International Journal of Agricultural Sustainability

ISSN: 1473-5903 (Print) 1747-762X (Online) Journal homepage: www.tandfonline.com/journals/tags20

Step by step to higher yields? Adoption and impacts of a sequenced training approach for climate-smart coffee production in Uganda

Manuela Kristin Günther, Christine Bosch, Hanna Ewell, Raphael Nawrotzki & Edward Kato

To cite this article: Manuela Kristin Günther, Christine Bosch, Hanna Ewell, Raphael Nawrotzki & Edward Kato (2025) Step by step to higher yields? Adoption and impacts of a sequenced training approach for climate-smart coffee production in Uganda, International Journal of Agricultural Sustainability, 23:1, 2545042, DOI: 10.1080/14735903.2025.2545042

To link to this article: https://doi.org/10.1080/14735903.2025.2545042

Published online: 01 Sep 2025.

INTERNATIONAL JOURNAL OF AGRICULTURAL SUSTAINABILITY
2025, VOL. 23, NO. 1, 2545042
https://doi.org/10.1080/14735903.2025.2545042

Step by step to higher yields? Adoption and impacts of a sequenced training approach for climate-smart coffee production in Uganda

Manuela Kristin Günther [a,b], Christine Bosch [b,c], Hanna Ewell [d,e,g], Raphael Nawrotzki [c] and Edward Kato [f]

[a]Adam Smith Business School, University of Glasgow, Glasgow, UK; [b]ImpactLoop LTD, London, UK; [c]Hans-Ruthenberg-Institute for Tropical Agricultural Sciences, Social and Institutional Change in Agricultural Development, University of Hohenheim, Stuttgart, Germany; [d]Deutsche Gesellschaft für Internationale Zusammenarbeit /Fund International Agriculture Research, Bonn, Germany; [e]Knowledge, Technology and Innovation Group, Wageningen University and Research, Wageningen, The Netherlands; [f]International Food Policy Research Institute, Kampala, Uganda; [g]International Center for Tropical Agriculture (CIAT), Nairobi, Kenya

ABSTRACT

Climate change further exacerbates sustainability challenges in coffee cultivation. Addressing these requires effective delivery mechanisms for sustainable farming practices, particularly in smallholder contexts. We assess a novel public-private extension approach in Uganda, called Stepwise, comprising a sequence of climate-smart and good agricultural practices in four incremental steps. Using a mixed-method approach, an index that captures adoption intensity rather than binary uptake, and survey data from 915 Robusta and Arabica coffee farmers, we find adoption levels around 46% and relatively uniform amongst treated, spillover and comparison farmers. Regional variations suggest differing benefits across coffee varieties. Qualitative findings identify barriers to adoption, including financial and labour constraints, suboptimal training delivery, and input and output market imperfections. Despite relatively low uptake, adoption of more than half of the Stepwise practices is associated with substantial gains: inverse probability weighted regression adjustment reveals a 23% increase in yield and a 32% increase in revenue. Our findings add to the adoption literature, which often highlights limited uptake, and have important policy implications. Strengthening producer organizations, delivering targeted training but also innovative solutions for access to inputs and fair pricing, hold considerable potential to increase the adoption of climate-smart practices, particularly among resource-constrained farmers.

ARTICLE HISTORY
Received 17 July 2024
Accepted 3 August 2025

KEYWORDS
Climate-smart agriculture; sustainability; coffee value chain; East Africa; matching; Generalised Poisson; IPWRA

1. Introduction

Coffee is an important source of livelihood for rural people around the world. Despite substantial efforts for productivity improvement, coffee yield gaps in some regions remain high (Wang et al., 2015). Coffee is susceptible to climatic changes (Bunn et al., 2015; Pham et al., 2019; Wang et al., 2015), through drought stress and increased pest and disease occurrences, among others (Jaramillo et al., 2011; Kagezi et al., 2018; Liebig et al., 2018, 2019; van Asten et al., 2011).

Several sustainable coffee farming approaches promise synergies between climate change adaptation and mitigation, as well as between economic, social and environmental sustainability goals. These include good agricultural practices (GAP) and organic production as demanded by certification standards (Ssebunya et al., 2019), sustainable intensification (Rahn et al., 2018), intercropping with banana or shade trees (Jassogne et al., 2013; Rahn et al., 2018; Sarmiento-Soler et al., 2022; van Asten et al., 2011), and climate-smart agriculture (CSA) (Campbell et al., 2014), which has seen renewed attention for its potential to balance productivity and resilience (de Pinto et al., 2020; Raile et al., 2021). While some approaches focus more on the farm level and others include business models and entire value chains, there are considerable overlaps and complementarity between them (Campbell et al., 2014; Haggar et al., 2021). The reasons farmers adopt specific practices are often shaped by trade-offs between productivity, environmental

CONTACT Manuela Kristin Günther Manuela@impactloop.org

sustainability, and long-term climate change adaptation (FAO, 2017). Best-fit practices are often context-dependent, varying based on agroecological, climatic, socio-economic, and institutional factors.

Generally, the adoption of most such approaches remains limited in developing countries (Ruzzante et al., 2021), particularly in sub-Saharan Africa (e.g. Arslan et al., 2022; Lipper et al., 2014, 2017), including within the coffee sector (Abegunde et al., 2019; Raile et al., 2021; Sebatta et al., 2019). Various factors influence adoption. These include affordability, limited access to agricultural advisory services, socio-demographic and farm characteristics, past weather shocks, and cognitive traits such as risk tolerance and proactiveness—which can act as both barriers and drivers (Kangogo et al., 2021; Sebatta et al., 2019; Verburg et al., 2019). Further, it is suggested that the common approach of training these practices as a one-size-fits-all package may overwhelm farmers and reduce adoption rates (Jassogne et al., 2017).

The Stepwise approach is a novel private-public extension approach. While the practices that are introduced are well-known GAP and CSA practices, the Stepwise approach breaks them down into four sequenced steps and uses farmer-led demonstration plots and private-sector partnerships for the training. By that, the approach builds on already proven extension approaches, in particular farmer field schools (Davis et al., 2012), farmer-to-farmer training through contact or lead farmers (Fisher et al., 2018; Ragasa, 2020), and farmer demonstration plots (Sseguya et al., 2021). The private sector has been increasingly involved, offering direct advisory and other services to farmers (Sloan et al., 2019) to ensure and increase high-quality coffee supply and promote sustainable practices.

The Stepwise approach was conceptualized and implemented by the International Institute of Tropical Agriculture (IITA), together with private sector partners. Almost 2,000 farmers were trained in the Stepwise approach in several regions in Uganda. We use cross-sectional plot-level survey data collected from treated, spillover and comparison farmers in 2022, three years after completion of the intervention in 2019, to understand the impact of the adoption of this novel extension approach on coffee yield and revenue among smallholder coffee farmers. Specifically, we seek answers to the following two research questions:

- What are the key determinants influencing the adoption of practices trained with the help of the Stepwise approach?
- What is the impact of adopting these practices on coffee yield and farm revenue?

By answering these questions on a novel extension approach, with limited prior research focused on immediate pre-post effects (Mukasa et al., 2025), our study contributes new quasi-experimental evidence to the growing body of literature on the longer term adoption and impact of sustainable agricultural practices (Arslan et al., 2022; Ruzzante et al., 2021), especially in East Africa. The adoption of a package of practices constitutes a series of separate decisions (Ward et al., 2018). As such, this study introduces an adoption index that captures both the combination and sequential implementation of trained practices, offering a nuanced measure of adoption intensity and its effect on livelihood outcomes. This approach addresses a gap in the existing literature, where adoption is frequently treated as a binary decision (Arslan et al., 2022; Hörner & Wollni, 2022).

2. Literature review and context

2.1. The coffee sector in Uganda

Coffee plays a vital role in Uganda's economy. In 2021, Uganda exported 6.55 million coffee bags valued at USD 657 million, benefiting around 1.7 million smallholder farmers (UCDA, 2021) and casual wage workers (Cramer et al., 2016; Wedig & Wiegratz, 2018).

The Ugandan coffee sector is primarily composed of small farms, typically less than two hectares in size (Mugoya, 2018). Uganda produces both Robusta and Arabica coffee, grown in distinct agroecological zones. Robusta is primarily grown in Uganda's lower-altitude districts in central western, and eastern lowland regions, and parts of the Lake Victoria basin, where yields are sensitive to rainfall variability and prolonged droughts. Arabica coffee, by contrast, is cultivated at higher altitudes (above 1,300 metres) in the eastern highlands, south-western, and north-western regions, where it is more affected by temperature fluctuations.

Despite its economic importance, coffee production in Uganda remains constrained by limited use of inputs and low adoption of recommended agronomic practices (Mugoya, 2018). These include practices such as mulching, application of chemical fertilizers, replanting unproductive coffee plants, shade tree management (Wang et al., 2015), manure use, irrigation, water harvesting, trenching, improved planting material, integrated pest and disease management, weed control, pruning, and stumping (Mugoya, 2018), all of which have all shown the potential to boost coffee yields.

2.2. Adoption of sustainable practices

Although the adoption of sustainable practices varies by context and crop, research consistently shows that individual, farm-level, and institutional factors play an important role in East Africa. At the individual level, traits like risk aversion, proactiveness, and entrepreneurship (Kangogo et al., 2021; Margiotta & Giller, 2018), knowledge of the practices and their benefits (Senyolo et al., 2021), past weather shocks and climate change perceptions are relevant (Mulinde et al., 2019). At the household and farm level, location, altitude, climate, farm and household size, resource endowments, land tenure, soil quality, access to labour, socio-economic status (e.g. off-farm employment or labour sales to other farms), market access (Mulinde et al., 2019), and gender roles, influence adoption decisions (Bernier et al., 2015; Eriksen et al., 2019; Jassogne et al., 2013; Margiotta & Giller, 2018), and the importance of the crop for the household (Bongers et al., 2015). At an institutional level, access to support services, such as extension, credit and savings, are key. Joining savings, credit and producer organizations, and certification schemes can alleviate financial constraints, and collective action makes it possible to pool resources and bargain for better prices (Akoyi & Maertens, 2018; Chiputwa et al., 2015; Ruzzante et al., 2021; Verburg et al., 2019). These benefits have so far not fully materialized for Ugandan coffee producer organizations (Latynskiy & Berger, 2016).

2.3. The Stepwise approach

Building on the insight that farmers frequently struggle with one-size-fits-all training packages that can overwhelm them and reduce adoption rates (Jassogne et al., 2017), the Stepwise approach offers a sequenced, context-specific training package tailored to Ugandan coffee farmers (Mukasa et al., 2025). The approach consists of a sequenced package of up to 17 CSA and GAP practices tailored to Robusta and Arabica growing conditions (see Table 1). Beginning with basic, low-cost practices, farmers advance through steps that require progressively greater investment but offer the potential for higher yields (see Figure 1). These combined practices aim to mitigate pests and diseases, enhance soil quality through mulching,

Table 1. Stepwise recommended practices and sequences by region Region Central Eastern.

Region	Central	Eastern
District	Luweero	Sironko and Bulambuli
Coffee Variety	Robusta	Arabica
Implemented by	Partner A	Partner B
Step 1: Basic (coffee farm) management	Weeding (at least three times a year, on specific dates)	Weeding (at least three times a year, on specific dates)
	Desuckering	Desuckering
		Pruning
		Intercropping with banana and legumes
		Cover crops
Step 2: Cultural control of pests and diseases	Pruning	
		Shade trees
		Stumping
		Gap filling
	Cultural pest control	Cultural pest control
	Organic fertilizer	Organic fertilizer
Step 3: Enhancement of soil fertility and water retention	Mulching	
		Trenches
		Inorganic fertilizer
Step 4: Intensification using pesticides and inorganic fertilizer	Inorganic fertilizer	
		Desilting of trenches
	Chemical pest control	Chemical pest control
		Pruning of shade trees
		Irrigation
	Herbicide application	Herbicide application
		Mulching

Source: Training manuals for Robusta (Central region) and Arabica coffee (Eastern region)

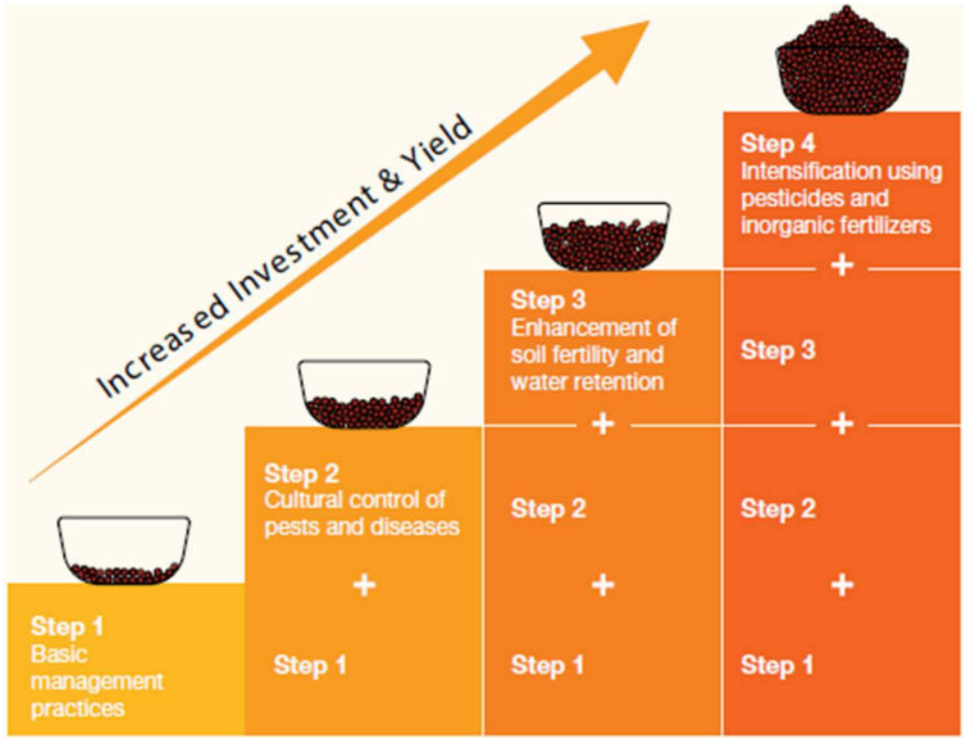

Figure 1. The Stepwise approach. Source: IITA. www.propas.iita.org/en/solutions/stepwise-approach.

increase tree density, and optimize fertilizer and pesticide application. The practices and steps can be best described as sustainable intensification, primarily focused on increasing yields while incorporating aspects of sustainable resource management. Henceforth, we refer to them simply as sustainable practices.

The Stepwise approach was implemented through IITA and two private sector partners (referred to as Partners A and B henceforth). Extension officers, the private sector and farmer trainers facilitate comprehension and encourage spillover effects at demonstration plots. Farmers also received support through savings and loan groups and the private-sector partners (Bunn et al., 2019). This approach aimed to strengthen the connection between research and farmers (see e.g. Douthwaite et al., 2003). It tailors training to farmers' needs and capacity for innovation, and, through partner engagement, seeks to address market failures such as lack of access to credit and inputs. Further information on the Stepwise approach, including implementation differences by the two partners, which we capture through regional dummies is available in Appendix C[1].

3. Methodology

3.1. Adoption index

Borrowing from utility theory, adoption is often captured in a conceptual framework that treats potential adopters as economic agents who maximize utility in the presence of uncertainty (Feder et al., 1985). Following Asfaw et al. (2012), the differential utility from adopting (UA_i) and non-adopting (UN_i) sustainable practices may be represented by A*. A utility-maximising farmer, i, will adopt a practice if the utility gained from adoption is greater than the utility of non-adoption ($A^* = UA_i - UN_i > 0$). Cognizant of the unobservability of these utilities, they can be formulated as a function of observable elements in a latent variable model, where G_i indicates observed adoption:

$$A_i^* = \beta X_i + u_i \, with \, G_i = \begin{cases} 1 \; if \; A_i^* > 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

However, there is still no clear consensus on how adoption is defined—specifically, how many practices a farmer must adopt and on what proportion of their cultivated land to be considered an adopter (Andersson

Table 2. Stepwise index.

Step	Points allocated for each practice	Weighting (by step)	Points deducted (if the combination of recommended practices is not applied)
Step 1	Counting each adopted practice on each	1	0.5
Step 2	coffee plot (calculated as a share across	2	1
Step 3	plots) in each step, according to the region.	3	1.5
Step 4		4	2
Index	Aggregated: total points obtained divided by maximum value per region * 100 = %		

Lamichhane et al. (2022)

& D'Souza, 2014; Glover et al., 2016). When presented with a package of practices, farmers may adopt these to a varying extent, aiming to maximize benefits and manage risk, which may be influenced by the cognitive weight farmers assign to individual adaptation measures within their specific socio-ecological context (Adesina & Zinnah, 1993; Sidibé, 2005). This implies that adoption may not simply be captured as a binary variable when the adoption of a package of recommended practices is concerned, and importantly, may change over time.

Following a growing body of literature using adoption indices rather than a binary variable (Below et al., 2012; Dhakal et al., 2015; Lamichhane et al., 2022; Ofuoku et al., 2008), we developed an index to measure the intensity of adoption of recommended practices and the sequences promoted through the Stepwise approach. The index accounts for regional variation in recommended practices due to differing climatic conditions. An overview of the point system used in constructing the index is provided in Table 2. Following Lamichhane et al. (2022), the index can be expressed as follows:

$$AI_H = \sum_{i=1}^{N} \frac{\left(\frac{a_{iHR}}{\max a_{iHR}}\right) * (w_{iH} - d_{iH})}{N * \max w_{iHR}} \quad (2)$$

where AI_H is the Stepwise adoption index for farm household H; a_{iHR} r denotes the proportion of plots managed by household H in region R on which recommended practice i was adopted. This value is normalized by the maximum possible adoption rate max a_{iHR} and multiplied by a weight w_{iH} adjusted by a practice-specific deduction term d_{iH} . To understand which of the recommended practices in each step were adopted, please see Table D1 in Appendix D. The sum of these adjusted values across all N recommended practices is divided by $N*$ max w_{iHR}, where the latter denotes the maximum weight assigned to any practice in region R.

The reasoning behind the structure of the index—specifically the use of plot-level shares, weighting, deductions, and normalization—is as follows. Using the share of plots allows us to capture partial uptake of practices within a household's production area, reflecting more nuanced adoption behaviour. The weight reflects the increasing investment effort required for each step and is assigned according to the practice's position in the Stepwise sequence for that region (e.g. Step 1 = 1, Step 2 = 2, etc.). The Stepwise approach prescribes not only a set of practices but also a sequence of adoption, with increasing investment efforts designed to boost the effectiveness of the previous individual practices. When the order of practices in a prior step is not followed, the effectiveness of subsequent steps will decline. For instance, weeding (Step 1) reduces competition for moisture and nutrients between weeds and coffee, thereby increasing the effect of fertilizer (which is a Step 3 practice for Arabica and a Step 4 practice for Robusta). To reflect this logic, we reduced half of the weighting in each step for each recommended practice from prior steps that were not implemented. For example, if a household does not practise recommended weeding (Step 1) but uses inorganic fertilizer, we deduct two points for Robusta coffee (for which inorganic fertilizer is a Step 4 practice) and 1.5 points for Arabica (for which inorganic fertilizer is a Step 3 practice). Lastly, normalization allows for comparison across regions.

3.2. Empirical framework

3.2.1. Empirical strategy for estimating adoption intensity

The Stepwise index relies largely on count data i.e. the number of practices adopted across plots. Count data models, such as a Poisson model (e.g. Cameron & Trivedi, 2005; Winkelmann, 2008), can be used even if data is not strictly 'counts' but some positive non-integer numbers that follow a Poisson distribution. To understand the drivers and obstacles of the adoption intensity, we use a Generalised Poisson model. Following Mahama et al. (2020), the standard Poisson model can be expressed as Equation (3):

$$Prob(\pi_i = y_i|x_i) = \frac{\pi^{\lambda_i}\lambda^{y_i}}{y_i!}, \ \ \lambda_i \in K^+, \ \ y_i = 0, 1, 2, \ \ \ldots \tag{3}$$

In the above equation: $\lambda_i = E(y_i|x_i) = V(y_i|x_i)$ and the mean is defined as $y_i = \exp(x_i\beta)$, where x is a vector of socio-economic and farm-level characteristics of farm household i, and β is a vector of unknown parameters to be estimated. The Poisson model assumes equi-dispersion, in that the conditional mean $E(y_i|\mu_i) = \mu_i$ equals the conditional variance $V(y_i|\mu_i) = \mu_i$. In the case of over-dispersion, when the variance is greater than the mean, a negative binomial may produce a bitter fit. Whilst for under-dispersion, when the variance is smaller than the mean, a generalized Poisson regression is recommended (Harris et al., 2012). An initial inspection of the Stepwise index shows that the mean is larger than the variance. Assuming the generalized Poisson function normalizes for the intensity of adoption (the dependent variable, y_i, , i.e. the Stepwise index) the probability mass function can be specified as Equation (4):

$$f(y_{i,}\pi_i, \ \ \delta) = \frac{\pi_i(\pi_i + \delta y_i)^{\lambda_i^{-1}}\lambda^{\pi_i - \delta\gamma_i}}{y_i!}, \ \ y_i = 1, \ 2, \ 3\ldots \tag{4}$$

Where $\pi_i > 0$ and $\max(-1, \ \ \pi_i) < \delta, \ \ 1$, y_i denotes the practices adopted by the farmer in line with the stepwise approach. If $\delta < 0$ this indicates underdispersion and the generalized Poisson model is preferred. A version of the Poisson model is widely applied in modelling the adoption intensity, i.e. the number of agricultural practices or technologies adopted (Ali, 2021; Ehiakpor et al., 2021; Mahama et al., 2020). As a robustness check, we employ a linear Tobit model for censored regressions (Greene, 2019; Wooldridge, 2010), since our Stepwise index measures the share of practices adopted on a plot, is normalized to facilitate regional comparison, and upper-bound censored in that only the practices that fall under the Stepwise approach are observed.[2]

3.2.2. Empirical strategy for estimating impact on yield and revenue

In the absence of an experimental design, estimating the impact of adopting Stepwise practices and sequences on yield and revenue may be biased by both unobservable and observable heterogeneity. There is thus a need to control for a set of observable and unobservable confounding characteristics that may influence treatment and outcomes. We use a three-fold strategy to address potential selection bias from non-random assignment; applying propensity score matching (PSM), Inverse Probability Weights (IPW), and Inverse Probability Weighted Regression Adjustment (IPWRA), following other studies that also adopted a similar empirical approach (Ojo et al., 2021; Tufa et al., 2019; Wossen et al., 2017). First, we employ PSM, as first proposed by Rosenbaum and Rubin (1983), a conditional probability measurement of treatment ('high' adoption), given a set of observable covariates, denoted $p(X)$, where Equation (5):

$$p(X) = Prob\ [Treatment = 1|X \tag{5}$$

The propensity score is estimated using a probit model, controlling for a set of observable variables that may be associated with the decision of above-average adoption of Stepwise-recommended practices, based on the conditional independence assumption, which states Equation (6):

$$Y_0, \ \ Y_1 \perp Treatment|p(X) \tag{6}$$

This infers that the decision to adopt above-average Stepwise recommended practices and sequence (referred to as 'Treatment') remains independent of outcomes Y_0 (pertaining to the comparison group) and Y_1 (for the treatment group) subsequent to controlling for the propensity score, denoted as p(X). Effectively, by controlling for $p(X)$, we can mitigate selection bias. Leveraging the similarity of $p(X)$, we construct a matched sample on observable characteristics. Once matched, PSM operates under the assumption that there are no systematic differences in unobservable characteristics between treated and untreated farmers. We then utilize this matched sample to estimate the impact, i.e. average treatment effect (AT), of above-average adoption of Stepwise practices on coffee yield and revenue, achieved by averaging the differences in the outcomes of interest between 'low' and 'high' adopters.

Yet, the presence of misspecification in the estimation of propensity scores may lead to biased AT estimates. To address this issue, we also utilize the inverse probability weighting (IPW) method. This involves weighting the outcome of interest by the inverse of each individual's probability of being assigned to a specific treatment, given a set of observed covariates (X), represented by the propensity score (denoted in Equation (5)). For individuals in the treatment group, the weight is $\frac{1}{\hat{P}(X)}$, while for those in the comparison group, it is $\frac{1}{1-\hat{p}(X)}$. The effect of adopting protected cultivation can be estimated using the IPW estimator (Equation (7)):

$$\hat{\tau}^{IPW} = \frac{\dfrac{\sum_{i=1}^{N} Y_i Treatment_i}{\hat{P}(x_i)}}{\dfrac{\sum_{i=1}^{N} Y_i Treatment_i}{\hat{P}(x_i)}} - \frac{\dfrac{\sum_{i=1}^{N} Y_i(1-Treatment_i)}{1-P(x_i)}}{\dfrac{\sum_{i=1}^{N} Y_i(1-Treatment_i)}{1-P(x_i)}}$$

In the IPW method, we employ a probit model to estimate the propensity score and then re-weight the outcome of interest accordingly. However, the IPW estimator is highly sensitive to the accuracy of the propensity score. To address this concern, we further apply IPWRA, which combines the strengths of Ordinary Least Squares (OLS) and IPW methods. Notably, IPWRA provides an unbiased estimate of treatment effect even when the OLS regression model is correctly specified but the propensity score model is not. IPWRA allows for potential misspecifications in either the OLS or IPW models, which aim to measure two potential outcomes. While consistency in estimates from IPWRA, in the presence of misspecification, may be attainable for either the treatment or outcome model, it may not be achieved for both simultaneously. Consequently, the inverse probability weighted adjusted regression estimator offers a 'double advantage' with the property of double robustness, ensuring dependable and consistent estimates. IPWRA can be implemented by conducting a weighted least squares regression model using the inverse probability as the sampling weight.

3.3. Sampling and data collection

We used a mixed-methods research design. We began by collecting qualitative data to understand training practices, adoption enablers and barriers, and the mechanisms through which adoption leads to outcomes. Insights from this phase informed the questionnaire design and guided our quantitative sampling strategy. We also used the qualitative data to construct the adoption index and interpret the quantitative outcomes.

The Stepwise approach reached nearly 2,000 farmers: approximately 1,500 in Luweero and 260 in Sironko, trained through 10 and 6 demo plots, respectively. These plots served both as official training sites and informal diffusion hubs. The programme promoted peer learning and spillovers through proximity and social networks.

We first conducted 17 key informant interviews (KIIs), 15 focus group discussions (FGDs), and 10 in-depth interviews (IDIs) with project and private sector staff, spillover farmers, demo plot owners, and non-treated farmers (see Table 3). We selected participants through purposive sampling.

For the quantitative survey, we randomly selected treated farmers in Luweero from official training lists. In Sironko, where no such lists were available, demo plot owners helped identify trained farmers. Spillover farmers were selected using a snowball approach in villages within 3 km of demo plots. Comparison farmers were drawn from villages 10–15 km away. In Sironko, we sampled comparison farmers from

Table 3. Qualitative data collection.

	Interviewees	Number
KII	Implementation team, private sector partners, district agricultural officers	17
FGD	Farmers trained at demo plots; farmers trained after Stepwise project ended	8 female groups and 7 male groups, with 2–8 participants per group
IDI	Spillover farmers, demo plot owners, a casual labourer and farmers in neighbouring villages	10
Total Participants		92

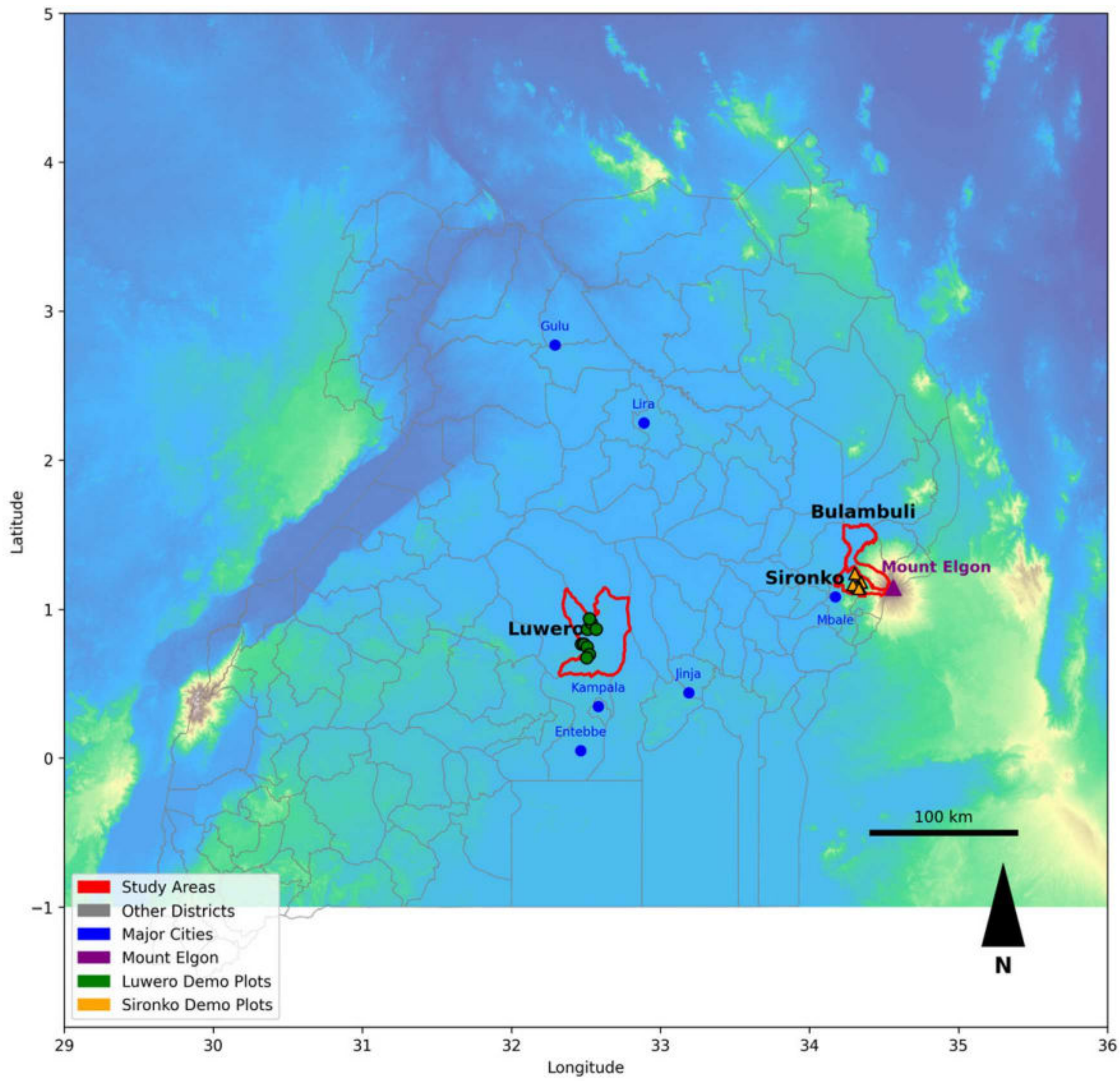

Figure 2. Demo plots and study districts.

neighbouring Bulambuli to ensure agroecological similarity (see Figure 2). All respondents underwent screening through targeted questions to confirm their correct group classification. In September 2022, we surveyed 1,026 Arabica and Robusta coffee households across 139 villages (Table 4). After excluding 111

Table 4. Sample distribution.

				Sample	
Arm	Population	District	Sampling selection	Villages	N
Treatment	Coffee farmers trained in the Stepwise approach	Luweero	Randomly chosen from list.	25	248
		Sironko	No list available; demo plot owners asked to identify trained farmers. Screening questions for all.	34	161
			Subtotal	59	409
Spillover	Coffee farmers in the vicinity (+/−3 km) who did not participate in the official Stepwise training but visited the demo plot and/or were trained (informally) by treated farmers	Luweero	Snowball technique – demo plot owners and trained farmers asked plus screening questions	18	132
		Sironko		29	80
			Subtotal	47	212
Comparison	Coffee farmers not trained and not subject to spillover in adjacent parishes, located at a distance of at least 10–15 kilometres from demo plots	Luweero	Selected parishes that meet the criteria plus screening questions	19	249
		Bulambuli		14	156
			Subtotal	33	405
			Total	139	1026

households missing key data (e.g. coffee plots), the final sample was 915, still warranting over 80% power (see Appendix A for details).

4. Results & discussion

4.1. Summary statistics and variable description

Summary statistics and descriptions of explanatory variables are presented in Table 5. Our dependent variable selection was derived from the literature review and captures individual, household, farm-level and institutional characteristics.[3] For instance, in their meta-review Ruzzante et al. (2021) identified factors influencing agriculture technology adoption, such as education, household size, land size, access to credit, land tenure, access to extension services, and organization membership, whilst other studies show that proactiveness (Kangogo et al., 2021), and plot-level averages for soil erosion, fertility, and pest incidence matter for adoption (e.g. Teklewold et al., 2013).

Farmers in our sample are on average 51 years old, primary-level educated, live in a five-person household, operate 3.5 acres of farmland of which 2.2 acres are dedicated to growing coffee, and have on average 22 years of experience growing coffee. Treated and spillover farmers exhibit greater similarities compared to the comparison group. Particularly more treated and spillover farmers relative to comparison farmers, are members of a cooperative or coffee producer organization membership, as such membership is often a condition for participating in projects. Treated and spillover farmers also more often experienced a visit by an extension officer. Further, compared with both comparison and spillover farmers, treated

Table 5. Mean difference in explanatory variables by treatment status.

Variable and Description	#	Comparison (N-405)	Treatment (N-403)	Spillover (N-212)
Eastern Region (%)	Mean (SD)	38.5 (0.49)	39.4 (0.49)	37.7 (0.49)
Household Location	*P*-value	0.81		0.69
Age	Mean (SD)	49.6 (15.3)	52.5 (14.5)	50.1 (16.2)
Age of farmer in years	*P*-value	0.01**		0.06*
Female-headed household (%)	Mean (SD)	22.5 (0.42)	26.4 (0.44)	24.1 (0.43)
1 = female, 0 otherwise	*P*-value	0.19		0.53
Education	Mean (SD)	2.28 (0.67)	2.31 (0.7)	2.33 (0.67)
1 = none; 2 = primary; (…), 4 = higher	*P*-value	0.48		0.83
Household size	Mean (SD)	5.2 (2.49)	5.5 (2.61)	5.4 (2.62)
Number of household members	*P*-value	0.63		0.09*
Household Dependency Ratio (%)	Mean (SD)	47.3 (0.26)	49.0 (0.25)	47.0 (0.25)
Members aged <18 years or >65 years	*P*-value	0.26		0.42
Hired labour (%)	Mean (SD)	15.1 (0.36)	12.7 (0.33)	13.2 (0.34)
1 = in last 12 months = 1, 0 otherwise	*P*-value	0.33		0.862
Assets Index [b]	Mean (SD)	0.32 (0.20)	0.43 (0.25)	0.34 (0.21)
PCA; 0 = no assets – 1 = all assets	SD	0.00***		0.00***
Coffee land	Mean (SD)	2 (1.52)	2.2 (1.49)	1.9 (1.41)
In acres	*P*-value	0.26		0.02**
Coffee plots	Mean (SD)	1.7 (0.89)	1.8 (0.93)	1.6 (0.86)
Number of plots for coffee	*P*-value	0.02**		0.32
Experience in coffee farming	Mean (SD)	22.1 (14.25)	23.1 (13.92)	19.6 (14.83)
In years	*P*-value	0.29		0.00**
Land Security (%)	Mean (SD)	60.1 (0.48)	57.2 (0.495)	56.1 (0.50)
1 = confident land is not taken away in next 3 years, 0 = otherwise	*P*-value	0.27		0.80
Av. soil erosion across plots	Mean (SD)	1.71 (0.57)	1.78 (0.53)	1.74 (0.5)
1 = no erosion to 3 = severe erosion	*P*-value	0.08*		0.37
Av. soil fertility across plots	Mean (SD)	1.87 (0.58)	1.86 (0.53)	1.88 (0.48)
1 = not productive; 5 = very fertile	*P*-value	0.90		0.72
Av. pest incidence across plots	Mean (SD)	1.78 (0.41)	1.76 (0.47)	1.75 (0.47)
0 = none; 1 = low; 2 = high	*P*-value	0.49		0.40
Cooperative/ Producer organization (%)	Mean (SD)	6.2 (0.24)	53.1 (0.50)	28.8 (0.45)
1 = if member, 0 = otherwise	*P*-value	0.00***		0.00***
Proactiveness [b]	Mean (SD)	3.94 (0.7)	4.18 (0.67)	3.93 (0.74)
1 = do not agree – 5 = completely agree	*P*-value	0.00***		0.00***
Extension Service (%)	Mean (SD)	8.6 (0.24)	68.2 (0.47)	49.3 (0.50)
1 = in past 24 months, 0 = otherwise	*P*-value	0.00***		0.00***
Credit (%)	Mean (SD)	18.3 (0.39)	18.8 (0.39)	17.5 (0.38)
1 = in last 24 months = 1, 0 otherwise	*P*-value	0.84		0.68

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. SD = standard deviation. [A] winsorized at the 1st and 99th percentile. [B] please see Appendix B for further variable description.

Table 6. Mean difference in outcome variables by treatment status.

Variable and Description	#	Comparison (N-405)	Treatment (N-403)	Spillover (N-212)
Stepwise Score	Mean (SD)	43.3 (0.21)	48.9 (0.21)	45.1 (0.20)
Normalised: 0–100 in %	*P*-value	0.00***	0.04**	
High Adoption (50%) in %	Mean (SD)	44.2 (0.50)	54.1 (0.50)	44.8 (0.50)
score > = 60%, 0 = otherwise	*P*-value	0.03**	0.01***	
Yield in kg	Mean (SD)	495.7 (454.8)	420.8 (390.1)	358.2 (342.1)
Coffee yield per acre [ab]	*P*-value	0.02**	0.06*	
Coffee Revenue	Mean	2.12	2.05	1.61
Income derived from coffee sales in million UGX[a]	SD	(2.29)	(2.03)	(1.90)
	P-value	0.63	0.01**	

Results of group-mean T-test comparing treatment to comparison, and treatment to spillover; *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. SD = standard deviation. a winsorised at the 1st and 99th percentile. b please see Appendix B for further variable description.

farmers were slightly older, had slightly more land and plots dedicated to coffee growing, had a higher asset index[4] and higher self-reported proactiveness (Kangogo et al., 2021). We control for these differences in our econometric analysis.

As presented in Table 6, three years after the intervention, treated farmers adopted 48.9% of the stepwise approach (as measured by the index). This is only slightly higher than adoption by the spillover (+3.9%) and the comparison groups (+5.7%), although treated farmers are more likely to have a high adoption score (a score equal to or above 60%). Whilst other studies have also shown limited adoption rates in the coffee sector (Abegunde et al., 2019; Raile et al., 2021; Sebatta et al., 2019), we observed similar adoption rates across groups, which could be influenced by several factors. Firstly, the data collection occurred three years post the Stepwise training intervention, suggesting that the effects of the training may have waned over time. Additionally, various initiatives targeting climate-smart practices have been implemented in Uganda, which may have influenced farmers' adoption behaviours and could contribute to the comparable adoption levels observed across the different groups.[5] Although, qualitative insights revealed a positive impact of the Stepwise training on enhancing farmers' knowledge of individual practices, we also observed farmers' challenges related to understanding the interactions between practices, partly due to suboptimal delivery of the Stepwise training but also because of challenges related to individual practices, such as the lack of access to inputs and credits and incentives to invest capital and labour into coffee, and the cost-effectiveness of practices. While some practices and their interactions are knowledge-intensive, the most yield-increasing practices (e.g. use of mineral fertilizer, etc.) are unaffordable to most farmers, even with support from private-sector partners.

As shown in Figure 3.a, adoption of the Stepwise approach declines from step 1 to step 4, reflecting the greater financial investments and labour requirements needed for the more advanced and resource-intensive practices in the higher steps. Households with limited labour or financial resources face greater barriers to adopting advanced practices, despite their higher yield potential. Table D2 in Appendix D details challenges and benefits at each step, supported by relevant literature. Figure 3.b reveals substantial regional differences in adoption intensity, with higher levels in the Arabica-growing Eastern region served by partner B compared to the Robusta-growing Central region served by partner A. These differences may reflect distinct agroecological conditions and coffee varieties, as well as variations in partner implementation approaches. As such, we include regional dummy interactions in our econometric specifications to capture these variations, whilst Appendix C describes partner-specific strategies in detail. We further note that treated farmers, compared to spillover but not compared to comparison farmers, reported statistically significantly higher coffee yield and revenue[6], which we further investigate in our impact analysis.

4.2. Determinants of adoption

To address our first research question – what are the key determinants of adoption of the Stepwise practices? – Table 7 presents the results from several econometric models assessing adoption intensity, including Generalised Poisson, Poisson, Tobit, and Probit (for above-average adoption). Model diagnostic tests indicate that the Generalised Poisson model (column 1) provides the best fit and will therefore serve as the

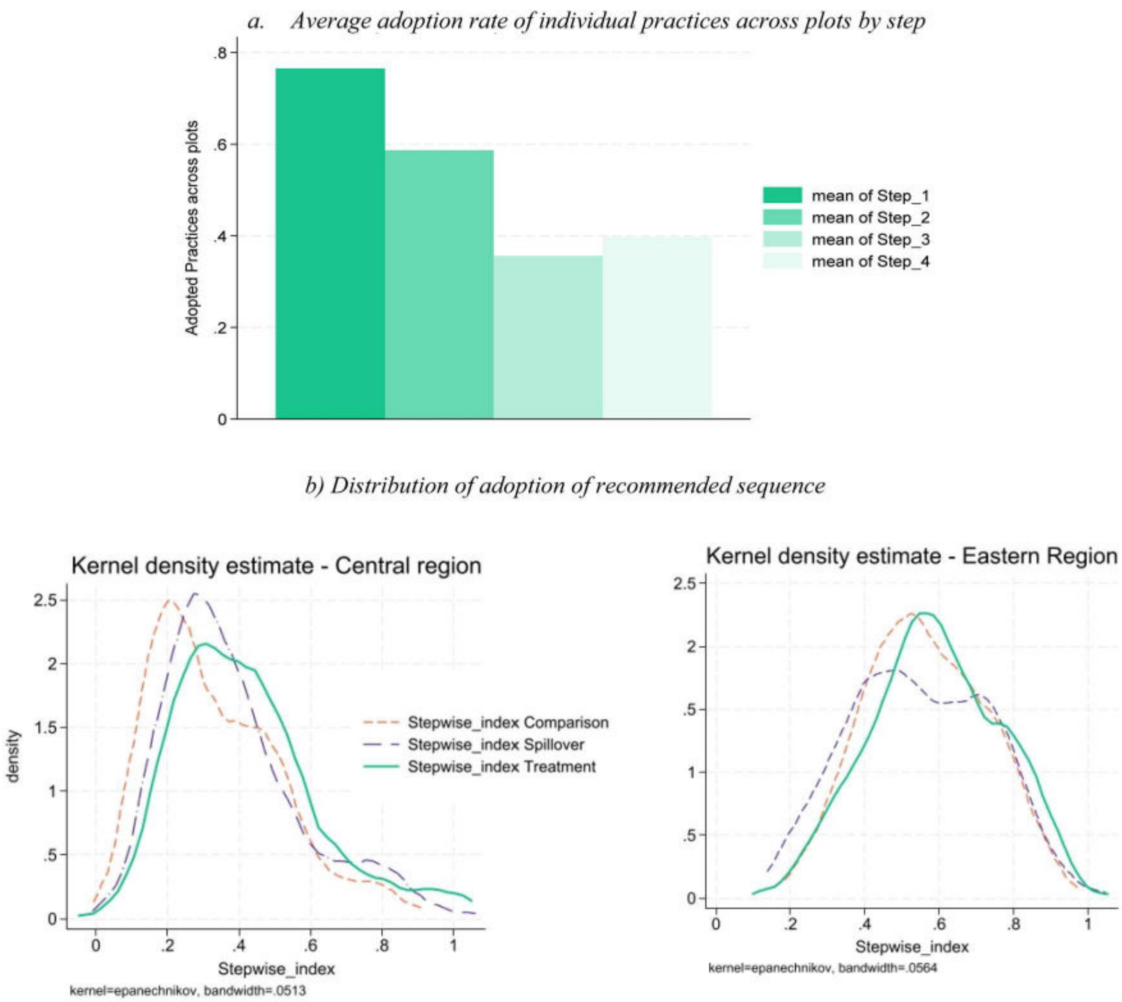

Figure 3. Adoption of practices (N-915). (a) shows the share of adopted practices across plots by step (not weighted and interacted to show the distribution in each step), whilst (b) shows the distribution of the weighted and interacted Stepwise index by treatment status and region.

primary basis for interpretation.[7] Whilst the parametric estimations across the specifications are relatively uniform, indicating the robustness of our results.

The model incorporates 20 variables, among which approximately 16 exhibit statistical significance.[8] Our analysis reveals that factors including years of coffee farming, extension visits, household and farm assets quantified through an asset index, hired labour (noteworthy in the GPR and Tobit model exclusively), land tenure security, average pest incidence, soil erosion across plots, and self-assessed proactiveness demonstrate a positive and statistically significant impact. Age, dependency ratio, and the number of coffee plots exhibit statistically significant negative effects on adoption intensity. Conversely, variables such as the sex of the household head, education, coffee land, average soil fertility, membership in a cooperative or coffee grower group (not shown) and credit, and lack statistically significant associations with heightened adoption intensity of the Stepwise-recommended practices and sequences.

After controlling for covariates, we find very similar adoption intensity amongst treated, spillover and comparison coffee farmers, averaging around 46%. However, interactions between treatment status and region – the latter also capturing differences in coffee type and training approach across the two private sector partners – reveal substantial variation.

Adoption intensity of Stepwise-recommended practices and sequences is significantly higher among treated, spillover, and comparison farmers in the Eastern (Arabica-growing) region compared to spillover farmers in the Central region. Summary statistics indicated that treated farmers across both regions had, on average, a slightly higher adoption intensity. Yet, once covariates are accounted for, comparison

Table 7. Determinants of adoption intensity.

	(1)	(2)	(3)	(4)
	Main model	Sensitivity Analysis		
Variable		Adoption Intensity (Stepwise Index)		Above 50% Adoption (0/1)
Estimation Technique	Generalised Poisson	Poisson	Tobit	Probit (dy/dx)
Treatment#Central	0.008	0.029	0.008	−0.060
	−0.022	−0.055	−0.021	−0.052
Treatment#Eastern	0.201***	0.423***	0.201***	0.379***
	−0.025	−0.057	−0.025	−0.573
Spillover#Central (control)	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000
Spillover#Eastern	0.190***	0.417***	0.191***	0.3031***
	−0.029	−0.064	−0.028	−0.064
Comparison#Central	−0.030	−0.096	−0.030	−0.040
	−0.023	−0.060	−0.021	−0.059
Comparison#Eastern	0.205***	0.443***	0.205***	0.354***
	−0.025	−0.059	−0.026	−0.059
Age	−0.002***	−0.004***	−0.002***	−0.004**
	−0.001	−0.001	0.000	−0.013
HH Size	0.005**	0.012***	0.005**	0.015**
	−0.002	−0.004	−0.002	−0.060
Dependency Ratio	−0.077***	−0.187***	−0.076***	−0.150**
	−0.024	−0.055	−0.025	−0.065
Hired Labour	0.0332**	0.049	0.0330**	0.056
	−0.016	−0.032	−0.017	−0.044
Asset Index	0.158***	0.351***	0.161***	0.162***
	−0.036	−0.077	−0.033	−0.082
Years in Coffee Farming	0.001**	0.003**	0.001**	0.002
	0.000	−0.001	0.000	−0.001
Number of Coffee Plots	−0.015**	−0.033**	−0.015**	−0.013*
	−0.008	−0.015	−0.008	−0.011
Land Security	0.029**	0.068**	0.028**	0.085**
	−0.012	−0.028	−0.012	−0.030
Av. Soil fertility	−0.015	−0.039	−0.015	−0.031
	−0.011	−0.025	−0.010	−0.027
Av. Soil Erosion	0.045***	0.098***	0.045***	0.154**
	−0.012	−0.027	−0.011	−0.029
Av. Pest Incidence	0.031**	0.071**	0.032**	0.078**
	−0.013	−0.029	−0.013	−0.033
Extension visit (0/1)	0.037***	0.076**	0.037***	0.084**
	−0.014	−0.030	−0.014	−0.035
Credit (0/1)	0.023	0.054*	0.022	0.027
	−0.015	−0.032	−0.015	−0.037
Proactiveness	0.044***	0.098***	0.044***	0.107***
	−0.008	−0.019	−0.008	−0.021
Constant	0.087	−1.591***	0.0277***	−3.754***
	−0.059	−0.132	−0.001	−0.547
Observations	915	915	915	915
Other variables#	Yes	Yes	Yes	Yes
Wald chi2(23)	819.310	623.590	417.500	213.670
Prob > chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.230	0.233	0.268	0.205
Log likelihood	−346.703	−638.830	−336.169	−494.559
AIC	645.407	1325.661	618.338	1037.119
BIC	529.780	1441.289	488.257	1152.747

Robust standard errors in parentheses clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects (dy/dx) are displayed for the probit model. #Other variables that were not statistically significant include those capturing if the farm household is female-headed, belongs to a Coop/Producer organization, if the respondent has secondary education or higher, the farms' average soil fertility and the land in acres dedicated to coffee plantation.

farmers in the Eastern region display the highest adoption intensity, though the difference to treated farmers in the Eastern region is only 0.04 percentage points.[9] In contrast, neither treated nor comparison farmers in the Central region exhibit a statistically significant association with higher adoption.

These regional differences may arise from the distinct characteristics of the two coffee varieties. Robusta, prevalent in the Central region, is known for its resilience, higher yield, and cost-effectiveness, requiring fewer inputs and less labour compared to Arabica, which is predominantly grown on steep hills. Consequently, the benefits of recommended practices may be more pronounced for Arabica farmers overall, not solely for those trained in Stepwise techniques. Additionally, Arabica farmers in the Eastern region, who rely more heavily on coffee farming as a livelihood strategy, dedicate a statistically significantly higher proportion of land (77%) to coffee compared to Robusta farmers (66%). Geographical factors, such as the Eastern region's more remote and isolated villages, may also contribute to these adoption disparities.-Qualitative interviews further provide a nuanced understanding of the reasons behind the low adoption of Stepwise practices and sequences among treated farmers. First, farmers displayed solid knowledge of individual Stepwise practices and their yield effects. In FGDs, they particularly stressed that pruning is implemented now more often, as they could observe higher yields after pruning on the demo plot. Other new practices were applying fertilizer not too close to the roots. However, farmers demonstrated a limited understanding of the sequential nature of the Stepwise approach and how the recommended practices interact with one another. This limited understanding can be attributed, in part, to the suboptimal delivery of Stepwise training, as detailed in Appendix C. Second, even when farmers received adequate training and were convinced of practices, they encountered difficulties with the labour and financial requirements associated with certain practices. A quote from an FGD illustrates this:

> Some [producer organisation] members have successfully implemented what they learned, but others have struggled and failed to reap benefits because the most productive stage is also the most challenging … You must mulch, apply fertiliser, and prune. Some managed only to weed, neglecting other crucial tasks.

A contact farmer reported scepticism regarding the feasibility of implementing Stepwise, as illustrated by the following statement: '*One farmer told me that he has no time for romance with the garden!*' This might also be related to general disincentives to invest in more intensified coffee cultivation, due to low coffee farmgate prices (Clay et al., 2018).

Whilst gender has no significant effect in our regression analysis, interviews and FGDs further showed women farmers were equally knowledgeable about the practices and identified similar barriers to men, although access to finance and labour was a more pronounced barrier to them. In addition, coffee households also face collective action problems, as women may not invest time to increase household coffee income, because they have little say in deciding how coffee income is spent (Lecoutere & Jassogne, 2019). Both partners included women in Stepwise training and used household-centric approaches. The training, which emphasized joint visioning by couples and included strategies for investing income from coffee, was valued by interviewed women, although they mentioned that some men would still want to have the final say. Couples seminars were found in previous studies to have increased women's decision-making power in Ugandan coffee farming households (Lecoutere & Wuyts, 2021). Some interviewed women also reported implementing practices that increased banana yields in coffee plots, where women would control harvesting and sales.

A farmer's age appears to impact adoption rates differently for various practices. Turinawe et al. (2015) find in Southwestern Uganda that age significantly determines agroforestry, but not trenching practices. Our data suggests younger farmers are marginally more inclined to adopt, possibly due to greater openness to new approaches.

In terms of education, Ruzzante et al. (2021), in their meta-analysis on the adoption of agricultural technologies in developing countries, based on 367 regression models, find that education matters for adoption; whilst extension services may substitute for education in the adoption of improved varieties for resource management, extension services and education act as complements. In our model, extension visits (by company/NGO/public and farmer extensionists) are positively associated with adoption intensity, but education is not, perhaps as there is too little educational variation in the data.

Hired labour, household size, and dependency ratio all demonstrate significance in our analysis, with the latter exhibiting a negative coefficient. Household size, often considered a proxy for labour availability, particularly with members of working age, or those who hired labour, are better positioned to implement labour-intensive practices, such as weeding. Furthermore, adoption intensity may have been higher during the extended Covid-19 lockdown in Uganda, as more family labour was available, potentially replacing hired labour (Pattenden et al., 2021).

Although land size demonstrates no influence on adoption, the presence of multiple coffee plots exerts a negative impact, possibly attributable to heightened labour demands associated with managing numerous plots, especially concerning their number and distance from the homestead (Turinawe et al., 2015). Larger farms, according to interviews, produce sufficient volume, enabling them to negotiate with traders and achieve higher prices, thus seeing fewer benefits in implementing Stepwise compared to smaller farms. Davis et al. (2012) similarly found that farmers with medium-sized farms benefited most from farmer field schools in Uganda. Additionally, our finding that land security positively correlates with adoption intensity aligns with other studies in Uganda (Ebanyat et al., 2010). Historically, farmers in Central Uganda have planted coffee to increase tenure security (Place & Otsuka, 2002), as landowners may claim back the land at any time, leading to uncertainty and loss (Doss et al., 2014). Additionally, increased occurrence of soil erosion and pest infestation, rather than soil fertility, positively influences adoption intensity. This indicates that farmers who have encountered adverse events in the past are more inclined to adopt, hoping to prevent such incidents in the future.

While membership in cooperatives or producer organizations typically influences adoption positively (e.g. Candemir et al., 2021), our analysis does not find a significant effect on adoption intensity. This underscores broader concerns regarding the inadequate support provided to coffee cooperatives in Uganda, perpetuating existing socioeconomic disparities (Wedig & Wiegratz, 2018). For example, poorer farmers or those with less social capital may face barriers to participating in collective activities such as bulk sales or coffee storage, limiting their ability to benefit from potentially higher prices later on (Wedig & Wiegratz, 2018). Moreover, in Uganda, farmer organizations are often used to govern farmers, overlooking social contexts such as gender aspects and relations between farmers and experts, thereby hindering adoption efforts (Eriksen et al., 2019).

In their meta-review, Ruzzante et al. (2021) emphasize the significance of credit access for credit-constrained farmers. However, our study finds that while obtaining credit in the past 24 months shows a positive sign, it lacks statistical significance (apart from a 10% significance level in the Poisson model). Further exploration reveals a positive impact of credit access in the Eastern region but not in the Central region. The timing of credit can also be crucial, as farmers tend to make adoption decisions on a seasonal basis rather than as one-time commitments. With only 18% of our sample accessing credit for coffee cultivation in the past 2 years, it suggests that farmers in need are likely the most credit-constrained.[10] Liquidity issues emerged as a recurring theme during focus group discussions, exacerbated by rising input prices in the prior season, as illustrated by a farmer in the Eastern region: '*… last season we didn't have fertiliser and just used cow dung … We even failed to buy pesticides to spray coffee because there was no money*.' Additionally, a higher number of household and farm assets, serving as a proxy for income, shows a positive and significant association with adoption intensity, with credit and assets exhibiting a positive correlation. Lastly, proactiveness emerges as a contributing factor to adoption intensity and high adoption rates, aligning with research by Kangogo et al. (2021) suggesting a positive correlation between proactiveness and the adoption of finance-intensive practices, but a negative correlation with labour-intensive ones.[11]

Our results on adoption intensity concur with other findings, such as Lecoutere and Jassogne (2019) who reported low levels of adoption for the intensification of coffee farming in Uganda. Davis et al. (2012) show that training outcomes depend on farmers' ability to apply knowledge, shaped by access to land, labour, and assets, a pattern reflected in our findings. Despite the conceptual acceptance of CSA by farmers, agricultural organizations, and policymakers, its implementation faces challenges, with farmers often seeking simpler protocols (de Pinto et al., 2020). Adoption of CSA remains generally low in developing countries (Kangogo et al., 2021; Lipper et al., 2014, 2017). Trade-offs and cost functions of individual practices, but also understanding drivers and barriers to adoption and their impacts, and the political economy of agrarian change, have not received enough attention (Eriksen et al., 2019, 2021; Lipper et al., 2017; Shikuku et al., 2015; Taylor, 2018) and warrant future research.

Table 8. The effect of above-average (50 pct) adoption on yield and revenue.

	Coffee Yield (kg/acre)				Coffee Revenue (in 1000 UGX)			
Method	Coefficient		SE	#Magnitude	Coefficient		SE	#Magnitude
PSM	97.980	***	32.374	22.4%	701.013	***	158.519	35.3%
IPW	95.163	***	25.643	21.8%	630.537	***	128.140	31.7%
IPWRA	98.959	***	32.770	22.7%	627.158	***	148.104	31.6%
N	915				915			

Note: All previous dependent variables are included. *$p < 0.01$; **$p < 0.01$; ***$p < 0.001$. PSM, and PWRA indicate the propensity score matching, and inverse probability weighting regression adjustment methods, respectively. # % of the sample mean.

4.3. Impact of adoption on coffee yield and revenue

As a next step, we investigate our second research question: What is the impact of adopting the Stepwise practices on yield and revenue? In our sample, receiving the treatment—i.e. Stepwise training—does not necessarily imply adoption of Stepwise practices or their sequence. However, adoption of these practices is observed across all three groups. Therefore, we investigate the impact on coffee yield and revenue amongst those farmers who adopted at least half of the recommended practices and sequence as outlined in the Stepwise index. The probit model estimating the drivers of adopting above average Stepwise adopting can be found in Table 7, column 4. To investigate the impact, we employ PSM, IPW and IPWR, for which the reliability and validity of results rely on the matching quality. Various tests confirm the robustness of our propensity score matching results (Appendix E). Table 8 displays the treatment effect estimates. Our discussion of the results will be largely focused on the IPWRA given its doubly robust nature. Overall, the reported estimates are fairly uniform and indicate robustness of the results. Whilst adoption at low levels does not have a significant effect, we find that above-average (50th percentile or higher) adoption leads to an increased yield of 98.9 kg per acre, which is the equivalent of 22.7% of the sample mean. Similarly, the same adoption intensity leads to a UGX 627,158,000 increase in revenue, which equals 31.6% of the sample mean.

These results highlight the impact potential of applying the Stepwise extension approach but need to be understood as within the bounds of adoption constraints described above. Despite the positive yield impacts for above-average adopters, we may observe downward-biased results. Reasons for this could be that some sustainability practices have lagged yield benefits, for example, stumping. Early adopters might have stumped more and replanted with improved varieties, something our study could not capture. The impact of other practices may not have been observed as they would only prove beneficial during drought spells (see e.g. Scognamillo & Sitko, 2021).

Our findings on the effects on yield and revenue align with evidence highlighting the importance of adoption uptake. In Uganda's coffee sector, Akoyi and Maertens (2018) find that outcomes are driven by adoption itself rather than programme participation, consistent with our focus on farmers who adopted at least half of the Stepwise-recommended practices. Arslan et al. (2022) further show that yield improvements depend on the intensity and combination of practices. Similar adoption-linked productivity and income gains have been reported outside East Africa, such as in Bangladesh (Günther et al., 2025; Islam & Farjana, 2024).

5. Limitations

This study's main limitations stem from the absence of baseline and longitudinal data. This ex-post evaluation design limits the ability to capture dynamics critical for understanding sustainability and impact trajectories (Angrist & Pischke, 2009). As such, the study was unable to address potential double selection bias (Wooldridge, 2010) – covering both the decision to adopt and to maintain practices – due to the heterogeneous nature of practices and lack of longitudinal data to track initiation and discontinuation over time. Given the ex-post design of this study, we were also unable to address simultaneous measurement bias, which occurs when the adoption decisions and outcome measures (such as yield) may be endogenously determined, i.e. arising from unobserved factors jointly influencing both adoption and outcomes (Wooldridge, 2010). Future studies should incorporate baseline and longitudinal data to track adoption trajectories and outcomes over time, enabling better control for simultaneity and selection biases and facilitating a better assessment of the sustainability of Stepwise's impacts. Conducted three years post-intervention, the study further coincided with similar projects (see Gabiri et al., 2022), potentially influencing adoption rates among spillover and comparison farmers. Despite efforts to collect comprehensive survey data, nuances of the Stepwise intervention, such as tailored training and costs, were not fully captured. Whilst we tried to capture variations in training and practice adjustments based on specific contexts and partner needs, the full extent of these may not always be accounted for. Furthermore, this study could not always capture the costs and benefits of individual practices and their combinations. For instance, while mulching reduced herbicide costs, it increased expenses for pesticides, fertilizers, and labour, rendering it cost-ineffective (Shikuku et al., 2015). Future research could explore these synergies and trade-offs, along with coffee's potential contribution to livelihoods and wages.

6. Concluding remarks

In this study, we assessed the longer term adoption intensity and effects of a novel sequenced extension approach — *Stepwise* — implemented in Uganda's coffee sector, which integrates climate-smart agriculture and good agricultural practices across four sequential steps. Our study contributes methodologically by developing an index to measure the intensity of adoption of recommended practices (denoted as sustainable practices) and their sequence within the Stepwise approach. Unlike most previous studies, which typically measure adoption as a binary decision, this index allows for a more nuanced understanding of adoption patterns.

Our study showed that adoption wasrather low – around 46%- and relatively uniform amongst treated, spillover and comparison farmers. It is essential to note that data were collected in 2022, threeto four years after the Stepwise intervention, during which some adopters may have discontinued practices (although Mukasa et al. 2025 show that most farmers had also not adopted all recommended practices in the 2018/19 season). Other climate-smart agriculture initiatives during this period (see Gabiri et al., 2022) likely also contributed to overlapping training exposure.

Regionally, our analysis also uncovers variations in adoption intensity, with the Eastern (Arabica growing) region exhibiting the highest levels. Robusta coffee requires fewer inputs compared to Arabica. Consequently, the benefits of recommended practices may be more evident for Arabica farmers overall.

While in theory a promising alternative to the common training model that teaches sustainable practices as one package, our study indicated the Stepwise approach faced implementation challenges in practice. Although the Stepwise approach highlights the potential synergy between private sector organizations and research and development institutions, it also exposes trade-offs and conflicting objectives among these stakeholders.

However, our impact analysis revealed that implementing more than half of the Stepwise recommended practices and sequence leads to substantial yield (23%) and revenue gains (32%). This underscores the substantial potential of the Stepwise approach in enhancing productivity and income generation but only when sufficiently adopted.

To attain higher adoption levels, our findings underscore the imperative for structural changes in the coffee value chains. Policy measures such as encouraging farmer investment in coffee through price incentives or premiums for specific practices can play a pivotal role in fostering economic and social sustainability. Strengthening producer organizations and cooperatives along the value chain is vital for attaining higher prices and mitigating power dynamics in the coffee sector. Additionally, ensuring the continued inclusion of women farmers in training and enhancing their bargaining power in decision-making around coffee incomes can increase incentives for women's involvement in coffee production and sales and drive higher adoption rates. Furthermore, higher coffee prices can incentivise farm investments, allow for living incomes and thereby indirectly benefit poorer and landless women and young people, who often rely on wage work for tasks like weeding and harvesting. Training young people in shade tree cultivation and coffee pruning might not only promote the uptake of yield-increasing practices but also create wage employment and incentivise young people to pursue livelihoods in coffee production.

In conclusion, while the adoption of sustainable agricultural practices remains generally low, our study contributes to advancing our understanding of the factors influencing adoption intensity and the potential impact of innovative extension approaches such as Stepwise. Given the critical importance of a sequential implementation of sustainable practices to boost productivity and thereby revenue from coffee, our research highlights the role of targeted and holistic training models such as Stepwise. As we look to the future, research and development interventions should prioritize accounting for the differentiated risks that farmers face and additional investment efforts for combined practices, while addressing the trade-offs and cost functions of individual practices and the socio-economic barriers to adoption such as access to credit, especially for marginalized groups like women and small-scale farmers. It is imperative to also explore institutional innovations aimed at incentivising investments in farms and processing, and increasing coffee farm-gate prices. Such studies might best be done in a participatory approach with the different actors in the coffee value chain.

Notes

1. For more information on the development of the Stepwise approach see Mukasa et al. (2025).
2. We also estimated a censored Poisson regression but did not find the model specification to be a good fit.
3. We confirm the absence of multicollinearity by employing the variance inflation factor (VIF), which if below 10 reveals the non-existence of multicollinearity (Gujarati, 2009), and the absence of heteroscedasticity using the Breusch–Pagan test (Gedefa, 2014; Wooldridge, 2002). Results can be obtained upon request.
4. Asset ownership may have been influenced by Stepwise as it includes pruning and bow saws, secateurs, knapsack sprayers, protective equipment and tarpaulins for drying coffee. These were handed out to contact/model farmers by IITA through Partner A and B to enable them to better train other farmers and adopt practices.
5. For instance, the Government of Uganda has introduced a range of CSA within the agriculture sector, such as the National CSA Framework Programme (2019–2030) with many donor organizations such as USAID, the World Bank, UNDP, etc. implementing CSA-related projects. For an overview of different initiatives see Gabiri et al. (2022).
6. We find no significant difference of yield and revenue by region, although the former appears higher in the Central region.
7. We performed different model diagnostic tests to determine the most suitable model, such as a goodness of fit test using the log-likelihood value to compare the count data models (Mahama et al., 2020), indicating that the generalized Poisson is the best fit for estimating adoption intensity. A test of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) further justifies the choice of the generalized Poisson model over the standard one, with the former reporting lower values (Fabozzi et al., 2014), whilst the Tobit model also appears a very good fit It should be kept in mind that when the data is not strictly count data, but positive non-integers, as is the case here, the log-likelihood, AIC and BIC may not behave as expected. As a further robustness check, we also employed an Ordinary Least Squares model (Angrist & Pischke, 2009), which yielded very similar results.
8. The full regression table including variables that do not show statistical significance, can be obtained upon request.
9. Whilst this was not included in this paper for space reasons, we also applied propensity-score matching and found that the treatment group relative to the comparison group has on average across regions a 4% higher adoption intensity (coefficient: 0.0406, standard error: 0.0213, *p*-value: 0.056) but only at the 10% significant level. Relative to spillover farmers, the treatment group does not exhibit a statistically significantly higher adoption intensity after matching. The results can be obtained upon request.
10. We also tested the membership in savings and lending groups but did not find a statistically significant effect.
11. In line with Kangogo et al., 2021, we also tested for innovativeness and risk-taking but did not find any statistically significant effect on adoption intensity.

Acknowledgements

This study was commissioned by GIZ GmbH Fund International Agricultural Research (FIA) and funded by the German Federal Ministry for Economic Cooperation and Development (BMZ). The Stepwise approach was developed under the International Institute of Tropical Agriculture (IITA) project Climate-Smart Coffee and Cocoa, also funded by BMZ between 2016 and 2019. The views expressed here are solely those of the authors and do not necessarily reflect those of partner organizations. We acknowledge the support of Julia Prenzel and Tobias Schmolke of GOPA GmbH for their administrative assistance, the Stepwise implementation team at IITA Uganda, Partner A Uganda, and Partner B, as well as Blaga Zlateva for their contributions to the design of data collection tools. We are also grateful to David Mukasa, Wilberforce Wodada from IITA, Robert Nangai, Hatchile Consult Ltd, for organizing the survey, and to Annet Namakula, Madrine Namubiru, Moses Mabonga, and Stacey Lunyolo for their field support, and to all the farmers who participated in both the quantitative survey and qualitative data collection. We also thank Thomas Miethbauer, Dr Arjunan Subramanian, and Prof Luis Angeles for their valuable comments, and Bartholomeow Aobe for the map in Figure 2. A special thanks goes to the three anonymous reviewers and the journal editor for their highly valuable feedback and comments, which have significantly enhanced the clarity and focus of this article. Lastly, we used ChatGPT Version 4.0 to simplify sentences, where appropriate, with the goal of reducing the overall word count.

Author contributions

CRediT: **Manuela Kristin Günther:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing; **Christine Bosch:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing; **Hanna Ewell:** Conceptualization, Funding acquisition, Project administration, Validation, Writing – review & editing; **Raphael Nawrotzki:** Conceptualization, Funding acquisition, Project administration, Validation, Writing – review & editing; **Edward Kato:** Data curation, Investigation, Validation, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by Deutsche Gesellschaft für Internationale Zusammenarbeit: [Grant Number].

Ethical clearance and consent

Ethical clearance for the study was obtained from The AIDS Support Organization (TASO) Research Ethics Committee in Uganda. Informed consent was obtained from all subjects involved in the study.

Data availability statement

The data are available upon request from the corresponding author.

Notes on contributors

Manuela Kristin Gunther is a PhD Researcher in Applied Economics at the University of Glasgow and a Senior Impact Evaluator at ImpactLoop LTD focused on experimental and quasi-experimental approaches in real-world impact evaluations.

Christine Bosch has a PhD in Agriculture Economics and is a post-doctoral researcher, both at the University of Hohenheim at the Division of Social and Institutional Change in Agricultural Development, and the head of the agriculture research division at ImpactLoop LTD.

Hanna Ewell is a former advisor at GIZ, a PhD researcher at the Wageningen University and a research specialist at the Accelerating Impacts of CGIAR Climate Research in Africa (AICCRA) program.

Raphael Nawrotzki holds a PhD in Sociology with specialisation in Environmental Demography from the University of Colorado Boulder and is currently a Management advisor at a GIZ project titled REACH (Resilience Against Climate Change).

Edward Kato is a Senior Research Analyst with the Natural Resources and Resilience Unit, and is based at IFPRI-Kampala.

ORCID

Manuela Kristin Günther http://orcid.org/0009-0008-4038-3372
Christine Bosch http://orcid.org/0000-0003-0241-8868
Hanna Ewell http://orcid.org/0009-0003-0304-3874
Raphael Nawrotzki http://orcid.org/0000-0002-1671-3676
Edward Kato http://orcid.org/0000-0001-8159-1057

References

Abegunde, V. O., Sibanda, M., & Obi, A. (2019). The dynamics of climate change adaptation in Sub-Saharan Africa: A review of climate-smart agriculture among small-scale farmers. *Climate*, *7*(11), 132. https://doi.org/10.3390/CLI7110132

Adesina, A. A., & Zinnah, M. M. (1993). Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural Economics*, *9*(4), 297–311. https://doi.org/10.1111/j.1574-0862.1993.tb00276.x

Akoyi, K. T., & Maertens, M. (2018). Walk the talk: Private sustainability standards in the Ugandan coffee sector. *Journal of Development Studies*, *54*(10), 1792–1818. https://doi.org/10.1080/00220388.2017.1327663

Ali, E. (2021). Farm households' adoption of climate-smart practices in subsistence agriculture: Evidence from Northern Togo. *Environmental Management*, *67*(5), 949–962. https://doi.org/10.1007/s00267-021-01436-3

Andersson, J., & D'Souza, S. (2014). From adoption claims to understanding farmers and contexts: A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in Southern Africa. *Agriculture, Ecosystems & Environment*, *187*, 116–132. https://doi.org/10.1016/j.agee.2013.08.008

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion* (1st ed.). Princeton University Press.

Arslan, A., Floress, K., Lamanna, C., Lipper, L., & Rosenstock, T. S. (2022). A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa. *PLOS Sustainability and Transformation*, *1*(7), e0000018. https://doi.org/10.1371/journal.pstr.0000018

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, *37*(3), 283–295. https://doi.org/10.1016/j.foodpol.2012.02.013

Becker, S. O., & Caliendo, M. (2007). Sensitivity analysis for average treatment effects. *The Stata Journal*, *7*(1), 71–83. https://doi.org/10.1177/1536867X0700700104

Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change*, *22*(1), 223–235. https://doi.org/10.1016/J.GLOENVCHA.2011.11.012

Bernier, Q., Meinzen-Dick, R., Kristjanson, P., Haglund, E., Kovarik, C., Bryan, E., Ringler, C., & Silvestri, S. (2015). *Gender and Institutional Aspects of Climate-Smart Agricultural Practices: Evidence from Kenya* (No. 79; CCAFS Working Paper).

Bold, T., Kaizzi, K. C., Svensson, J., & Yanagizawa-Drott, D. (2017). Lemon technologies and adoption: Measurement, theory, and evidence from agricultural markets in Uganda. *The Quarterly Journal of Economics*, *132*(3), 1055–1100. https://doi.org/10.1093/qje/qjx009

Bongers, G., Fleskens, L., Van De Ven, G., Mukasa, D., Giller, K., & Van Asten, P. (2015). Diversity in smallholder farms growing coffee and their use of recommended coffee management practices in Uganda. *Experimental Agriculture*, *51*(4), 594–614. https://doi.org/10.1017/S0014479714000490

Bouwman, T. I., Andersson, J. A., & Giller, K. E. (2020). Herbicide induced hunger? Conservation agriculture, Ganyu labour and rural poverty in Central Malawi. *The Journal of Development Studies*, *57*(2), 244–263. https://doi.org/10.1080/00220388.2020.1786062

Bunn, C., Läderach, P., Ovalle Rivera, O., & Kirschke, D. (2015). A bitter cup: Climate change profile of global production of Arabica and Robusta coffee. *Climatic Change*, *129*(1–2), 89–101. https://doi.org/10.1007/s10584-014-1306-x

Bunn, C., Lundy, M., Läderach, P., Fernández, P., & Castro-Llanos, F. (2019). *Climate-smart coffee in Uganda* (p. 24). International Center for Tropical Agriculture (CIAT).

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/J.1467-6419.2007.00527.X

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications* (1st ed.). Cambridge University Press.

Campbell, B. M., Thornton, P., Zougmoré, R., van Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture? *Current Opinion in Environmental Sustainability*, *8*, 39–43. https://doi.org/10.1016/j.cosust.2014.07.002

Candemir, A., Duvaleix, S., & Latruffe, L. (2021). Agricultural cooperatives and farm sustainability-A literature review. *Journal of Economic Surveys*, *35*(4), 1118–1144.

Chiputwa, B., Spielman, D. J., & Qaim, M. (2015). Food standards, certification, and poverty among coffee farmers in Uganda. *World Development*, *66*, 400–412. https://doi.org/10.1016/j.worlddev.2014.09.006

Clay, D. C., Bro, A. S., Church, R. A., Ortega, D. L., & Bizoza, A. R. (2018). Farmer incentives and value chain governance: Critical elements to sustainable growth in Rwanda's coffee sector. *Journal of Rural Studies*, *63*, 200–213. https://doi.org/10.1016/j.jrurstud.2018.06.007

Cramer, C., Johnston, D., Mueller, B., Oya, C., & Sender, J. (2016). Fairtrade and labour markets in Ethiopia and Uganda. *Journal of Development Studies*, *53*(6), 841–856. https://doi.org/10.1080/00220388.2016.1208175

Davis, K., Nkonya, E., Kato, E., Mekonnen, D. A., Odendo, M., Miiro, R., & Nkuba, J. (2012). Impact of farmer field schools on agricultural productivity and poverty in East Africa. *World Development*, *40*(2), 402–413. https://doi.org/10.1016/j.worlddev.2011.05.019

de Pinto, A., Cenacchi, N., Kwon, H. Y., Koo, J., & Dunston, S. (2020). Climate smart agriculture and global food-crop production. *PLoS One*, *15*(4), e0231764. https://doi.org/10.1371/JOURNAL.PONE.0231764

Dhakal, A., Cockfield, G., & Maraseni, T. N. (2015). Deriving an index of adoption rate and assessing factors affecting adoption of an agroforestry-based farming system in Dhanusha District, Nepal. *Agroforestry Systems*, *89*(4), 645–661. https://doi.org/10.1007/s10457-015-9802-1

Donner, A., & Klar, N. (2000). Cluster randomization trials. *Statistical Methods in Medical Research*, *9*(2).

Doss, C., Meinzen-Dick, R., & Bomuhangi, A. (2014). Who owns the land? Perspectives from rural Ugandans and implications for large-scale land acquisitions. *Feminist Economics*, *20*(1), 76–100. https://doi.org/10.1080/13545701.2013.855320

Douthwaite, B., Delve, R., Ekboir, J., & Twomlow, S. (2003). Contending with complexity: The role of evaluation in implementing sustainable natural resource management. *International Journal of Agricultural Sustainability*, *1*(1), 51–66. https://doi.org/10.3763/ijas.2003.0106

Ebanyat, P., de Ridder, N., de Jager, A., Delve, R. J., Bekunda, M. A., & Giller, K. E. (2010). Drivers of land use change and household determinants of sustainability in smallholder farming systems of Eastern Uganda. *Population and Environment*, *31*(6), 474–506. https://doi.org/10.1007/s11111-010-0104-2

Ehiakpor, D. S., Danso-Abbeam, G., & Mubashiru, Y. (2021). Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. *Land Use Policy*, *101*, 105142. https://doi.org/10.1016/j.landusepol.2020.105142

Eriksen, S. H., Cramer, L. K., Vetrhus, I., & Thornton, P. (2019). Can climate interventions open Up space for transformation? Examining the Case of Climate-Smart Agriculture (CSA) in Uganda. *Frontiers in Sustainable Food Systems*, *3*, 111. https://doi.org/10.3389/fsufs.2019.00111

Eriksen, S. H., Schipper, E. L. F., Scoville-Simonds, M., Vincent, K., Adam, H. N., Brooks, N., Harding, B., Khatri, D., Lenaerts, L., Liverman, D., Mills-Novoa, M., Mosberg, M., Movik, S., Muok, B., Nightingale, A., Ojha, H., Sygna, L., Taylor, M., Vogel, C., & West, J. J. (2021). Adaptation interventions and their effect on vulnerability in developing countries: Help, hindrance or irrelevance? *World Development*, *141*, 105383. https://doi.org/10.1016/J.WORLDDEV.2020.105383

Fabozzi, F. J., Focardi, S. M., Rachev, S. T., & Arshanapalli, B. G. (2014). *The basics of financial econometrics: Tools, concepts, and asset management applications*. John Wiley & Sons.

FAO. (2017). *Climate-Smart agriculture sourcebook*.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, *33*(2), 255–298.

Fisher, M., Holden, S. T., Thierfelder, C., & Katengeza, S. P. (2018). Awareness and adoption of conservation agriculture in Malawi: What difference can farmer-to-farmer extension make? *International Journal of Agricultural Sustainability*, *16*(3), 310–325. https://doi.org/10.1080/14735903.2018.1472411

Gabiri, G., Luswata, K. C., Sebuliba, E., & Nampijja, J. (2022). *Climate smart agriculture in Uganda*. https://hdl.handle.net/10568/125661

Gedefa, B. (2014). A double-hurdle approach to modeling of improved tef technolo-gies adoption and intensity use in case of Diga District of East Wollega zone. *Global Journal of Environmental Research*, *8*(3), 41–49. https://doi.org/10.5829/idosi.gjer.2014.8.3.1106

Glover, D., Sumberg, J., & Andersson, J. A. (2016). The adoption problem; or why we still understand so little about technological change in African agriculture. *Outlook on Agriculture*, *45*(1), 3–6. https://doi.org/10.5367/oa.2016.0235

Greene, W. (2019). *Econometric analysis*. Pearson Deutschland. https://elibrary.pearson.de/book/99.150005/9781292231150

Gujarati, D. N. (2009). *Basic econometrics*. New York: McGraw Hill Inc.

Günther, M. K., Lüttringhaus, S., Von Witzke, K., Ewell, H., Nawrotzki, R., & Miethbauer, T. (2025). Beyond rice: The rise of salt-tolerant potatoes and sweet potatoes in Bangladesh? *Q Open*, *5*(2), qoaf008. https://doi.org/10.1093/qopen/qoaf008

Haggar, J., Nelson, V., Lamboll, R., & Rodenburg, J. (2021). Understanding and informing decisions on sustainable agricultural intensification in Sub-Saharan Africa. *International Journal of Agricultural Sustainability*, *19*(5–6), 349–358. https://doi.org/10.1080/14735903.2020.1818483

Harris, T., Yang, Z., & Hardin, J. W. (2012). *Modeling Underdispersed Count Data with Generalized Poisson Regression*. https://journals.sagepub.com/doi/abs/10.11771536867X1201200412

Hill, R. V. (2010). Investment and abandonment behavior of rural households: An empirical investigation. *American Journal of Agricultural Economics*, *92*(4), 1065–1086. https://doi.org/10.1093/AJAE/AAQ055

Hill, R. V., Maruyama, E., Olapade, M., & Frölich, M. (2021). Strengthening producer organizations to increase market access of smallholder farmers in Uganda. *Agricultural and Resource Economics Review*, *50*(3), 436–464. https://doi.org/10.1017/AGE.2021.19

Hörner, D., & Wollni, M. (2022). Does integrated soil fertility management increase returns to land and labor?: Plot-level evidence from Ethiopia. *Agricultural Economics*, *53*(3), 337–355. https://doi.org/10.1111/agec.12699

International Coffee Agreement. (2007, September 28). (OJ L186/13).

Islam, M. K., & Farjana, F. (2024). Impact of climate-smart agriculture practices on multidimensional poverty among coastal farmers in Bangladesh. *Communications Earth & Environment*, *5*(1), 1–12. https://doi.org/10.1038/s43247-024-01570-w

Jaramillo, J., Muchugu, E., Vega, F. E., Davis, A., Borgemeister, C., & Chabi-Olaye, A. (2011). Some like it hot: The influence and implications of climate change on coffee berry borer (Hypothenemus hampei) and coffee production in east Africa. *PLoS One*, *6*(9), e24528. https://doi.org/10.1371/journal.pone.0024528

Jassogne, L., Mukasa, D., Bukomeko, H., Kemigisha, E., Kirungit, D., Giller, O., & Asten, P. (2017). *Redesigning Delivery: Boosting Adoption of Coffee Management Practices in Uganda. The climate smart investment pathway approach and the farmer segmentation tool. CCAFS Info Note.*

Jassogne, L., van Asten, P. J. A., Wanyama, I., & Baret, P. V. (2013). Perceptions and outlook on intercropping coffee with banana as an opportunity for smallholder coffee farmers in Uganda. *International Journal of Agricultural Sustainability*, *11*(2), 144–158. https://doi.org/10.1080/14735903.2012.714576

Kagezi, H. G., Kucel, P., Kobusinge, J., Olango, D., Nakibuule, N., Wagoire, L., & W, W. (2018). Predicting the response of insect pests and diseases of Arabica coffee to climate change along an altitudinal gradient in Mt. Elgon Region, Uganda. *Journal of Agriculture and Environmental Sciences*, *7*(1), 2334–2412.

Kangogo, D., Dentoni, D., & Bijman, J. (2021). Adoption of climate-smart agriculture among smallholder farmers: Does farmer entrepreneurship matter? *Land Use Policy*, *109*, 105666. https://doi.org/10.1016/J.LANDUSEPOL.2021.105666

Lamichhane, P., Hadjikakou, M., Miller, K. K., & Bryan, B. A. (2022). Climate change adaptation in smallholder agriculture: Adoption, barriers, determinants, and policy implications. *Mitigation and Adaptation Strategies for Global Change*, *27*(5), 32. https://doi.org/10.1007/s11027-022-10010-z

Latynskiy, E., & Berger, T. (2016). Networks of rural producer organizations in Uganda: What can be done to make them work better? *World Development*, *78*, 572–586. https://doi.org/10.1016/j.worlddev.2015.10.014

Lecoutere, E., & Jassogne, L. (2019). Fairness and efficiency in smallholder farming: The relation with intrahousehold decision-making. *Journal of Development Studies*, *55*(1), 57–82. https://doi.org/10.1080/00220388.2017.1400014

Lecoutere, E., & Wuyts, E. (2021). Confronting the wall of patriarchy: Does participatory intrahousehold decision making empower women in agricultural households? *Journal of Development Studies*, *57*(6), 882–905. https://doi.org/10.1080/00220388.2020.1849620

Liebig, T., Babin, R., Ribeyre, F., Läderach, P., van Asten, P., Poehling, H. M., Jassogne, L., Cilas, C., & Avelino, J. (2018). Local and regional drivers of the African coffee white stem borer (Monochamus leuconotus) in Uganda. *Agricultural and Forest Entomology*, *20*(4), 514–522. https://doi.org/10.1111/afe.12284

Liebig, T., Ribeyre, F., Läderach, P., Poehling, H. M., van Asten, P., & Avelino, J. (2019). Interactive effects of altitude, microclimate and shading system on coffee leaf rust. *Journal of Plant Interactions*, *14*(1), 407–415. https://doi.org/10.1080/17429145.2019.1643934

Lipper, L., McCarthy, N., Zilberman, D., Asfaw, S., & Branca, G. (2017). In L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, & G. Branca (Eds.), *Climate smart agriculture. Building resilience to climate change*. Springer International Publishing.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., … Torquebiau, E. F. (2014). Climate-smart agriculture for food security. *Nature Climate Change*, *4*(*12*), 1068–1072. https://doi.org/10.1038/nclimate2437

Mahama, A., Awuni, J. A., Mabe, F. N., & Azumah, S. B. (2020). Modelling adoption intensity of improved soybean production technologies in Ghana – A generalized poisson approach. *Heliyon*, *6*(3), e03543. https://doi.org/10.1016/j.heliyon.2020.e03543

Margiotta, S., & Giller, O. (2018). *Improving smallholder farmer adoption of climate smart agriculture practices*.

Margiotta, S., & Mukasa, D. (2018). *A learning exchange for improved extension for coffee farmers*. News. https://ccafs.cgiar.org/news/learning-exchange-improved-extension-coffee-farmers#.XG43bOgzbIU

Mugoya, T. (2018). *The financial viability of coffee farming in Uganda. Study report*.

Mukasa, D., Rusinamhodzi, L., van Asten, Piet. J. A., Amwonya, D., Sseguya, H., Okiror, F. A., … Jassogne, L. (2025). A stepwise approach to facilitate adoption of climate smart practices for smallholder coffee production in Uganda. *International Journal of Agricultural Sustainability*, *23*(1). https://doi.org/10.1080/14735903.2025.2513790

Mulinde, C., Majaliwa, J. G. M., Twinomuhangi, R., Mfitumukiza, D., Komutunga, E., Ampaire, E., Asiimwe, J., Van Asten, P., & Jassogne, L. (2019). Perceived climate risks and adaptation drivers in diverse coffee landscapes of Uganda. *NJAS – Wageningen Journal of Life Sciences*, *88*(1), 31–44. https://doi.org/10.1016/J.NJAS.2018.12.002

Mwongera, C., Shikuku, K. M., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., Twomlow, S., & Winowiecki, L. A. (2017). Climate smart agriculture rapid appraisal (CSA-RA): A tool for prioritizing context-specific climate smart agriculture technologies. *Agricultural Systems*, *151*, 192–203. https://doi.org/10.1016/J.AGSY.2016.05.009

Ofuoku, A. U., Olele, N. F., & Emah, G. N. (2008). Determinants of adoption of improved fish production technologies among fish farmers in delta state, Nigeria. *The Journal of Agricultural Education and Extension*, *14*(4), 297–306. https://doi.org/10.1080/13892240802416186

Ojo, T. O., Baiyegunhi, L. J. S., Adetoro, A. A., & Ogundeji, A. A. (2021). Adoption of soil and water conservation technology and its effect on the productivity of smallholder rice farmers in southwest Nigeria. *Heliyon*, *7*(3), e06433. https://doi.org/10.1016/j.heliyon.2021.e06433

Pattenden, J., Campling, L., Castañón Ballivián, E., Gras, C., Lerche, J., O'Laughlin, B., Oya, C., Pérez-Niño, H., & Sinha, S. (2021). Introduction: Covid-19 and the conditions and struggles of agrarian classes of labour. *Journal of Agrarian Change*, *21*(3), 582–590. https://doi.org/10.1111/JOAC.12440

Pham, Y., Reardon-Smith, K., Mushtaq, S., & Cockfield, G. (2019). The impact of climate change and variability on coffee production: A systematic review. *Climatic Change*, *156*(4), 609–630. https://doi.org/10.1007/s10584-019-02538-y

Place, F., & Otsuka, K. (2002). Land tenure systems and their impacts on agricultural investments and productivity in Uganda. *Journal of Development Studies*, *38*(6), 105–128. https://doi.org/10.1080/00220380412331322601

Ragasa, C. (2020). Effectiveness of the lead farmer approach in agricultural extension service provision: Nationally representative panel data analysis in Malawi. *Land Use Policy*, *99*, 104966. https://doi.org/10.1016/j.landusepol.2020.104966

Rahn, E., Liebig, T., Ghazoul, J., van Asten, P., Läderach, P., Vaast, P., Sarmiento, A., Garcia, C., & Jassogne, L. (2018). Opportunities for sustainable intensification of coffee agro-ecosystems along an altitudinal gradient on Mt. Elgon, Uganda. *Agriculture, Ecosystems & Environment*, *263*, 31–40. https://doi.org/10.1016/j.agee.2018.04.019

Rahn, E., Vaast, P., Läderach, P., van Asten, P., Jassogne, L., & Ghazoul, J. (2018). Exploring adaptation strategies of coffee production to climate change using a process-based model. *Ecological Modelling*, *371*(January), 76–89. https://doi.org/10.1016/j.ecolmodel.2018.01.009

Raile, E. D., Young, L. M., Kirinya, J., Bonabana-Wabbi, J., & Raile, A. N. W. (2021). Building public will for climate-smart agriculture in Uganda: Prescriptions for industry and policy. *Journal of Agricultural and Food Industrial Organization*, *19*(1), 39–50. https://doi.org/10.1515/jafio-2021-0012

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

Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development*, *146*, 105599. https://doi.org/10.1016/j.worlddev.2021.105599

Sarmiento-Soler, A., Rötter, R. P., Hoffmann, M. P., Jassogne, L., van Asten, P., Graefe, S., & Vaast, P. (2022). Disentangling effects of altitude and shade cover on coffee fruit dynamics and vegetative growth in smallholder coffee systems. *Agriculture, Ecosystems & Environment*, *326*, 107786. https://doi.org/10.1016/j.agee.2021.107786

Scognamillo, A., & Sitko, N. J. (2021). Leveraging social protection to advance climate-smart agriculture: An empirical analysis of the impacts of Malawi's Social Action Fund (MASAF) on farmers' adoption decisions and welfare outcomes. *World Development*, *146*, 105618. https://doi.org/10.1016/j.worlddev.2021.105618

Sebatta, C., Mugisha, J., Bagamba, F., Ernst, A., Domptail, S. E., Kowalski, B., Hoeher, M., Ijala, A. R., Karungi, J., Sebatta, C., Mugisha, J., Bagamba, F., & Ernst, A. (2019). Pathways to sustainable intensification of the coffee-banana agroecosystems in the Mt. Elgon region. *Cogent Food & Agriculture*, *5*(1611051), 1611051–28. https://doi.org/10.1080/23311932.2019.1611051

Sebuliba, E., Majaliwa, J. G. M., Isubikalu, P., Turyahabwe, N., Eilu, G., & Ekwamu, A. (2022). Characteristics of shade trees used under Arabica coffee agroforestry systems in Mount Elgon Region, Eastern Uganda. *Agroforestry Systems*, *96*(1), 65–77. https://doi.org/10.1007/s10457-021-00688-6

Senyolo, M. P., Long, T. B., Blok, V., Omta, O., & van der Velde, G. (2021). Smallholder adoption of technology: Evidence from the context of climate smart agriculture in South Africa. *Journal of Development and Agricultural Economics*, *13*(2), 156–173. https://doi.org/10.5897/JDAE2020.1191

Shikuku, K. M., Laederach, P., Winowiecki, L., & Mwongera, C. (2015). A cost function analysis of trade-offs within climate smart agriculture: Does mulching save the cost of crop production among smallholder farmers in Uganda? *Agriculture in an Interconnected World*.

Shikuku, K. M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J. G., Mwongera, C., & Läderach, P. (2017). Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management*, *16*, 234–245. https://doi.org/10.1016/J.CRM.2017.03.001

Sidibé, A. (2005). Farm-level adoption of soil and water conservation techniques in northern Burkina Faso. *Agricultural Water Management*, *71*(3), 211–224. https://doi.org/10.1016/j.agwat.2004.09.002

Sloan, K., Teague, E., Talsma, T., Daniels, S., Bunn, C., Jassogne, L., & Lundy, M. (2019). One size does not fit all: Private-sector perspectives on climate change, agriculture and adaptation. In T. S. Rosenstock, A. Nowak, & E. Girvetz (Eds.), *The climate-smart agriculture papers. Investigating the business of a productive, resilient and low emission future* (pp. 227–234). Springer Open.

Ssebunya, B. R., Schader, C., Baumgart, L., Landert, J., Altenbuchner, C., Schmid, E., & Stolze, M. (2019). Sustainability performance of certified and Non-certified smallholder coffee farms in Uganda. *Ecological Economics*, *156*(July 2016), 35–47. https://doi.org/10.1016/j.ecolecon.2018.09.004

Sseguya, H., Robinson, D. S., Mwango, H. R., Flock, J. A., Manda, J., Abed, R., & Mruma, S. O. (2021). The impact of demonstration plots on improved agricultural input purchase in Tanzania: Implications for policy and practice. *PLoS One*, *16*(1), e0243896. https://doi.org/10.1371/journal.pone.0243896

Taylor, M. (2018). Climate-smart agriculture: What is it good for? *Journal of Peasant Studies*, *45*(1), 89–107. https://doi.org/10.1080/03066150.2017.1312355

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597–623. https://doi.org/10.1111/1477-9552.12011

Tufa, A. H., Alene, A. D., Manda, J., Akinwale, M. G., Chikoye, D., Feleke, S., Wossen, T., & Manyong, V. (2019). The productivity and income effects of adoption of improved soybean varieties and agronomic practices in Malawi. *World Development*, *124*, 104631. https://doi.org/10.1016/j.worlddev.2019.104631

Turinawe, A., Drake, L., & Mugisha, J. (2015). Adoption intensity of soil and water conservation technologies: A case of South Western Uganda. *Environment, Development and Sustainability*, *17*(4), 711–730. https://doi.org/10.1007/s10668-014-9570-5

UCDA. (2021). *Uganda coffee development authority (UCDA)*. Monthly report, October 2020-November 2021. Report 2021/22 Issue 1

van Asten, P. J. A., Wairegi, L. W. I., Mukasa, D., & Uringi, N. O. (2011). Agronomic and economic benefits of coffee – banana intercropping in Uganda's smallholder farming systems. *Agricultural Systems*, *104*(4), 326–334. https://doi.org/10.1016/J.AGSY.2010.12.004

Verburg, R., Rahn, E., Verweij, P., van Kuijk, M., & Ghazoul, J. (2019). An innovation perspective to climate change adaptation in coffee systems. *Environmental Science & Policy*, *97*, 16–24. https://doi.org/10.1016/j.envsci.2019.03.017

Wang, N., Jassogne, L., van Asten, P. J. A., Mukasa, D., Wanyama, I., Kagezi, G., & Giller, K. E. (2015). Evaluating coffee yield gaps and important biotic, abiotic, and management factors limiting coffee production in Uganda. *European Journal of Agronomy*, *63*, 1–11. https://doi.org/10.1016/J.EJA.2014.11.003

Ward, P. S., Bell, A. R., Droppelmann, K., & Benton, T. G. (2018). Early adoption of conservation agriculture practices: Understanding partial compliance in programs with multiple adoption decisions. *Land Use Policy*, *70*, 27–37. https://doi.org/10.1016/j.landusepol.2017.10.001

Wedig, K., & Wiegratz, J. (2018). Neoliberalism and the revival of agricultural cooperatives: The case of the coffee sector in Uganda. *Journal of Agrarian Change*, *18*(2), 348–369. https://doi.org/10.1111/JOAC.12221

Winkelmann, R. (2008). *Econometric analysis of count data*. Springer Science & Business Media.

Woolridge, J. M. (2002). *Introductory Econometrics: a modern approach, 4. izdaja*. Cincinnati: Thomson South-Western.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT press.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., 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

Appendices

Appendix A. Details on sampling strategy

Sample size calculations followed the cluster design approach described by Donner and Klar (2000) to account for intracluster correlation. We assumed maximum variability ($p = 0.5$), a 95% confidence level, 80% power, a mean effect size of 0.25, a standard deviation of 0.7, and an intracluster correlation coefficient (ICC) (rho) of 0.03, based on available baseline data for Bulambuli (close to Sironko) collected by IITA in 2016 (Power calculations determined a sample size of 200 per arm. To ensure adequate statistical power, a sample of 600 was allocated across regions, proportional to assumed treated households, aiming to sample 1,000 Arabica and Robusta-growing households in Luweero (central region) and Sironko and Bulambuli (Eastern region), with 400 treated, 200 spillover, and 400 comparison farmers, distributed across 52 clusters (villages), achieving 81% power. Data collection occurred in September 2022, facilitated by Hatchile Consulting LTD.

Appendix B. Variable description

Table B1. Variable description.

Variable	Description
Asset index	An asset index was built with the help of principal component analysis (PCA). The following variables were selected for the final index: possession of pruning and bow saw, secateurs, coffee huller, knapsack sprayer and protective equipment, tarpaulin for drying coffee, solar panel, motorbike, bicycle, radio, television and smartphone. Cronbach's alpha value is greater than 0.7 (0.758), indicating a high degree of internal consistency.
	Asset ownership may have been influenced by Stepwise, which is why we do not include it in our matching model. Pruning and bow saws, secateurs, knapsack sprayers, protective equipment and tarpaulins for drying coffee. were handed out to contact/model farmers by IITA through Partner A and B to enable them to better train other farmers and adopt practices.
Land Security	For measuring land security, we asked respondents to "completely agree", "agree", "neither agree nor disagree", "disagree" or "completely disagree" with the following statement: 'We feel safe that our land will not be taken away in the next 3 years'.
Proactiveness	For measuring proactiveness, the statements were (1) We/I respond more quickly to changes in the environment of our/my farm compared to other farmers, (2) We/I are/am among the first farmers to adopt new farming practices in my village, (3) We/I are/am constantly looking out for new ways to improve our/my farm.
Yield	We measure yield in terms of the quantity sold. KIIs showed that farmers would often only know the exact quantity produced when selling. Coffee is also aggregated across plots and sold jointly. We therefore asked for the selling stage (red cherries, kiboko, fair average quality or parchment) and the amount sold at each stage. Coffee sales and yields are given in red cherries, using the conversion factors established by the International Coffee Agreement (2007) to convert the amount sold to red cherries (see Tables B2 and B3).
	We consider possible deductions from the price for quality, bulking and credit extended to farmers at the beginning of the season (usually for fertilizer, chemicals or labour costs, but also for school fees) and deducted from the amount paid by the buyer and credit provider (IBERO, Partner B, middlemen, etc.). Additionally, buyers deduct kilograms for quality issues and bulking services and a certain amount of money for credit repayment. Deductions in both kilograms and money were added to the yield.

Table B2. Conversion of yield (ICO conversion factors).

Sales stage	Coffee Type	Dry Cherries	Green beans
ARABICA COFFEE	ARABICA COFFEE	DRY CHERRIES (KIBOKO) KG	GREEN BEANS (KG)
Red cherries	6 kg		1
Parchment	1 kg		0.8
Red cherries	5 kg	1	0.8
ROBUSTA COFFEE	ROBUSTA COFFEE	DRY CHERRIES (KIBOKO) KG	GREEN BEANS (KG)
Red cherries	1 kg	0.43	
Dry coffee cherries	1 kg		0.5

Table B3. Conversion of yield.

Sales stage	CONVERSION
At flowering stage	No adjustment
Red cherries	No adjustment
Kiboko (only Robusta)	kg * 2.32558
Parchment (only Arabica)	kg * 5
Pulped beans (only Arabica)	kg * 1.25
Fair average quality (FAQ, only Robusta)	kg * 2

Appendix C. Details on the stepwise approach & implementation

The International Institute of Tropical Agriculture (IITA) project Climate-Smart Coffee and Cocoa: From Theory to Practice, which developed the Stepwise approach, was funded by BMZ between 2016 and 2019. Approximately 1,760 farmers were trained in the Stepwise approach over the course of the three-year project. IITA Uganda was supported by Partner B and Partner A. As part of the project, ten demonstration (demo) plots were established for Robusta coffee in Luweero by Partner A with support from the United States Agency for International Development (USAID), and six demo plots were set up for Arabica coffee in Sironko by Partner B.

Stepwise training is currently still offered; Partner A is part of a project financed by USAID and Café Africa among others, and Partner B is participating in the BMZ-financed Employment and Skills for Development in Africa (E4D) project.

Partner A works with existing coffee producer organizations (POs, also called depot committees), some of which are part of cooperatives or in the process of becoming cooperatives. The Partner A farm support model consists of a three-tier organizational structure established to provide technical and commercial services to farmers. Partner A identified extensionists at the PO level and then trained them to further train contact farmers, who facilitated farmer field school meetings for about 25 to 30 farmers. The extensionists were charged with monitoring and backstopping five FFS contact farmers each. In addition, they played a role in assisting PO marketing managers in coffee bulking, processing and marketing at the village level, sometimes directly to exporters (Margiotta & Mukasa, 2018). Partner A also provided support to coffee farmers through on-farm training and technical backstopping for extensionists (see Figure C2).

Robusta sales could be in four stages: (1) unharvested coffee to middlemen for very low prices, where the buyer would organize labour, (2) harvested red coffee cherries, (3) sun-dried red coffee cherries (kiboko) and (4) green coffee beans, also labelled fair average quality (FAQ), usually dehusked/milled at the cooperative level (Chiputwa et al., 2015). POs and cooperatives aim to buy coffee from farmers and process it collectively, but few farmers can afford to participate in such schemes because payment takes too long. Value addition depends on the technical

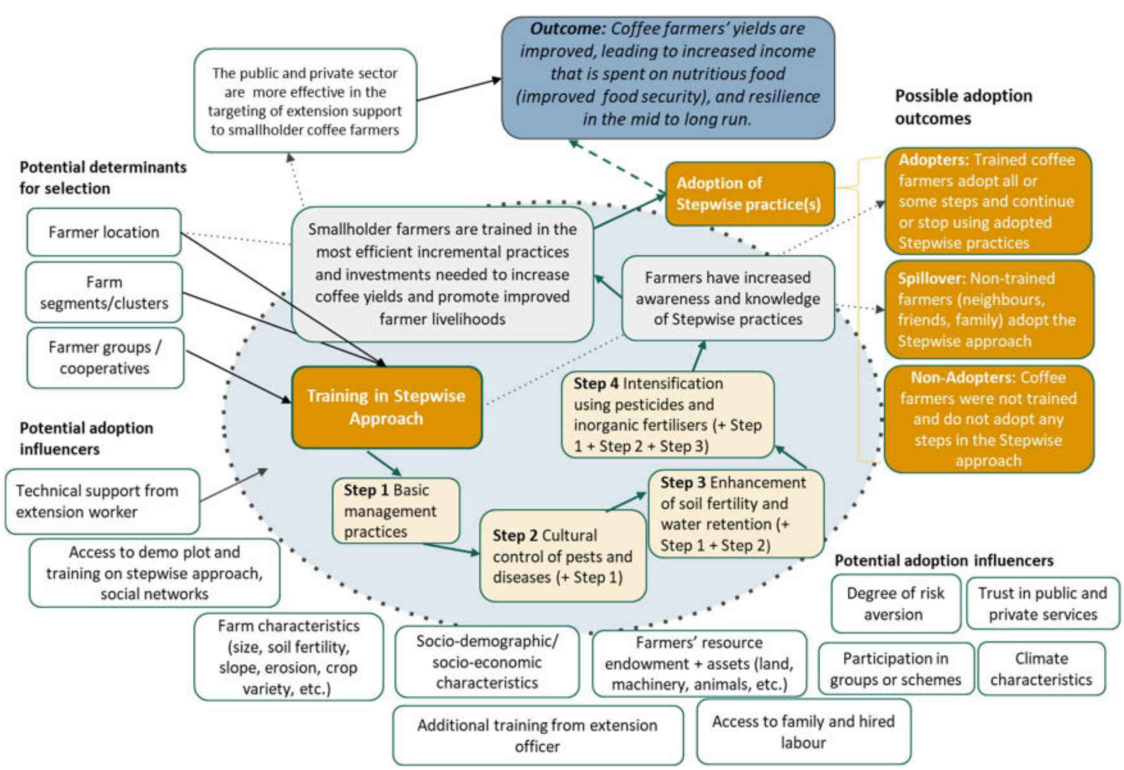

Figure C1. Theory of change.

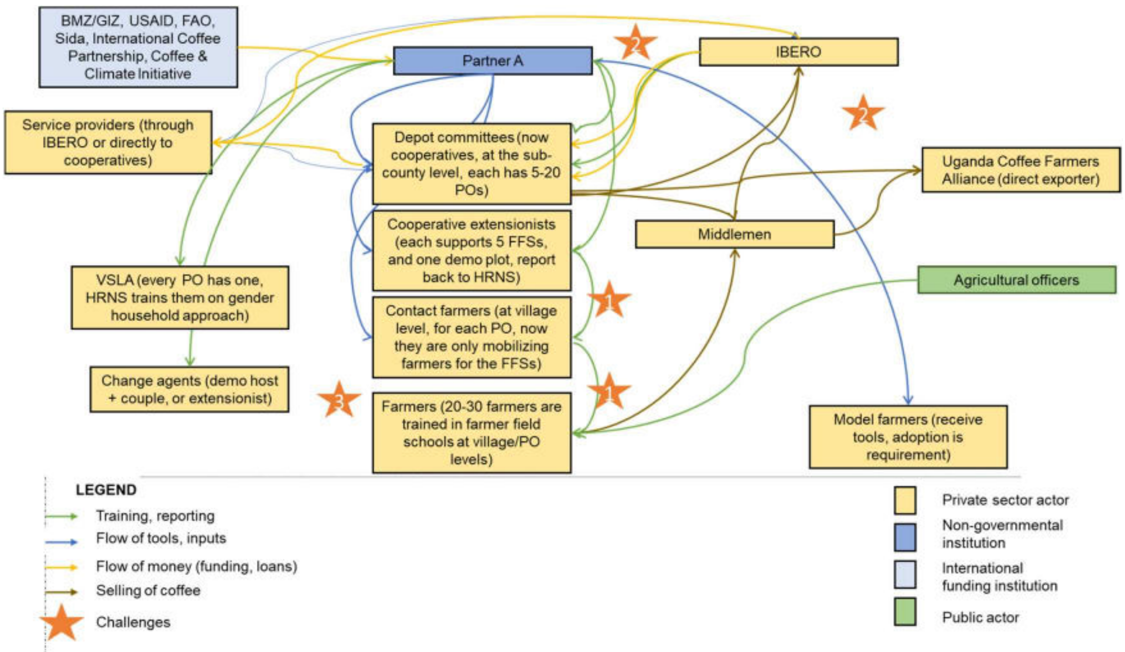

Figure C2. Partner A training approach.

ability of the cooperative, but also on access to buyers and sustainability certificates (Chiputwa et al., 2015; Latynskiy & Berger, 2016). Certificates are either owned by cooperatives, enabling them to sell milled beans to the highest bidder, or by export companies, who usually buy red cherries and set the prices themselves (Chiputwa et al., 2015). In our case, only Partner B holds sustainability certificates.

Partner B sources coffee from individual registered farmers, from whom demo plot hosts and training participants were selected. Partner B's farmer support was delivered through field-based coordinators offering training and technical support. The training at the demonstration plots was carried out by Partner B extension officers and IITA research and field technicians, who typically served around 150 farmers. Within these larger groups, smaller savings groups were promoted. These groups are also used for pay-outs and to deal with any grievances with regard to the premium payment Partner B receives for its different certifications, including Common Code for Coffee Community (4C), and Rainforest Alliance and Starbucks Coffee And Farmer Equity (C.A.F.E.) Practices. Partner B has a dense network of field staff and lead farmers who monitor yield and buy coffee (see Figure A3). The company considers training and the provision of subsidized inputs as services for registered farmers and therefore tries to reduce side-selling to a minimum. In the case of Arabica, as well as selling coffee unharvested or as red cherries, farmers also sell (home-processed) pulped or fully washed coffee (Akoyi & Maertens, 2018). In the Eastern region, washing stations are common and widely used by farmers.

1) Training-related challenges

a. Information loss/distortion from Partner A to cooperative extensionists to contact farmers to farmers. Partner A addressed this, and contact farmers are now only used for mobilization purposes and not for training. Cooperative extensionists have understood their subject matter quite well and get the message across, and they also receive coaching and refresher training. Corporate extensionists are usually early adopters, who then help make other model farmers.
b. Field visits showed that the Farmer Segmentation Tool was not used by the two implementing partners. The tool was designed by IITA taking into account the diversity of coffee farm households in order to provide targeted training to meet their specific needs and abilities (Margiotta & Giller, 2018). Partner A only trains POs and cooperatives, and Partner B groups farmers according to villages (Partner B works with individual farmers but also promotes savings organizations, for example).
c. The four steps were not as clearly distinguishable as intended, and the importance of implementing them consecutively was not consistently emphasized during training sessions. This was because practices were taught according to the agricultural season, and certain practices were selected regardless of the order of the steps. This is highlighted by a public extension officer in the Eastern region: … *all the theory was covered in the first meeting. After that, the practices were covered one by one in the subsequent training sessions. But the challenge is that we have low attendance so it's not practical to have only one topic, say, on stumping and the following day, you call them again. Usually, if they are to come, they associate it with an incentive. We have that challenge … so sometimes when we meet with them, we try to compress everything into that session. So, you want to introduce them to everything and then expand on it in follow-up visits.*

2) Market-related challenges

a. IBERO gives cash loans for fertilizer and other inputs, for hiring workers and for personal issues at low or no interest. Some farmers reported that IBERO would send representatives to receive the first harvest as repayment, which farmers usually sell to middlemen to satisfy urgent financial needs (compare Hill et al., 2021).

b. Partner A and IBERO are independent entities and would not share data, although both are implementing training (IBERO focuses more on marketing and post-harvest strategies, among other subjects). Partner A indicated that farmers would be free to sell their coffee to any company, but some understood that the two would share data and they would be required to sell to IBERO if they got training with Partner A.

c. According to both Partner B and Partner A, there is rising competition for coffee, for example, from Uganda Coffee Farmers Alliance, and some cooperatives prefer selling to them. The practices of middlemen vary significantly; reports from both farmers and key informants refer to them buying unharvested coffee at very low prices, farmers losing coffee gardens when they were unable to pay back debts and the purchase of low-quality coffee which Partner B would reject. Owing to quality issues, Partner B also operates a washing station in Mbale and prefers to buy unprocessed red cherries to better control the processing and therefore the quality of the coffee. They would therefore encourage farmers to save on processing costs and sell red cherries to them. Partner B also buys part of the coffee from middlemen for their non-certified operations. Given the competition, mostly from middlemen, Partner B developed a farmgate strategy. They would hire collection centres for the season, where extension workers, field-based coordinators and enumerators would buy coffee on a daily basis.

d. In the past, Partner B has provided fertilizer on credit to registered farmers. According to interviews, some farmers would then side-sell their coffee and not pay back the loan, which led to Partner B deciding to only provide inputs against direct cash payment. Many farmers equated this (and the rejection of coffee) with the company not keeping their promises. While Partner A decided not to replace worn-out tools, such as saws and secateurs, Partner B would replace them.

3) Incentives

a. Farmer trainers receive personal items, coffee farming tools and monetary compensation for training, which seems to work as an incentive for participating in projects. However, this also seems to act as a disincentive for spillover farmers. One female coffee farmer reported that she taught fellow farmers about Stepwise, but they made fun of her, as she was apparently doing the job of a farmer trainer but without receiving any compensation.

b. Field visits also showed that some demo plot owners and farmer trainers dropped out because, after the project, they had no incentive to share tools and knowledge with others. Other active coffee development projects might also bias incentives. One FGD participant reported: '*Another benefit that I have got is a job because right now there is an organisation called … They were looking for young people to train and two of us were selected … I am going to*

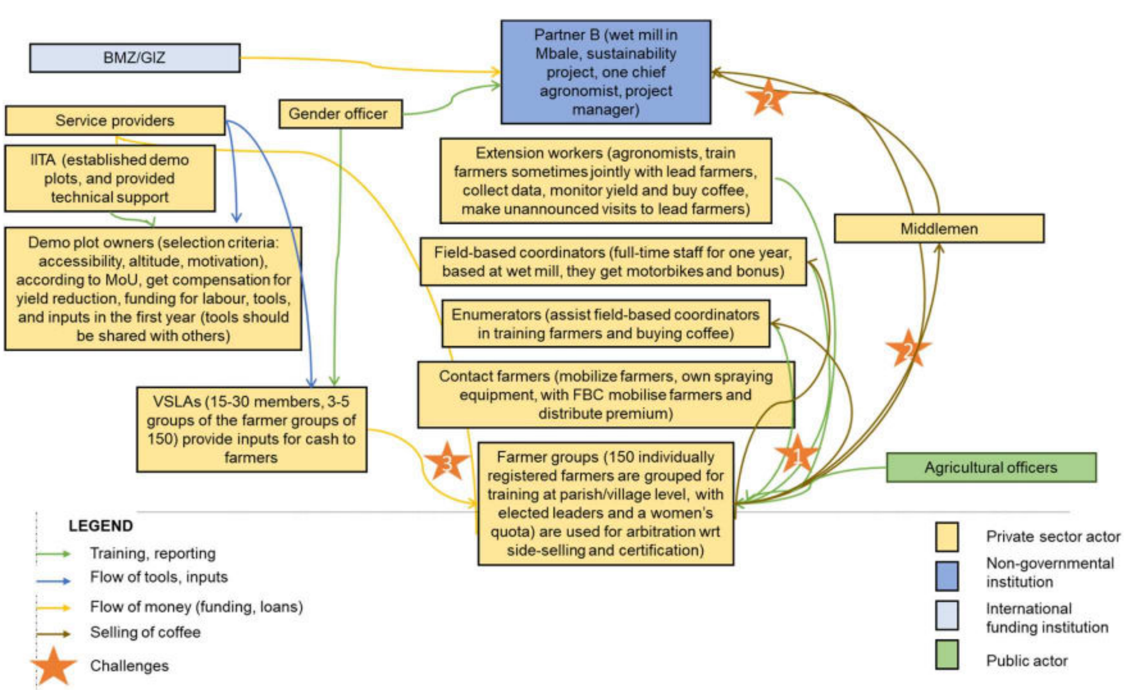

Figure C3. Partner B training and marketing approach.

be trained to stump coffee plants because, honestly, I have never done it before and don't know how it's done. And when we stump the coffee plants, they will pay us!'

c. Training was often perceived as time-intensive and not beneficial for farmers. Partner B trainers, in particular, mentioned the difficulty of mobilizing farmers if no additional benefits were provided. Many farmers were disappointed by Partner B because they expected to receive support for coffee production, including fertilizer and tools. This low trust is illustrated by a quote from an FGD with women: '*But there are those who refuse to adopt and accuse us of being agents of Partner B and receiving money from Partner B.*'

d. As part of its certification programmes, Partner B pays out a premium, also called second payment, to their registered farmers, depending on the quantity of coffee they sell to it. This is, however, only paid out months after the sale, and many farmers reported in FGDs that, despite this second payment, they would still rather sell to those offering the highest price during harvest.

Appendix D. Adoption of individual practices

Table D1. Average implementation of practices by coffee type and treatment group.

	Coffee (Region)	Robusta (Luwero)						Arabica (Eastern)					
	Group	Treated (n-214)		Spillover (n-107)		Comparison (n-211)		Treated (n-150)		Spillover (n-77)		Comparison (n-156)	
STEPS	Measure	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Step 1	Weeding (at least 3 times)	69%	0.45	64%	0.47	75%	0.43	64%	0.46	58%	0.46	38%	0.47
	Desuckering (partially/whole plot)	98%	0.14	98%	0.12	98%	0.14	90%	0.29	86%	0.31	76%	0.39
	Pruning (partially/whole plot)							70%	0.43	66%	0.44	60%	0.46
	Intercropping with banana (partially/whole plot)							91%	0.21	86%	0.27	92%	0.18
	Intercropping with legumes (at least partially)							33%	0.39	40%	0.43	43%	0.41
	Average implemented	**83%**	0.24	**81%**	0.24	**86%**	0.24	**70%**	0.19	**67%**	0.22	**62%**	0.20
Step 2	Pruning (partially/whole plot)	86%	0.33	85%	0.35	84%	0.36						
	Organic fertilizer (partially/whole plot)	55%	0.47	55%	0.47	0.31	0.46	70%	0.39	71%	0.36	75%	0.38
	Cultural pest control (at least partially)	58%	0.47	46%	0.48	36%	0.47	36%	0.42	35%	0.40	41%	0.46
	Shade trees (at least partially)							84%	0.30	75%	0.34	63%	0.41
	Stumping (at least partially)							47%	0.44	45%	0.44	47%	0.41
	Gap filling (at least partially)							61%	0.42	64%	0.42	58%	0.44
	Average implemented	**66%**	0.26	**62%**	0.26	**0.50**	0.28	**60%**	0.23	**58%**	0.25	**57%**	0.22
Step 3	Mulching (partially/whole plot)	24%	0.41	21%	0.39	15%	0.36						
	Trenches (at least partially)							71%	0.39	62%	0.39	71%	0.39
	Inorganic fertilizer (partially/whole plot)							40%	0.48	35%	0.45	57%	0.47
	Average implemented	**24%**	0.41	**21%**	0.39	**15%**	0.36	**55%**	0.31	**49%**	0.33	**64%**	0.31
Step 4	Herbicide application (at least partially)	51%	0.48	45%	0.48	39%	0.48						
	Inorganic fertilizer (partially/whole plot)	34%	0.46	18%	0.37	6%	0.24						
	Chemical pest control (at least partially)	59%	0.47	58%	0.49	46%	0.48	34%	0.42	29%	0.39	45%	0.46
	Desilting of trenches (partially/whole plot)							54%	0.46	50%	0.44	53%	0.46
	Pruning of shade trees (partially/whole plot)							68%	0.39	55%	0.41	40%	0.41
	Irrigation (partially/whole plot)							11%	0.25	10%	0.22	9%	0.22
	Mulching (partially/whole plot)							55%	0.46	52%	0.46	36%	0.43
	Average implemented	**48%**	0.34	**40%**	0.32	**30%**	0.31	**45%**	0.22	**39%**	0.23	**37%**	0.22
	TOTAL average	**55%**	0.17	**51%**	0.17	**46%**	0.17	**57%**	0.17	**53%**	0.18	**55%**	0.16

Table D2. Adoption of individual practices – Descriptives and qualitative evidence.

Practice	Descriptive	Qualitative evidence	Discussion with literature
Weeding	• Weeding was applied more often by the comparison group in the Robusta-producing region, whereas in the Arabica-producing region, treatment and spillover groups reported weeding more than the comparison group.	• This pattern could be due to training on other weed-suppressing practices, such as mulching or applying herbicides. Indeed, we saw higher herbicide application among the treatment and spillover group in Luweero and higher mulching application in both regions. • Herbicides are labour-saving, so farmers with less access to family or hired labour might prefer to use herbicides. • We also observed a widespread belief that herbicides (and pesticides) destroy the soil. • Younger farmers, in particular, said labour-intensive practices were a '*waste of time and energy*'. • In the Eastern region, when intercropping coffee with legumes and vegetables, farmers would also remove weeds. This might not be considered weeding and therefore might not be captured by our survey.	Bouwman et al. (2020) found that herbicide use by mostly better-off farmers became disassociated from promoted practices and came with trade-offs; while reduced the work load of women farmers, poorer agricultural workers were no longer hired for weeding.
Pruning and desuckering	• Pruning and desuckering were carried out slightly more by treatment and spillover farmers and slightly more in Luweero than in the Eastern region, where implementation was higher among the comparison group.	• This pattern could be due to Partner A's focus on pruning (and stumping). • In relation to pruning and stumping, where farmers fear losing their harvest, seeing might be believing, so the demo plots might be especially useful for promoting such practices. At the same time, stumping might not be relevant for all farmers and might lead to yield losses in the first years.	Several authors refer to the old age of many coffee cultivars in Uganda (e.g. Hill, 2010; Wang et al., 2015).
Organic and inorganic fertiliser	• Organic and inorganic fertilizer was used less by spillover and comparison farmers in Luweero and comparatively more in the Eastern region.	• Livestock keeping is more common in the Eastern region, which might explain the higher use of manure. • Applying inorganic fertilizer has been consistently mentioned as the practice with the highest yield effect. • One reason for the pattern we observed could be a negative selection bias: farmers who cannot access or afford fertilizer might be more willing to join POs and therefore also Stepwise training. This might be especially true for Luweero where farmers have the option of acquiring fertilizer on credit through the POs. Development projects often include fertilizer distributions and farmers would join them for accessing inputs. A public extension officer in the Eastern region reported in an interview that farmers often did not have questions on the training content, but rather asked if they would be given inputs. • Farmers reported counterfeit inorganic fertilizer (and other inputs) as a demotivating factor. Spillover farmers in particular also reported a lack of knowledge about fertilizers and pesticides.	Bold et al. (2017) found that adoption of inorganic fertilizer in Uganda is linked to quality; on average, 30% of nutrients are missing.Sebatta et al. (2019) found that, in Uganda's Mount Elgon region, resource-rich farmers intensify by making capital investments, e.g. in fertilizer and equipment, while resource-poor farmers use more family labour and more labour-intensive practices.
Cultural and chemical pest control	• In Luweero, treatment farmers were more likely to apply both cultural and chemical control, whereas in the Eastern region, treatment farmers were less likely than others to implement such measures.	• During FGDs in Luweero, some farmers, especially from the spillover group, reported using urine or ash to control pests and diseases. Some would not burn infected trees directly but use them for firewood instead. • Some pests spread rapidly to neighbouring farms if not all farmers controlled or sprayed pests. While UCDA organized mass spraying, advisory services (and also the Stepwise approach) preferred to provide farmers with protective equipment and train them to spray themselves. • The differences might also be related to different pests and diseases for Arabica (coffee white stem borer (CWSB), coffee berry borer (CBB) and coffee leaf rust (CLR)) and Robusta (black coffee twig borer (BCTB) and coffee wilt disease (CWD)). CWD, for instance, can only be mitigated with cultural pest control measures or by rejuvenating coffee farms with improved varieties. Arabica in genera is more susceptible to disease. • In the Eastern region, Partner B is also considering applying for organic certification which, contrary to other third-party certifications, would not allow the responsible use of pesticides (Mwongera et al., 2017). This might disincentivise chemical pest control and explain lower use by trained and registered farmers.	Hill (2010) found that in Uganda, only wealthier farmers replaced wilt-affected coffee plants, while the majority would not do so, due to liquidity constraints.

(*Continued*)

Table D2. Continued.

Practice	Descriptive	Qualitative evidence	Discussion with literature
Mulching	• Mulching was applied more in the Eastern region and more by treatment farmers, due to the greater availability of mulching material, among other factors.	• Livestock ownership is more common in the less densely populated Eastern region. Even coffee farmers not owning livestock reported that they could collect manure for free from others. • In Luweero, mulching has been reported to be more complicated, due to a high prevalence of termites and because there is less common land where mulching material can be collected. • A contact farmer at one of the demo plots, when asked whether he was still implementing practices, responded: '*I am still applying manure but no longer mulching because the land where we used to cut grass for mulching has been sold off by the landowner. We are no longer allowed to go and cut grass there. I now do weeding, pruning, stumping; those are the ones that I practice. And whenever I get money, I also buy fertilisers.*'	Shikuku et al. (2015) found that, in the Rakai district of Uganda, while mulching reduced the cost of herbicides, it increased expenditure on pesticides, fertilizer and labour and was not cost-effective (see also Shikuku et al., 2017)
Shade trees	Shade trees and their management were only promoted in the Eastern region. Treated farmers had significantly more coffee plots with shade trees and were more likely to manage them than spillover and comparison farmers.	• In about half of the FGDs both in Luweero and the Eastern region, female and male farmers reported that they had been trained in shade tree management. Many farmers would rather have too much shade (trees) in their coffee gardens. • In the Eastern region, farmers also intercrop with vegetables which does not work for everyone, due to high shade tree cover: 'We don't grow cover crops like beans because they don't do well due to shade trees. Sometimes we grow pumpkins as a cover crop, but they also end up growing without flowering due to the shade. So, we just decided to maintain intercropping coffee with bananas.'	Sebuliba et al. (2022) provide a detailed report on shade trees and related trade-offs in the Eastern region of Uganda. Farmers in Sironko reported falling trees and branches damaging the understorey, competition for space and water, and pests and diseases (potentially also leading to yield decline) as the most common challenges posed by shade trees (Sebuliba et al., 2022)
Other		• During FGDs in both regions, farmers reported learning about post-harvesting techniques, such as drying coffee on tarpaulins and not on cold surfaces, harvesting only red cherries and not damaging coffee plants. The importance of post-harvest strategies has also been highlighted by agricultural production officers. Because of certification requirements, in the Eastern region farmers were also taught to use protective equipment, not store chemicals in the house and not leave or burn plastic waste in the coffee garden. • These other practices are not captured by the Stepwise index. They might not have yield effects but could influence coffee quality and prices.	

Appendix E. Matching quality

The probit estimates of the propensity equations are given in Table 7 in the main text, column 4, which correctly classified high adoption at 73.4%. Table E1 provides estimates for the matching quality, such as the pseudo-R2, LR chi2*p*-value, mean and median standardized bias (all before and after matching), indicating a good fit. For instance, the overall covariate balancing test shows that the standardized mean difference for all covariates used in the PSM was reduced from 16.2% pre-matching to 2.6% post-matching for the adoption at half of the Stepwise recommended sequence and practice. Figure 1A.a also shows the reduction in bias of the various covariates after matching. A visual inspection of Figure 1A.b also shows a considerable overlap of propensity scores between the treated and comparison cases, implying that the match is good and balanced. All high-adopters have matches from the low-adopters which is a sufficient condition to estimate AT (Caliendo & Kopeinig, 2008). Lastly, we follow Becker and Caliendo (2007) in conducting a Rosenbaum bounds sensitivity analysis to assess the robustness of our propensity score matching results to potential hidden bias. The bounds, presented in Table E2, indicate that the estimated treatment effects on coffee yield and revenue remain statistically significant up to a Γ value of 2. This suggests that even in the presence of moderate unobserved heterogeneity in treatment assignment, our results remain robust, allowing us to reject the hypothesis that hidden bias fully explains the observed effects.

Table E1. Propensity score matching quality test.

Matching quality indicators	
Pseudo R2 before matching	0.084
Pseudo R2 after matching	0.004
LR x^2 (*p*-value) before matching	106.33 ($p > chi^2 = 0.000$)
LR x^2 (*p*-value) after matching	4.87 ($p > chi^2 = 1.000$)
Mean standardized bias before matching	16.200
Mean standardized bias after matching	2.600
Median standardized bias before matching	14.800
Median standardized bias after matching	2.400
Mean propensity score	0.420

Figure E1.a displays the difference in the sample means of each explanatory variable before and after matching. Figure E1.b displays the distribution of propensity scores and common support region for above-average adoption. All treated individuals are on support, meaning they found a suitable match.

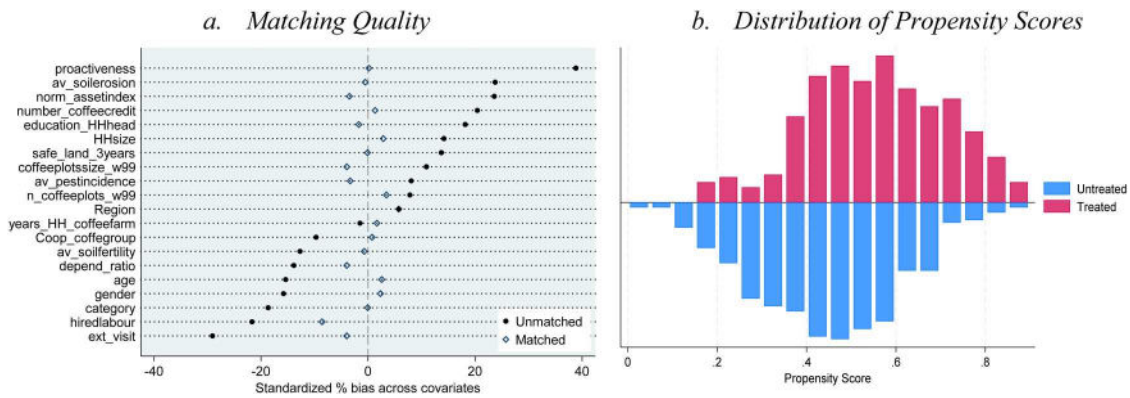

Figure E1. Propensity score matching.

Table E2. Rosenbaum bounds for yield and income ($N = 457$ matched pairs).

Yield							Revenue						
Gamma	sig+	sig−	t-hat+	t-hat-	CI+	CI−	Gamma	sig+	sig−	t-hat+	t-hat-	CI+	CI−
1	0	0	393.643	393.643	355.869	437.431	1	0	0	2000	2000	1850	2300
1.05	0	0	384.234	403.41	347.222	448.889	1.05	0	0	2000	2100	1790	2400
1.1	0	0	375.415	413.333	340.111	460.12	1.1	0	0	2000	2190.25	1750	2500
1.15	0	0	367.401	422.555	333.237	470.509	1.15	0	0	1910	2250	1750	2500
1.2	0	0	360.411	432.255	326.389	481.587	1.2	0	0	1890	2250	1700	2550
1.25	0	0	353.861	440.211	320.472	492.442	1.25	0	0	1820	2325	1650	2650
1.3	0	0	347.048	448.995	314.823	503.24	1.3	0	0	1790	2400	1600	2700
1.35	0	0	341.318	458.018	309.839	513.571	1.35	0	0	1750	2500	1550	2750
1.4	0	0	336.033	467.197	304.762	524.3	1.4	0	0	1750	2500	1500	2750
1.45	0	0	330.603	474.564	299.904	534.722	1.45	0	0	1732.5	2500	1500	2830
1.5	0	0	324.924	483.488	295.745	545.278	1.5	0	0	1685	2550	1500	2900
1.55	0	0	320.617	492.248	291.227	555.34	1.55	0	0	1650	2650	1500	2980
1.6	0	0	315.963	500.278	287.543	566.051	1.6	0	0	1625	2690	1450	3000
1.65	0	0	311.825	508.726	283.598	576.412	1.65	0	0	1595	2750	1400	3000
1.7	0	0	307.981	517.112	280.067	587.209	1.7	0	0	1550	2750	1400	3050
1.75	0	0	304.103	525.678	276.511	597.47	1.75	0	0	1500	2775	1350	3150
1.8	0	0	300.454	533.044	273.189	607.114	1.8	0	0	1500	2812.5	1325	3200
1.85	0	0	297.132	541.68	269.815	617.006	1.85	0	0	1500	2890	1300	3250
1.9	0	0	293.696	549.617	266.787	626.18	1.9	0	0	1500	2938	1280	3250
1.95	0	0	290.494	557.818	263.654	635.743	1.95	0	0	1480	3000	1250	3350
2	0	0	287.564	565.97	260.834	643.801	2	0	0	1450	3000	1250	3438

*gamma	log odds of differential assignment due to unobserved factors
sig+	upper bound significance level
sig−	lower bound significance level
t-hat	upper bound Hodges-Lehmann point estimate
t-hat	lower bound Hodges-Lehmann point estimate
CI+	upper bound confidence interval (a= .95)
CI−	lower bound confidence interval (a= .95)