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Mechanization and Agricultural Intensification: The Case of Rice Farming in Tanzania

Eustadius Francis Magezi[*], Yuko Nakano[†], and Keijiro Otsuka[‡]

Abstract

Agricultural intensification in sub-Saharan Africa (SSA) has long been a major development issue. Yet, the extent to which the use of draft animals and tractors promotes agricultural intensification has seldom been examined. This study assesses the effects of mechanization and the use of draft animals on agricultural intensification by analyzing rice farming in Tanzania. Tanzania is uniquely suited for our purpose because four-wheel tractors (4WTs), two-wheel tractors (2WTs), draft animals (DAs), and hand tools (HTs) are used concurrently. We apply a multinomial endogenous switching regression (MESR) framework to a panel dataset collected in 2018 and 2025. We find that the use of 4WTs, 2WTs, and DAs significantly reduces labor use for land preparation compared with HTs. However, the effects on the adoption of rice technologies and subsequent cultivation practices and productivity differ significantly. Notably, the use of 2WTs has the largest impact on yield, income, and profit per hectare because their suitability for puddling and harrowing promotes the adoption of labor-intensive cultivation practices and greater use of hired labor. Conversely, the ride-on 4WTs are used for plowing without a corresponding intensification of rice farming.

Keywords: Agricultural mechanization, Rice production, Agricultural productivity, Sub-Saharan Africa, Tanzania
JEL Codes: N57, O12, O13, Q16, Q18

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1. Introduction

Improving agricultural productivity remains essential to ensuring food security in sub-Saharan Africa (SSA), where demand for food is rising rapidly, driven primarily by high population growth despite limited room to expand cultivation areas (United Nations 2024; Holden and Otsuka 2014). Although maize is the most important crop in SSA, its technology is highly location-specific and thus difficult to disseminate, whereas rice is considered a more promising crop because of the high transferability of Asian rice technology to SSA (Otsuka and Larson 2016; Otsuka, Mano, and Takahashi 2023; Otsuka et al. 2024). This study therefore focuses on the intensification of rice farming.

Farm mechanization has attracted attention as a means of improving agricultural productivity and addressing the declining rural workforce due to rural-to-urban migration (Adu-Baffour, Daum, and Birner 2019; Christiaensen and Maertens 2022; Diao et al. 2020; Gollin 2023; Takeshima, Nin-Pratt, and Diao 2013). Following the induced innovation hypothesis (Hayami and Ruttan 1985), labor-saving technologies such as animal traction or machinery are expected to be adopted in response to labor scarcity. However, in SSA, the adoption of animal traction has historically been constrained by ecological conditions, such as the prevalence of the tsetse fly (Alsan 2015). This led many governments in SSA to promote mechanization through state-led large-scale programs during the 1960s and 1970s. Yet, these initiatives generally failed because of poor management, low operational efficiency, inadequate maintenance, and financial unsustainability (Binswanger and Rosenzweig 1986; Pingali 2007; Ruthenberg 1980).

Recently, notable changes have been occurring in regional machinery markets. While four-wheel tractors (4WTs) imported from Europe and North America have dominated since the colonial era and during government-led mechanization periods, recent mechanization in rice farming has increasingly been driven by market-based service provision and private investment, accompanied by the spread of two-wheel tractors (2WTs), or power tillers, supplied by Asian manufacturers (FAO and AUC 2018). This diversification and increased competition have lowered costs, making mechanization more accessible to both large and mid-sized farmers purchasing equipment and smallholders using rental markets (Adu-Baffour, Daum, and Birner 2019; Cabral and Amanor 2022; Diao et al. 2014; Jayne et al. 2019; Takeshima and Lawal 2020; Van Loon et al. 2020).

Despite the growing trend of farm mechanization, evidence on whether mechanization facilitates agricultural intensification in SSA remains inconclusive. Mechanization is often viewed as labor-saving rather than land-productivity-enhancing (Binswanger 1986), as seen in Asia where labor-intensive tasks, such as land preparation, were mechanized first (Pingali 2007; Pingali, Bigot, and Binswanger 1987). In SSA, however, findings are mixed. Some studies show that tractor use does not lead to yield gains, while others suggest that it can enhance land productivity by improving

land preparation and increasing returns to fertilizer use, promoting the adoption of modern varieties (MVs), and improving agronomic practices (e.g., Baudron et al. 2012; Bhattarai et al. 2020; Diao, Takeshima, and Zhang 2020; Mano, Takahashi, and Otsuka 2020). The evidence on the effects of mechanization on labor use is also ambiguous. While mechanization reduces labor requirements for land preparation, some studies suggest that it facilitates the adoption of subsequent labor-intensive agronomic practices and thereby increases total labor use (e.g., Adu-Baffour, Daum, and Birner 2019; Mano, Takahashi, and Otsuka 2020).

The historical experience of rice mechanization in Asia also provides an interesting comparison. Although systematic data on tractor adoption are limited, mechanization in Asian rice farming has largely involved power tillers (2WTs), with some exceptions. According to David and Otsuka (1994), the adoption of modern improved rice varieties expanded during the 1970s, whereas power tiller adoption increased mainly during the 1980s. This suggests that power tiller adoption was not a major driver of the initial intensification of rice farming in Asia, partly because water buffaloes were already widely used for land preparation and served as close substitutes for power tillers. We hypothesize that these inconsistent results arise partly because the effects of 2WTs and 4WTs differ but have not been differentiated in past studies, and partly because tractors replace either hand tools (HTs) or draft animals (DAs) depending on study sites.

This study examines the differing effects of 2WTs, 4WTs, and DAs on the adoption of new rice technologies and improved cultivation practices, labor use, and land productivity, as well as the causes of their differential impacts, using a two-year panel dataset of lowland rice farmers in Tanzania. Tanzania provides a unique setting because the country has been at the forefront of the shift toward small-scale mechanization. Since the early 2000s, the government has promoted agricultural mechanization through import-duty and value-added-tax exemptions and concessional loans, while providing specific support for 2WTs through subsidies and the development of machinery-hiring services (Magezi, Nakano, and Sakurai 2021, 2023; Mrema, Kahan, and Agyei-Holmes 2020). Consequently, Tanzania has one of the largest concentrations of 2WTs in SSA, while 4WTs, draft animals (DAs), and hand tools (HTs) remain widely used. This coexistence of alternative sources of farm power makes Tanzania particularly suitable for examining their comparative effects on rice intensification.[1]

To address the endogeneity issue in the selection of land preparation methods, we employ a multinomial endogenous switching regression (MESR) model combined with the Mundlak and Chamberlain (MC) approach (Bourguignon, Fournier, and Gurgand 2007; Chamberlain 1982; Mundlak 1978). In addition, for robustness checks, we use a panel correlated random effects (CRE) model and a pooled ordinary least squares (OLS) model with an MC specification (Joshi

[1] According to Mrema, Kahan, and Agyei-Holmes (2020), about 70 percent of all 2WTs in SSA are concentrated in Tanzania, Madagascar, and South Africa.

and Wooldridge 2019; Wooldridge 2019). Although these approaches mitigate selection bias arising from observed and unobserved heterogeneity, they cannot eliminate all potential sources of endogeneity. Accordingly, we interpret our estimates as suggestive, rather than definitive, causal effects.

This study contributes to the literature in two ways. First, we examine the differential impact of 2WT, 4WT, and DA use on the intensification of rice cultivation. Although the effects of agricultural mechanization on land productivity, cultivated area expansion, and other outcomes have been widely examined (Baudron et al. 2015; Benin 2015; Berhane et al. 2017; Magezi, Nakano, and Sakurai 2023; Mano, Takahashi, and Otsuka 2020; Takeshima, Nin-Pratt, and Diao 2013), to our knowledge, this study is the first to rigorously compare the effects of 4WTs, 2WTs, and DAs with those of HTs in SSA.[2] Most importantly, we find that the use of 2WTs increases the adoption of labor-intensive and yield-enhancing cultivation practices and technologies such as straight-row transplanting, fertilizer-responsive MVs, and chemical fertilizer, thereby resulting in the highest paddy yield, income, and profit per hectare. 2WTs are used not only for plowing but also for puddling and harrowing, unlike 4WTs and DAs, which are mainly used for plowing. This enhances weed control and nutrient uptake by plants, resulting in higher yields and profitability for 2WT users. In contrast, the use of 4WTs and draft animals does not contribute much to the adoption of fertilizer-responsive MVs and chemical fertilizer. The finding that DAs do not generate yield gains casts some doubt on the argument of Alsan (2015) that ecological constraints to animal traction, such as the prevalence of the tsetse fly, historically hindered productivity growth in agriculture and eventually overall economic development in SSA.

The second contribution of this study is to uncover the mechanisms behind the differential impacts of mechanization by explicitly distinguishing between family and hired labor across production activities. While the use of 2WTs, 4WTs, and DAs all reduces hired labor use for land preparation, 2WT use increases hired labor use for crop establishment through straight-row transplanting and for harvesting due to increased yield. In contrast, 4WT use increases hired labor for weeding, due to lower adoption of straight-row transplanting, as well as for puddling and harrowing. These findings highlight that 2WTs promote agricultural intensification through the complementary use of hired labor, particularly for straight-row transplanting, whereas 4WTs primarily substitute for labor without enhancing productivity. While 2WT or 4WT use reduces family labor use for land preparation, such a reduction is not observed on DA plots because draft animals require daily maintenance and can only work for limited hours, constraining the overall labor-saving effect. Our findings contribute to the policy discussion on agricultural mechanization in SSA (Daum et al. 2023; Diao et al. 2020; FAO and AUC 2018; Otsuka, Mano, and Takahashi 2023) by

[2] Magezi, Nakano, and Sakurai (2023) use two-year panel data and a fixed effects model to investigate the association between mechanization and extensification, adoption of rice technologies, and yield. Their study, however, does not examine the effects of mechanization on income, profitability, or labor use.

demonstrating that 2WTs and 4WTs should be selectively adopted for rice intensification, taking into account their distinct comparative advantages.

The rest of this paper is organized as follows: Section 2 provides a description of the study area and data collection process. In Section 3, descriptive analyses are presented, followed by the estimation methods in Section 4. The estimation results are reported and discussed in Section 5, and the conclusions and implications of the research are presented in Section 6.

2. Study site and data

2.1 Study site

The surveys for this study were conducted in the Morogoro, Mbeya, and Shinyanga regions of Tanzania, located in the Eastern, Southern Highlands, and Lake agroecological zones, respectively. Two rice-growing districts were selected in each region, namely Mvomero and Kilombero in Morogoro, Shinyanga Rural and Kahama in Shinyanga, and Kyela and Mbarali in Mbeya. There are two cropping seasons in our study sites: (i) the main rainy season, which starts in October and ends in June, and (ii) the short rainy season, which starts in July and ends in September. During the main season, rice is cultivated in both irrigated and rainfed lowlands. Upland plots are used to grow other crops such as maize, beans, sunflower, and sesame, mostly under rainfed conditions. In the short season, most rainfed plots remain uncultivated, except where permanent crops are grown. By contrast, irrigated lowlands are used primarily for vegetable production. Thus, our analysis focuses exclusively on rice cultivation during the main season.

Farmers in our study sites use 4WTs, 2WTs, DAs, or HTs to perform a range of land-preparation activities, including plowing, leveling, harrowing, and puddling.[3] 4WTs are often used for plowing in rainfed lowlands before plots are flooded and are preferred on heavy clay soils because of their powerful engines. In contrast, 2WTs are commonly used not only for plowing but also for puddling and harrowing under standing water conditions, particularly in irrigated plots or rainfed rice plots with bunds, as they are less prone to bogging in muddy conditions. 4WTs and 2WTs are widely used across most rice-growing regions of Tanzania, except in the Lake Zone and parts of the Southern Highlands. Farmers generally access these machines through custom hire services provided by private operators. In most cases, private entrepreneurs based in urban centers own 4WTs and 2WTs and rent them to operators, who make arrangements with rice farmers in nearby villages to provide land preparation services. Draft animals are supplied by agro-pastoralists, who mainly perform only plowing, whereas puddling and harrowing are seldom carried out, presumably because of their lack of knowledge about the latter activities. The fees for custom machinery and DA hire services are not regulated; rather, they are determined by

[3] Leveling refers to creating a flat and even surface to ensure uniform water distribution and prevent waterlogging. Harrowing involves breaking large soil clods into smaller particles to produce a smooth seedbed before flooding or direct seeding. Puddling is the process of thoroughly mixing the soil in flooded paddy fields before transplanting rice.

agreements between service providers and farmers.

2.2 Data

Although our empirical analysis uses a balanced two-year panel dataset constructed from the 2018 and 2025 survey rounds, this panel was derived from a series of surveys conducted over a longer period. The first survey was conducted in 2009. Using the 2002–2003 agricultural census data as the sampling reference, 76 villages were selected through stratified random sampling. The number of villages sampled from each district was determined by the distribution of irrigated and rainfed rice-growing villages. Then, ten rice-growing households were randomly selected from each village, resulting in a total sample of 760 households. The survey collected information on general household characteristics and rice cultivation in each household's most important plot. The same households were revisited in 2012. When an original household could not be traced, it was replaced by a randomly selected household from the same village. Because the 2009 and 2012 surveys collected information on machinery use only for each household's most important rice plot, they were not suitable for the plot-level analysis of mechanization conducted in this study.

In 2018, we returned to the same 76 villages and revisited the existing sample households, including replacement households introduced in earlier rounds where applicable. During this survey, we collected detailed information on the use of 4WTs, 2WTs, DAs, and HTs, adoption of rice technologies, production costs, and rice productivity across all rice-growing plots. Since it is difficult to collect detailed labor use data for all rice plots, we asked farmers to identify their most important plot for rice production and collected detailed data on labor use and costs for that specific plot.

In 2025, with the aim of constructing panel data to evaluate the impact of mechanization, we noted from previous rounds that most farmers in the Kahama, Shinyanga Rural, and Kyela districts are agro-pastoralists who rely almost exclusively on draft animals for land preparation. Because machinery use was limited in these areas, we excluded 42 villages from these three districts in the 2025 survey and retained 34 villages across the remaining three districts. Our goal was to revisit all households interviewed in 2018 (i.e., 340 households across 34 villages), regardless of whether they were part of the original 2009 sample or later replacements, to reduce attrition. However, 78 households could not be reached. During the data cleaning process, we removed 9 households with missing data for key variables.[4] This resulted in a clean sample of 253 households (i.e., 506 household observations over the two survey rounds). Because the survey covered all lowland rice plots cultivated by these households, the final panel dataset consists of 846 plot-level observations. For the analysis of profit and labor use, the number of observations

[4] To reduce the influence of outliers on the analysis, we winsorized all continuous dependent variables at the 1st and 99th percentiles. We adjusted all monetary values for inflation and expressed them in constant 2009 Tanzanian shillings (TShs). In 2009, one U.S. dollar (USD) was approximately equivalent to TShs 1,300.

is 506 because these variables are based on the household's most important plot (one lowland rice plot per household in each survey round).

In addition to the household survey, we interviewed village leaders in all 34 villages about rice cultivation and access to public extension services and markets. We also used data obtained from secondary sources to calculate village-level population density and the total amount of rainfall during the main cultivation season. The population datasets were compiled by the Global High-Resolution Population Denominators Project (WorldPop and CIESIN 2025), available at a spatial resolution of 30 arcseconds, equivalent to roughly 1 kilometer at the equator. We extracted the population density values for the survey years (i.e., 2018 and 2025) and computed the total population within a 1-kilometer radius of each village center, then combined these data with other village-level variables. For rainfall, we used the precipitation data collected by the Climate Hazards Group (CHG) and the U.S. Geological Survey (Climate Hazards Center 2025). We extracted rainfall amounts corresponding to each village center and merged them with the other village-level variables.

To account for potential attrition bias due to the inability to re-interview baseline households, we calculated an inverse probability weight (IPW) using 2018 observations. We estimated a probit model where the dependent variable is a dummy that takes the value 1 if the household was re-interviewed in the follow-up survey and 0 otherwise (Appendix Table A1). The independent variables include basic household and plot characteristics as well as district fixed effects. We then calculated the attrition weight as the inverse of the predicted probability of being re-interviewed in subsequent surveys and applied it during estimation. Appendix Table A2 provides the summary statistics for the main variables, and Appendix Table A3 provides summary statistics for the most important plot variables. We also present Table A4 to show how machinery access and use changed between 2018 and 2025. Overall, the use of 2WTs increased substantially, while the use of 4WTs and HTs declined. At the village level, the number of owners of 2WTs also increased, suggesting improved access to 2WT services. The real wage rate for land preparation declined significantly over the same period, consistent with the expansion of labor-saving mechanized land preparation. Since these trends are broadly consistent with those reported in previous studies (Magezi, Nakano, and Sakurai 2021, 2023; Mrema, Kahan, and Agyei-Holmes 2020), we refrain from discussing them in detail here for brevity.

3. Descriptive analyses

Table 1 presents the average values of rice cultivation variables by the type of farm implement used for land preparation in 2018 and 2025. We divide the sample plots into four categories based

on the implements used, namely, 4WTs, 2WTs, DAs, and HTs.[5] We then conduct a *t*-test comparing plots prepared using 4WTs, 2WTs, and DAs with the reference category (HT plots). As farmers may cultivate only part of a plot and leave the rest fallow, we distinguish between plot size and the area actually cultivated and report these variables in Panel A. The results show that plots prepared using 2WTs, 4WTs, and DAs are approximately twice as large as those prepared using HTs. These results suggest that mechanized land preparation and the use of DAs contribute almost equally to the expansion of the area under rice cultivation. In other words, mechanization does not contribute to the extensification of rice farming areas if draft animals are available. Since tractorization and the use of draft animals are more common on larger plots, it is necessary to control for plot size in the empirical analysis.

Panel B shows variables related to land preparation methods and technology adoption. In our study areas, crop establishment is carried out either by transplanting seedlings or by direct seeding. Transplanting can be done randomly or in straight rows, while direct seeding includes broadcasting, dibbling, and seed drilling.[6] We focus on straight-row transplanting because it makes it easier to manage plant density and control weeds. Although this practice is labor-intensive, it is essential for achieving high yields (Otsuka and Larson 2016). The results indicate that while both tractors and DAs are used for plowing, plots prepared using 2WTs and DAs are more likely to be puddled or harrowed than HT plots. This is important because puddling and harrowing are essential for later-stage crop management, as they enhance water retention, nutrient availability, and weed control. Although 2WT and HT plots have comparable adoption rates of straight-row transplanting and MVs, 2WT plots have higher rates of chemical fertilizer application. In contrast, plots prepared using 4WTs and DAs have lower adoption rates of straight-row transplanting and MVs, and chemical fertilizer application in 4WT plots does not differ significantly from that of HT plots.

Panel C shows productivity variables, namely, paddy yield, income, and profit. Income per hectare is defined as the difference between the gross value of output and paid-out costs, expressed on a per-hectare basis. Paid-out costs include expenditures on fertilizer, seed, insecticides and herbicides, hired labor, and machinery or draft animal hire. Profit per hectare is defined as the difference between income and the imputed costs of family labor and the use of household-owned machinery and draft animals. The costs of unpaid family labor and the use of household-owned machinery and draft animals are valued using the village median wage rate and

[5] About 9 percent of sample plots were prepared using more than one type of farm implement. After closely examining the survey data and the contents of the questionnaire, these households were classified according to their primary method of land preparation.

[6] Dibbling is a direct seeding method that involves making small holes in the soil at regular intervals with a pointed stick into which seeds are placed. Seed drilling involves making shallow grooves in the soil with tools, such as a wooden rake, to plant seeds in straight rows. Although dibbling and seed drilling allow for direct seeding in straight rows, they have yet to be widely adopted in our study areas, as shown in Appendix Table A5.

rental rates, respectively.

The results show that 2WT plots have a significantly higher paddy yield of about 5 tons per hectare compared to the 3.6 tons per hectare achieved on HT plots. Note that the yield of 2WT plots is much higher than the average yield in SSA, at about 2.4 tons per hectare, and comparable with that of South and Southeast Asian countries (Silva et al. 2022). Additionally, 2WT plots have significantly higher income and profit than HT plots. In contrast, plots prepared using 4WTs and DAs have lower yields and income per hectare than HT plots.

The descriptive comparison of the use of hired and family labor across rice plot preparation methods is presented in Table 2. Panel A reports aggregate hired and family labor use, including labor used in the preparation of rice plots, crop establishment (through direct seeding or transplanting), weeding, and harvesting. We distinguish between family and hired labor because family labor is used for care-intensive activities and for the supervision of hired labor, for which shirking may occur in the absence of supervision (Hayami and Otsuka 1993). Total hired and family labor use is lower on plots prepared using 2WTs and 4WTs, suggesting that tractorization reduces overall labor requirements in rice production. In contrast, hired labor use is significantly lower on plots prepared using DAs.

To better understand activity-level differences in labor use, we examine disaggregated labor use and report the results in Panel B. Interestingly, although hired labor use for plot preparation is similarly low among 2WT, 4WT, and DA plots, labor use for subsequent activities varies. Specifically, hired labor use for crop establishment, weeding, and harvesting in 2WT plots is relatively high and nearly identical to that of HT plots. This may be because, compared with plots prepared using 4WTs and DAs, 2WT plots have a higher adoption rate of labor-intensive, yield-enhancing straight-row transplanting. While straight-row transplanting makes weeding easier, the higher yield achieved on these plots may simultaneously increase labor demand for harvesting. In contrast, plots prepared using 4WTs and DAs use less hired labor for crop establishment and harvesting, likely due to the low adoption of straight-row transplanting. This lower adoption of improved agronomic practices, combined with the lack of weed-suppressing puddling and harrowing, may also explain the higher hired labor demand for weeding observed on 4WT-prepared plots. Additionally, 2WT and 4WT plots have significantly lower family labor use than HT plots across all activities, while on DA plots, family labor use for crop establishment and harvesting is similar to that on HT plots. These patterns suggest that tractor-based land preparation may lower subsequent family labor requirements, presumably because land preparation can be completed within a shorter period of time, which allows for more synchronized activities by hired labor. In contrast, such reductions are less evident on DA plots, reflecting the time-consuming nature of animal traction.

4. Estimation methods

In evaluating the effects of mechanization on input intensification, we employ a multinomial endogenous switching regression (MESR) model with the Mundlak–Chamberlain (MC) approach to control for time-invariant unobserved heterogeneity, as we discuss below (Di Falco 2014; Kassie et al. 2015; Khonje et al. 2018; Wooldridge 2010). Although this empirical strategy is intended to mitigate selection bias arising from both observed and unobserved heterogeneity, it cannot eliminate all potential sources of endogeneity. We therefore interpret our estimates as suggestive, rather than definitive, evidence of causal effects.

4.1 First stage of MESR

In the first stage, we model farmers' mechanization decisions using a random utility framework. We construct a categorical variable U_{ijt}, for rice plot i of household j in year t, which equals 1 if 2WTs are used, 2 if 4WTs are used, 3 if DAs are used, and 4 if only HTs are used. About 9 percent of the plots in our dataset were prepared using multiple implements. We categorized these plots according to the primary implement used for land preparation, making our mechanization categories mutually exclusive.[7] We consider that the farmer j's decision to prepare their rice plot using implement k (where $k \in \{1, 2, 3, 4\}$ for 2WTs, 4WTs, DAs, and HTs) over any other alternative implement m can be described by the latent model (U^*_{ijkt}).

Farmers choose the implement $k \in \{1, 2, 3, 4\}$ that maximizes their expected utility, provided that the utility differential relative to any alternative $m \neq k$ is positive. Formally, a farmer j chooses implement k if $\tau_{ijkt} = \underset{m \neq k}{max}(U^*_{ijmt} - U^*_{ijkt}) < 0$. Following Bourguignon, Fournier, and Gurgand (2007), we assume that the random errors in the latent utility function are independently and identically Gumbel distributed, yielding the following multinomial logit (MNL) model:

$$P_{ijkt} = Pr(\tau_{ijkt} < 0 \mid \boldsymbol{X}_{ijt}) = \frac{\exp(\alpha_k \boldsymbol{X}_{ijt} + \omega_k \overline{\boldsymbol{X}}_{ij})}{\sum_{m=1}^{K} \exp(\alpha_m \boldsymbol{X}_{ijt} + \omega_m \overline{\boldsymbol{X}}_{ij})}. \quad (1)$$

where the vector $\boldsymbol{X}_{ijt}$ includes basic household and plot characteristics, namely, household size, the household head's age and years of schooling, a dummy variable for female-headed households, total household landholdings, the value of nonfarm household assets, household credit received, rice plot size, and dummy variables for soil type and irrigation status. It also includes village-level variables, such as distance to district capitals, rainfall during the main season, and population density, as well as district and year fixed effects. The MC specification, $\overline{\boldsymbol{X}}_{ij}$, contains the over-time averages of the time-varying control variables.

[7] We define the primary implement as the implement used for the main seasonal land preparation tasks, namely, plowing, puddling, and harrowing. Other activities, such as land clearing and leveling, are not widely performed every season and, when conducted, are often performed together with the main tasks, resulting in multiple implements being used on the same plot.

4.2 Second stage of MESR

In the second stage, we estimate regime-specific rice cultivation outcome equations for each mechanization choice k (where $k \in \{1, 2, 3, 4\}$), using hand tools ($k = 4$) as the reference category. The regime-specific outcome equation is specified as:

$$y_{ijkt} = \beta_k \boldsymbol{Z}_{ijt} + \theta_k \overline{\boldsymbol{Z}}_{ij} + \mu_{ijkt} \quad \text{if } U_{ijt} = k \tag{2}$$

where y_{ijkt} is the outcome variable (such as paddy yield, technology adoption, and labor use) for plot i, of household j under regime k in year t; $\boldsymbol{Z}_{ijt}$ is a set of explanatory variables, and $\overline{\boldsymbol{Z}}_{ij}$ denotes the MC specification. The error terms μ_{ijkt} are assumed to satisfy $E(\mu_{ijkt} \mid \boldsymbol{Z}_{ijt}, \overline{\boldsymbol{Z}}_{ij}) = 0$ and $\text{Var}(\mu_{ijkt} \mid \boldsymbol{Z}_{ijt}, \overline{\boldsymbol{Z}}_{ij}) = \sigma_k^2$. $\boldsymbol{Z}_{ijt}$ and $\overline{\boldsymbol{Z}}_{ij}$ contain control variables similar to those in $\boldsymbol{X}_{ijt}$ and $\overline{\boldsymbol{X}}_{ij}$ in Section 4.1.

To address the endogeneity issue, we include in Eq. (2) the selection correction terms proposed by Bourguignon, Fournier, and Gurgand (2007).[8] In the multinomial choice setting, there are $K - 1$ selection correction terms, one for each choice of mechanization implement. Following Khonje et al. (2018) and Di Falco (2014), the selection-corrected second-stage outcome equation is specified as follows:

$$y_{ijkt} = \beta_k \boldsymbol{Z}_{ijt} + \theta_k \overline{\boldsymbol{Z}}_{ij} + \sum_{m=1}^{K} \sigma_{km} \hat{\lambda}_{mijt} + \mu_{ijkt} \quad \text{if } U_{ijt} = k \tag{3}$$

where σ_{km} is the coefficient associated with the m-th selection correction term in the outcome equation for regime k, and $\hat{\lambda}_{mijt}$ denotes the generated selection correction terms computed from the estimated probabilities in Eq. (1). We bootstrap the standard errors in Eq. (3) to account for heteroscedasticity that arises from the generated regressors due to the two-stage estimation procedure.

In addition to the selection correction terms that are automatically generated, it is necessary for the $\boldsymbol{X}$ vector in the MNL model to include an instrumental variable (IV) that is not part of $\boldsymbol{Z}$. This allows the model to be identified via an exclusion restriction. Therefore, we add to $\boldsymbol{X}$ the total number of 4WTs and 2WTs in the village. The marginal effects of factors associated with the use of 4WTs, 2WTs, and DAs for land preparation are presented in Tables A6 and A7 in the Appendix. Our results show that a greater number of 2WTs and 4WTs in villages increases the probability of using them and decreases the probability of using DAs and HTs. These findings are consistent with the prevalence of rental markets, given that fewer than 1 percent of farmers in our sample used their own 4WTs, and only about 5 percent used their own 2WTs. We also find that

[8] This approach is a flexible variant of the Dubin and McFadden (1984) method. It constructs an explicit selection correction term for every alternative regime category to fully purge selection bias from the error terms, allowing correlation parameters to vary freely across all possible alternatives without imposing the restrictive assumptions common in single-term estimators (Bourguignon, Fournier, and Gurgand 2007).

the use of 2WTs is conducive to intensive rice cultivation in irrigated fields, whereas the use of 4WTs is preferable on large plots in rainfed areas.

Since there is no direct way to test whether our IV satisfies the exclusion restriction, we follow Di Falco (2014) and conduct falsification tests to examine the validity of our IV. The basic idea is that if the IV satisfies the exclusion restriction, it should not affect outcome variables except through mechanization. Therefore, we examine the association between the IV and the outcome variables of interest using a sample of rice plots that were prepared using only HTs (i.e., $k = 4$). We use pooled OLS regression with the MC specification. As shown in Appendix Tables A8 and A9, the instrumental variable (IV) is statistically insignificant across almost all outcome variables, suggesting that the exclusion restriction holds. However, straight-row transplanting is an exception, possibly due to limited variation and the small number of observations in the HT subsample. We further assess this concern by conducting robustness checks using alternative models, as discussed later in Section 4.4.

4.3 Estimation of treatment effects

Using the MESR framework, we estimate the average treatment effects on the treated (ATT). Here, we compare the expected values of outcomes for plots prepared using 4WTs, 2WTs, and DAs ($k \in \{1, 2, 3\}$) with the hand tools reference category ($k = 4$) under both actual and counterfactual scenarios. Therefore, after estimating Eq. (3), we use the resulting estimates to predict the actual and counterfactual expected values. We then calculate the ATT by taking the difference between the two as follows:

$$\begin{aligned} ATT &= E\left(y_{ijkt} \mid U_{ijt} = k, \boldsymbol{Z}_{ijt}, \overline{\boldsymbol{Z}}_{ij}, \hat{\lambda}\right) - E\left(y_{ij4t} \mid U_{ijt} = k, \boldsymbol{Z}_{ijt}, \overline{\boldsymbol{Z}}_{ij}, \hat{\lambda}\right) \\ &= \boldsymbol{Z}_{ijt}(\beta_k - \beta_4) + \overline{\boldsymbol{Z}}_{ij}(\theta_k - \theta_4) + \sum_{m=1}^{K}(\sigma_{km} - \sigma_{4m})\hat{\lambda}_{mijt} \end{aligned} \quad (4)$$

Thus, Eq. (4) captures the expected mean difference between the outcome under the actual mechanization or draft-animal regime and the outcome that would have been observed for the same plots under HT preparation.

4.4 Robustness checks

Although we believe that MESR is the most suitable framework for our case, there may be concerns about the parametric and distributional assumptions required to account for endogeneity. Therefore, we confirm the robustness of our MESR results quantitatively by estimating a correlated random effects (CRE) model and pooled OLS with the Mundlak–Chamberlain approach (denoted hereafter as POLS-MC). In estimating these two models, we use control variables $\boldsymbol{Z}_{ijt}$ and $\overline{\boldsymbol{Z}}_{ij}$, similar to those in the MESR framework. We report robust standard errors, clustered at the village level to account for the two-stage stratified sampling design. These results are presented along with the MESR estimates.

5. Estimation results

Table 3 presents the estimated effects of mechanization on land preparation and technology adoption. Panel A reports the multinomial endogenous switching regression (MESR) estimates, while Panels B and C report CRE and POLS-MC estimates, respectively, for comparison. Although some coefficients differ in magnitude and statistical significance across specifications, the signs of the estimated effects are generally consistent, with only a few exceptions. For brevity and consistency, our discussion focuses primarily on the MESR results in Panel A.

We find that, while 2WTs, 4WTs, and DAs are all positively and significantly associated with puddling, harrowing, and plowing, the magnitude of these effects is substantially larger for 2WT plots. We also find that 2WTs significantly increase the adoption of straight-row transplanting, MVs, and chemical fertilizer application. In contrast, although 4WTs have positive effects on the application of chemical fertilizer per hectare, they are associated with lower MV adoption. It should also be noted that while the use of DAs is negatively associated with MV adoption, it has no significant effect on straight-row transplanting or chemical fertilizer application. These results suggest that one possible explanation for the greater adoption of improved cultivation practices on 2WT plots is that 2WTs are lighter and can be easily maneuvered, making them better suited for puddling and harrowing in muddy paddy fields, whereas 4WTs are generally too heavy to perform these operations efficiently. Although DAs have significant effects on puddling, harrowing, and plowing, they are unlikely to be as effective as 2WTs because they tend to take longer to complete these activities, which may delay or disrupt the timing of subsequent production activities. In addition, the quality of mechanized plowing is likely to be higher because the soil is plowed more deeply.

The estimated effects of mechanization on land productivity and labor use are presented in Table 4. As with Table 3, our discussion is again primarily based on the MESR estimates in Panel A. Most importantly, we find that 2WT use results in an increase in yield of about 1.49 tons per hectare compared with the use of HTs. This yield increase leads to higher income and profit per hectare. In contrast, 4WT use increases income per hectare but has no significant effect on paddy yield or profit per hectare. It is worth emphasizing that the magnitude of the income effect associated with 4WT use is much smaller than that associated with 2WTs. Additionally, we find that the use of DAs is negatively associated with yield, income, and profit. These results strongly suggest that 2WTs are more effective than other implements in driving the intensification and profitability of rice farming. Specifically, efficient puddling, harrowing, and plowing with 2WTs is likely to increase the returns to adopting improved technologies and intensive cultivation practices, thereby enabling farmers to achieve higher yields and profits.

Regarding aggregate labor use, our estimates show that 4WTs and 2WTs significantly reduce both hired and family labor, whereas DAs reduce only hired labor and have no significant effect

on family labor. To investigate this further, we examine how 2WTs, 4WTs, and DAs influence labor use across disaggregated rice production activities and present the results in Table 5. For this analysis, however, we rely on the CRE and POLS-MC estimates instead of the MESR estimates. This is because the disaggregated labor-use variables contain many zero observations, and for some regime-specific labor activities, only a small number of plots have positive labor use, as shown in Appendix Figures A1 and A2. Since MESR relies on regime-specific counterfactual predictions, such limited variation may make the predicted mean values sensitive to the selection-correction structure and model specification (Bourguignon, Fournier, and Gurgand 2007).[9]

We find that 2WTs and 4WTs reduce family labor demand for all activities, while DAs have no significant effect. Again, the most important finding is that the use of 2WTs increases hired labor use for crop establishment, enabling the adoption of row transplanting, and also raises hired labor demand for harvesting, likely reflecting higher yields. Conversely, the use of 4WTs increases labor demand for weeding due to inadequate weed control, partly because 4WT users are less likely to adopt row transplanting, which leads to higher weeding costs. This is consistent with the adoption of more labor-intensive practices such as transplanting in straight rows for 2WT users, which contributes to intensification. In contrast, the use of 4WTs reduces labor inputs without inducing the adoption of such labor-intensive practices, aligning with our finding that 4WTs do not contribute to intensification.

6. Conclusion

This study examined whether the adoption of 2WTs or 4WTs is more effective in rice intensification than other methods using two-year panel data collected in Tanzania, one of the major rice-producing countries in SSA. Unlike previous studies, we compared the use of 4WTs, 2WTs, DAs, and HTs for land preparation simultaneously. We employed a multinomial endogenous switching regression model with a Mundlak–Chamberlain specification to address the potential endogeneity arising from farmers' self-selection into particular land preparation methods.

The most important finding is that the use of 2WTs is more effective than 4WTs and DAs in enhancing the intensification and profitability of rice farming. We find that 2WT use induces the adoption of yield-enhancing technologies, which in turn increases paddy yield without reducing hired labor demand as severely as the use of 4WTs and DAs. Our results are consistent with Mano,

[9] The MESR estimates for labor use across disaggregated rice production activities are reported in Appendix Table A10, and the associated falsification tests are reported in Appendix Table A11. Given the distributional features of the activity-specific labor variables, these estimates are presented as supplementary evidence to the CRE and POLS-MC results.

Takahashi, and Otsuka (2020), who also find that 2WT use is associated with higher land productivity. In our analysis of land-preparation activities performed using 2WTs, 4WTs, and DAs, we find that all three implements are used not only for plowing but also for puddling and harrowing. However, the estimated effects are substantially larger for 2WTs than for 4WTs and DAs. In all likelihood, the positive effect of 2WT use on paddy yield is due to the efficiency of 2WTs in performing puddling and harrowing, thereby creating favorable agronomic conditions for crop establishment and subsequent crop care activities. Additionally, we find that while DA use reduces hired labor demand by facilitating land preparation activities, it is associated with lower adoption of MVs, resulting in lower yields, income, and profit per hectare.

Our further analyses of family and hired labor use by production activity reveal the underlying mechanisms driving these outcomes. While the use of 2WTs, 4WTs, and DAs reduces labor use for land preparation, their impacts on family and hired labor use for subsequent activities differ markedly. The family labor use for plots prepared by 2WTs and 4WTs decreases, whereas we do not observe this effect in DA plots. One possible explanation is that mechanized land preparation with 2WTs and 4WTs can be completed more quickly than animal traction, which is slower. The quality of mechanized land preparation is also likely to be higher. This shorter duration and higher quality of land preparation, as well as the implementation of puddling and harrowing, lead to changes in subsequent labor use on 2WT and 4WT plots. Importantly, 2WT use is associated with increased hired labor use for labor-intensive practices such as straight-row transplanting, which can be carried out within a short period without disruption, whereas the use of 4WTs and DAs is associated with greater use of family labor for weeding. These results suggest that only 2WTs promote intensification of rice cultivation by supporting careful crop establishment and the adoption of yield-enhancing practices, while 4WTs and DAs primarily substitute for labor without contributing to productivity-enhancing intensification. The finding that DAs do not contribute to yield gains qualifies the argument of Alsan (2015), who suggests that difficulties in the adoption of animal traction, due to ecological conditions such as the prevalence of the tsetse fly, have historically constrained productivity increases and subsequent economic growth in SSA.

Our findings also contribute to policy discussions about promoting appropriate mechanization in rice farming by highlighting the distinct contributions of 4WTs and 2WTs to food security in SSA (Diao et al. 2020). In areas where labor-intensive agronomic practices such as straight-row transplanting are appropriate, particularly under irrigated conditions, the use of 2WTs can promote the intensification of rice farming. However, caution should be exercised in generalizing these findings, as the effects of mechanized tillage may vary across locations and crops, even though rice production technologies and practices are not highly location-specific (Daum et al. 2023; Otsuka et al. 2024). The important point is that the effects of mechanization are closely related to the presence or absence of irrigation, the thoroughness of land preparation, and the adoption of improved agronomic practices. Policies to promote mechanization must properly

consider the interrelationships between mechanization, the adoption of yield-enhancing MVs and fertilizer, and improved cultivation practices.

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Table 1: Rice production variables by farm implement used to prepare rice plots (2018 and 2025)

	(1)	(2)	(3)	(4)	(1)-(4)	(2)-(4)	(3)-(4)
Variables	2WT	4WT	DA	HT		Difference	
Panel A: Plot size and cultivated area							
Plot size (ha)	1.35	1.29	1.38	0.62	0.73***	0.68***	0.76***
Plot area under rice cultivation (ha)	1.22	1.14	1.14	0.56	0.66***	0.58***	0.58***
Panel B: Land preparation methods and technology adoption							
Puddling/harrowing (dummy)	0.93	0.61	0.82	0.52	0.42***	0.09	0.30***
Plowing (dummy)	0.94	0.92	0.96	0.75	0.19***	0.17***	0.21***
Adoption of straight-row transplanting (dummy)	0.33	0.08	0.14	0.41	-0.08	-0.33***	-0.27***
Adoption of modern variety (dummy)	0.64	0.31	0.31	0.72	-0.08	-0.42***	-0.41***
Chemical fertilizer application (kg/ha)	131.57	32.84	35.86	52.81	78.76***	-19.97***	-16.95
Panel C: Land productivity							
Paddy yield (tons/ha)	5.00	2.88	2.93	3.58	1.42***	-0.71***	-0.66**
Income (‘000 TSh/ha)	1,320.87	655.23	784.72	860.38	460.48***	-205.15***	-75.66
Profit (‘000 TSh/ha)	1,171.09	465.75	544.92	548.41	622.69***	-82.66	-3.49
Observations (rice plots)	268	375	84	119			
Number of households	166	200	55	85			

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in *t*-test comparisons between the use of 2WT, 4WT, DA, and HT. (ii) The number of observations for each variable is 846 lowland rice plots cultivated by 253 households over a two-year period (2018 and 2025). (iii) For profit, land preparation variables, and labor use, the number of observations is 506 because these variables are based on the household’s most important rice plot (one plot per household in each survey round). (iv) All monetary values are adjusted for inflation using 2009 as the base year. (v) In 2009, USD 1 was approximately equivalent to TSh 1,300.

Table 2: Labor use by farm implement used to prepare rice plots (2018 and 2025)

	(1)	(2)	(3)	(4)	(1)-(4)	(2)-(4)	(3)-(4)
Variables	2WT	4WT	DA	HT		Difference	
Panel A: Aggregate labor use							
Hired labor (person-days/ha)	47.61	37.41	30.32	69.00	-21.39***	-31.59***	-38.68***
Family labor (person-days/ha)	10.57	17.61	27.87	37.23	-26.67***	-19.62***	-9.36
Panel B: Labor use across rice production activities							
Hired labor use for:							
Preparing rice plot (person-days/ha)	4.36	2.74	5.20	26.30	-21.94***	-23.56***	-21.10***
Crop establishment (person-days/ha)	14.61	2.47	3.55	10.39	4.22	-7.93***	-6.85***
Weeding (person-days/ha)	11.34	15.64	10.08	10.84	0.51	4.81**	-0.76
Harvesting activities (person-days/ha)	18.27	16.56	11.50	21.76	-3.49	-5.20**	-10.26***
Family labor use for:							
Preparing rice plot (person-days/ha)	1.56	2.04	3.19	7.63	-6.06***	-5.59***	-4.44*
Crop establishment (person-days/ha)	0.81	0.50	3.05	2.99	-2.18***	-2.49***	0.06
Weeding (person-days/ha)	4.63	9.80	10.30	16.60	-11.97***	-6.80***	-6.30*
Harvesting activities (person-days/ha)	3.57	5.27	11.36	10.14	-6.57***	-4.87**	1.22
Number of rice plots	166	200	55	85			

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in *t*-test comparison between the use of 4WT, 2WT, DA, and HT.

Table 3: Estimated effects of mechanization on land preparation method and technology adoption

VARIABLES	(1) Puddling/harrowing (dummy)	(2) Plowing (dummy)	(3) Adoption of straight-row transplanting (dummy)	(4) Adoption of modern variety (dummy)	(5) Chemical fertilizer application (kg/ha)
Panel A: MESR estimates (ATT)					
2WT vs HT	0.98***	0.96***	0.29***	0.12***	66.31***
	(0.028)	(0.047)	(0.046)	(0.029)	(4.708)
4WT vs HT	0.26***	0.24***	-0.00	-0.17***	14.34***
	(0.019)	(0.017)	(0.034)	(0.013)	(4.118)
DA vs HT	0.58***	0.62***	-0.12	-0.18***	3.37
	(0.055)	(0.036)	(0.087)	(0.042)	(12.165)
IV's falsification test (*p*-value)	0.786	0.814	0.000551	0.247	0.187
Panel B: CRE estimates					
Use of 2WT (dummy)	0.33***	0.10	0.22***	0.05	57.63***
	[0.051]	[0.066]	[0.072]	[0.064]	[11.970]
Use of 4WT (dummy)	0.09*	0.13***	-0.12**	-0.18***	2.69
	[0.050]	[0.034]	[0.051]	[0.043]	[8.724]
Use of DA (dummy)	0.13***	0.12***	0.12	-0.10	10.90
	[0.040]	[0.032]	[0.075]	[0.072]	[12.182]
Panel C: POLS-MC estimates					
Use of 2WT (dummy)	0.33***	0.10	0.24***	0.07	59.42***
	[0.052]	[0.067]	[0.077]	[0.066]	[11.906]
Use of 4WT (dummy)	0.09	0.13***	-0.12**	-0.19***	2.53
	[0.051]	[0.035]	[0.052]	[0.045]	[9.234]
Use of DA (dummy)	0.13***	0.12***	0.14*	-0.06	14.34
	[0.042]	[0.034]	[0.078]	[0.075]	[12.093]
Number of rice plots	506	506	846	846	846
Number of households	253	253	253	253	253

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Bootstrapped standard errors (200 replications) in parentheses and robust standard errors clustered at the village level in brackets. (iii) The number of observations for crop establishment method is 846 lowland rice plots, as these questions were asked for all households' rice plots. (iv) For plot preparation and labor use, the number of observations is 506 because for these variables, we included only the most important rice plot per household in each survey round.

Table 4: Estimated effects of mechanization on land productivity and labor use

VARIABLES	(1) Paddy yield (tons/ha)	(2) Income ('000 TSh/ha)	(3) Profit ('000 TSh/ha)	(4) Hired labor use (person-days/ha)	(5) Family labor use (person-days/ha)
Panel A: MESR estimates (ATT)					
2WT vs HT	1.49***	783.77***	777.10***	-47.22***	-8.26**
	(0.219)	(110.581)	(122.578)	(5.698)	(4.121)
4WT vs HT	0.22	145.66**	100.21	-38.07***	-32.90***
	(0.134)	(68.066)	(71.187)	(4.058)	(3.497)
DA vs HT	-2.31***	-954.31***	-1,289.77***	-57.88***	-11.25
	(0.356)	(176.450)	(174.070)	(8.225)	(9.262)
IV's falsification test (*p*-value)	0.371	0.263	0.607	0.143	0.460
Panel B: CRE estimates					
Use of 2WT (dummy)	1.03***	268.19***	369.25***	5.13	-13.72***
	[0.321]	[103.258]	[117.978]	[5.053]	[3.867]
Use of 4WT (dummy)	0.15	3.35	126.15	-14.29***	-14.44***
	[0.270]	[92.476]	[98.437]	[5.277]	[4.144]
Use of DA (dummy)	-0.27	-70.09	7.18	-12.19**	-0.32
	[0.335]	[129.502]	[148.160]	[4.863]	[5.263]
Panel C: POLS-MC estimates					
Use of 2WT (dummy)	1.08***	279.56**	360.44***	5.27	-14.71***
	[0.353]	[114.830]	[122.096]	[4.942]	[3.910]
Use of 4WT (dummy)	0.13	-7.74	132.32	-13.30**	-15.89***
	[0.260]	[87.648]	[95.193]	[5.169]	[4.672]
Use of DA (dummy)	-0.15	-29.96	-0.02	-11.81**	-0.77
	[0.373]	[150.777]	[159.743]	[4.917]	[5.436]
Number of rice plots	846	846	506	506	506
Number of households	253	253	253	253	253

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Bootstrapped standard errors (200 replications) in parentheses and robust standard errors clustered at the village level in brackets. (iii) The HT user (i.e., k= 4) is the reference category. (iv) The number of observations for each variable is 846 lowland rice plots, cultivated by 253 households over a two-year panel dataset (2018 and 2025). (v) For profit, the number of observations is 506 because for these variables, we included only the most important rice plot per household in each survey round.

Table 5: Estimated effects of mechanization on labor use across rice production activities (unit: person-days/ha)

VARIABLES	(1) Hired labor use for preparing rice plot	(2) Hired labor use for crop establishment	(3) Hired labor use for weeding	(4) Hired labor use for harvesting activities	(5) Family labor use for preparing rice plot	(6) Family labor use for crop establishment	(7) Family labor use for weeding	(8) Family labor use for harvesting activities
Panel A: CRE estimates								
Use of 2WT (dummy)	-8.69***	5.43**	2.73	5.95***	-2.77**	-1.89**	-5.84***	-3.78**
	[2.558]	[2.117]	[2.228]	[1.745]	[1.219]	[0.850]	[1.615]	[1.605]
Use of 4WT (dummy)	-14.95***	-1.54	4.91**	-3.22	-3.92***	-2.01***	-4.66***	-3.98**
	[3.020]	[1.945]	[1.927]	[2.324]	[1.477]	[0.774]	[1.621]	[1.816]
Use of DA (dummy)	-6.85***	-2.91	-0.35	-2.76	-1.84	0.32	-0.92	2.25
	[2.018]	[1.985]	[2.666]	[2.662]	[1.204]	[0.741]	[2.136]	[2.479]
Panel B: POLS-MC estimates								
Use of 2WT (dummy)	-8.14***	5.31**	2.68	5.67***	-2.68**	-1.90*	-6.31***	-3.91**
	[2.480]	[2.180]	[2.249]	[1.821]	[1.309]	[0.952]	[1.690]	[1.636]
Use of 4WT (dummy)	-14.15***	-1.85	5.17**	-2.93	-4.16**	-2.20**	-5.19***	-4.46**
	[2.904]	[1.968]	[1.950]	[2.372]	[1.618]	[0.844]	[1.846]	[1.877]
Use of DA (dummy)	-6.70***	-3.33	-0.64	-2.05	-2.01	0.24	-1.11	2.05
	[2.080]	[2.133]	[2.640]	[2.676]	[1.281]	[0.854]	[2.365]	[2.576]
Number of rice plots	506	506	506	506	506	506	506	506
Number of households	253	253	253	253	253	253	253	253

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Bootstrapped standard errors (200 replications) in parentheses and robust standard errors clustered at the village level in brackets.

Table A1: Attrition probit estimates

VARIABLES	(1) Remained household (dummy)
Household rice area	-0.081
	(0.054)
Age of household head	-0.009
	(0.006)
Years of schooling of household head	0.023
	(0.031)
Number of working age adults	-0.004
	(0.050)
Female-headed household (dummy)	0.148
	(0.185)
Value of nonfarm household assets (mil. TSh)	0.333**
	(0.158)
Total landholdings (ha)	0.053
	(0.035)
Amount of credit received by the household ('00,000 TSh)	-0.064*
	(0.034)
Number of bulls owned	-0.038
	(0.031)
Size of the plot (ha)	0.010
	(0.076)
Irrigated plot (dummy)	0.537**
	(0.212)
Sample plot has clay soil (dummy)	-0.027
	(0.158)
Total rainfall during land preparation season (mm)	0.000
	(0.001)
Mvomero district (dummy)	-0.322
	(0.367)
Mbarali district (dummy)	-0.152
	(0.337)
Constant	0.721
	(0.880)
Observations	332

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Robust standard errors clustered at the village level in parentheses.

Table A2: Summary statistics of household-level variables

	(1)	(2)	(3)	(4)
Variables	Mean	SD	Min	Max
Age of household head (years)	53.32	11.71	23.00	94.00
Female-headed household (dummy)	0.15	0.36	0.00	1.00
Education of household head (years)	6.85	2.35	0.00	16.00
Household size	5.91	2.59	1.00	19.00
Household nonfarm assets (million TSh)	0.98	1.25	0.00	14.75
Amount of credit received (million TSh)	0.11	0.48	0.00	4.20
Total household landholdings (ha)	3.63	4.08	0.00	37.23
Plot is irrigated (dummy)	0.28	0.45	0.00	1.00
Plot size (ha)	1.22	1.36	0.10	12.14
Plot area under rice cultivation (ha)	1.09	1.15	0.10	12.14
Plot soil type is clay (dummy)	0.39	0.49	0.00	1.00
Use of 2WTs (dummy)	0.32	0.47	0.00	1.00
Use of 4WTs (dummy)	0.46	0.50	0.00	1.00
Use of DAs (dummy)	0.16	0.37	0.00	1.00
Hand tools used (dummy)	0.14	0.35	0.00	1.00
Adoption of modern varieties (dummy)	0.47	0.50	0.00	1.00
Chemical fertilizer application (kg/ha)	67.22	92.38	0.00	494.19
Paddy yield (tons/ha)	3.65	2.35	0.01	9.60
Rice revenue (‘000 TSh/ha)	1,295.07	861.29	1.83	3,935.36
Income (‘000 TSh/ha)	907.81	793.97	-665.15	3,576.39
Adoption of straight-row transplanting (dummy)	0.21	0.41	0.00	1.00
Total paid-out cost (‘000 TSh/ha)	387.26	230.40	0.00	1,408.00
Paid-out costs for:				
Seed (‘000 TSh/ha)	16.76	35.06	0.00	288.98
Fertilizer (‘000 TSh/ha)	41.18	57.64	0.00	416.14
Pesticide/herbicide (‘000 TSh/ha)	19.51	15.47	0.00	77.87
Hired labor (‘000 TSh/ha)	170.82	169.40	0.00	1,201.81
Machinery and animal use (‘000 TSh/ha)	138.99	117.79	0.00	792.20
Population density (‘000 persons/km^2)	1.50	1.57	0.11	8.53
Distance to district capital (10 km)	6.55	4.55	0.48	18.70
Total rainfall during main season (100 mm)	11.38	3.60	5.00	16.26
Number of 2WTs and 4WTs in the village	16.22	27.09	0.00	153.00
Year 2025 (dummy)	0.50	0.50	0.00	1.00
Year 2018 (dummy)	0.50	0.50	0.00	1.00
Mvomero district (dummy)	0.30	0.46	0.00	1.00
Kilombero district (dummy)	0.44	0.50	0.00	1.00
Mbarali district (dummy)	0.26	0.44	0.00	1.00

Notes: (i) The number of observations is 846 lowland rice plots cultivated by 253 households over a two-year period (2018 and 2025). (ii) All monetary values are in Tanzanian shillings (TSh), adjusted for inflation using 2009 as the base year.

Table A3: Summary statistics for the variables observed in the household's most important rice plot

	(1)	(2)	(3)	(4)	(5)
Variables	Mean	SD	Min	Max	N
Plot is irrigated (dummy)	0.31	0.46	0.00	1.00	506
Plot size (ha)	1.44	1.60	0.10	12.14	506
Plot area under rice cultivation (ha)	1.26	1.34	0.10	12.14	506
Plot soil type is clay (dummy)	0.42	0.49	0.00	1.00	506
Use of 2WT (dummy)	0.33	0.47	0.00	1.00	506
Use of 4WT (dummy)	0.42	0.49	0.00	1.00	506
Use of DA (dummy)	0.19	0.39	0.00	1.00	506
Hand tools used (dummy)	0.17	0.37	0.00	1.00	506
Adoption of modern variety (dummy)	0.50	0.50	0.00	1.00	506
Chemical fertilizer application (kg/ha)	67.76	91.83	0.00	370.64	506
Paddy yield (tons/ha)	3.51	2.37	0.01	9.60	506
Rice revenue ('000 TSh/ha)	1,285.26	909.62	1.83	3,935.36	506
Income ('000 TSh/ha)	875.50	842.44	-665.15	3,576.39	506
Profit ('000 TSh/ha)	719.64	868.52	-1,418.89	3,529.67	506
Straight-row transplanting (dummy)	0.21	0.41	0.00	1.00	506
Puddling/harrowing (dummy)	0.72	0.45	0.00	1.00	506
Plowing (dummy)	0.90	0.30	0.00	1.00	506

continued

Table A3: continued

Variables	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Total paid-out cost (‘000 TSh/ha)	409.76	248.65	0.00	1,408.00	506
Paid-out cost for current inputs (‘000 TSh/ha)	75.17	74.14	0.00	510.54	506
1. Seed (‘000 TSh/ha)	17.84	41.09	0.00	288.98	506
2. Fertilizer (‘000 TSh/ha)	39.65	53.37	0.00	211.92	506
3. Pesticide/herbicide (‘000 TSh/ha)	17.68	15.84	0.00	75.35	506
Paid-out cost for hired labor (‘000 TSh/ha)	196.84	186.22	0.00	1,201.81	506
1. Plot preparation (‘000 TSh/ha)	34.35	72.28	0.00	449.53	506
2. Crop establishment (‘000 TSh/ha)	37.58	61.56	0.00	373.77	506
3. Weeding (‘000 TSh/ha)	44.31	59.37	0.00	398.16	506
4. Harvesting activities (‘000 TSh/ha)	80.60	107.14	0.00	752.28	506
Paid-out cost for machinery and DA use (‘000 TSh/ha)	137.74	119.83	0.00	792.20	506
1. Plot preparation and crop establishment (‘000 TSh/ha)	83.77	77.35	0.00	642.19	506
2. Harvesting activities (‘000 TSh/ha)	53.97	76.37	0.00	363.39	506
Total imputed cost (‘000 TSh/ha)	155.87	217.94	0.00	2,138.15	506
Imputed costs for using own-produced seed (‘000 TSh/ha)	24.06	44.44	0.00	249.18	506
Imputed costs for family labor (‘000 TSh/ha)	112.89	212.48	0.00	2,138.15	506
1. Plot preparation (‘000 TSh/ha)	21.85	75.13	0.00	828.16	506
2. Crop establishment (‘000 TSh/ha)	9.70	37.19	0.00	320.51	506
3. Weeding (‘000 TSh/ha)	45.70	98.76	0.00	689.28	506
4. Harvesting activities (‘000 TSh/ha)	35.63	92.32	0.00	650.25	506
Imputed costs of using own machinery and DAs (‘000 TSh/ha)	18.92	47.19	0.00	295.41	506
1. Plot preparation and crop establishment (‘000 TSh/ha)	14.94	41.26	0.00	192.66	506
2. Harvesting activities (‘000 TSh/ha)	3.97	13.95	0.00	102.75	506

continued

Table A3: continued

Variables	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Hired labor use (person-days/ha)	45.29	39.12	0.00	182.85	506
1. Preparing rice plot (person-days/ha)	7.49	15.42	0.00	79.07	506
2. Crop establishment (person-days/ha)	7.90	16.28	0.00	207.56	506
3. Weeding (person-days/ha)	12.82	16.57	0.00	61.77	506
4. Harvesting activities (person-days/ha)	17.45	19.68	0.00	69.19	506
Family labor use (person-days/ha)	19.71	33.44	0.00	231.19	506
1. Preparing rice plot (person-days/ha)	2.95	8.92	0.00	66.56	506
2. Crop establishment (person-days/ha)	1.30	5.35	0.00	45.30	506
3. Weeding (person-days/ha)	9.30	16.95	0.00	74.13	506
4. Harvesting activities (person-days/ha)	6.19	14.65	0.00	90.50	506

Notes: (i) The number of observations is 506 lowland rice plots because for these variables, we included only the most important rice plot per household in each survey round. (ii) All monetary values are in Tanzanian shillings(TSh), adjusted for inflation using2009 as the base year.

Table A4: Mechanization access and related variables

Variables	(1) 2018	(2) 2025	(2) - (1) Mean difference
Farm implements used by households to prepare rice plots			
2WTs (%)	24.88	38.57	13.69***
4WTs (%)	49.30	43.57	-5.72*
DAs (%)	16.20	16.43	0.23
HTs (%)	16.67	11.43	-5.24**
Observations (rice plots)	426	420	
Mechanization access and wage rate at the village level			
Number of 2WTs	8.26	18.41	10.15*
Number of 4WTs	3.38	2.82	-0.56
2WT hire fee (‘000 TSh/acre)	32.05	28.22	-3.83
4WT hire fee (‘000 TSh/acre)	25.18	24.87	-0.31
DA hire fee (‘000 TSh/acre)	22.71	20.74	-1.97
Wage rate for land preparation (‘000 TSh/acre)	29.80	17.91	-11.89***
Observations (villages)	34	34	

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in *t*-test comparisons between the labeled categories. (ii) All monetary values are adjusted for inflation using 2009 as the base year. (iii) As of 2009, USD 1 was approximately equivalent to TSh 1,300. (iv) Since not all villages have machinery and draft animal hire markets, the fees are based on villages where these markets exist.

Table A5: Crop establishment method by farm implement used to prepare rice plots

	(1)	(2)	(3)	(4)	(1)-(4)	(2)-(4)	(3)-(4)
Variables	2WT	4WT	DA	HT	Difference		
Transplanting							
1. Straight rows (dummy)	0.33	0.08	0.14	0.41	-0.08	-0.33***	-0.27***
2. Random transplanting (dummy)	0.44	0.03	0.23	0.39	0.06	-0.35***	-0.16**
Direct seeding							
1. Broadcasting (dummy)	0.20	0.81	0.56	0.18	0.01	0.63***	0.37***
2. Dibbling (dummy)	0.01	0.05	0.05	0.01	-0.00	0.04*	0.04*
3. Seed drilling (dummy)	0.02	0.03	0.02	0.01	0.01	0.02	0.02
Observations: all household rice plots	268	375	84	119			
Number of households	166	200	55	85			

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in *t*-test comparisons between the use of 2WT, 4WT, DA, and HT.

Table A6: First stage marginal effects (based on MNL estimates for all lowland rice plots)

VARIABLES	(1) 2WT	(2) 4WT	(3) DA	(4) HT
Number of 2WTs and 4WTs in the village	0.003**	0.005***	-0.003**	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)
Population density ('000 persons/km2)	-0.005	-0.013	-0.004	0.022***
	(0.016)	(0.016)	(0.022)	(0.006)
Distance to district capital (10 km)	-0.001	-0.015***	0.020***	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Total rainfall during main season (100 mm)	0.014	-0.066***	0.025	0.027**
	(0.016)	(0.018)	(0.016)	(0.013)
Age of household head (years)	-0.005	0.001	0.000	0.003*
	(0.003)	(0.003)	(0.003)	(0.002)
Female-headed household (dummy)	0.001	0.068	-0.001	-0.068**
	(0.044)	(0.046)	(0.031)	(0.029)
Education of household head (years)	-0.002	-0.005	-0.003	0.010**
	(0.006)	(0.007)	(0.005)	(0.005)
Household size	0.001	-0.003	0.003	-0.000
	(0.010)	(0.012)	(0.011)	(0.009)
Household nonfarm assets (million TSh)	0.026	0.037	0.014	-0.077***
	(0.028)	(0.028)	(0.029)	(0.026)
Amount of credit received (million TSh)	-0.011	0.111**	-0.021	-0.079
	(0.051)	(0.045)	(0.039)	(0.049)
Total household landholdings (ha)	-0.002	-0.013*	-0.002	0.016***
	(0.007)	(0.007)	(0.005)	(0.006)
Plot is irrigated (dummy)	0.155***	-0.324***	0.054**	0.114***
	(0.032)	(0.035)	(0.026)	(0.020)
Plot size (ha)	0.000	0.072***	0.015	-0.088***
	(0.017)	(0.025)	(0.015)	(0.024)
Plot soil type is clay (dummy)	-0.015	0.018	-0.014	0.011
	(0.025)	(0.029)	(0.022)	(0.020)
Year 2025 (dummy)	0.131***	-0.141***	0.034	-0.024
	(0.034)	(0.033)	(0.029)	(0.022)
Mvomero district (dummy)	-0.347***	0.862***	-0.378***	-0.137**
	(0.089)	(0.086)	(0.088)	(0.062)
Kilombero district (dummy)	-0.422***	1.073***	-0.349**	-0.302***
	(0.145)	(0.145)	(0.149)	(0.113)
MC specification	Yes	Yes	Yes	Yes
Hausman's test of IIA assumption (χ^2)	54.514	53.098	26.738	31.971
Hausman's test of IIA assumption (p-value)	0.241	0.284	0.994	0.964
Wald's joint significance test of IV (χ^2): 12.88***				
Observations: 846 rice plots				

Notes: (i) Robust standard errors in parentheses. (ii) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7: First stage marginal effects (based on MNL estimates for the most important plot)

VARIABLES	(1) 2WT	(2) 4WT	(3) DA	(4) HT
Number of 2WTs and 4WTs in the village	0.004***	0.004**	-0.002*	-0.006**
	(0.002)	(0.002)	(0.001)	(0.002)
Population density ('000 persons/km2)	-0.009	-0.011	-0.001	0.021**
	(0.017)	(0.019)	(0.017)	(0.009)
Distance to district capital (10 km)	0.002	-0.018***	0.020***	-0.004
	(0.004)	(0.004)	(0.003)	(0.004)
Total rainfall during main season (100 mm)	0.006	-0.053***	0.005	0.041**
	(0.019)	(0.020)	(0.019)	(0.017)
Age of household head (years)	-0.006**	0.003	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.002)
Female-headed household (dummy)	0.049	0.029	0.022	-0.101***
	(0.047)	(0.055)	(0.035)	(0.039)
Education of household head (years)	0.002	-0.010	-0.004	0.012**
	(0.008)	(0.009)	(0.007)	(0.006)
Household size	0.003	-0.009	0.001	0.005
	(0.011)	(0.013)	(0.011)	(0.010)
Household nonfarm assets (million TSh)	0.023	0.060**	-0.011	-0.072**
	(0.026)	(0.030)	(0.026)	(0.034)
Amount of credit received (million TSh)	0.058	0.082*	-0.009	-0.131**
	(0.057)	(0.049)	(0.039)	(0.060)
Total household landholdings (ha)	-0.003	-0.009	-0.006	0.018***
	(0.009)	(0.008)	(0.005)	(0.006)
Plot is irrigated (dummy)	0.149***	-0.314***	0.051	0.115***
	(0.039)	(0.040)	(0.033)	(0.023)
Plot size (ha)	0.036	0.087**	0.024	-0.147***
	(0.024)	(0.034)	(0.024)	(0.037)
Plot soil type is clay (dummy)	-0.028	0.034	-0.006	-0.000
	(0.035)	(0.035)	(0.028)	(0.026)
Year 2025 (dummy)	0.141***	-0.123***	-0.037	0.019
	(0.039)	(0.037)	(0.031)	(0.027)
Mvomero district (dummy)	-0.291***	0.781***	-0.273***	-0.216***
	(0.103)	(0.090)	(0.093)	(0.075)
Kilombero district (dummy)	-0.312*	0.936***	-0.178	-0.446***
	(0.167)	(0.163)	(0.170)	(0.151)
MC specification	Yes	Yes	Yes	Yes
Hausman's test of IIA assumption (χ^2)	34.128	38.775	26.487	26.519
Hausman's test of IIA assumption (*p*-value)	0.935	0.827	0.995	0.995
Wald's joint significance test of IV (χ^2): 9.63**				
Observations: 506 rice plots				

Notes: (i) Robust standard errors in parentheses. (ii) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Falsification test for land preparation method and technology adoption

VARIABLES	(1) Puddling/harrowing (dummy)	(2) Plowing (dummy)	(3) Adoption of straight-row transplanting (dummy)	(4) Adoption of modern variety (dummy)	(5) Chemical fertilizer application (kg/ha)
Number of 2WTs and 4WTs in the village	-0.003	-0.001	0.028***	0.008	2.322
	[0.010]	[0.005]	[0.008]	[0.007]	[1.741]
Population density (‘000 persons/km2)	0.042*	0.028*	0.028	0.020	-5.142*
	[0.024]	[0.016]	[0.022]	[0.020]	[2.989]
Distance to district capital (10 km)	0.005	-0.018	0.033**	-0.011	-0.266
	[0.029]	[0.022]	[0.015]	[0.022]	[2.464]
Total rainfall during main season (100 mm)	0.011	0.036	-0.025	0.070	-4.486
	[0.076]	[0.052]	[0.046]	[0.047]	[6.693]
Household- and plot-level variables	Yes	Yes	Yes	Yes	Yes
MC specification, district and year FE	Yes	Yes	Yes	Yes	Yes
Constant	-0.536	-0.302	-1.061**	0.000	120.413*
	[0.585]	[0.495]	[0.427]	[0.507]	[67.248]
Observations	85	85	119	119	119
Adjusted R-squared	0.167	0.276	0.131	0.0243	0.152
Wald test of selected IVs (F-statistic)	0.0745	0.0557	13.08	1.362	1.778
Wald test of selected IVs (p-value)	0.786	0.814	0.000551	0.247	0.187

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Robust standard errors clustered at the village level in brackets.

Table A9: Falsification test for land productivity and labor use

VARIABLES	(1) Paddy yield (tons/ha)	(2) Income ('000 TSh/ha)	(3) Profit ('000 TSh/ha)	(4) Hired labor use (person-days/ha)	(5) Family labor use (person-days/ha)
Number of 2WTs and 4WTs in the village	0.048	22.862	11.722	-1.092	0.539
	[0.053]	[20.248]	[22.680]	[0.736]	[0.726]
Population density ('000 persons/km2)	-0.003	-49.783*	-32.712	6.734***	-1.757
	[0.071]	[29.539]	[39.415]	[2.456]	[2.773]
Distance to district capital (10 km)	0.201**	130.997***	136.984**	0.302	2.989
	[0.098]	[27.246]	[56.914]	[2.794]	[2.378]
Total rainfall during main season (100 mm)	-0.628***	-224.328***	-131.272	6.841	-7.302
	[0.206]	[71.604]	[112.864]	[5.856]	[5.755]
Household- and plot-level variables	Yes	Yes	Yes	Yes	Yes
MC specification, district and year FE	Yes	Yes	Yes	Yes	Yes
Constant	9.694***	2,516.251***	2,571.068**	6.667	78.380
	[2.119]	[784.876]	[1,087.891]	[49.471]	[57.602]
Observations	119	119	85	85	85
Adjusted R-squared	0.294	0.235	0.190	0.265	0.271
Wald test of selected IVs (F-statistic)	0.812	1.275	0.267	2.197	0.552
Wald test of selected IVs (p-value)	0.371	0.263	0.607	0.143	0.460

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Robust standard errors clustered at the village level in brackets.

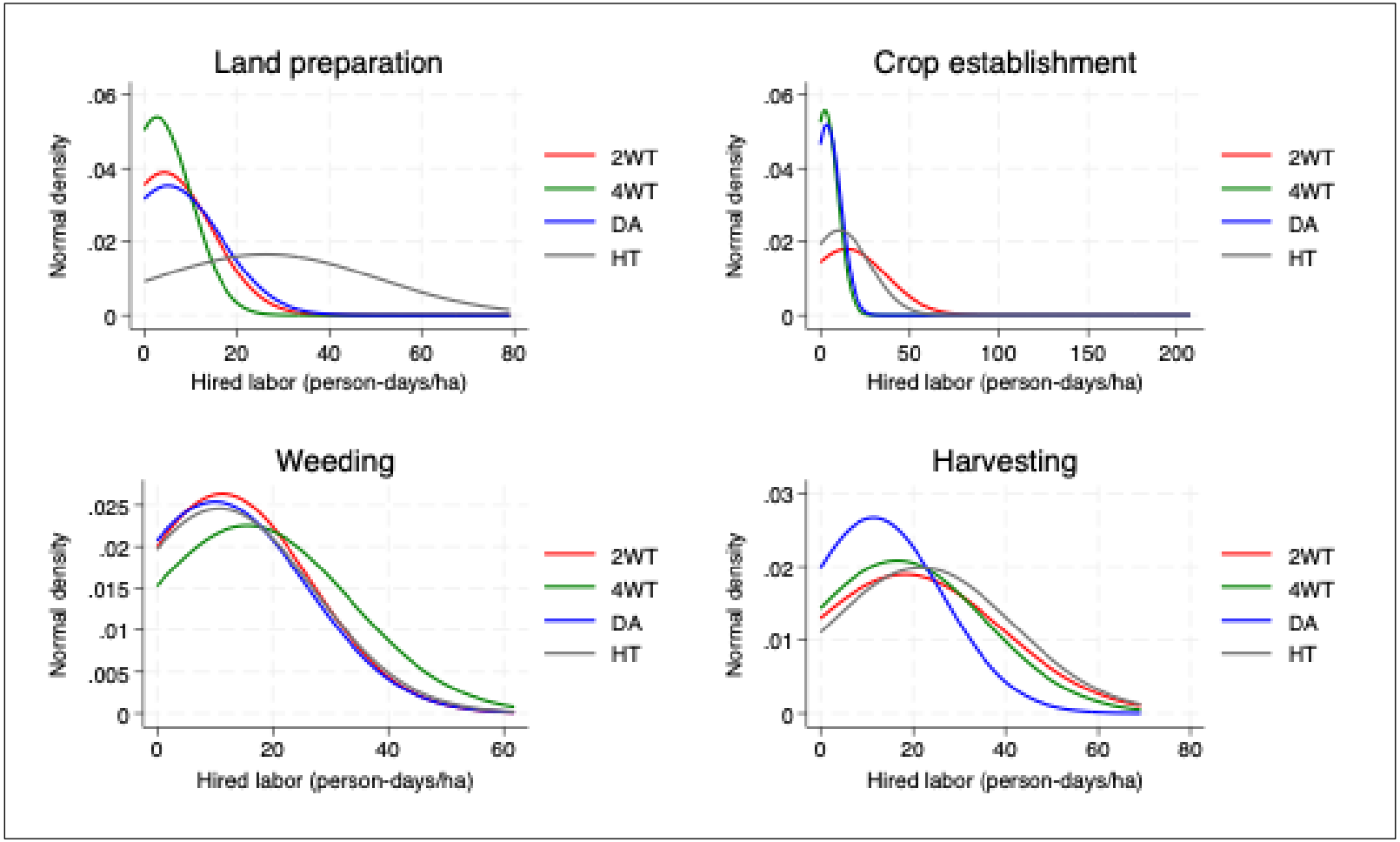


Figure A1: Fitted normal density of hired labor use by mechanization regime

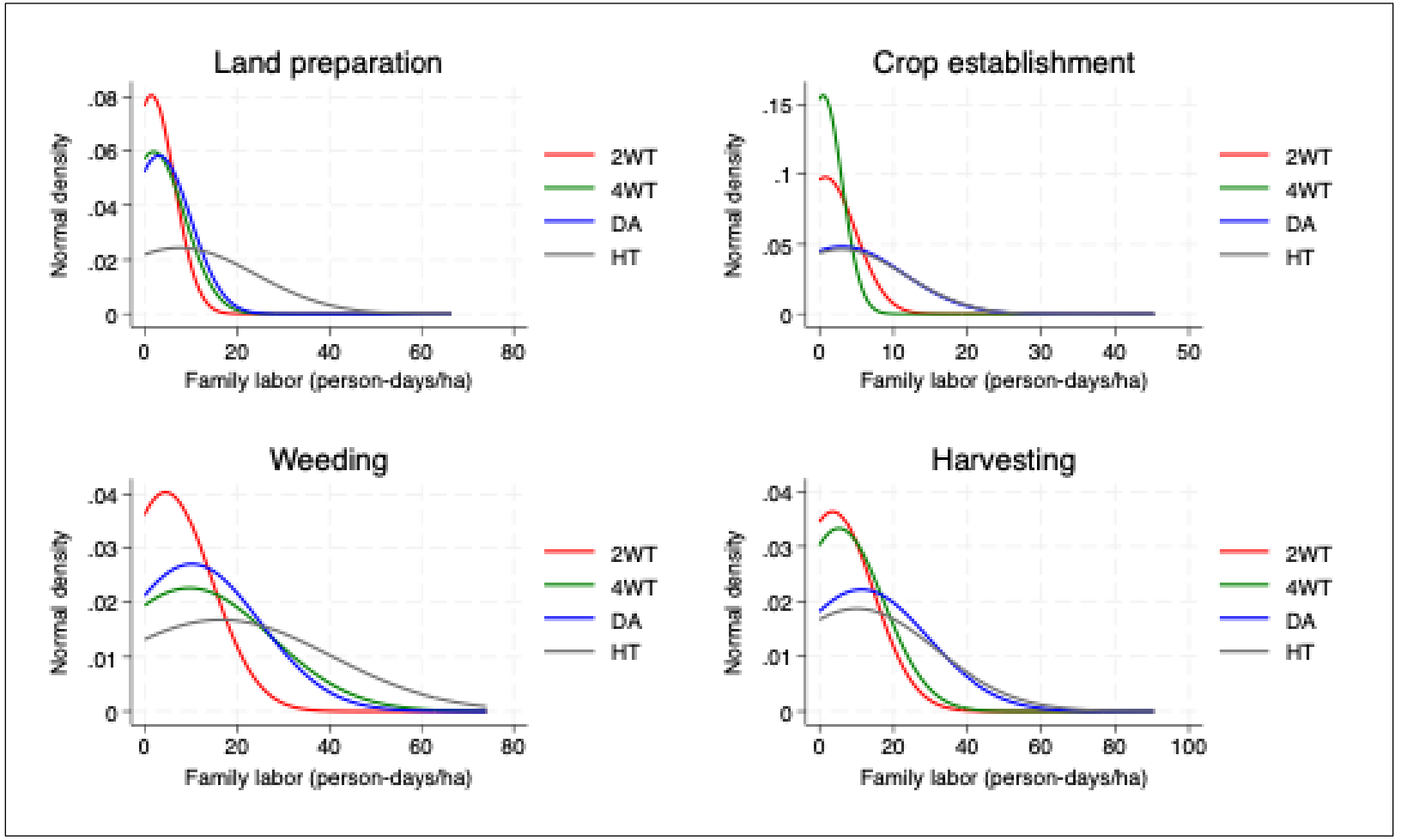


Figure A2: Fitted normal density of family labor use by mechanization regime

Table A10: MESR estimated ATT effects of mechanization on labor use across rice production activities (unit: person-days/ha)

VARIABLES	(1) Hired labor use for preparing rice plot	(2) Hired labor use for crop establishment	(3) Hired labor use for weeding	(4) Hired labor use for harvesting activities	(5) Family labor use for preparing rice plot	(6) Family labor use for crop establishment	(7) Family labor use for weeding	(8) Family labor use for harvesting activities
2WT vs HT	-15.32***	2.12	-11.99***	-22.09***	-2.88***	-3.49***	-4.21***	1.88
	(1.968)	(1.931)	(1.464)	(2.647)	(0.954)	(0.610)	(1.623)	(1.617)
4WT vs HT	-29.80***	-2.97***	-2.98**	-2.13	-13.14***	-2.20***	-7.48***	-10.07***
	(1.891)	(0.972)	(1.305)	(1.497)	(0.884)	(0.396)	(1.404)	(1.304)
DA vs HT	-14.38***	-4.19**	-21.32***	-18.31***	-13.24***	8.19***	-7.97**	1.66
	(3.464)	(1.990)	(2.698)	(2.786)	(2.265)	(1.228)	(3.501)	(3.605)
IV's falsification test (*p*-value)	0.255	0.209	0.436	0.932	0.373	0.284	0.914	0.843
Number of rice plots	506	506	506	506	506	506	506	506
Number of households	253	253	253	253	253	253	253	253

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Bootstrapped standard errors (200 replications) in parentheses.

Table A11: Falsification test for labor use across rice production activities (unit: person-days/ha)

VARIABLES	(1) Hired labor use for preparing rice plot	(2) Hired labor use for crop establishment	(3) Hired labor use for weeding	(4) Hired labor use for harvesting activities	(5) Family labor use for preparing rice plot	(6) Family labor use for crop establishment	(7) Family labor use for weeding	(8) Family labor use for harvesting activities
Number of 2WTs and 4WTs in the village	-0.450	-0.397	-0.186	-0.047	0.226	0.211	0.047	0.053
	[0.391]	[0.313]	[0.238]	[0.544]	[0.252]	[0.195]	[0.437]	[0.266]
Population density (‘000 persons/km2)	3.539***	0.835	1.101	1.303	-1.223*	-0.616	-0.287	0.338
	[1.204]	[0.742]	[0.923]	[1.370]	[0.626]	[0.446]	[1.284]	[1.483]
Distance to district capital (10 km)	-0.542	-1.015	0.356	1.531	1.403	0.109	1.400	0.082
	[1.358]	[0.801]	[0.901]	[1.048]	[1.221]	[0.438]	[1.248]	[0.975]
Total rainfall in main season (×100 mm)	1.612	4.540***	3.496*	-2.701	-4.788**	-0.397	-3.068	1.122
	[3.051]	[1.705]	[2.050]	[2.478]	[2.384]	[1.068]	[3.301]	[2.516]
Household- and plot-level variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MC specification, district and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.716	-9.147	-18.481	38.427*	35.383*	-2.055	41.353	0.335
	[25.999]	[16.754]	[17.397]	[20.098]	[19.139]	[18.800]	[29.050]	[22.548]
Observations	85	85	85	85	85	85	85	85
Adjusted R-squared	0.206	0.338	0.118	0.168	0.186	-0.0532	0.105	0.0892
Wald test of selected IVs (F-statistic)	1.321	1.610	0.614	0.00734	0.805	1.166	0.0118	0.0396
Wald test of selected IVs (*p*-value)	0.255	0.209	0.436	0.932	0.373	0.284	0.914	0.843

Notes: (i) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (ii) Robust standard errors clustered at village-level in brackets.

Abstract (in Japanese)

要　約

サブサハラ・アフリカ（SSA）における農業集約化は、長年にわたり重要な開発課題とされてきた。しかし、役畜やトラクターの利用が農業集約化をどの程度促進するのかについては、これまで十分に検証されてこなかった。本研究では、タンザニアの稲作を対象として、農業機械化および役畜利用が農業集約化に与える影響を分析する。タンザニアでは、四輪トラクター（4WT)、二輪トラクター（2WT)、役畜（DA)、手作業用農具（HT）が併存して利用されており、本研究の目的に適した分析対象である。

分析には、2018 年および 2025 年に独自に収集したパネルデータを用い、Multinomial Endogenous Switching Regression（MESR）モデルを適用した。その結果、四輪トラクター、二輪トラクター、および役畜の利用はいずれも、手作業用農具と比較して土地準備に必要な労働投入を有意に削減することが明らかとなった。しかし、その後の稲作技術の採用や栽培管理、生産性への影響は、それぞれ大きく異なっていた。

特に、二輪トラクターは代かきに適しているため、労働集約的な栽培管理技術の採用や雇用労働の活用を促進し、その結果として単位面積当たりの収量、所得、および利益を最も向上させることが分かった。一方、乗用型の四輪トラクターは主として耕起作業に利用されるものの、それに伴って稲作の集約化が進むわけではないことが示された。

キーワード： 稲作、農業機械化、農業生産性、サブサハラ・アフリカ、タンザニア

JEL コード： N57、 O12、 O13、Q16、 Q18