., Wossen, T., & Awotide, B. (2018). Impacts of improved maize varieties in Nigeria: Ex-post assessment of productivity and welfare outcomes. *Food Security*, *10*(2), 369–379. https://doi.org/10.1007/s12571-018-0772-9

Ainembabazi, J. H., Abdoulaye, T., Feleke, S., Alene, A., Dontsop-Nguezet, P. M., Ndayisaba, P. C., … Manyong, V. (2018). Who benefits from which agricultural research-for-development technologies? Evidence from farm household poverty analysis in Central Africa. *World Development*, *108*, 28–46.

Ali, A., & Abdulai, A. (2010). The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics*, *61*(1), 175–192. https://doi.org/10.1111/j.1477-9552.2009.00227.x

Asfaw, S., Kassie, M., Simtowe, F., & Lipper, L. (2012). Poverty reduction effects of agricultural technology adoption: A Micro-evidence from rural Tanzania. *Journal of Development Studies*, *48*(9), 1–18. https://doi.org/10.1080/00220388.2012.671475

Atkinson, A. B. (1992). Measuring poverty and differences in family composition. *Economica*, *59*(23), 1–16. https://doi.org/10.2307/2555062

Austin, P. (2009). Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. *Statistics in Medicine*, *2009*(28), 3083–3107. https://doi.org/10.1002/sim.3697

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World Development*, *38*(7), 1024–1035. https://doi.org/10.1016/j.worlddev.2009.11.017

Cadilhon, J. (2013). *A conceptual framework to evaluate the impact of innovation platforms on agrifood value chains development*. In: Paper prepared for the 138th EAAE seminar on pro-poor innovations in food supply chains, Ghent, Belgium, September 11–3, 2013.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Fatunbi, A. O., Youdeowei, A., Ohiomoba, S. I., Adekunle, A. A., & Akinbanijo, O. O. (2016). *Agricultural innovation platforms: Framework for improving sustainable livelihoods in Africa*. Accra, Ghana: Forum for Agricultural Research in Africa (FARA).

Feleke, S., Manyong, V., Abdoulaye, T., & Alene, A. (2016). Assessing the impacts of cassava technology on poverty reduction in Africa. *Studies in Agricultural Economics*, *118*, 101–111. https://doi.org/10.7896/j.1612

Fernandez-Cornejo, J., Hendricks, C., & Mishra, A. (2005). Technology adoption and off-farm household income: The case of herbicide-tolerant soybeans. *Journal of Agricultural and Applied Economics*, *37*(3), 549–563. https://doi.org/10.1017/S1074070800027073

Harvest Choice (2011). International Food Policy Research Institute, Washington, DC. and University of Minnesota, St. Paul, MN; 2015. Tropical Livestock Units (TLU, 2005). http://harvestchoice.org/data/an05_tlu

Kaaria, S., Njuki, J., Abenakyo, A., Delve, R., & Sanginga, P. (2008). Assessment of the Enabling Rural Innovation (ERI) approach: Case studies from Malawi and Uganda. *Natural Resources Forum*, *32*(1), 53–63.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in Eastern Zambia. *World Development*, *66*, 695–706. https://doi.org/10.1016/j.worlddev.2014.09.008

Lee, L. F. (1978). Unionism and wage rates: A simultaneous equations model with qualitative and limited dependent variables. *International Economic Review*, *19*(2), 415–433. https://doi.org/10.2307/2526310

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *Stata Journal*, *4*(3), 282–289. https://doi.org/10.1177/1536867X0400400306

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics*. Cambridge, UK: CUP. https://doi.org/10.1017/CBO9780511810176

Maddala, G. S. (1986). Disequilibrium, self-selection and switching models. In Z. Grilliches, & M. Intrilligator (Eds.), *Handbook of econometrics III* (pp. 1633–1688). Amsterdam, The Netherlands: Elsevier Science Publishing. https://doi.org/10.1016/S1573-4412(86)03008-8

Magreta, R., Zingore, S., & Magombo, T. (2010). Analysis of effective market linkage in promoting investments in natural resource management in the rice-based farming system in Malawi: A case of Nkhate irrigation scheme. Paper presented at the Symposium of the Innovation and Sustainable Development in Agriculture and Food (ISDA) held in Montpellier, France from 28 June to 1 July 2010.

Manda, J., Alene, A., Tufa, A., Abdoulaye, T., Wossen, T., Chikoye, D., & Manyong, V. (2019). The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development*, *122*, 261–271. https://doi.org/10.1016/j.worlddev.2019.05.027

Mapila, M., Kirsten, J. F., & Meyer, F. H. (2012). The impact of agricultural innovation systems interventions on rural livelihood outcomes in Malawi. *Development Southern Africa*, *29*(2), 303–315. https://doi.org/10.1080/0376835X.2012.675699

Martin, A. (2009). So what difference does it make? Assessing the outcomes and impacts of farmer participatory research. In I. Scoons, & J. Thompson (Eds.), *Farmer first revisited: farmer-led innovation for agricultural research and development*. Practical Action Publishing Ltd., Rugby, UK, pp. 276-281. ISBN 978-1-85339-682-3 (pbk).

Meyer, B. D., & Sullivan, J. X. (2003). *Measuring the well-being of the poor using income and consumption*. Working Paper 9760. Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/papers/w9760

NARO (2011). *The baseline survey report for the Eastern Africa Agricultural Productivity Project*. Namulonge, Uganda: The National Crops Resources Research Institute (NaCRRI).

NARO (2014). *The baseline survey report for the Cassava Seed Systems project*. Namulonge, Uganda: The National Crops Resources Research Institute (NaCRRI).

Pamuk, H., Bulte, E., Adekunle, A., & Diagne, A. (2015). Decentralized innovation systems and poverty reduction: Experimental evidence from Central Africa. *European Review of Agricultural Economics*, *42*(1), 99–127. https://doi.org/10.1093/erae/jbu007

Pound, B., & Conroy, C. (2017). The innovation systems approach to agricultural research and development. In S. Snapp, & B. Pound (Eds.), *Agricultural systems: Agroecology and rural innovation for development* (pp. 371–405). Cambridge, Massachusetts: Academic Press. https://doi.org/10.1016/B978-0-12-802070-8.00011-6

Rajalahti, R. Janssen, W., & Pehu, E. (2008). *Agricultural Innovation Systems: From Diagnostics toward Operational Practices*. Washington, D.C: Agriculture and Rural Development Department, World Bank.

Rosenbaum, P. & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1): 41-55.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, *44*, 272–284. https://doi.org/10.1016/j.foodpol.2013.09.012

Spielman, D. J. (2006). A critique of innovation systems perspectives on agricultural research in developing countries. *Innovation Strategy Today*, *2*(1), 25–38.

Tambo, J., & Wünscher, T. (2017). Farmer-led innovations and rural household welfare: Evidence from Ghana. *Journal of Rural Studies*, *55*(2017), 263–274. https://doi.org/10.1016/j.jrurstud.2017.08.018

Tufa, A., Alene, A., Manda, J., Akinwale, M. G., Chikoye, D., Feleke, S., … Manyong, V. (2019). The productivity and income effects of adoption of improved soybean varieties and agronomic practices in Malawi. *World Development*, *124*(2019), 104631.

UBOS (2015). *Uganda Bureau of Statistics. Uganda 2015 National Statistical Abstract*. Kampala, Uganda: UBOS.

Wellard, K. D., Chancellor, T., Okecho, G., Ndagire, S., & Mugarura, S. (2015). *Evaluation of the East African Agricultural Productivity Program (EAAPP)*. Natural Resources Institute and Africa Innovations Institute. (AfrII). Final Report. ASARECA, Entebbe, Uganda.

Wellard, K., Rafanomezana, J., Nyirenda, M., Okotel, M., & Subbey, V. (2013). A review of community extension approaches to innovation for improved livelihoods in Ghana, Uganda and Malawi. *Journal of Agricultural Education and Extension*, *19*(1), 21–35. https://doi.org/10.1080/1389224X.2012.714712

Wossen, T., Abdoulaye, T., Alene, A., Haile, M., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, *54*, 223–233. https://doi.org/10.1016/j.jrurstud.2017.06.022

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). New York, NY: Harper and Row.

**How to cite this article:** Ahimbisibwe BP, Morton JF, Feleke S, et al. Household welfare impacts of an agricultural innovation platform in Uganda. *Food Energy Secur*. 2020;9:e225. https://doi.org/10.1002/fes3.225