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Adoption and impacts of improved post-harvest technologies on food security and welfare of maize-farming households in Tanzania: a comparative assessment

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Abstract
During the last decade, post-harvest losses (PHL) reduction has been topping the agenda of governments as a pathway for addressing food security, poverty, and nutrition challenges in Africa. Using survey data from 579 households, we investigated the factors that affect farmers' decisions to adopt post-harvest technologies: mechanized shelling, drying tarpaulins, and airtight storage validated for reducing PHL in Tanzania's maize-based systems, and the impacts on households' food security and welfare. Mechanized shelling addressed a labor issue, while tarpaulins and airtight storage addressed product quality and quantity concerns. The results revealed large farm sizes and location in higher production potential zones (proxies for higher production scale) and neighbors' use of the technologies as universal drivers for adoption. Access to credit and off-farm income were unique determinants for airtight storage, while group membership increased the probability of adopting drying tarpaulin and airtight storage. The technologies have positive impacts on food security and welfare: drying tarpaulins and airtight storage significantly increased food availability (18–27%), food access (24–26%), and household incomes (112–155%), whereas mechanized shelling improved food and total expenditures by 49% and 68%, respectively. The share of total household expenditure on food decreased by 42%, 11%, and 51% among tarpaulin, mechanized shelling, and airtight storage adopter households, signaling significant improvements in food security and reductions in vulnerability. The results point to the need for policy support to enhance the adoption of these technologies, knowledge sharing among farmers, and financial resources access to support investments in the technologies.

Keywords Sustainable intensification · Food loss mitigation · Post-harvest technologies · Impacts · Farm households

1 Introduction

Smallholder farms in East and Southern Africa provide food, income, and employment to millions of rural families. For this reason, the deployment of affordable best practices and innovative arrangements to enhance income and food security through reduced wastage and prevention of food quality loss among this group of farmers is crucial. Following the renewed interest in agriculture during the last decade, governments and development agencies focused on scaling-up of investments in post-harvest food loss (PHL) reduction as a critical action point for improving food security and welfare objectives while reducing pressure on natural resources as envisioned in the sustainable development goals (UN, 2015). PHLs are exceptionally high in developing countries due to inadequate harvesting, handling, processing, and storage techniques and practices (Ali et al., 2021). Therefore, the deployment of affordable best practices and innovative arrangements to reduce PHLs is crucial. In particular, the critical points where the most significant losses occur must be addressed with proven technologies, taking into account the objectives of the various food system actors (Cattaneo et al., 2021).

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PHLs deny farmers opportunities to increase returns on investment, weakening the capacity to secure improved livelihoods. They involve opportunity cost, resource misallocation, and wastage (Tesfaye & Tirivayi, 2018). The losses decrease food supplies and diminish the market value, nutritional content, and safety (Affognon et al., 2015). The causes of food losses at various stages of the post-production chain are varied but generally involve a complex interaction of biological, physical, and socio-economic factors. Post-harvest operations exacerbate these interactions by their tedious, labor-intensive, and time-consuming nature. In Tanzania, drying, threshing, and storage are critical points where economically significant grain PHLs occur (Abass et al., 2014).

Proper drying ensures that the grain will endure threshing and storage without spoilage. Drying is also part of the grain trading system (De Groote et al., 2021). The shelled grain should be dried to $\leq$ 13.5% moisture under safe conditions to avoid contaminations with fungi. Many smallholder farmers dry grain directly on the ground, which also contaminates it with soil-borne residues. The process is slow and encourages spillage and pest attacks. Grain losses equivalent to 2–9.5% occur in various African countries during drying (Hodges et al., 2014). The Africa RISING (Research in Sustainable Intensification for the Next Generation)[1] program validated and promoted the GrainPro Collapsible Dryer Case™ (CDC), a plastic sheet envelope designed for quicker and protected sun-drying. In use, the reinforced polyvinyl chloride sheet (optimized for solar energy absorption) is spread out, and the produce (cobs, pods, or the threshed grains) is placed on top. In bad weather (rains), the tarpaulin is folded to enclose the produce in a zipped envelope. This action saves labor and time needed to gather and move the produce away; the drying is continued after the rain by simply opening the envelope again. Farmers adapt the technology in several ways; some use damp-proof coating sheets available from local hardware shops, while others use canvas or stitched woven polypropylene sheets that ably protect the produce from direct contact with soil. The use of the CDC® decreased maize grain drying time by 28%, avoided loss of 32 kg/ton of grain, and reduced impurities (30%) and moldy grain (42%) (IITA, 2019). In Kenya, simple plastic sheets for grain drying lowered aflatoxin contamination by about 50% compared to direct drying on bare ground (Pretari et al., 2019).

Threshing operations facilitate grain handling, storage, and marketing. As commonly practiced in Tanzania, manual grain threshing is labor-intensive, tiresome, time-consuming, and delays processing for storage (Abass et al., 2014). Significant post-harvest losses also occur through mechanical damage and spillage. In Zimbabwe, up to 3.5% losses occurred during maize shelling, while rice threshing and winnowing operations in Madagascar and Ethiopia were associated with 8.5% and 11% losses, respectively (Hodges et al., 2014). To overcome threshing inefficiencies among smallholder maize producers, Africa RISING validated and promoted a low-cost motorized sheller (4 horsepower, capital cost $630) that completes shelling and grain winnowing work all at once. Using the sheller reduced shelling losses from 6.8% to 2.0%. Farmers who switched to this technology reduced drudgery by 58 – 74% (Mutungi et al., 2022) and improved labor efficiency by 77 – 90%, saving costs and freeing time to undertake other farm and household activities.

Adequate storage enables households to have a consistent supply of food and increases farmer incomes by enabling them to engage in temporal arbitrage, taking advantage of seasonal price fluctuations (Kotu et al., 2019). Many rural farmers still use traditional storage techniques (Edoh Ognakossan et al., 2016). While easily accessible and cheap, the traditional techniques can fail to protect the stored produce affecting safe food provisioning in the lean season. Africa RISING validated and promoted chemical-free grain storage in hermetic containers (metal silo/plastic silo/hermetic bags). The technologies decreased storage losses by more than 85% (Abass et al., 2018; Mutungi et al., 2020), hence proved to be a valuable tool for addressing food security and income objectives among rural households (Kotu et al., 2019). Furthermore, the technology reduced the likelihood of aflatoxin accumulation 5–eightfold in Kenya (Ng'ang'a et al., 2016).

Farmers adopt new technologies when they are convinced beyond doubt that using them would better address household objectives such as food security and decent livelihoods (Kotu et al., 2019). To date, evidence on the impacts of post-harvest technologies on various sustainable intensification domains is still needed in sub-Saharan Africa (Affognon et al., 2015; Sheahan & Barrett, 2017). Thus far, the few studies available limit the scope to storage (Brander et al., 2021; Gitonga et al., 2013; Omotilewa et al., 2018; Tesfaye & Tirivayi, 2018). To the extent that economically significant PHLs occur at multiple farm-level stages, extending the grasp of farmers' decision-making processes to other post-harvest technologies is important. Broadly, mechanized shelling (MS) addresses a labor issue, while drying tarpaulins (DT) and airtight storage (AS) address product quality and quantity issues that characterize PHLs. Overlaps, however, do exist.

This study aimed to investigate the differences in farmers' adoption decision behavior for MS, DT, and AS, and assess the potential contribution of the three technologies to rural households' food security and welfare in Tanzania. The study contributes to the literature in the following ways: First, we generate

[1] Project was implemented in 2011—2021. The goal was, through action research and development partnerships, to create opportunities for smallholder farm households to move out of hunger and poverty through sustainably intensified farming systems that improve food, nutrition, and income security, particularly for women and children, and conserve or enhance the natural resource base. https://africa-rising.net/

knowledge of farmers' decisions to adopt a suite of post-harvest technologies for losses mitigation at the most critical farm-level steps. To our knowledge, not many studies have compared the adoption of multiple post-harvest technologies. Second, we estimate the technologies' food security and welfare benefits and elucidate the factors influencing the outcomes among households. Unlike previous studies, e.g., Gitonga et al. (2013) that established causality between the adoption of post-harvest technologies and welfare outcomes at the household level using methods that only correct for observed characteristics, we employ the endogenous switching regression model (ESRM) to control for both observed and unobserved characteristics. By estimating separate outcome regressions for adopters and non-adopters of each of the three post-harvest technologies using the ESRM, we explore the structural differences between the two groups. We organize the rest of the article as follows: Section 2 describes the data, sampling strategy, and outcome indicators, Section 3 the conceptual and empirical frameworks, Section 4 presents the results and discussion, whereas the last section draws conclusions and policy recommendations.

2 Data, sampling strategy and specification of variables

2.1 Data and sampling strategy

This study uses household survey data collected from 579 households across Tanzania's four regions of Manyara, Dodoma, Iringa, and Songwe, where Africa RISING program validated and promoted the three improved post-harvest technologies (IPHTs) namely: drying tarpaulins (DT), motorized maize shellers (MS), and air-tight storage containers (AS) in 2013—2020. The survey covered 10 out of 64 intervention wards in four purposively selected districts: Babati (Manyara), Kilolo (Iringa), Kongwa (Dodoma), and Mbozi (Songwe). The wards were selected using probability proportional to size sampling (PPS) and 14 villages were selected randomly. Survey households were selected randomly from village household lists, and one adult member was interviewed using a structured questionnaire prepared for this purpose. In half of the cases, we interviewed male household members (mostly the head), and in the remaining cases, female household members (mostly the spouse or a female head) based on a prior random assignment. Enumerators received training on the theoretical and practical aspects of the IPHTs, and the use of the computer-assisted personal interviewing software (*Surveybe*®, EDI Global, United Kingdom) deployed for the survey. All participants received a clear explanation of the survey objectives and were requested to give verbal consent; we interviewed only those who consented.

Apart from post-harvest related data (e.g., awareness, adoption, and cost of IPHTs) the survey collected rich household data such as age, education, and marital status of the household head, size of the household, and assets owned. The survey also collected comprehensive data on crop production, yields and marketing, and household expenditures.

2.2 Outcome variables

Food security is a state in which "all people at all times have the physical, social, and economic access to sufficient, safe, and nutritious food to meet dietary needs and food preferences for productive and healthy life (CFS, 2012). This definition reflects different dimensions, including food availability, access, utilization, and stability. Availability connotes the physical existence of food from own production, held stocks, or market. Food access requires that households have enough economic or physical resources to obtain or produce food in sufficient quantity, quality, and diversity, and concerns household resources, incomes, expenditure, markets, and food prices. Utilization in the socio-economic sense concerns aspects determined by knowledge and habits that shape decisions on what food to produce or purchase and how to prepare, allocate and consume it within the household. Stability concerns the temporal dimension of food security and visualizes a relative constancy in food availability, access, and utilization. Welfare relates to living standards or the economic and social conditions of households and is proxied by measures of consumption or income (Moratti & Natali, 2012). In measuring welfare, consumption is favored over income as individuals derive material well-being from the actual consumption of goods and services rather than receiving income per se (Citro & Michael, 1995).

For the present study, we considered four indicators—months of food insecurity (MFI), household food insecurity access scale (HFIAS), and per capita monthly food consumption expenditure (FCE) as measures of food security. As indicator of household welfare, per capita monthly total consumption expenditure (TCE) was used. We constructed these indicators as follows:

- MFI gave the frequency of household food insecurity in the past year reflecting the availability and stability components. We computed MFI as the average number of months households spent an entire day without three meals due to inadequate food supplies the year preceding the survey.
- HFIAS measured the degree of food insecurity by evaluating responses to a set of standard questions representative of three universal domains of food access in terms of a household's anxiety and uncertainty about (i) inadequate food supply; (ii) insufficient quality; and (iii)

insufficient food intake within a 30-day recall period during the lean period (Coates et al., 2007). HFIAS captures the behavior of being worried about access to quality, quantity, and acceptability of food (Carletto et al., 2013). We calculated the HFIAS (which takes the value of a whole number between 0 and 27) by summing up the codes for each frequency-of-occurrence of nine key food security questions in the three domains as detailed elsewhere (Coates et al., 2007). The higher the score, the more food insecurity (access) the household experienced.

- FCE measured the monthly value of the food consumed by household members at home or away from home and captured improvements in household food access. The FCE was the average value of food consumed per household member from own production, purchase from the market, gifts, in-kind payments, and other sources, including restaurants, canteens, food courts, and street food. All food acquired that was not purchased was valued using the corresponding market prices.
- TCE proxied income improvements and reflected households' living standards by capturing asset ownership and other non-consumption expenditures such as contributions to health, education, taxes, social security transfers, or gifts and donations. We estimated the TCE by summing up the food and non-food consumption expenditures divided by household size.

2.3 Explanatory variables

The factors that are likely to affect the adoption of IPHTs include age, education, household size, landholding, and asset ownership representing the capital strength of households. The effect of age could go either way; older farmers may adopt IPHTs more readily because they have more dependents, capital, and preferential access to financial resources (Sall et al., 2000), while younger households might have longer planning horizons and therefore more willing to take risks (Adegbola & Gardebroek, 2007). Good education increases adoption through a better ability to interpret technical knowledge and allocate resources. Household size is a proxy for labor availability — studies show larger households are more likely to adopt improved agricultural technologies (Abdulai & Huffman, 2014). Gender influences adoption decisions through differential access to resources and information (Fischer et al., 2021). Other farm and system-level factors, including experience of production shocks, contact with extension, membership to a group, nearness to market, access credit, and agroclimatic conditions, also contribute to farmers decisions to adopt new technologies (Abdulai & Huffman, 2014; Alene & Manyong, 2007; Tesfaye & Tirivayi, 2018). We hypothesized that households confronted more with production shocks, e.g., crop failure will look for information on IPHTs. We considered contact with extension and social networks (i.e., group membership, and neighborhood effects) as indicators of exposure to information. At the same time, nearness to market, access to credit, and bank and mobile money ownership would encourage IPHTs adoption by providing an incentive to produce for the market and easing liquidity barriers. More wealth and off-farm income facilitate IPHTs adoption (Sall et al., 2000).

3 Conceptual and empirical frameworks

3.1 Conceptual framework

Post-harvest losses shrink harvest volumes and degrade the quality of harvested products. As a result, households experience a direct reduction of the safe and nutritious food available to them. In the market space, the losses connote higher food prices or lost market opportunity for households who produce and sell to earn income. Improved post-harvest technologies can yield food security and welfare gains through several pathways. Direct benefits result from reduced losses in quantity and quality that can contribute to more food availability. Thus, technologies such as improved storage increase the available food stocks, stabilize the supply, and raise the marketable surpluses, contributing directly to food access and ability of households to settle financial obligations. The storage technologies allow farmers to choose the best time to sell their product and tap into higher prices during the lean season as grain prices are always lower at harvest than later. Technologies that reduce time and labor requirements in tedious and labor-intensive operations, e.g., mechanized shelling, potentially impact food security through positive time and labor adjustments enabling households to generate more food and income from additional on-farm or off-farm activities. Such adjustments can raise household welfare through increased and diversified expenditures while enhancing ability to cope with food supply and income disruptions.

3.2 Empirical framework

Given that we use cross-sectional data, estimating the impact of IPHTs on food security and welfare is not trivial. Some previous studies e.g., Becerril and Abdulai, (2010) and Gitonga et al. (2013) used propensity score-based methods such as propensity score matching (PSM) to estimate impacts of improved agricultural technologies on smallholder farmers' welfare. However, PSM only controls for observed characteristics and therefore may result in biased estimates if unobserved characteristics such as motivation, managerial capacity, and technical abilities of the farmers in understanding and using new technologies are not controlled for (Abdulai & Huffman, 2014).

To account for observed and unobserved characteristics, we use the ESRM (Lee, 1978). By modeling both selection and outcome equations, ESRM controls for factors that affect the treatment (adoption/non-adoption) while disentangling the factors influencing the outcomes between the adopters and non-adopters (Besley & Case, 2000). Previous empirical studies have employed this framework to study the impacts of agricultural technologies' adoption (Abdulai & Huffman, 2014; Asfaw et al., 2012; Khonje et al., 2018; Manda et al., 2019; Shiferaw et al., 2014; Tesfaye & Tirivayi, 2018; Tufa et al., 2019; Wossen et al., 2017).

3.3 Empirical specification

(a) ***Technology adoption decision***

A household's decision to adopt an IPHT is a case of constrained optimization. The household decides to adopt the IPHT when there is a positive difference between the marginal net benefits of adopting and not adopting the technology. Let P^* denote this difference so that $P^* > 0$ corresponds to the net benefit of adopting the technology exceeding that of not adopting, and it is under this condition, the farmer decides to adopt the technology. However, P^* is not observable; what is observed is P, which represents the observed behavior of the farmer regarding the adoption of the technology. Let P_i be a binary variable representing a farm household's adoption status for IPHT (MS or DT or AS), which take the value of 1 for households who decide to adopt and 0 otherwise. A household's decision to adopt the stated IPHT is represented by the latent variable framework below:

$$P_i^* = \alpha Z_i + \varepsilon_i \tag{1}$$

with

$$P_i = \begin{cases} 1, if\ P_i^* > 0 \\ 0, if\ P_i^* \leq 0 \end{cases} \tag{2}$$

where Eq. 1 represents a probit model of adoption of IPHT, α is a vector of parameters to be estimated, Z is a vector that represents characteristics (household, farm-level, system-level, and agroclimatic) that comprise decision determinants to adopt or not adopt the IPHT, and ε is the random error term with mean zero and variance σ_ε^2. The error term includes measurement error and factors not observed by the researcher but known to the farmer (Alene & Manyong, 2007).

(b) ***Impact evaluation***

Conditional on the IPHT adoption decision, we can observe the actual outcomes, which are a function of improved technology use alongside observed variables such as household characteristics, farm-level factors, system-level factors, agroclimatic conditions, and unobserved variables such as innate abilities and managerial capacity. The outcomes are represented by a switching regime as:

$$Regime\ 1: y_{1i} = \beta_1 x_{1i} + w_{1i}\ if\ P_i = 1 \tag{3a}$$

$$Regime\ 2: y_{2i} = \beta_2 x_{2i} + w_{2i}\ if\ P_i = 0 \tag{3b}$$

where y_{1i} and y_{2i} are the outcome variables for adopters and non-adopters of IPHT, respectively; x_{1i} and x_{2i} are vectors of explanatory variables assumed to be weakly exogenous; β_1 and β_2 are parameters to be estimated and w_{1i} and w_{2i} are error terms. The error terms in the selection Eq. (1) and outcome Eqs. (3a, 3b) are assumed to have a trivariate normal distribution with zero mean and covariance matrix such that:

$$cov(\varepsilon, w_1, w_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_{w1}^2 & . \\ \sigma_{\varepsilon 2} & . & \sigma_{w2}^2 \end{bmatrix} \tag{4}$$

where σ_ε^2= variance (ε), σ_{w1}^2= variance (w_1), σ_{w2}^2= variance (w_2), $\sigma_{\varepsilon 1}$= covariance (ε, w_1), and $\sigma_{\varepsilon 2}$= covariance (ε, w_2). Since y_1 and y_2 are not observable simultaneously, the covariance between w_1 and w_2 is not defined (Maddala, 1983). Also, since the error term of the selection function (Eq. 1) is correlated with the error terms of the outcome functions (Eqs. 3a and 3b), the expected values of w_1 and w_2 conditional on the sample selection are non-zero and can be defined as:

$$E\left(w_{1i}|P = 1\right) = \sigma_{\varepsilon 1}\frac{\theta\left(Z_i\alpha\right)}{\phi\left(Z_i\alpha\right)} \equiv \sigma_{\varepsilon 1}\lambda_1 \tag{5}$$

$$E\left(w_{2i}|P = 0\right) = \sigma_{\varepsilon 2}\frac{\theta\left(Z_i\alpha\right)}{1 - \phi\left(Z_i\alpha\right)} \equiv \sigma_{\varepsilon 2}\lambda_2 \tag{6}$$

where θ is the standard normal probability density function, ϕ is the standard normal cumulative density function. Equations (5) and (6) simplify to: $\lambda_{1i} = \frac{\theta(Z_i\alpha)}{\phi(Z_i\alpha)}$ and $\lambda_{2i} = \frac{\theta(Z_i\alpha)}{1-\phi(Z_i\alpha)}$, respectively, where λ_1 and λ_2 are the inverse mills ratio (selectivity terms) calculated from the selection equation and are included in the outcome equations to correct for selection bias in the endogenous (regime) switching regression model by substituting Eq. (5) and (6) in (3a) and (3b) as follows:

$$Regime\ 1: y_{1i} = \beta_1 x_{1i} + \sigma_{\varepsilon 1}\lambda_{1i}\ if\ P_i = 1 \tag{7a}$$

$$Regime\ 2: y_{2i} = \beta_2 x_{2i} + \sigma_{\varepsilon 2}\lambda_{2i}\ if\ P_i = 0 \tag{7b}$$

For the ERSM to be identified, there is a need to include at least one instrumental variable (IV) in the selection model

Table 1 Adoption of IPHTs by district

Variable	Babati ($N=68$)		Kilolo ($N=170$)		Kongwa ($N=137$)		Mbozi ($N=204$)		All ($N=579$)	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
DT	0.706	0.459	0.535	0.500	0.336	0.474	0.799	0.402	0.601	0.490
MS	0.824	0.384	0.435	0.497	0.277	0.449	0.794	0.405	0.570	0.496
AS	0.441	0.500	0.488	0.501	0.080	0.273	0.373	0.485	0.345	0.476

DT Drying tarpaulins; *MS* Mechanized shelling; *AS* Airtight storage

(Eq. 1). An IV should significantly affect the adoption of IPHT conditional on other covariates (relevance condition) and affect the outcome variables (MFI, HFIAS, FCE, TCE) only through adoption, but not directly (exclusion restriction). We used farmer's neighbor adoption decision (1 if neighbor adopted a particular IPHT and 0 otherwise) as an IV. While the selection of instrumental variables is empirically challenging, others, e.g., Adegbola and Gardebroek (2007), have stated that source of information is a vital element influencing the adoption of agricultural technologies. Such information may be transmitted through spatial relationships, especially when farmers closely rely on their friends and neighbors for improved farm practices (Tessema et al., 2016). A neighbor's adoption of IPHT is likely to be correlated with a household's adoption decision but not with food security and welfare outcomes. We checked whether our instrument correlated with the adoption status (relevance condition), and the reported results in Table 2 show that the instrument is relevant. Several previous studies used similar instruments, e.g., Abdulai and Huffman (2014) and Wossen et al. (2019).[2]

The outcome equations for adopters and non-adopters of the IPHTs were estimated using ordinary least squares (OLS) regression with selectivity correction. To estimate the impacts, we compared the observed and counterfactual scenarios of expected values of the outcomes for adopters. For an adopter of a named IPHT, the expected value of the outcome variable is expressed as:

$$E\{y_{1i}|P=1;x\}=\beta_1 x_{1i}+\sigma_{\varepsilon 1}\lambda_{1i} \tag{8a}$$

The expected values for the same farmer had he/she decided not to adopt the IPHT (counterfactual) is given as:

$$E\{y_{2i}|P=1;x\}=\beta_2 x_{1i}+\sigma_{\varepsilon 2}\lambda_{1i} \tag{8b}$$

Therefore, the impact of adoption on the outcome variables for those who adopted IPHT, i.e., the average treatment effect on the treated (*ATT*), is calculated as the difference between Eqs. (8a) and (8b):

$$\begin{aligned} ATT &= E\{y_{1i}|P=1;x\}-E\{y_{2i}|P=1,x\} \\ &= (\beta_1-\beta_2)x_{1i}+(\sigma_{\varepsilon 1}-\sigma_{\varepsilon 2})\lambda_{1i} \end{aligned} \tag{9}$$

4 Results and discussion

4.1 Descriptive statistics

Table 1 presents the means of the primary treatment variable, i.e., IPHTs (DT, MS and AS) adoption disaggregated by districts. The variable took a value of 1 if the household reported having used the IPHTs in the season preceding the survey, otherwise, 0. On average, about 60% and 57% of the survey respondents adopted DT and MS, respectively. The adoption of DT and MS superseded AS, possibly because the former have been promoted longer than the latter in Tanzania. Mbozi district had the highest DT adoption rate (80%) while Babati district recorded the highest MS adoption (82%). Overall, Kongwa district had the lowest adoption rates across the three IPHTs.

Descriptive statistics of the outcome and explanatory variables are presented in Appendix Table 4 (see Appendix). Adopters of the IPHTs had significantly fewer days of food insecurity and lower food insecurity (access) scores. They also had significantly higher food and total consumption expenditures. The adopters and non-adopters of the three technologies were distinguishable by household heads' education, ownership of bank/mobile money account, group membership, and neighbors' technology use status. Additionally, a higher proportion of the male-headed households used DT and MS than the female-headed ones. MS adopter households were also likely to be larger than the non-adopter households, possibly due to higher production linked to the availability of farm labor. Adopters of AS were more likely to have access to credit than non-adopters. In contrast, MS and DT adopters and non-adopters did not differ on credit access. DT and AS adopters were more likely to have contacted government extension than non-adopters. Contrastingly, the likelihood for such contact among MS adopters and non-adopters did not differ, suggesting a weaker public extension engagement on mechanization. Adopters of DT were likely to be located further away from the market than the non-adopters; a need

[2] Although the use of neighbour's adoption decisions as our identifying instrument is consistent with other previous studies and meets the required conditions of a valid instrument (e.g., relevance) there is still a possibility that the model may still not be properly identified; hence the results must be interpreted with caution.

Table 2 Endogenous switching regression estimates of the determinants of IPHTs' adoption

Variables	Technology		
	DT	MS	AS
Sex	0.120 (0.201)	0.032 (0.178)	-0.056 (0.191)
Age	-0.002 (0.006)	-0.004 (0.005)	0.005 (0.006)
Education	0.031 (0.030)	0.012 (0.022)	0.032 (0.026)
Household size	0.016 (0.028)	-0.023 (0.027)	0.003 (0.028)
Farm size	0.127** (0.043)	0.184** (0.061)	0.107** (0.041)
Off-farm income	-0.097 (0.150)	-0.133 (0.135)	0.241* (0.146)
Access to credit	-0.158 (0.240)	0.067 (0.210)	0.694*** (0.197)
Bank account	0.443** (0.214)	0.577** (0.208)	0.215 (0.176)
Mobile money account	0.012 (0.204)	0.354* (0.186)	0.538** (0.218)
Group membership	0.696*** (0.172)	0.150 (0.149)	0.355** (0.141)
Production shock	0.217 (0.218)	0.137 (0.201)	0.001 (0.206)
Value of owned assets	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)
Government extension	0.285 (0.247)	-0.095 (0.201)	0.244 (0.201)
Neighbor uses technology	2.145*** (0.204)	1.399*** (0.218)	1.053*** (0.148)
Distance to nearest village market	0.032 (0.024)	0.019 (0.019)	-0.004 (0.019)
Private transfers	0.061 (0.166)	-0.376** (0.155)	-0.018 (0.169)
Kilolo	-0.596** (0.235)	-0.986*** (0.232)	0.078 (0.211)
Kongwa	-1.019*** (0.250)	-1.523*** (0.245)	-0.888*** (0.249)
Mbozi	0.005 (0.240)	-0.075 (0.240)	-0.216 (0.212)
Constant	-2.035*** (0.556)	-0.865* (0.509)	-2.366*** (0.515)
Model diagnosis			
Observations	578	578	578
Wald χ2 (19)	*168.61****	*156.75****	*176****
Pseudo R-squared	*0.432*	*0.316*	*0.297*
Log likelihood	*-220.693*	*270.038*	*-261.963*

Robust standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

for improved storability to ensure sufficient stocks and less reliance on market purchases could motivate distantly located households to use the technology. Finally, non-adopters of MS were more likely to receive private transfers than the adopters, a distinction not seen with DT and AS—this could be linked to lower agricultural production of these households as they also were distinguishable as having less farmland.

4.2 Empirical results

4.2.1 Determinants of the adoption of improved post-harvest technologies

First stage ESRM results (Table 2) show that households with larger farms were more likely to adopt all three technologies. Farm size is related to production scale. High production is more profitable due to economies of scale and is likely to incentivize demand for IPHTs. The results are consistent with other studies (Abdulai & Huffman, 2014; Gitonga et al., 2013; Manda et al., 2016).

Off-farm income and access to credit increased the probability of AS adoption but not MS and DT. This observation might suggest that households accessed DT and MS more affordably; the two technologies were accessed mainly through local service providers. With this option, households could negotiate payment terms (e.g., payment-in-kind) and access the technology more easily than AS (hermetic bags and silos) that required prior settlement before acquisition. In addition, having a bank account or mobile money facility increased the likelihood of adopting the three technologies. These facilities bridged farmers with credit sources hence relaxing liquidity constraints. Mobile banking is particularly attractive for its convenience as a source of soft credit and reduces transaction costs (Nan et al., 2021). In recent years, mobile telephone messaging has also become a mode of extension, enabling farmers to receive technical information and basic financial services, which might have encouraged IPHT adoption.

Membership to a group increased the probability of adopting DT and AS. Group membership increases social networking and information flow regarding the benefits of new technologies (Abdulai & Huffman, 2014; Kassie et al., 2011). In Tanzania, farmer groups are important sources of credit and technology access. Some groups organize around the village-based community banking model. Others operate informal rotating savings and credit accounts and are platforms for farmer learning and consolidated inputs acquisition, which might encourage the adoption of technologies on a case-to-case basis (Sseguya et al., 2021).

Households that received private transfers were less likely to adopt the technologies, particularly MS. Private transfers are a component of the total household income. Households with elderly members or meagre farm resources (e.g., land) are more likely to receive such support from their next-of-kin working away from home. The elderly and poorly endowed households are less likely to engage in productive farming; hence, the transfers could only increase the budget allocation for necessities such as food (Maitra & Ray, 2003). Receiving transfers could also discourage technologies' adoption because of assured alternative food sources.

Neighbors' decision to adopt IPHTs correlated positively with households' use of the three IPHTs, suggesting vital signals regarding the technologies emanated from acquaintances. Abdulai and Huffman (2014) have termed neighbors as social network nodes that help clarify aspects of modern technologies; hence doubts diminish as farmers get to know more farmers in their vicinity who have adopted. Furthermore, farmers living near each other may emulate one another due to shared experiences and space-specific characteristics, including bio-physical and socio-economic conditions (Muthoni et al., 2017).

District dummies show that households in Kilolo and Kongwa were less likely to adopt the IPHTs than those in Babati. Production potentials of the different agricultural environments may explain this observation. Babati is a relatively higher crop production zone where humid/sub-humid conditions support maize production and various crops ranging from rice and cotton in the lower-lying plains to wheat and potatoes in the higher elevations. Farmers also keep livestock on a semi-intensive scale. Fairly similar (humid) agroclimatic conditions characterize Mbozi district. In contrast, Kongwa and parts of Kilolo are semi-arid zones with lower production potential — the maize-based systems in these districts integrate with lower-value crops, including drought-tolerant sorghum, millet, pigeon peas, groundnuts, and livestock on a pastoral scale. Our data also revealed wealth, dependency, and information access differences across the districts. The households in Babati were wealthier and less likely to receive transfers than those in Kilolo and Kongwa. Household members in Babati were also more likely to belong to farmer groups and receive extension services from development agencies.

4.2.2 Determinants of food security and welfare

Second stage ESRM results (Eqs. 7a and 7b) are presented in Table 3 (as well as Appendix Tables 5 and 6). Due to space limitations, only the ESRM estimates for DT (Table 3) are discussed. The significant positive coefficients on the sex of household head and value of assets among DT non-adopters show that female-headed and poorer households were likely to have lower consumption expenditures (TCE and FCE) than male-headed and wealthier households. Likewise, among the non-adopters, being older and more educated contributed positively to food access (proxied by HFIAS). Households whose heads were more educated also had higher food consumption expenditures. Conversely, household wealth, age, sex, and education of household heads were not key factors in explaining food security and welfare impacts among the adopters. This observation might suggest that using the technology produced social balancing effects. In the same vein, among the adopters and non-adopters alike, larger households were likelier to experience more days of food insecurity (proxied by MFI). However, the non-adopters were further likely to experience diminished food access and lower food consumption expenditures, thus severer food insecurity.

Having a large farm contributed positively to food availability and total consumption expenditure among DT adopters. The marginal impact of DT use on food security and welfare was thus greater among the larger producers, potentially due to economies of scale. Kotu et al. (2019) reported similar scale-dependency of farm-level technology benefits, specifically the profitability of AS bags and metal silos. On the contrary, having off-farm income decreased food access and total consumption expenditure among the non-adopters. According to Wozniak (1984), involvement in off-farm activities may restrict decision-making in farm activities leading to low farm productivity. Moreover, farmers engaging in off-farm income-generating activities may simply be doing so to shield against the effects of low farm production (Abdulai & Huffman, 2014). This explanation is sound considering that the non-adopters owned averagely smaller farms and were more likely to have liquidity constraints (see Fig. 1). The bank account and mobile money coefficients indicate that the two variables enhanced food availability, food access, and consumption expenditures among DT adopters and non-adopters. Among the non-adopters, these facilities might have encouraged remittances that smoothen income flows hence food availability and access through purchases in times of shortage (Nan et al., 2021). Bank/mobile money facilities potentially relaxed liquidity constraints and reduced transaction costs among the adopters, enhancing the technology's contribution to food availability and access.

Belonging to a group contributed positively to food security and welfare among DT adopters. The negative coefficients on MFI and HFIAS suggest that this factor improved food availability and access. These impacts are attributable to network effects that simplify technology access and use. The positive coefficient of group membership on the adopters' TCE further implies that social networks expanded incomes. Other authors averred that social networks reduced costs associated with adopting new technologies and enabled farmers to market their products (Abdulai & Huffman, 2014). Longer distances to the market generally diminished food access among households. Furthermore, DT adopters located further away had lower food consumption expenditures signaling reduced purchases potentially due to better storability of their food stocks.

Private transfers correlated negatively with food access among DT adopters and non-adopters. This observation is intriguing, although others (Lentz et al., 2005) have argued that receiving aid can adversely affect the recipient's behavior and discourage self-assurance investments as alternative food/income sources exist. Contact with public extension services

Table 3 DT endogenous switching regression estimates for the determinants of food security and welfare

Variables	MFI		HFIAS		FCE (TZS '000)		TCE (TZS '000)	
	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter
Sex	0.012 (0.461)	0.685 (0.489)	-0.784 (0.674)	-0.538 (0.737)	6734.074 (23846.008)	24991.912* (14755.717)	9018.781 (27095.077)	40584.726** (19087.153)
Age	0.009 (0.016)	0.010 (0.018)	0.015 (0.015)	-0.043* (0.026)	-530.919 (428.712)	846.157 (528.211)	218.367 (919.570)	-111.540 (690.749)
Education	-0.110 (0.079)	-0.033 (0.043)	-0.107 (0.087)	-0.180* (0.105)	-1119.878 (3227.598)	6534.852** (2404.620)	14970.692 (11060.004)	1205.763 (3840.317)
Household size	0.128* (0.073)	0.299** (0.107)	0.076 (0.086)	0.237** (0.102)	1408.545 (1735.431)	-5273.874** (2038.203)	6610.824* (3981.416)	-6666.380 (5160.428)
Farm size	-0.176** (0.068)	-0.084 (0.126)	-0.130 (0.085)	-0.162 (0.209)	2371.410 (3273.993)	1796.580 (3652.243)	20901.652** (7770.121)	18276.298 (11918.204)
Off-farm income	-0.230 (0.341)	0.763 (0.501)	0.507 (0.408)	2.526*** (0.636)	-7210.906 (11637.684)	-19320.389 (22606.154)	39,946.868* (20711.402)	10298.046 (28865.116)
Access to credit	0.372 (0.574)	-0.516 (0.821)	-0.654 (0.582)	0.741 (1.291)	-8953.345 (16982.461)	-14978.271 (19352.088)	-14499.760 (28070.815)	-4436.830 (24414.751)
Bank account	-0.784** (0.363)	-1.616** (0.808)	-0.565 (0.432)	-1.881* (0.999)	50039.215** (17505.125)	13325.444 (19279.085)	91043.733** (37097.517)	68953.922** (27807.108)
Mobile money	-0.471 (0.703)	-2.059*** (0.560)	-0.267 (0.657)	-1.774** (0.842)	19186.951 (12674.010)	33405.830** (10246.004)	29332.119* (17717.800)	57142.275*** (15902.254)
Group membership	-0.696* (0.407)	-1.185 (0.756)	0.253 (0.431)	-2.266** (0.680)	18221.683 (13001.200)	29259.643 (32431.730)	46649.212* (24845.285)	46540.561 (35001.912)
Production shock	0.840* (0.465)	2.144*** (0.560)	0.818** (0.401)	1.851** (0.615)	-15475.728 (22106.572)	-47887.139 (34666.926)	-8197.412 (29538.096)	13951.680 (34149.214)
Value of assets	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)
Distance to nearest village market	-0.008 (0.043)	0.034 (0.097)	0.102* (0.066)	0.256* (0.143)	-2130.157** (1054.812)	2867.438 (1938.739)	-2958.572 (1847.671)	1258.159 (2736.850)
Private transfers	-0.248 (0.406)	-0.216 (0.547)	1.008* (0.547)	2.066** (0.666)	2032.246 (12631.760)	11650.424 (20103.814)	-7834.990 (20150.878)	-60.584 (21896.502)
Government extension	-0.321 (0.419)	-0.766 (0.895)	1.512** (0.556)	-0.423 (0.952)	-2329.523 (11301.624)	2631.017 (15620.683)	-22,474.169 (20554.806)	6744.085 (23487.381)
Mbozi	0.607 (0.614)	1.424* (0.836)	0.324 (0.563)	0.575 (1.070)	-24602.656 (20502.381)	-50909.470 (51365.888)	-50991.789 (32122.010)	-84125.841 (54322.792)
Kilolo	-0.074 (0.541)	2.458*** (0.731)	-0.045 (0.552)	0.700 (0.892)	10008.377 (23681.540)	-56583.467 (53020.156)	32989.517 (46981.863)	-93868.678* (53855.266)
Kongwa	0.332 (0.592)	3.797*** (0.719)	0.050 (0.763)	1.336 (0.835)	10490.688 (27088.580)	-27433.241 (50829.892)	-21403.681 (35368.231)	-67594.242 (54094.005)
Mills1	-0.131 (0.400)		0.495 (0.672)		-11165.770 (11658.837)		-30774.407 (21175.925)	
Mills2		-2.158*** (0.488)		-1.847** (0.616)		12447.941 (12826.524)		43337.539** (17994.214)
Constant	1.487 (1.385)	-3.679** (1.676)	0.915 (1.611)	1.780 (1.985)	97419.866* (51708.141)	52399.036 (43773.146)	-82173.904 (124308.191)	97594.446 (68936.522)
Observations	348	230	348	230	296	195	348	230

Robust standard errors in parentheses; * *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01

appeared to dampen the food access impact among DT adopters, which might mirror the scope of the extension services provided. Location fixed effects were significant determinants of food security and incomes among DT non-adopters; those in Kongwa, Kilolo, and Mbozi were more food insecure than the non-adopters in Babati. Additionally, DT non-adopters in Kilolo had significantly lower TCE. These differences across locations with different farming potentials did not occur among the adopter households. Results in Appendix Tables 5 and 6 (ESRM estimates for MS and AS) can be interpreted similarly.

An interesting finding in Table 3, Appendix Tables 5, and 6 is the significance level of the coefficient estimates on the variables Mills1 and Mills2. These are the inverse mills ratios used to correct for selection bias as indicated in Eq. 5

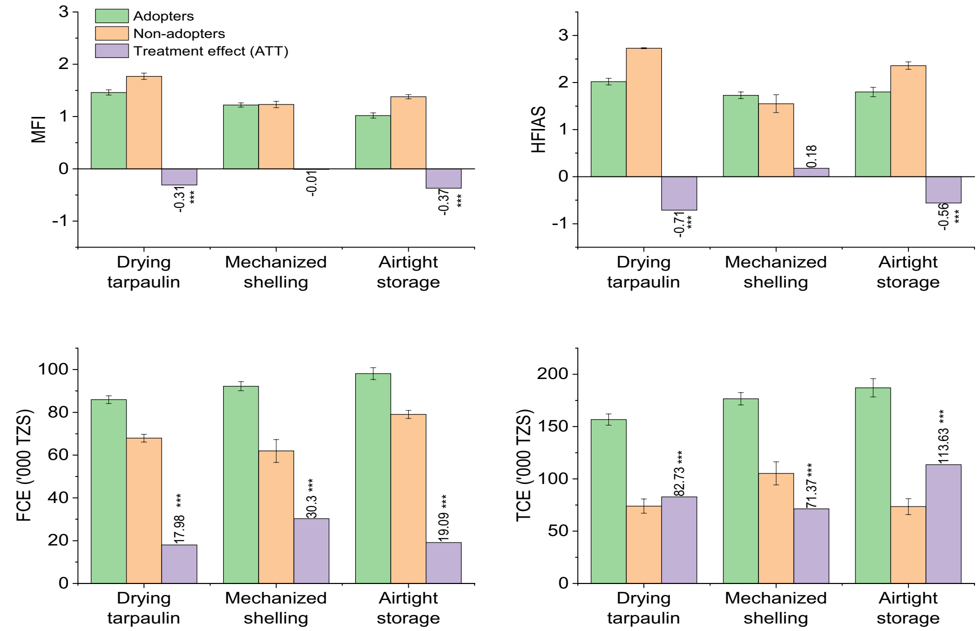

Fig. 1 Endogenous switching regression treatment effects on adopters of improved post-harvest technologies. MFI: months of food insecurity; HFIAS: household food insecurity access scale; FCE: monthly food consumption expenditure per capita; TCE: monthly total consumption expenditure per capita. *** $p < 0.01$

and Eq. 6. We reject the null hypothesis of no sample selection as some of the coefficient estimates for the inverse Mills are significant, implying that there is a selectivity problem, and one should not rely on OLS which ignores this problem.

4.3 Impacts of adoption on food security and welfare of households

Figure 1 shows the average effects of IPHT adoption on the various outcome variables. Unlike the mean outcome differences presented in Appendix Table 4, which may confound the impact of adoption with the influence of other characteristics, the ESR estimates reveal causal effects. The results show that DT use had significant causal effects on all outcome indicators. The technology decreased MFI by 0.31 months, representing an 18% increase in the duration of food availability. On average, adopters of DT would have spent about ten full days per year without three meals had they not used such technologies. The technology also decreased HFIAS by 0.7 units, representing a 26% gain on the food access scale. DT also significantly increased consumption: adopter households would have forfeited US$ 7.82 and US$35.96 on food and total consumption expenditures, respectively, had they chosen not to use the technology.[3] These consumption expenditure gains (food: 26%, total: 112%) could be attributable to improved grain storability and better marketable quality. More food expenditure might mean that households can access diverse foods, including commodities they did not produce.

The adoption of MS had causal effects on consumption expenditures. The monthly food consumption expenditure per capita among adopters of MS increased by TZS 30,297 (US$ 13.17), and the total consumption expenditure increased by TZS 71,367 (US$ 30.03), representing 49% and 68% gains compared to the counterfactual situation. The increase in consumption expenditures is potentially the result of savings on labor costs and income generation from productive utilization of freed time. Contrary to expectation, MS had statistically insignificant impacts on MFI and HFIAS. It is important to note that the main impact pathway through which MS is expected to affect the food security and welfare outcomes is freeing up labor and labor cost savings. This collaborates the positive and significant MS impacts on food consumption and total consumption expenditure. Our results agree with Daum et al. (2020), who reported a perceived increase in financial security and income as farm mechanization's main positive socio-economic effect. With MS, households would have had more time for off-farm activities to generate extra income to buy more food and pay for various non-food expenditures.

AS use had significant causal effects on all four indicators. Food insecurity (MFI) decreased by at least 11 days representing a 27% gain in the duration of food availability, while food access (HFIAS) improved by 24%. The results agree closely with others. Using propensity score matching, Gitonga et al. (2013) reported that metal silo adopters in Kenya reduced the duration of food insecurity by at least one month, Chegere et al. (2020) observed a 31% reduction in HFIAS among hermetic bag adopters in Tanzania. Our results further show significant increases in food (24%) and total (115%) consumption

[3] The average exchange rate during the survey was 1US$ = TZS 2298: See https://www.bot.go.tz/ExchangeRate/previous_rates?__RequestVerificationToken=LqNNWkdv-vmpeOKb4CTlrn6olCj_n5SCxMbuX8zj1Dvc3-Fnd92_BcCZ76-btb2CMZk1mUMAGv38hkpy2N3XgYHRcDdmH_LS5kiesd3WjhU1&exchangeDate=08%2F11%2F2020

expenditures; the AS adopters would have lost US$ 8.26, and US$ 49.40 in food and total consumption expenditures per capita had they decided not to use the technology. Thus, AS enabled households to have a stable supply of own-produced food and higher incomes from temporal arbitrage, avoided losses, and possibly lower storage costs. Earlier investigations in the study area found the mean per capita economic impact of using AS bags to be US$ 5–14 from both arbitrage (82%) and loss abatement effects (18%) (Kotu et al., 2019). Other authors (e.g. Omotilewa et al., 2018; Ricker-Gilbert & Jones, 2015) reported that effective reduction of storage losses improved productivity by incentivizing farmers to invest in yield-increasing technologies that could contribute to the increased incomes and welfare of households.

Increasing incomes can change consumption patterns. Our results suggest that with the adoption of the technologies, the incomes of households increased, which likewise increased the expenditure on food while expenditure on other items increased even more. The share of household expenditure on food (FCE: TCE ratio) declined by 40%, 11%, and 51% (from 0.92 to 0.55; 0.59 to 0.52; 1.07 to 0.52) among DT, MS, and AS adopters, respectively compared to the counterfactual situation. These declines signaled reduction in households' vulnerability. Smith and Subandoro (2007) categorized households spending > 75% of their total incomes on food as being highly vulnerable and food insecure, and those spending < 50% as having low food insecurity.

5 Conclusions and policy implications

Tanzania's Agricultural Sector Development Program II: 2017/18–2027/28 (GoT, 2017) prioritizes post-harvest management through promotion and dissemination technologies that encourage better handling and storage of food to achieve food security and improved livelihoods in line with the United Nations Sustainable Development Goals (UN, 2015). This study examined the factors that influence the adoption of farm-level post-harvest technologies and their impacts on households' food security and welfare in Tanzania. The findings revealed marked differences in the adoption determinants of IPHTs. Generally, large farms, locations in higher potential zones, and neighbor's use are universal adoption drivers. These observations have implications for policy guidelines leaning towards increased productivity in farms and learning among farmers to increase adoption of the technologies for the targeted benefits. Farm size and potential are related to production scale. Since expanding farmland for food production is unsustainable, options that involve the use of more efficient technologies and management practices should be encouraged. The fact that neighbor's use encouraged the adoption of the three technologies underscores the importance of neighborhood effects. To this end, stronger integration of progressive farmers to lead promotional programs can speed up the adoption of the IPHTs. The positive influence of group membership on the adoption of DT and AS further points to the importance of strengthening farmer associations as avenues for enhancing adoption.

Limited access to capital and financing options remain significant challenges to agricultural technologies' adoption among rural farmers (Balana et al., 2020). Access to credit and off-farm income were especially unique determinants for AS adoption because, unlike MS and DT, the acquisition was not open to negotiated arrangements. Engaging in off-farm employment is a strategy for stabilizing household income and supporting agricultural investments (Anang et al., 2020). Other studies have observed that policies to promote the adoption of rural technologies should include mechanisms for breaking barriers to financial services' access. Concerning formal credit, the traditional focus has been addressing supply-side factors, e.g., improving proximity to credit sources and reducing the cost of borrowing. Balana et al. (2020) have found that demand-side factors such as financial illiteracy and fear of risk (e.g., due to market failure — economic benefits are particularly key as borrowers need enhanced returns to repay) are equally responsible for low agricultural credit use in Tanzania hence polices should focus addressing demand-side constraints as well. Opportunities to increase off-farm income in the rural areas include service provision, value addition, and trade. The decision to engage in off-farm labor market is subject to individual and household characteristics such as the ability to supply off-farm labor. Given the low education levels of farmers in the present study areas, relevant policies would include human capacity development (education) for off-farm labor market participation. However, as already discussed, off-farm engagements can adversely affect decision-making in farm activities, and hence the appropriate models should be found.

The three technologies positively impacted households' food security and welfare. A synthesis of the associations between the impacts and various household- and farm-level variables shows distinctive trends across adopter and non-adopter households, pointing to potential system-level impacts. With MS, impacts among adopters are driven more by productive factors: production scale (farm size) and investment support factors (access to credit and off-farm incomes). However, among the non-adopters, impacts appear to be driven by factors that simplify social support, including bank account/mobile money ownership and group membership that also expedite social transfers. The impacts of DT and AS among the adopters, unlike the non-adopters, were not driven by socio-demographic (sex, age, education, household size) and locational factors. Therefore, adopting the technologies could enhance social equity and reduce spatial disparities brought about by agroclimatic factors. Further studies should investigate system-level impacts in detail. These include the general equilibrium impacts such as how the interventions affect non-adopting farm households or the welfare of value chain actors downstream, including consumers who are not producers. Moreover, there is a need to unravel the intrahousehold distribution of the benefits, which we did not achieve in this study due to data constraints.

Appendix

Table 4
Table 5
Table 6

Table 4 Description of outcome and explanatory variables by the adoption of IPHTs

Variable	Definition	DT		MS		AS	
		Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Outcome variables							
MFI	Frequency of household food insecurity (number of months)	1.463	2.558***	1.218	2.803***	1.015	2.367***
HFIAS	Household food insecurity access scale (Number)	2.02	3.208***	1.730	3.506***	1.800	2.860***
FCE	Per capita monthly food consumption expenditure (TZS '000)	87	66**	94	60***	100	67***
TCE	Per capita total household consumption expenditure (TZS '000)	156	104**	177	82***	187	109***
Independent variables							
Sex	Sex of the hh 1 = male; 0 otherwise	0.876	0.758***	0.870	0.775**	0.850	0.818
Age	Age of the household in years	47.936	48.454	47.642	48.454	49.035	47.441
Education	Education of hh head (formal years)	6.911	5.656***	6.821	5.867***	7.085	6.056***
Household size	Number of household members	5.796	5.489	5.909	5.361*	5.755	5.630
Farm size	Total land holding in hectares	1.966	1.507**	2.093	1.371***	2.036	1.650**
Off-farm income	1 if has an off-farm income activity; 0 otherwise	0.443	0.481	0.415	0.514	0.485	0.443
Access to credit	1 if has access to credit; 0 otherwise	0.141	0.108	0.133	0.121	0.250	0.063***
Bank account	1 if a household member own a saving account; 0 otherwise	0.264	0.074***	0.282	0.064***	0.300	0.129***
Mobile money	1 if a household member has a mobile money account; 0 otherwise	0.897	0.792***	0.903	0.791***	0.935	0.813***
Group membership	1 if a household member belongs to a group; 0 otherwise	0.454	0.191***	0.397	0.285**	0.535	0.251***
Production shock	1 if household reported; 0 otherwise	0.897	0.879	0.894	0.884	0.890	0.889
Asset value	Value of assets at current price (TZS '000)	6528.126	4512.173	5028.399	6654.097	6326.630	5408.100
Distance to nearest village market	Distance to nearest village market in kilometres	2.821	2.299*	2.730	2.459	2.815	2.507
Private transfers	1 if the household receives; 0 otherwise	0.189	0.255	0.149	0.305***	0.195	0.227
Contact with government extension	1 if had contact; 0 otherwise	0.175	0.069***	0.146	0.117	0.170	0.114**
Neighbour uses technology	1 if a neighbour uses; 0 otherwise	0.968	0.429***	0.964	0.711***	0.870	0.377**

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ indicate significant difference between adopters and non-adopters

Table 5 MS endogenous switching regression estimates for the determinants of food security and welfare

Variables	MFI		HFIAS		FCE (TZS '000)		TCE (TZS '000)	
	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter
Sex	0.141 (0.295)	0.901 (0.550)	-0.371 (0.538)	-0.669 (0.762)	26167.701 (16957.221)	4175.363 (17943.780)	38074.223 (29872.025)	12475.186 (17101.721)
Age	0.009 (0.017)	0.016 (0.017)	0.022 (0.014)	-0.029 (0.024)	-457.669 (472.192)	748.044 (471.449)	-420.017 (1166.740)	530.695 (412.648)
Education	0.003 (0.075)	-0.042 (0.048)	-0.093 (0.071)	-0.153 (0.102)	1968.519 (1842.294)	768.694 (3423.519)	12021.243 (11338.423)	-309.586 (1696.918)
Household size	0.147* (0.083)	0.266** (0.096)	0.231** (0.076)	-0.016 (0.116)	-1140.717 (2005.440)	-1161.703 (1530.575)	-1131.846 (5430.389)	2477.632 (1841.400)
Farm size	-0.109 (0.077)	-0.146 (0.162)	-0.191** (0.076)	-0.099 (0.211)	1292.420 (2319.289)	-797.332 (2968.276)	20801.810** (7696.863)	378.564 (3357.587)
Off-farm income	-0.614** (0.296)	1.080** (0.519)	0.620* (0.344)	2.026** (0.695)	-18,198.983 (13376.635)	3833.488 (13473.084)	36039.499 (22860.396)	20113.808 (13510.630)
Access to credit	0.027 (0.556)	-0.160 (0.784)	-0.884* (0.487)	0.010 (1.126)	-8232.560 (16289.523)	4075.210 (11253.831)	-47085.610 (35608.118)	24376.809* (12969.962)
Bank account	-0.581 (0.406)	-2.373*** (0.640)	-0.256 (0.489)	-2.666** (0.875)	12361.118 (14399.574)	51254.545 (57119.200)	33683.070 (47400.468)	72660.739 (49780.695)
Mobile money	0.106 (0.571)	-1.844** (0.674)	0.341 (0.459)	-1.611* (0.863)	12312.749 (13221.529)	26622.071* (15764.165)	42240.471 (25689.130)	31806.735** (13403.157)
Group membership	-0.206 (0.418)	-1.477** (0.584)	-0.097 (0.400)	-1.157** (0.581)	31546.518** (15306.444)	-6934.896 (11692.897)	68879.007** (28560.342)	1538.970 (12722.652)
Production shock	0.670 (0.456)	2.240*** (0.546)	0.443 (0.421)	2.334*** (0.565)	-16698.010 (20088.781)	-60600.217 (38020.431)	-2392.562 (30605.431)	-18763.594 (27945.691)
Value of assets	-0.000 (0.000)	0.000 (0.000)	-0.000** (0.000)	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	0.002 (0.002)	0.000* (0.000)
Distance to nearest village market	-0.045 (0.043)	0.067 (0.086)	0.055 (0.071)	0.207 (0.128)	-2823.766** (1408.308)	-715.879 (1931.467)	-2951.933 (2230.542)	-1761.395 (1481.743)
Private transfers	-0.429 (0.346)	-0.479 (0.558)	1.262** (0.563)	1.650** (0.677)	36049.983 (25421.012)	-6801.766 (13904.579)	25430.723 (29936.325)	1789.941 (14111.540)
Government extension	0.262 (0.501)	-0.800 (0.720)	1.814** (0.596)	0.355 (0.711)	4684.495 (13267.977)	198.304 (13775.578)	-14176.113 (20672.203)	8666.662 (15331.835)
Mbozi	0.505 (0.565)	1.629 (1.161)	0.073 (0.499)	0.191 (1.495)	-33485.484 (23481.230)	4175.709 (18892.326)	-48498.601 (33597.299)	-33498.376* (20074.492)
Kilolo	-0.030 (0.592)	1.832 (1.128)	-0.080 (0.617)	0.688 (1.602)	14286.950 (25304.445)	27,228.589 (19,890.056)	80857.902 (61814.126)	-2838.061 (22587.661)
Kongwa	0.710 (0.680)	2.793** (1.315)	0.509 (0.889)	1.476 (1.815)	70427.088** (34622.894)	32,581.015* (19,102.208)	142758.096 (97376.613)	10687.750 (23427.191)
Mills1	-0.002 (0.530)		-0.788 (0.807)		-75585.026** (23478.707)		-136777.784** (68243.557)	
Mills2		-1.098 (0.854)		-1.202 (1.055)		-8937.572 (13580.134)		-17529.681 (16349.676)
Constant	-0.311 (1.302)	-2.850 (1.916)	-0.109 (1.286)	2.551 (2.439)	114458.591** (46187.478)	27943.566 (35301.651)	11835.469 (130550.831)	1498.313 (41536.016)
Observations	330	248	330	248	284	207	330	248

Robust standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6 AS endogenous switching regression estimates for the determinants of food security and welfare

Variables	MFI		HFIAS		FCE (TZS ‘000)		TCE (TZS ‘000)	
	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter
Sex	-0.197 (0.435)	0.790* (0.452)	-0.309 (0.569)	-0.804 (0.663)	2613.803 (31357.963)	21785.477** (9454.760)	7735.372 (45265.319)	35129.733* (17972.756)
Age	-0.001 (0.022)	0.022 (0.015)	-0.001 (0.018)	-0.010 (0.019)	-126.735 (631.874)	7.129 (407.313)	2001.348 (1702.772)	-883.608 (567.027)
Education	-0.103 (0.104)	-0.016 (0.048)	-0.104 (0.085)	-0.173* (0.094)	-776.980 (4901.367)	1692.312 (1491.640)	23003.907 (17487.521)	-1607.958 (3389.166)
Household size	0.073 (0.082)	0.255** (0.082)	-0.021 (0.078)	0.191* (0.099)	564.370 (3057.854)	-1969.875 (1506.903)	-2280.894 (7756.343)	1567.719 (3904.930)
Farm size	0.005 (0.107)	-0.211** (0.097)	-0.239** (0.086)	-0.127 (0.124)	2985.433 (5026.657)	1072.088 (2208.876)	28080.212** (9598.489)	13129.576* (7546.010)
Off-farm income	-0.495 (0.404)	0.701* (0.411)	0.566 (0.441)	1.743** (0.531)	-22007.993 (24465.767)	-10540.074 (8146.680)	22351.962 (29646.299)	20651.977 (18718.611)
Access to credit	0.015 (0.701)	0.379 (0.749)	-0.484 (0.713)	-0.186 (1.084)	-35368.597 (24027.519)	-5494.206 (13257.694)	-120388.540** (52676.038)	30583.500 (33955.644)
Bank account	-0.062 (0.446)	-1.710*** (0.494)	-0.482 (0.472)	-0.907 (0.672)	51199.213 (31700.997)	26115.132* (14415.022)	42683.669 (71951.742)	78429.921** (25511.054)
Mobile money account	-0.674 (0.847)	-1.119** (0.554)	-0.398 (1.080)	-1.144* (0.668)	14955.063 (26442.397)	10913.471 (10372.608)	6212.569 (34916.363)	22479.012* (13317.700)
Group membership	-0.439 (0.538)	-0.673 (0.487)	-0.309 (0.444)	-0.928* (0.528)	39641.939** (15741.039)	-5862.158 (10909.288)	84936.721** (34309.228)	-3510.791 (15838.674)
Production shock	1.122** (0.397)	1.560*** (0.431)	0.728 (0.550)	1.655*** (0.435)	1341.392 (34578.470)	-46777.795* (24102.567)	-28562.545 (42646.018)	17737.985 (25693.413)
Value of assets	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000* (0.000)
Distance to nearest village market	-0.007 (0.044)	0.002 (0.060)	0.133* (0.068)	0.136* (0.099)	-3716.858* (2177.252)	-666.648 (1134.276)	-5862.443* (3509.837)	-1888.267 (1813.330)
Private transfers	-0.144 (0.476)	-0.366 (0.426)	1.398** (0.613)	1.324** (0.562)	14522.821 (36571.063)	3466.057 (8466.529)	-53020.844 (52319.364)	2343.728 (13426.508)
Government extension	0.819 (0.668)	-0.935** (0.472)	1.583** (0.619)	0.816 (0.672)	1090.401 (17693.508)	-8192.654 (10298.706)	-11236.675 (27867.308)	-31572.218* (16093.586)
Mbozi	0.163 (0.616)	1.610** (0.754)	-0.769 (0.604)	1.006 (0.743)	-23400.568 (34919.182)	-32741.022 (24874.514)	-36563.017 (48546.497)	-71480.336** (33177.510)
Kilolo	0.436 (0.727)	1.321* (0.700)	-0.816 (0.651)	0.817 (0.773)	16785.480 (39434.503)	-42140.683 (28,226.778)	51083.975 (58575.294)	-80879.692** (33330.601)
Kongwa	1.228 (0.995)	2.151** (0.766)	1.311 (1.284)	1.304* (0.766)	14742.520 (44985.649)	1796.657 (23904.543)	34114.547 (60327.818)	-26414.061 (33093.080)
Mills1	-0.211 (0.760)		-0.482 (0.847)		-9064.296 (29969.907)		-78626.762 (48652.452)	
Mills2		-0.154 (0.780)		-1.102 (0.979)		-31680.898 (21595.451)		-71137.694** (29420.647)
Constant	1.428 (2.181)	-2.172 (1.448)	3.355 (2.224)	1.082 (1.684)	80086.740 (82789.458)	93799.841** (42112.670)	-68455.183 (153090.696)	77698.706 (62771.281)
Observations	200	378	200	378	182	309	200	378

Robust standard errors in parentheses; * *p < 0.10, ** p < 0.05, *** p < 0.01*

Data Availability The data is available at: https://dataverse.harvard.edu/dataverse/AfricaRISING.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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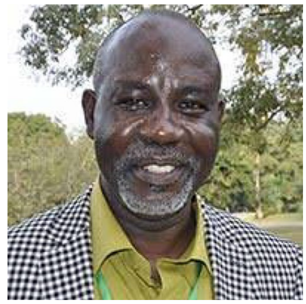

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