Developing Country Studies
ISSN 2224-607X (Paper) ISSN 2225-0565 (Online)
Vol.16, No.1, 2026

Effect of Appropriate Agricultural Mechanization on Smallholder Farmers' Household Incomes in Uganda

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This study was privately sponsored under the College of Agricultural and Environmental Sciences Research Ethics Committee grant number CAES-REC-2025-113.

Abstract

Appropriate agricultural technologies are essential in facilitating smallholder farmers with regard to implementation of sustainable intensification. These practices such as conservation agriculture, precision agriculture in the application of seeds, fertilizer and water thus contributing greatly to increased efficiency and timeliness in operations. This would translate into reduced acute labor shortages and high production costs among smallholder rural farmers. This in addition creates jobs, result into production of more food, improve nutrition and boost rural incomes. There is limited knowledge on how use of appropriate agricultural mechanization affects incomes of smallholder farmers. This study ought to show the drivers of access and use of appropriate agricultural mechanization, impact of using appropriate agricultural mechanization on incomes and drivers of these impacts using an endogenous switching regression model. Results show that region, marital status, access to credit, land ownership and access to extension influence farmers use of appropriate agricultural mechanization technologies. Use of appropriate agricultural mechanization by smallholder farmers was found to impact total farm income. This means that access and use of appropriate agricultural technologies is essential for poverty reduction among smallholder farmers. To achieve better results, farmer location specifics and their socio-economic characteristics such as marital status, land ownership, credit access, access to extension and level of education should be put into consideration. Development and promotion of appropriate agricultural mechanization results into poverty reduction and should be promoted and emphasized. Extension should focus on strategic opportunities such as appropriate mechanization. There is need to reach as many farmers as possible through groups and financial institutions.

Keywords: Appropriate Agricultural Mechanization, Smallholder farmers, Endogenous Switching Regression, Income

DOI: 10.7176/DCS/16-1-03

Publication date: February 28th 2026

1. Introduction

Agriculture is one of the five strategic sectors that have been identified to fast truck transformation of Uganda's economy from low to middle income status (NDPIII, 2021; MAAIF, 2020). However, the sector is faced with low production and productivity in developing countries especially in Sub-Saharan Africa which is mostly attributed to limited application of science and technology (Gebiso *et al*. 2023; Paudel *et al*., 2022; Özpinar & Anıl, 2018). Appropriate agricultural technologies are essential in facilitating smallholder farmers with regard to implementation of sustainable intensification practices such as conservation agriculture, precision agriculture in the application of seeds, fertilizer and water thus contributing greatly to increased efficiency and timeliness in operations (Paudel *et al*., 2022; Özpinar & Anıl, 2018; Mrema *et al*., 2018; Kienzle & Sims, 2014). As a result, increased use of appropriate agricultural mechanization would reverse the low land and labour productivity which are primarily a consequence of insufficient power availability for agricultural production together with low levels of agricultural mechanization (Paudel *et al*., 2022; Özpinar & Anıl, 2018).

This is in addition to increased capacity to manage large acreages thus promoting commercial production, creating viable employment opportunities for rural youth and women as service providers and market actors along the value chain and contributing to the achievement of the United Nations Sustainable Development Goals (SDGs) of zero hunger (SDG2) and no poverty (SDG1) (Gebiso *et al*. 2023; Paudel *et al*., 2022; Özpinar & Anıl, 2018). The agricultural mechanization policy seeks to promote access to and utilization of suitable farm equipment, enhancing farmer capacity and fostering a supportive environment for private sectors engagement

(MAAIF, 2020). As a result, policymakers have shifted their focus to promoting appropriate farm mechanization as a means of overcoming acute labor shortages and high production costs among smallholder rural farmers so as to create jobs, produce more food, improve nutrition and boost rural incomes (Gebiso *et al*. 2023; Paudel *et al*., 2022; Van Loon *et al*., 2020).

However, about 80% of agricultural operations among smallholder farmers in developing countries are performed by human beings (Goyal and Singh, 2020). This results into poor food supply since smallholder farmers produce about 80% of the of global crop and livestock products mainly for food and income thus contributing enormously to foreign exchange and food security of their respective economies (Sayed *et al*., 2022; Bold *et al*., 2021; Epule *et al*., 2017; Samberg *et al*., 2016). In addition, these smallholder farmers have been described as very vulnerable and struggling with challenges related to lack of appropriate agricultural mechanization, labor shortage, increased wages, climate change, and poor access to modern inputs, credit, and markets (Gebiso *et al*. 2023; Sayed *et al*., 2022; Özpinar & Anıl, 2018). There is therefore, a need for renewed efforts to interest smallholder farmers in Africa into use of appropriate agricultural mechanization for increased sustainable intensification practices to increase food production and the input use efficiency for better quality products and yields (Gebiso *et al*. 2023; Sayed *et al*., 2022).

In Uganda, Agricultural production is dominated by human labor-intensive technologies with about 90% of farmers still relying on use of human muscle powered tools and methods for all farming operations (Wanyama *et al*., 2016). Agricultural production using the current level of technology in Uganda is constrained to ensure food security and increase income for the rapidly growing population at about 3% annually (UBOS, 2022; MAAIF, 2020; Wanyama *et al*., 2016). There is need for increased investment in production enhancing, post-harvest handling and value addition agricultural labour-saving technologies for increased production, productivity, quality of produce and incomes among smallholder farmers in Uganda (Bold *et al*., 2021; Epule *et al*., 2017; Wanyama*et al*., 2016).

Agricultural Engineering and Appropriate Technology Research Institute Namalere (AEATRI) together with partners have developed and promoted a number of appropriate mechanization technologies for smallholder farmers (Wanyama *et al*., 2016: MAAIF, 2020). The objective has been to promote mechanization and reduce drudgery. These developed mechanization tools include; Animal drawn light weight plough, Power tiller drawn moldboard plough, Animal drawn ripper planter, Animal drawn inter-row weeder, Motorized rice thresher, motorized maize sheller, Wind powered pump system for water delivery, Low head hydraulic ram pump, Two-wheel tractors, Low-cost multipurpose tractor and the four-wheel tractors (Wanyama *et al*., 2016). These machines are designed with low-cost durable materials which makes them cheaper, easy to operate and use, easy access to spare parts and highly compatible with local conditions especially soils and topography (Epule *et al*., 2017; Wanyama *et al*., 2016).

These would result into potential on-farm responses from smallholder households which include diversifying income among multiple crops and non-farm sources (Aryal *et al*. 2019), changing the intensification of crops/varieties and livestock for improved profits (Daum, 2023; Peng *et al*., 2022), timeliness in farming operations thus improving quality of the products and better market access (Daum, 2023; Wanyama *et al*., 2016), improved soil tillage for improved soil and water conservation (Daum, 2023; Gebiso *et al*., 2023; Sayed *et al*., 2022; Özpinar & Anıl, 2018), and attracting women and youth into agricultural businesses (Kirui, 2019). If the sector is mechanized, it would increase its growth from the present 2.2%, its contribution to GDP which now stands at 24.1% and to the country's exports which also stands at 40% of total exports (Umali-Deininger, 2018; UBOS, 2022).

However, there is limited knowledge on how use of appropriate agricultural mechanization affects incomes of smallholder farmers. Such information is necessary for ensuring that farmers, development partners and policy makers promote a strategy that is cost-effective and thus can contribute to better incomes and reduced poverty. There is thus growing need for evidence that agricultural mechanization has an effect on household incomes. This study seeks to show the drivers of access and use of appropriate agricultural mechanization, impact of using appropriate agricultural mechanization on incomes and drivers of these impacts using an endogenous switching regression model.

2. Empirical Analysis of Related Literature

The debate on the effect of agricultural mechanization on agriculture started off with two main approaches. The first is production function approach that specifies a relationship between use of the technology and agricultural output, and uses this to simulate the impacts of using agricultural mechanization on the farm (Yang *et al*. 2020).

The theory on farm-level use of appropriate agricultural mechanization suggests that at each moment decision makers select appropriate agricultural mechanization with the best-expected net benefits, and thus, when a new technology is available, decision-makers continuously evaluate whether or not to use them; when the discounted expected benefits of use are greater than the cost, the technology is going to be used by farmers (Mendelsohn, 2012). This is where the literature prevailingly involves use of static expected utility portfolio model a framework of choice for most applied work in agricultural economics, where the main goal of a decision maker is to maximize his/her profits and, through that, utility (Zhao *et al*. 2014). Recent studies emphasize that adoption decisions are dynamic, shaped by evolving perceptions of risk, returns, and institutional support (Yang *et al*., 2023; Gebiso *et al*., 2023).

Economic theory thus suggests that use actions are efficient and thus desirable only if their benefits exceed their costs, and also that private uses are likely to be efficient because the benefits and cost accrue to the decision maker (Mendelsohn, 2012). Studying use has claimed to be central to the question of how much the estimated impact of an agricultural technology can be used to determine long-run effects of use of the technology (Yang *et al*. 2023; Hsiang 2016). The central questions here are how do, economic agents which are smallholder farmers perceive use of agricultural mechanization with respect to incomes that accrue from their use and how they adjust their expectations in response. A more realistic understanding of farmer decision making related to use of appropriate agricultural technologies could fast track commercialization of agriculture, food security and poverty alleviation through increased production and productivity (Gebiso *et al*. 2023; Ayele, 2022; Sayed *et al*., 2022; Özpinar & Anıl, 2018).

There is an expectation that use of appropriate agricultural mechanization improves efficiency of smallholder farmers in terms of timeliness and precision (Paudel *et al*., 2022). This results into better land and labour productivity together with better prices, incomes, food security and asset accumulation. We recognize the possibility of a bidirectional causality between appropriate agricultural mechanization use and farmer characteristics such as productivity and incomes. Therefore, smallholder farmers that use appropriate agricultural mechanization technologies will experience enhanced crop yields and crop sales and vice versa. Just like Mpuuga *et al*., (2023), smallholder farmers and the firm are interdependent, whereby appropriate agricultural mechanization technologies are purchased, and the produced agricultural outputs are sold in the markets thus making smallholder farmers both producers and consumers. Appropriate mechanization has consequently been proposed to improve on-farm efficiency, agricultural productivity and food security; hence, it has the potential for the structural transformation of rural economies, especially in areas where smallholder-based (<2 ha) farming systems are most common, out migration is most intense and mechanization is yet to hold (Mpuuga *et al*., 2023; Paudel *et al*., 2022; Adams & Jumpah, 2021). Technology greatly contributes to fostering sustainable improvements in the physical, social, and economic well-being of individuals and society (Mpuuga *et al*., 2023). In addition, Chavas and Nauges (2020) conclude that technology adoption leads to economic growth through improved food security and improved farm productivity.

Simoes *et al*. (2020) compared three adoption rates (slow, medium, and fast) via two groups of farm size (small and large) and revealed that depending on farm size and rates, technological adoption effects differ in the short and long term. Technology adoption is profitable since unit costs of production are lower with high-income shares for adopters. Similarly, Verkaart *et al*. (2017) found that technology adoption significantly increases household income thus, reducing poverty. While the adoption of a new technology favored all farm sizes, the impacts on income were greater with small farm size holders. The impact of technology adoption on the welfare of beneficiaries and the factors influencing adoption is well documented in the literature (Ayenew *et al*., 2020; Justice & Tobias, 2016; Kekonnen, 2017). In analyzing the potential impact of improved agricultural technologies on smallholder's crop productivity and welfare in Ethiopia, Kekonnen (2017) found a positive and significant effect of improved technology adoption on crop productivity and welfare of farmers. However, larger household size negatively affects the welfare of households and this tends to reduce the gains generated from technology adoption.

Previously, Amare *et al*. (2012) examined the causal impact of technology adoption on household welfare and reported that maize-pigeon pea adoption has a positive and significant impact on the income and consumption expenditures of households. Thus, farmers who adopt improved maize have about 30–33% higher income per capita compared to non-adopters. Maize and pigeon pea adopters have 15–22% higher consumption expenditures compared to non-adopters. Justice and Tobias (2016) observed significant increases in households' gross farm income (GH¢852.00) and consumption expenditures for innovative farmers in northern Ghana, which they attributed directly to the adoption of improved varieties of cereals. However, the positive productivity and income effects do not significantly translate into nutritious diets. Improvement in farmers' welfare is conditional on farmer participation in the output market (Awotide *et al*., 2016). This means that, beyond agricultural technology adoption, commercialization and access to output markets also impact farmers' welfare.

Teka and Lee (2020) analyzed the impact of participation in integrated farm package programmes on smallholder farmers' welfare in Ethiopia. The results revealed that household income, consumption expenditure and asset per capita of the households increased across the 3 years surveyed. Participated households had a positive significant impact on their consumption expenditures and calorie per adult equivalent but the income and asset per capita of the household although positive were not significant. Participants in the programme had a 37.8% increase in household expenditure per adult equivalent and a 45.3% change in calorie intake per adult equivalent. This shows the positive role of the programme in boosting welfare, improving food security, and reducing poverty. Family size, the total area cultivated, livestock holding, and level of package integration were some of the factors that determined welfare.

Similarly, Ayenew *et al*. (2020) observed that the adoption of improved maize and wheat has a positive and significant effect in enhancing farm households' welfare. Ogundar and Bolarinwa (2019) also observed a positive and significant effect of technology adoption on household welfare measures (nutrition and income) and indicators of farm production using the meta-analysis technique. However, the magnitude of the impact was relatively small (weak relationship). Ali and Awade (2019) observed that formal education and participation in extension programmes increases farmers' welfare. Increasing land cultivation and adopting intercropping techniques has a positive and significant impact on women's welfare.

In the study about farmer-led mechanization and its effect on smallholder productivity and incomes in Kenya and Uganda, access and use of appropriate agricultural mechanization especially through community-based access like cooperative machinery schemes have been found to results into significant increase in crop yield and income, especially for maize and rice (Adolwa *et al*., 2023). With appropriate and locally adapted agricultural mechanization, income gains are expected to be more sustainable over time. FAO and African Union, (2022) in the study on the role of mechanization in agricultural transformation in Africa, use of small mechanized equipment such as threshers and planters was found to reduce post-harvest losses by up to 30%, thereby increasing net income. This was mainly as a result of reduced household dependence on external labor, thus cutting production costs.

Also, according to Takeshima & Muraoka (2021) access to rental services for appropriate mechanization is strongly associated with income gains among smallholder farmers. Tractor service users experienced a 10–25% increase in agricultural income per hectare compared to non-users.in addition, access and use of appropriate mechanization such as low-horsepower tractors, conservation tillage tools have been found to leads to higher labor productivity and increased gross margins per hectare. Therefore, mechanization has been found to reduce labor bottlenecks during peak seasons thus enabling timely operation which translates to increased yields and incomes (Baudron *et al*., 2021)

In sum, the review has shown mixed outcomes relating to technology adoption. While positive and significant welfare outcomes of technology adoption have been documented by most studies, statistically not significant and negative outcomes also exist. Generally, though the adoption of technologies appears to have positive welfare effects on farmers, other welfare indicators such as income are less explored.

3.Research Approach and Sample Determination

This study used primary data from a quasi-experiment research design comparing users and non-users of appropriate agricultural mechanization in Uganda. The qualitative data was essential for identifying the issues while the quantitative data was used measure the issues identified. The two types of data thus complemented each other in evaluating production, productivity, and welfare measured by total farm income. For this study, the outcome variable was income from all activities in the farming household.

3.1 Sample Determination

The difference in socio-economic and biophysical characteristics guided the formation of regions and clusters. A stratified cluster random sampling was used in designing the study. The country was divided into four clusters with fairly homogeneous biophysical and socio-economic characteristics. The four clusters (Western, Central, Eastern and Northern regions) are the four administrative regions used in government documents (UBOS, 2023).

3.2 Effect size

Use of appropriate technologies in Uganda lacks clear estimates of expected effect sizes. Beyond the first-order effect of using appropriate technologies by smallholder farmers in Uganda, it is likely to have significant impacts on labor, production, profitability, incomes, food security and household welfare. Using appropriate technologies is expected to produce second-order effects due to farmers' own innovations and difference in soil and weather patterns. The sum of all these small effects results into significant aggregate labor savings or productivity outputs.

Use of appropriate agricultural technologies among smallholder farmers have been found to increase crop productivity and reduce harvest loss by 50–100% (Nkonya *et al*., 2020). In addition, access to extension and farmer training on use of appropriate technologies has been reported to increase income and employment with an effect size ranging between 7–100%, with most programmes experiencing an effect size of 20–100% (Blattman *et al*. 2011; Garissom and Kim, 2012). Based on this, the study used an effect size of 35 per cent.

3.3 Intra-cluster correlation estimation

Using data from the 2019/2020 Uganda National Household Survey (UBOS 2021), farmers were grouped by farm size and the Intra-cluster correlation (ρ) was calculated at regional levels which gave about 264 households per region and a power of 0.80. The regional level cluster size design for evaluating regional-level effects also gives a sample of 100 participants in each region for both users and non-users of appropriate technologies. Farmers were grouped by region and farm size and filtered these subgroups for outliers (log-transforming the data and iteratively filtering points that had z-scores greater than two in the log scale). Using Optimal Design software (Raudenbush et al. 2002), intra-cluster correlation (ρ) was calculated at region.

3.4 Total sample

The sample size was determined using sampsi formula in Stata. The formula was used to determine power and sample size in clusters of the study since the outcome of using or not using the appropriate agricultural mechanization is binary in nature. The command requires the power for a given set of design parameters to calculate the sample size of a prespecified number of clusters or number of subjects per cluster for a given power (Batistatou *et al*., 2014). It is specified as follows;

clsampsi #1 #2, k1(#) k2(#) k(#) m1(#) m2(#) varm1(#) varm2(#) varm(#) rho1(#) rho2(#) cv1(#) cv2(#) ni(#) alpha(#) power(#) onesided ratio(#) rangek1(#)rangek2(#) (#) minimum(#) maxm1(#) maxm2(#) maxm(#) sampsisampnctiarcsinlogodds) (1)

#1 #2 specifies to proportions of the two samples, according to UBOS, (2023), 0.61 is the proportion in the target population estimated to have characteristics being measured which is 0.61 for this study (61% of Uganda's population is engaged in agriculture), 0.50 is the alternative proportion (when a farmer is randomly selected, the probability that she/he uses an appropriate agricultural mechanization is 0.5) as a default.

k specifies number of clusters

m specifies to cluster sizes in samples

varm specifies to cluster size variations in samples

rho specifies to interclass correlation coefficient in samples

cv specifies to coefficient of variation of outcome in sample

ni(#) specifies the sample size for integrating the noncentral F distribution. The default is ni(10000).

Alpha (#) specifies the significance level of the test. The default is alpha (0.05).

power (#) specifies the power of the test. The default is power (0.90).

onesided indicates a one-sided test. The default is a two-sided test.

Ratio (#) specifies the allocation ratio between sample 2 and sample 1 (= N2/N1, where N1andN2 are the total sample sizes of sample 1 and sample 2, respectively).

Rangek (#) adds (#−1) clusters to the prespecified k(#) number of clusters.

Minimum (#) determines the minimum sample size of subjects required to achieve the specified power (#) for given m1() and m2()

We estimated sample size for two-sample comparison of proportions at the effect size of 35, alpha of the desired level of precision (0.5%) and power desired for detecting a difference in the means of the sample units of 0.8.

The estimated required sample size for the alternative proportion: n=264 per region

Our design generated a randomized sample of around 264 smallholder farmers using and not using any appropriate agricultural mechanization in each region of the study as shown in Table 1.

Table 1: Sample size per region

Region	Users	Non-users	Total
Western	132	132	264
Central	132	132	264
Eastern	132	132	264
Northern	132	132	264
Total	**528**	**528**	**1056**

The 132 farmers composed of users of the different appropriate agricultural mechanization and for comparison purposes, an equal number of 132 farmers that are non-users of appropriate agricultural mechanization were randomly selected and interviewed. This makes a total sample of 264 of farmers per region. A sample frame was obtained from the Agricultural Engineering and Appropriate Technology Research Institute Namalere (AEATRI) and any other leading supplier of the technologies. After obtaining the sample frames of smallholder farmers using the technologies, a random sample of 132 users was selected. Using propensity score matching, a smallholder farmer not using the technology was identified and interviewed in the neighborhood.

After identifying users of appropriate agricultural mechanization in a village with a help of Local Council one chairperson, data on their age, household size, level of education, farm size and access to extension would be collected. Similar data would be collected on the list if all non-users of appropriate agricultural mechanization in the village. Using a binary logit model on the data for both users and non-users, a score would be predicted and used to match users and non-users using kernel weighted average of all control units' weights based on distance.

3.5 Data Analysis

Impacts of use of the different technology on the welfare of smallholder farmers have been studied using a number of techniques; two-stage least square regression technique (Quach, 2016), IV estimation (Amendola *et al*., 2017), Propensity Score Matching (PSM) (Olwande and Smale, 2014) and Endogenous Switching Regression (Manja & Badjie, 2022; Liu *et al*., 2021; Bocher *et al*., 2017). However, the first three techniques have a possibility of failing to sufficiently handle endogeneity. However, the Endogenous Switching Regression (ESR) model has an advantage of dealing with heterogeneity and endogeneity effects in the estimation of the model results. The ESR is used in this study to estimate the impact of using appropriate agricultural mechanization among smallholder farmers in Uganda. Use of appropriate agricultural mechanization by farming households is a non-random and voluntary choice since farmers themselves decide (self-select) whether to use or not. In addition, the decision is influenced not only by observable characteristics but also by non-observable characteristics (such as a farmer's innate abilities) that may be correlated with the outcome variables. To address this, the Endogenous Switching Regression (ESR) model because it explicitly accounts for selection bias and endogeneity simultaneously. Lee (1982) developed the model as a generalization of the Heckman selection model (Abdulai and Huffman, 2014). The model has since gained prominence in solving the problem of self-selection bias in empirical analyses. Although the propensity score matching (PSM) is also used to address the issue of self-selection bias, it has the drawback that it is unable to address selection bias originating from unobserved factors. The ESR model accounts for the self-selection bias and unobservable factors in the estimation by bringing in instrumental variable and counterfactual analysis.

The estimation of the ESR model proceeds in two stages: Probit regression is used in the first stage to determine the probability of using appropriate agricultural mechanization. The second-stage regression estimates the determinants of impact on income as an outcome variable respectively, for users of appropriate agricultural mechanization and non-users of appropriate agricultural mechanization. Nevertheless, this two-stage approach causes the problem of heteroskedastic residuals, which cannot be used to obtain consistent standards errors without cumbersome adjustments (Lokshin and Sajaia, 2004). Therefore, the full information maximum likelihood estimator is used to overcome the problem through a simultaneous estimation of the two stages involving one selection and two outcome equations (Lokshin and Sajaia, 2004). The conceptual framework employed here is based on the assumption that farmers choose to either use appropriate agricultural mechanization or not to perform their different agricultural activities at the farm. We assume here that farmers are risk-neutral, and they take into account the expected benefit (B^*e) derived from using appropriate agricultural mechanization and the expected profit (B^*n) obtained from not using appropriate agricultural mechanization. The difference in the expected incomes between users of appropriate agricultural mechanization and non-users of appropriate agricultural mechanization is defined as B^*i, that is, $B^*i = B^*e - B^*n$. If $B^*i > 0$, then the smallholder farmer would use an appropriate agricultural mechanization in his/her agricultural production. However, B^*i cannot be observed, it can be expressed as a function of observable elements in the latent variable model as below:

$B_i^* = \beta_i X_i + \mathcal{E}i$ 1

And that, $B_i = 1$ if $B^*i > 0$

$B_i = 0$ if $B^*_i \leq 0$ 2

where B_i is a binary variable which takes the value of 1 if the smallholder farmer uses appropriate agricultural mechanization i in agricultural production and 0 otherwise; Xi is a vector of factors influencing the choice of using appropriate agricultural mechanization, such as the characteristics of the farmer, institutional characteristics and technology characteristics; β_i is a vector of unknown parameters to be estimated; and $\mathcal{E}i$ is an error term assumed to be normally distributed with zero means. Accordingly, two separate outcome equations are specified for users of appropriate agricultural mechanization and non-users of appropriate agricultural mechanization:

First regime (users of appropriate agricultural mechanization)

$Y_{iu} = \beta_{iu} X_i + \mathcal{E}_{ui}$ if $B_i = 1$ 3

Second regime (no-users of appropriate agricultural mechanization)

$Y_{in} = \beta_{in} X_i + \mathcal{E}_{ni}$ if $B_i = 0$ 4

Where *Yiu* and *Yin* are annual income outcomes for users and non-users appropriate agricultural mechanization respectively; *Xi* is a vector of exogenous variables that may impact the outcomes at farm level; $\mathcal{E}_{ui}$ and $\mathcal{E}_{ni}$ are random disturbance terms associated with the outcome variable in the two groups. While the variables *Xi* in the selection equation (1) and variables *Xi* in the outcome equations (3) and (4) are allowed to overlap. In our case, the selection equation (1) is estimated based on all explanatory variables specified in the outcome equations (3) and (4) plus access to extension as an instrumental variable. The valid instrumental variable is required to influence the choice of using appropriate agricultural mechanization but does not impact the income of farmers as an outcome variable. The three error terms $\mathcal{E}i$, $\mathcal{E}_{ui}$ and $\mathcal{E}_{ni}$ in equations (1), (3) and (4) are assumed to have a triumvirate normal distribution with zero mean and covariance matrix (Lokshin and Sajaia, 2004):

$$\Sigma = \begin{bmatrix} \delta_\eta^2 & \delta_{u\eta} & \delta_{n\eta} \\ \delta_{u\eta} & \delta_u^2 & \cdot \\ \delta_{n\eta} & \cdot & \delta_n^2 \end{bmatrix} \qquad 5$$

Where $\delta^2_{\mathcal{E}}$ is a variance of the error term in the selection equation (1), and $\delta^2_{\mathcal{E}u}$ and $\delta^2_{\mathcal{E}n}$ are the variances of the error terms in the outcome equations (3) and (4); $\delta_{\mathcal{E}}$ is a covariance of $\mathcal{E}_i$ and δ_{ui} and δ_{ni} is a covariance of $\mathcal{E}_{ui}$ and $\mathcal{E}_{ni}$. On the other hand, Y_{iu} and Y_{in} are not observed simultaneously, which implies that the covariance between $\mathcal{E}_{ui}$ and $\mathcal{E}_{ni}$ is not defined and is therefore indicated as dots in the covariance matrix (Lokshin and Sajaia, 2004; Akpalu and Normanyo, 2014). Considering that the error term of the selection equation (1) is correlated with the error terms of the outcome equations (3) and (4), the expected values of the error terms $\mathcal{E}_{ui}$ and $\mathcal{E}_{ni}$ conditional on the sample selection is non-zero and are defined as:

$$\mathrm{E}[\varepsilon_{ui} | B_i = 1] = \sigma_{u\eta} \frac{\oint(Z_i\alpha)}{\phi(Z_i\alpha)} = \sigma_{u\eta}\lambda_{ui} \qquad 6$$

$$\mathrm{E}[\varepsilon_{ni} | B_i = 0] = \sigma_{n\eta} \frac{\oint(Z_i\alpha)}{1-\phi(Z_i\alpha)} = \sigma_{n\eta}\lambda_{ni} \qquad 7$$

Where $\oint$ (•) and $\emptyset$ (•) are the standard normal probability density function and normal cumulative density function, respectively, $\lambda ei = \oint (Zi\alpha)\ \emptyset(Zi\alpha)$ and $\lambda ni = \oint (Zi\alpha)\ 1-\ \emptyset(Zi\alpha)$. If the estimated covariance $\hat{\sigma} u\eta$ and $\hat{\sigma} n\eta$ are statistically significant, then use of appropriate agricultural mechanization and farm income as the outcome variable are correlated. It implies that there is evidence of endogenous switching and the null hypothesis indicating the absence of sample selectivity bias is rejected. Specifically, the ESR model addresses the selectivity bias issue resulting from unobserved factors as a missing variable problem (Ma and Abdulai, 2016). After the selection equation is estimated, the inverse Mills ratios (λei and λni) and the covariance terms ($\sigma e\eta$ and $\sigma n\eta$) are calculated and taken back to equations (3) and (4). In this regard, the inverse Mills ratios (λei and λni) control for selectivity bias resulting from unobservable factors. Following Lokshin and Sajaia (2004), the coefficients from the ESR model can be employed to calculate the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). The observed and unobserved counterfactual farm income as outcome variable for appropriate agricultural mechanization are presented below:

Users of appropriate agricultural mechanization (observed):

$$E\left[Y_{ui} \middle| D_i = 1\right] = X_i\beta_{ui} + \sigma_{u\eta}\lambda_{ui} \quad \ldots 8$$

Non-users of appropriate agricultural mechanization (counterfactual):

$$E\left[Y_{ni} \middle| D_i = 1\right] = X_i\beta_{ni} + \sigma_{n\eta}\lambda_{ni} \quad \ldots 9$$

Where equation (8) is the expected income of farmers as an outcome variable of users of appropriate agricultural mechanization, given that farmers used appropriate agricultural mechanization. Equation (9) is the counterfactual farm income as the expected outcome of a non-users of appropriate agricultural mechanization, given that the farmer used appropriate agricultural mechanization. Following Heckman *et al*. (2001) and Di Falco *et al*. (2011), farm income as the expected outcomes in equations (8) and (9) are used to derive unbiased treatment effects (ATT):

$$\begin{aligned} ATT &= E\left[Y_{ui} \middle| D_i = 1\right] - E\left[Y_{ni} \middle| D_i = 1\right] \\ &= X_i\left(\beta_{ui} - \beta_{ni}\right) + \lambda_{ui}\left(\sigma_{u\eta} - \sigma_{n\eta}\right) \quad \ldots 10 \end{aligned}$$

3.6 Instrumental variable

This study employs access to extension as instrumental variable thus a falsification test is presented in Table 2.

The results to check the validity of these instrumental variable as done in Di Falco *et al*., (2011) and Shiferaw *et al*., (2014). A valid instrumental variable is supposed to be significantly correlated with farmers' use of agricultural mechanization but hardly has a direct effect on the farm income as an outcome variable. Evidence in Table 1 largely confirms this argument, showing that the instrumental variables used significantly decreases the probability of using appropriate agricultural mechanization but has no significant impact on farm income as the outcome variable of smallholder farmers in the study area for the subsamples in which appropriate agricultural mechanization is not used. This implies that the instrumental variable access to extension is valid.

Table 2: Results of the Falsification Test on the Instrumental Variable

Variable	Use of mechanization	Log of income
Access to extension	-0.195(0.067)***	-0.273(0.104)
Years of schooling	0.003(0.005)	0.013(0.004)***
Age of farmer	-0.001(0.002)	0.001(0.003)
Household size	0.001(0.007)	0.009(0.009)
Farming experience	0.002(0.002)	0.001(0.004)
Land size	0.004(0.001)***	0.002(0.002)
Male farmers	0.026(0.019)	0.236(0.049)***
Access to credit	0.244(0.042)***	0.328(0.099)***
Married	0.099(0.031)***	-0.075(0.065)
Eastern	0.425(0.054)***	-0.039(0.076)
Central	0.184(0.087)**	-0.124(0.141)
Western	0.332(0.058)***	-0.235(0.087)***
Constant	0.037(0.097)	16.367(0.136)***
District FE	YES	YES
R^2	-	0.456
F	-	40.38
Observations	1068	1068

4. Results and Discussions

This section provides results of use of appropriate agricultural mechanization and its effect on total farm income.

The appropriate agricultural mechanization used by rice and maize farmers that composed the sample included; maize shellers, rice threshers, motorized sprayers, motorized teller and weeder and walking tractors. Total farm income was calculated by summing up all income from crop production, off-farm income, remittances and any other income from sale of farm products such as wood, manure, honey, milk, poultry, and livestock among others. The income was calculated on annual basis. As depicted, the dependent variable in the outcome equation for this study is total annual farm income in Uganda shillings while that of the selection equation is use or non-user of appropriate agricultural mechanization. Table 3 shows the comparison of the dependent variable in the outcome variable and independent variables between users and non-users of appropriate agricultural mechanization.

Table 3: Comparison of all Variables Between Users and Non-users of Appropriate Agricultural Mechanization

Variable	Users (n=534)	Non-users (n=534)	Pooled (n=1068)	T/Chi-value
Total farm income (Log)	17.05(0.78)	16.39(1.02)	16.72(0.97)	11.9296***
Years of schooling (Years)	8.74(4.81)	7.08(6.96)	7.91(6.03)	4.5403***
Age of farmer (Years)	41.83(10.39)	42.07(12.33)	41.95(11.39)	0.3435
Household size (Members)	5.98(3.62)	5.45(3.36)	5.72(3.51)	2.4619**
Farming experience (Years)	17.84(11.38)	19.87(14.11)	18.85(12.85)	2.5852***
Land size (Acres)	5.73(12.11)	5.35(12.01)	5.54(12.05)	0.5120
Male farmers (%)	53.54	46.46	71.35	13.3562***
Married farmers (%)	56.15	43.85	68.54	35.1727***
Access to credit (%)	62.41	37.59	62.27	108.4957***
Access to extension (%)	25.67	74.33	24.44	81.7833***

*, **, and *** are P< 0.10, P< 0.05, and P< 0.01 respectively, in parentheses are standard deviation.

The results of the difference in means show that farm income for users of appropriate agricultural mechanization is significantly higher than that of non-users of appropriate agricultural mechanization. In addition, all the other variable that present household characteristics and institutional characteristics significantly differ between users of appropriate agricultural mechanization and non-users of appropriate agricultural mechanization. Specifically, in the case of users of appropriate agricultural mechanization, the household heads have more years of education, larger families, less experience in farming, are composed of more male farmers, more married farmers, less access to extension and greater access to credit. These significant differences indicate that these factors may impact use of appropriate agricultural mechanization among smallholder farmers in Uganda. This also reflects the existence of self-selection bias in response to use of appropriate agricultural mechanization which has been addressed by the Endogenous Switching Regression model.

4.1 Factors Influencing Use of Appropriate Agricultural Mechanization and Its Impact on Incomes of Smallholder Farmers.

The estimates of the factors that influence use of appropriate agricultural mechanization and the impact of their use on smallholder farmer's income was done using the Endogenous Switching Regression model. The selection part of the model shows factors that influence use of appropriate agricultural mechanization while the outcome equation shows factors that influence the effects of using appropriate agricultural mechanization on farmers' incomes. As earlier presented in the methodology section, the full information maximum likelihood estimator is used to estimate the selection and outcome equations jointly. The results of the likelihood ratio test in Tables 4 show that the selection and outcome equations are correlated, which indicates that it is appropriate to estimate these three equations jointly. Specifically, the results under the column of selection equation in Table 4 show the determinants of using appropriate agricultural mechanization while impacts of using appropriate agricultural mechanization on smallholder farmers' income for both users and non-users of appropriate agricultural mechanization are presented under the columns of outcome equations in the same Table 4.

Table 4: Endogenous Switching Regression Model Results on Factors Influencing Use of Appropriate Agricultural Mechanization and their Impact on Incomes of Farmers

Variable	Selection equation	Outcome equation (Log Income)	
		Users	Non-users
Eastern	0.899(0.152)***	-0.274(0.219)	-0.266(0.226)
Central	0.637(0.152)***	-0.093(0.176)	-0.341(0.144)**
Western	0.989(0.159)***	-0.369(0.205)*	-0.484(0.176)***
Married	0.321(0.114)***	-0.131(0.101)*	-0.211(0.113)*
Male	0.111(0.112)	0.129(0.092)*	0.297(0.108)***
Access to credit	0.772(0.093)***	-0.005(0.119)	0.242(0.116)**
Land size	0.012(0.004)***	0.002(0.003)	-0.005(0.004)
Farming experience	0.006(0.005)	-0.001(0.005)	-0.001(0.005)
Household size	0.003(0.015)	0.011(0.011)	0.013(0.016)
Age of farmer	-0.004(0.005)	0.001(0.005)	0.001(0.005)
Years of schooling	0.009(0.007)	-0.001(0.008)	0.016(0.006)**
Access to extension	-0.678(0.109)***		
Contant	-1.504(0.228)***	17.234(0.421)***	16.175(0.195)***
Σu*i*		-0.265(0.031)***	
Σn*i*			-0.025(0.033)
Pu*i*		-0.012(0.268)**	
Pn*i*			-0.124(0.187)
LR test of indep. eqns.	0.44		
Log likelihood	-1934.4236		
Observations	1068	1068	1068

*, **, and *** are P< 0.10, P< 0.05, and P< 0.01, respectively and in parentheses are standard errors

The *ρui* is significant as presented in Table 4 which indicates that total farm incomes of users of appropriate agricultural mechanization are significantly different from that of a random individual from the sample. Considering that the dependent variable is taken as the logarithm, the negative *ρei* actually means that total farm income of the farmers using appropriate agricultural mechanization are higher than that of a random individual from the sample. *ρni* are not significant, which indicates that total farm income of farmers using appropriate agricultural mechanization are not different from that of a random individual from the sample.

Results in Table 4 show that the model marginal effects under the selection equation column are consistent. The coefficient of the variable of the farmers' location being eastern, central and western Uganda were significant and positive, indicating that farmers from these locations were more likely to use appropriate agricultural mechanization compared to those farmers from northern Uganda which as used as a comparison category. In addition, a farmer being married was also found to be significant and positively related to use of appropriate agricultural mechanization. The results show that married farmers were more likely to use appropriate agricultural mechanization compared to their non-married counterparts. These results on location and marital status of the farmer and use of appropriate agricultural mechanization are in agreement with Gebiso *et al*. (2023), Ayele, (2022), Sayed *et al*., (2022) and Özpinar & Anıl, (2018) who all reported that being married enhances that ability of a farmer to use improved technologies due to knowledge sharing and great ability for resource mobilization. The authors also found that location of the farmer influences use of agricultural technologies with households among highly agricultural areas having greater likelihood of using agricultural technologies due to greater exposure to such technologies.

The results further showed that farmers' access to credit is positively associated with use of appropriate agricultural mechanization. The model coefficients show that farmers with credit access were more likely to use appropriate agricultural technologies compared to their counterparts with no access to credit. This underscores the role of credit in enabling smallholder farmers to access improved technologies for increased production and productivity. The relationship between credit and use of appropriate agricultural mechanization are in agreement with Ayenew *et al*., (2020), Justice & Tobias, (2016) and Kekonnen, (2017) who all reported that increases access to credit enables smallholder farmers to afford use of improved agricultural technologies through either purchasing or hire.

Results on land ownership show that farmers' size of land owned is significant and positively associated with use of appropriate agricultural mechanization. The model coefficients show that farmers with larger pieces of land owned more likely to use appropriate agricultural mechanization. In this regard, these results reveal that size of land owned is vital in determining whether a farmers use appropriate agricultural mechanization or not. The results on the relationship between land ownership and use of appropriate agricultural mechanization are in agreement with Blattman *et al*. (2011), Benin *et al*. (2010), King *et al*. (2012), and Attanasio *et al*. (2011) who all found out that agricultural mechanization is vital for increasing commercialization in areas with land as a favorable resource for increasing both scale and intensification of agricultural production.

Ultimately, the marginal effects of the instrumental variable which is access to extension is significant and negative, showing that farmers are less likely to use appropriate agricultural mechanization if they were accessing more extension visits. This could be attributed to the issue of extension messages not being specifically tailored to appropriate agricultural mechanization access and use. These results on the relationship between appropriate agricultural mechanization use and access to extension are in disagreement with Ali and Awade (2019) who found out that farmers with more access to extension were more likely to use improved agricultural technologies. This relationship can be explained by limited extension on agricultural mechanization in Uganda. As reported by Daum (2023), agricultural mechanization has been missing on the agenda of agricultural development but needs to be given priority due to its potential to increase agricultural production and productivity.

The estimated results under the columns of outcome equation present the impacts of use of appropriate agricultural mechanization on total farm income of smallholder farmers for both users and non-users of appropriate agricultural mechanization. The model coefficient of variables western and being married for users of appropriate agricultural mechanization is significant and negative. This implies that farmers from western Uganda and those that are married exerts a significant and negative effect on use of appropriate agricultural mechanization. Considering that being married and from western Uganda were found to determine the use of appropriate agricultural mechanization, it is inferred that when majority of households from western and married may be involved in other off-farm work, instead of focusing on investing in agricultural mechanization, which would drive negative impacts on the total income from the farming activities. On the other hand, male farmers were found to have coefficients that are significant and positive in relation to use of appropriate agricultural mechanization. This indicates the role of gender relations in access and use of agricultural mechanization socially among smallholder rural households where male headed households have more access to productive resources.

The model results on access to credit show that farmers' access to credit is significant and positively associated with use of appropriate agricultural mechanization. The marginal effects on the selection model show that farmers with access to credit were found to be more likely to use appropriate agricultural mechanization. The results show that access to credit is vital in determining whether a farmers use appropriate agricultural mechanization or not and the income from the farm. This is explained by the role of credit in enabling farmers access to appropriate agricultural mechanization through hiring or purchasing inputs. Credit allows farmers to act promptly, avoiding delays that reduce yields or crop quality. This finding is in agreement with Takeshima *et al*. (2020) and Baudron *et al*. (2021) who both found a positive relationship between access to credit and use of appropriate agricultural mechanization.

Results on level of education show no significant relationship with use of appropriate agricultural mechanization. However, the results in the outcome model show that the level of education is significantly associated with farm income especially for non-users. This can be explained by the ability of educated farmers to get non-farm businesses thus being less attracted to agriculture and agricultural mechanization. Educated farmers earning more from non-farm business compared to their counterparts involved in agricultural production.

The estimates for the average treatment effects on the treated (ATT), which present the overall effects of using appropriate agricultural mechanization on total income of smallholder farmers are presented in Table 5.

Table 5: Average Expected Incomes from Use of Appropriate Agricultural Mechanization by Smallholder Farmers

Farmer category	Users	Non-users	Treatment effects (ATT/ATU)	t-test	% Change in income
Users	28,540,000	25,480,000	3,060,000	591.42***	12.009
Non-users	13,160,000	11,430,000	1,730,000	334.36***	15.136

These ATT estimates are based on the ESR model account for selection bias resulting from both observable and unobservable characteristics as with Goyal, (2008) and Courtois and Subervie, (2015). It reveals that the use of appropriate agricultural mechanization by smallholder farmers significantly increases total farm income by

12.009%. In addition, the estimates for average treatment effects on the untreated (ATU) show that using appropriate agricultural mechanization would increase incomes of non-users by 15.136%.

5. Conclusion, Recommendations and Policy Implications

This study examined the determinants of smallholder maize and rice farmers' decisions to adopt appropriate agricultural mechanization in Uganda, using data from 1,068 households across the country's four major regions. Employing an endogenous switching regression (ESR) model to address self-selection bias, the results revealed that region, marital status, access to credit, land ownership, and extension services significantly influence appropriate agricultural mechanization adoption. Importantly, adoption of appropriate agricultural mechanization was found to have a positive and significant impact on total farm income, underscoring its role in poverty reduction and rural transformation. These findings highlight that both farmer-specific socio-economic characteristics and location-specific conditions must be considered when designing appropriate agricultural mechanization policies and programs.

The findings provide several important implications for agricultural policy and rural development:

Appropriate agricultural mechanization is a driver of rural transformation. Therefore, adoption of appropriate agricultural mechanization enhances productivity, incomes, and commercialization, making it a critical pathway for poverty reduction and food security in Uganda.

Extension services gap exists among smallholder farmers. While farmers access extension services, these may not adequately emphasize appropriate agricultural mechanization. Strengthening appropriate agricultural mechanization-focused extension is essential to improve awareness and adoption.

Policies should prioritize smallholder farmers, particularly those with limited land and credit access, by leveraging farmer groups, cooperatives, and financial institutions to improve reach and effectiveness.

Appropriate agricultural mechanization policies must account for gender, youth, and regional disparities to ensure equitable access and adoption.

Appropriate agricultural mechanization adoption can generate additional employment opportunities (e.g., machinery operation, repair services, marketing), suggesting broader economic benefits than captured in farm income alone.

Based on the study findings, the following recommendations are proposed:

Strengthen appropriate agricultural mechanization-focused extension services. Extension providers should integrate mechanization training, demonstrations, and farmer field schools to build confidence and skills among smallholders.

Expand access to affordable finance. Governments and financial institutions should design credit schemes tailored to smallholders, including group lending, microfinance, and pay-as-you-use models for appropriate agricultural machinery services.

Promote community-based appropriate agricultural mechanization schemes. Cooperative machinery rental services and shared ownership models can reduce costs and increase access, especially for farmers with small landholdings.

Enhance information dissemination. Use radio, mobile phones, and digital platforms to popularize appropriate agricultural mechanization benefits, focusing on user-friendliness, affordability, and crop-specific relevance.

Target crop and location-specific interventions. Appropriate agricultural mechanization programs should align with the crops and regions where technologies are most effective, ensuring context-specific adoption strategies.

Encourage inclusive participation. Policies should actively involve women and youth farmers by promoting appropriate agricultural mechanisation suited to their farming contexts and providing targeted training and incentives.

Support market linkages**.** Strengthen rural market infrastructure and value chains so that increased production from appropriate agricultural mechanization translates into higher incomes and sustained adoption.

Invest in local innovation and adaptation. Encourage research and development of locally adapted appropriate agricultural mechanization technologies that align with cultural practices and smallholder realities.

While this study provides novel insights, future research should broaden the scope to include other crops beyond maize and rice, as appropriate agricultural mechanization impacts may vary across commodities. Additionally, household welfare effects beyond farm income such as employment creation, nutrition, and asset accumulation should be explored to capture the full economic and social benefits of appropriate agricultural mechanization adoption.

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Institutional Review Board Statement: This study was approved by the College of Agricultural and Environmental Sciences Research Ethics Committee, Makerere University, Uganda, under protocol number CAES-REC-2025-113, dated September 15, 2024. Prior to data collection, the purpose and procedures of the study were explained to all participants, and informed verbal consent was obtained. Participation was voluntary, and participants were informed of their right to withdraw at any time without penalty. All data were anonymized during analysis to protect participant confidentiality, and no personally identifiable information is included in this publication.

Authors' Contributions: Fred Ssajakambwe designed the research methodology, developed data collection instruments, supervised field data collection, performed the statistical analysis, prepared figures and tables, and wrote the original draft manuscript. Fredrick Bagamba provided guidance on research design, supervised the analytical approach, and contributed to interpretation of results. Bernard Bashaasha provided conceptual framing, guided the literature review, and contributed critical revisions on policy implications. Rosemary Emegu Isoto contributed to sampling design, provided methodological guidance, and reviewed the econometric analysis. All authors reviewed, edited, and approved the final manuscript.

Acknowledgments: The authors gratefully acknowledge the cooperation of the 1,056-smallholder rice and maize farmers across Uganda who participated in this study. We thank the Agricultural Engineering and Appropriate Technology Research Institute Namalere (AEATRI) for providing sampling frames and technical support during data collection. We also acknowledge the enumerators who assisted with field data collection.