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Mechanization, Intensification, and Extensification of Agriculture: Evidence from Rice Farming in Tanzania

Eustadius Francis Magezi*, Yuko Nakano†, Takeshi Sakurai‡

Abstract

The use of agricultural machinery is increasingly common in sub-Saharan Africa. However, its potential benefits for smallholder farmers remain unclear. This study uses three-year panel data collected from rice farmers in Tanzania to examine the effects of four-wheeled tractors, small two-wheeled tractors, and draft animals on the expansion of the cultivated area (extensification), adoption of yield-enhancing technologies, land productivity (intensification), and labor productivity. We apply a multinomial endogenous treatment effect model with Mundlak-Chamberlain devices to account for the endogeneity problem. We find that large four-wheeled tractor use contributes to the extensification and increased labor productivity but has a negative effect on land productivity. On the other hand, small two-wheeled tractor use contributes to extensification, the adoption of yield-enhancing technologies, and an increase in paddy yield but has no impact on labor productivity. Our results suggest that large- and small-size tractors play different roles, but both can contribute to enhancing rice production in sub-Saharan Africa.

Keywords: Rice production, Agricultural Mechanization, Agricultural productivity; Sub-Saharan Africa; Tanzania

JEL classification: N57, O12, O13, Q16, Q18

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1. Introduction

An increase in agricultural productivity is needed to ensure food security in sub-Saharan Africa (SSA), where the population has been growing at an annual rate of 2.5 percent, and arable land per capita is continuously decreasing (Binswanger-Mkhize and Savastano 2017; Jayne and Rashid 2013; Larson and Otsuka 2016; Otsuka and Larson 2013; UN-DESA 2022). Recently, farm mechanization has been attracting attention as an effective means of expanding the area under cultivation (extensification) and improving land productivity (intensification) in SSA (Diao, Silver et al. 2020; FAO and AUC 2018; Daum and Birner 2020). Previous government-sponsored initiatives to promote large-scale mechanization in the 1960s and 1970s were unable to be sustained due to the lack of adequate demand and poor management of machinery (Pingali 2007). Over the past three decades, however, the demand for mechanization has begun to emerge, partly due to the rise of global food prices in the late 2000s and the development of a domestic rental machinery and repair service market by the private sector (Kirui and von Braun 2018; Diao, Silver et al. 2020; FAO and AUC 2018; Adu-Baffour, Daum, and Birner 2019; Houssou et al. 2013; Takeshima, Nin-Pratt, and Diao 2013).

Despite this increased interest in agricultural mechanization, rigorous empirical analyses on its impact remain rare, with three issues requiring thorough investigation. The first question is whether mechanization contributes to the expansion of the cultivated area. Mechanization is thought to help farmers address labor constraints and expand cultivated areas. Often, extensification effects are reported among large- and medium-scale farmers who own tractors (Chancellor 1971). It remains unclear, however, whether tractors can facilitate extensification in smallholder farms. For example, the contribution of mechanization for land expansion of small-scale farmers has been reported in empirical studies conducted in Zambia (Adu-Baffour, Daum, and Birner 2019), Ghana (Houssou and Chapoto 2014; Kansanga et al. 2019), and southern Nigeria (Takeshima, Nin-Pratt, and Diao 2013). By contrast, Takeshima, Nin-Pratt, and Diao (2013) found that the use of tractors in northern Nigeria was not associated with extensification because draft animals are widely used in the region as an intermediary labor-saving technology. Since the effects of mechanization on extensification seem to depend on the availability of excessive land and agroecological conditions, such as the availability of irrigation (Takeshima 2017; Diao, Silver, and Takeshima 2016), further accumulation of empirical evidence is warranted.

Second, it remains unclear if tractor use can result in higher land productivity (Baudron et al. 2019; Benin 2015; Berhane et al. 2017). Pingali (2007) argues that tractors are generally ineffective in facilitating land productivity improvement. On the other hand, some studies argue that mechanization can contribute to the increase in land productivity (Adu-Baffour, Daum, and Birner 2019). For example, Mano, Takahashi, and Otsuka (2020) examined the impact of tractor use on lowland rice in Cote d'Ivoire and found that tractor use induces intensive applications of chemical fertilizers and yield-enhancing agronomic practices, resulting in higher land productivity.

Third, there is some ambiguity in the potential effects of tractors on family and hired labor use and labor productivity (Adu-Baffour, Daum, and Birner 2019; Caunedo and Kala 2021; Dorward 2013; Mano, Takahashi, and Otsuka 2020). In the early stages of agricultural development in Asia (Otsuka, Liu, and Yamauchi 2016) and the United States, the introduction of tractors allowed the agricultural workforce to migrate to non-farm sectors (Hayami and Ruttan 1985). In SSA, however, agriculture employs more than 50 percent of the active workforce, and there are limited opportunities for non-farm employment (McCullough 2017). This has been part of the concern that policies promoting labor-saving technologies are not "pro-poor" because they may lead to the displacement of agricultural laborers. On the contrary, if family labor is freed from land preparation activities, farmers could use labor for different activities in rice cultivation or the generation of income from other sources. Since reductions in family and hired labor have different implications for farmers and agricultural laborers, it is important to distinguish the impact of mechanization on family and hired labor.

It should also be emphasized that a comparison between small two-wheeled tractors (2WTs), large four-wheeled tractors (4WTs), and draft animals (DAs) is missing from the existing empirical literature. Given that the promotion of small-scale mechanization is increasingly becoming a focus of policy debates, it is important to investigate if there are any differences in the effects of 2WTs, 4WTs, and DAs on extensification, as well as land and labor productivity (FAO and AUC 2018; Daum et al. 2022).

This paper examines the effects of large- and small-scale mechanization and draft animal use on land expansion, technology adoption, and land and labor productivity, using three-year panel data from lowland rice farmers in Tanzania. We also investigate how the use of family and hired labor is affected when land preparation activities are mechanized. Tanzania gives us a unique opportunity to examine the differential effects of large- and small-sized farm machinery as well as that of draft animals. Unlike other SSA countries, Tanzania has strongly promoted small-scale mechanization since the 2000s. As a result, farmers in Tanzania use 4WTs, 2WTs, DAs, and hand tools (HTs), including hand hoes, to prepare land for rice cultivation, which enables us to compare the use of these implements.

To examine the effects of mechanization, we take into account that farmers make their own decisions on whether to use agricultural machinery or other implements, which causes endogeneity bias in estimating the impact of machinery on various outcome variables. To mitigate this problem, we apply multinomial endogenous treatment effect (METE) models (Deb and Trivedi 2006a, 2006b). The model allows us to evaluate the impact of multiple farm implements (i.e., 4WTs, 2WTs, DAs, and HTs) while correcting for time-varying unobservable heterogeneity. We also combine the METE model with the Mundlak-Chamberlain approach, where the over-time averages of household-level explanatory variables are included. This further enables us to control for time-invariant households' innate characteristics (Wooldridge 2010).

Our main findings can be summarized as follows. First, our results show that both 4WTs and 2WTs are associated with the expansion of the area under rice cultivation. Second and most importantly, we find that 2WTs increased the adoption rates of yield-enhancing technologies, such as transplanting in rows and the use of chemical fertilizer, resulting in high paddy yield, while we do not observe such a tendency for 4WT or DA use. This might be due to 2WTs' ability to perform land preparation, especially puddling,[1] in a timely and efficient manner. In fact, recent empirical studies in SSA show that efficient land preparation using machinery enhances the return to biochemical inputs and the adoption of labor-intensive agronomic practices, such as planting in rows and weeding (Mano, Takahashi, and Otsuka 2020; Nin-Pratt and McBride 2014). Our results are consistent with these observations.

Third, we find that both 4WTs and 2WTs are associated with a decrease in the use of family labor. Interestingly, however, especially contribute to an increase in the use of hired labor, possibly due to the increased adoption of labor-intensive agronomic practices. We also find that 4WTs significantly reduce total labor use and increase labor productivity. In contrast, 2WTs do not increase labor productivity, as they are associated with high adoption rates of labor-intensive technologies.

Our contribution to the literature is twofold. First, we compare the effects of 4WTs, 2WTs, and DA on the area expansion and land and labor productivity and find the differential impact of each

[1] Puddling is the process of the thorough mixing of soil in flooded fields. The process involves soaking harrowed plots with water, then using farm implements to break the remaining soil lumps to form a thick soil paste before direct seeding or transplanting seedling.

implement. Although several studies have examined the impact of agricultural mechanization on land productivity, area expansion, and several other indicators (Baudron et al. 2015; Benin 2015; Berhane et al. 2017; Daum et al. 2022; Mano, Takahashi, and Otsuka 2020; Takeshima, Nin-Pratt, and Diao 2013), to the authors' knowledge, this is the first rigorous empirical study that compares the effects of 4WTs, 2WTs, and DAs with HTs in SSA. We find the positive effects of 2WTs on extensification and land productivity, while for 4WTs, the effects were on extensification and labor productivity, suggesting that both 2WTs and 4WTs can play significant but different roles in agricultural development in SSA.

The second contribution is that we distinguish between hired and family labor use, looking at how each was affected by the use of 4WTs, 2WTs, and DAs, respectively. Specifically, the positive effect of 2WTs on hired labor use has an important implication that the adverse effects of mechanization, such as labor displacement, can be avoided when small-scale machinery is adopted. Our results partly confirm the discussions of Mano, Takahashi, and Otsuka (2020), who found that mechanization increased the application of hired and family labor due to the adoption of labor-intensive agronomic practices, although they did not differentiate small-scale 2WTs and large-scale 4WTs.

Our results contribute to policy debates that promote appropriate mechanization by showing that 4WTs and 2WTs play different roles in ensuring food security in SSA (Diao et al. 2016; Diao, Takeshima, et al. 2020; FAO and AUC 2018). In areas where land is abundant but the labor supply is a constraining factor, especially in the rainfed lowlands, 4WTs can have a significant role in increasing food production by facilitating extensification and improving labor productivity. On the other hand, 2WTs might help to enhance the intensification of rice farming in areas where it is difficult to achieve farm extensification due to population pressure or the presence of important agricultural infrastructure such as irrigation systems.

The rest of this paper is organized as follows: Section 2 offers an overview of mechanization in Tanzania, a description of the study site, and an explanation of data collection. Section 3 provides descriptive analyses and Section 4 presents the empirical methods. The estimation results are discussed in Section 5, while Section 6 presents our conclusions and the implications of the research.

2.The Trend Toward Mechanization in Tanzania, Data and Study Sites

2.1Mechanization in Tanzania

First, we discuss the overall trend of agricultural mechanization in Tanzania based on macro statistics and previous literature. Figure 1 presents the total number of tractors and tractors per 100 square kilometers from 1961 to 2002 based on FAO statistics. In the 1940s, before independence, colonial authorities introduced tractors as a part of economic recovery programs after World War II (Pingali, Bigot, and Binswanger 1987). Statistics show that by the time Tanzania gained independence in 1961, the total number of tractors was 16,550, and the number of tractors per 100 square kilometers of cultivated land was 31.8. Between 1967 and 1985, a period when the country introduced socialistic policies, the number of tractors declined (Bryceson 1982; Meertens 2000). Although Tanzania agreed in 1986, to transform its policies towards economic liberalization under Structural Adjustment Programs (SAP), the use of tractor remained low until the mid-1990s. However, a series of policies implemented during this period, including liberalization of financial and land markets, might have helped to induce investment in agriculture, leading to the observed increase in tractors from the late 1990s.

Among SSA countries, Tanzania has followed a unique path, with the country strongly promoting small-scale mechanization. In the early 2000s, 2WTs were first introduced in Tanzania, and along with 4WTs, they have continued to increase ever since (Agyei-Holmes 2016). Mrema, Kahan, and Agyei-Holmes (2020) show that between 2005 to 2015, the number of 2WTs in the country increased from roughly 300 to about 9,000. Around the same period, the number of operational 4WTs rose from 7,200 in 2005 to nearly 13,000 in 2014 (Mrema, Kahan, and Agyei-Holmes 2020). According to Mrema, Kienzle, and Mpagalile (2018), roughly 70 percent of all 2WTs in the SSA are located in three countries, namely, Tanzania, Madagascar, and South Africa.

2.2 Study Site

We focus on rice cultivation because, among the major staples grown in SSA, rice is increasingly important in the region (Larson and Otsuka 2016; Otsuka and Larson 2013). Rice is the second most important crop in Tanzania in terms of consumption and area planted after maize and the third in terms of production volume, after maize and cassava. Rice area accounts for about 8 percent (roughly 1.4 million hectares) of the country’s total area under cultivation (NBS 2017).
The surveys for this research were conducted in three major rice-growing regions in Tanzania, namely Morogoro (Eastern Zone), Mbeya (Southern Highland Zone), and Shinyanga (Lake Zone). In each region, two rice-growing districts were selected. These districts include Kilombero and Mvomero in Morogoro Region, Kahama and Shinyanga Rural in Shinyanga Region, and Mbarali and Kyela in Mbeya Region. In our study sites, there are two cropping seasons: (i) the main season

starting from October to June and (ii) the short season starting from July to September. During the main season, farmers grow rice in irrigated and rainfed plots, and other crops such as maize, beans, sunflowers, and sesame are mainly grown in rainfed farms. Most rainfed farms are left to fallow in the short season, except for those planted with permanent crops or irrigated lowlands where farmers mostly grow vegetables. Thus, our analysis focuses on rice cultivation in the main season.

4WTs and 2WTs are widely adopted in most rice-growing areas, except in the Lake Zone and some parts of the Southern Highlands. For rice plot preparation, farmers use 4WTs, 2WTs, DAs, and HTs depending on their accessibility and rice plot conditions. Some farmers can access machinery through hire services offered by private operators. In most cases, 4WTs and 2WTs are owned by private entrepreneurs in urban centers, and they are handed over to operators who make agreements with rice farmers in nearby villages to provide plowing, harrowing, and puddling services. The fees for custom machinery hire services are not regulated and depend on the agreement between service providers and farmers.

2.3. Data

We conducted three rounds of household surveys in 2009, 2012, and 2018. As explained earlier, the surveys were conducted in six districts in three regions. Seventy-six villages were selected by stratified random sampling based on the number of irrigated and rain-fed rice-growing villages. We use the information from the 2002–2003 agricultural census to determine the number of villages covered in each district. Within each village, ten rice-growing households were randomly selected, resulting in a total number of 760 observations at the baseline survey conducted in 2009.

The same sample households were revisited in 2012 and 2018. We interviewed a replacement household (refreshment sample) if the original household at the baseline was missing in the follow-up surveys.

Although the failure to re-interview the baseline farmers means that our results may be affected by attrition bias, it is difficult to solve this issue in the presence of a refreshment sample as the methodology regarding this is yet to be fully developed (Hirano et al. 2001; Watson and Lynn 2021). Therefore, we evaluate the potential attrition bias to estimate the attrition probit model using baseline observations. In our estimation, the dependent variable is a dummy that takes 1 if the household is attritted in the endline and 0 if otherwise. The independent variable is basic household and rice plot characteristics and district fixed effects. Our estimation results show that there are no household-level variables that are associated with attrition, although we found that sample farmers in Kilombero and Mvomero districts were less likely to be attritted. Even though we have tried to solve this by including district dummy variables in our estimation, we have to admit that attrition has not been fully controlled. Throughout data cleaning, we dropped some observations that had missing values in key variables.[2] As a result, we obtained unbalanced, three-year panel data with a total number of 2,159 households.

During surveys, we asked farmers to identify the most important plot for rice production (hereafter referred to as the sample plot) and asked in detail about technological adoption, production costs, and rice productivity. In addition to household-level surveys, we also conducted interviews with village leaders in all 76 villages. During these interviews, village leaders answered structured questions regarding rice cultivation and access to public services and markets. In addition, we gathered data on village-level population density from the database compiled by the Global High-Resolution Population Denominators Project (WorldPop and CIESIN 2022). The datasets are available in the CSV format with a resolution of 30 arcseconds (approximately 1 kilometer at the equator). We downloaded the country-level population density data for the survey years (i.e., 2009, 2012, and 2018) and converted them into GIS shapefiles. Then, we extracted the population density values and combined them with village-level variables.

We initially intended to examine the role of mechanization using the complete data set. However, we found that most of the farmers from the two districts of Shinyanga Region and Kyela district in the Mbeya region did not adopt tractors. In fact, farmers in these districts are agro-pastoralists and almost all of them use their draft animals for land preparation activities. Since there is no variation in machinery use in these districts after controlling for district fixed effects, we needed to omit these districts from our sample. Thus, we use the unbalanced panel data with a sample size of 983 households collected from Kilombero and Mvomero Districts in the Morogoro Region and Mbarali District in the Mbeya Region (Figure 2). The summary statistics are provided in Appendix Table A1.

3. Descriptive Analyses

Table 1 shows the changes in farm appliances for land preparation from 2009 to 2018 among our sample farmers (Panel A). We also present other key village-level variables, such as the

[2] We winsorized all continuous dependent variables at the 1st and 99th percentile to avoid the risk of outliers affecting the results of our analyses.

availability of machinery and draft animals in the village, machinery hire rates, and village-level population density (Panel B).

The descriptive results show that over time, the proportion of farmers using 4WTs and 2WTs has increased, while the use of HTs declined and the use of DAs remained nearly unchanged. By 2009, about 34 percent of the farmers in our sample were already using 4WTs. The percentage continued to rise, reaching about 46 in 2018. During the same period, the use of 2WTs increased from 7 percent in 2009 to about 22 percent in 2018. Unlike 4WTs and 2WTs, the use of DA declined slightly from 18 percent to 14 percent, while the use of HTs declined from about 39 percent in 2009 to 17 percent in 2018.

In Panel B, we also observe a significant increase in the amount of machinery in the village, particularly 2WTs. In 2009, each village had an average of 2.3 4WTs and 0.7 2WTs. By 2018, the average number of 4WTs per village had slightly increased to 3.4 units, while the number of 2WTs increased to 8.2 units. This increasing trend of 2WTs in the village is consistent with the country's policy, whereby 2WTs began to be imported in large numbers in 2009. It suggests that 2WTs are becoming more accessible to farmers due to the evolving services offering custom machine hire. During this period, the population density also increased, rising from 142 to 165 persons per square kilometer between 2009 and 2018. This suggests an increased labor supply and demand for food in rural areas.

In Table 2, we compare rice cultivation-related variables based on farm implements used for land preparation. We categorize our sample into irrigated and rain-fed and further divide it into 4WT, 2WT, DA, and HT users for land preparation. We conduct a *t*-test comparison between 4WT, 2WT, and DA against the reference category (HT). Variables presented include the size of the cultivated area and technology adoption in sample plots. Farmers sometimes grow rice in a part of their plots and leave the remaining part fallow. Therefore, we distinguish the area under cultivation in the sample plot from the size of the plot. Since some farmers grow rice in multiple plots, we also distinguish the size of the cultivated area within a sample plot and that of the household level, which we will discuss later. As important yield-enhancing technologies for rice cultivation, we show the adoption rate of fertilizer-responsive high-yield modern varieties (MVs), the adoption rate of transplanting in rows, and chemical fertilizer use. Transplanting in rows is important for controlling the plant density and ease of weeding. All these technologies are labor- and care-intensive but essential to achieve high paddy yield (Nakano et al. 2018; Otsuka and Larson 2013, 2016).

The descriptive results in Panel A show that farmers who use 4WTs—in both irrigated and rainfed plots—cultivate more area within a plot than hand-held tool users. In terms of technology adoption, 4WT users in both irrigated and rain-fed areas have lower adoption rates of transplanting in rows and MVs than HTs users. This is possibly because 4WT users do not want to adopt these labor- and care-intensive technologies after expanding their cultivating areas.
2WT users in both irrigated and rain-fed areas cultivate larger areas than HT users, similar to 4WT users. Their technology adoption pattern, however, differs from that of 4WT users. In irrigated lowlands, 2WT users apply more chemical fertilizers but have lower adoption rates of MVs. Contrary to 4WTs, farmers who use 2WTs in rainfed lowlands achieve higher adoption rates of transplanting in rows and chemical fertilizers. These results suggest that 2WTs are positively associated with the intensive use of yield-enhancing technologies.

In Panel B, we show the variables related to land productivity. The income per hectare here is defined as the gross output value minus paid-out costs, including costs for chemical fertilizer, seed, insecticide, and herbicides, hired labor costs, and machinery and animal hire costs, divided by area under rice cultivation. Imputed costs of family labor and owned animal per cultivated area are subtracted from income in defining profit per hectare.[3] The results show that the use of 4WTs is not associated with high paddy yield or any other land productivity variable. In rainfed lowlands, 4WT users achieve even lower paddy yield than HT users, possibly due to low adoption rates of yield-enhancing technologies. On the other hand, farmers who use 2WTs achieve paddy yields of about 4.4 tons per hectare in irrigated areas and 4.2 tons per hectare in rainfed areas, which are significantly higher than others. It is notable that the yield of 2WT users is much higher than the average yield in SSA, which is about 2.4 tons per hectare, and it is close to that of South-East Asian countries (Silva et al. 2022). The 2WT users' profit per hectare is also significantly higher than that of HT users.

In Table 3, we present the results of labor use and labor productivity in irrigated and rain-fed areas. The paid-out cost of hired labor includes the costs of hiring labor for preparing the rice plot, sowing (direct seeding or transplanting), weeding, and harvesting. We impute the costs of family labor by using the village median wage rate. We define labor productivity as the amount of paddy produced per unit of labor use (kg/person days). The results show that the users of 2WTs and 4WTs reduce the use of both family and hired labor, resulting in the overall reduction of labor requirement per hectare and high labor productivity.

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[3] To calculate the imputed costs of family labor as well as machinery and animals owned, we use the village-level median wage rate and hire rate for machinery and animals.

4. Estimation Methods

In this study, the endogeneity problem may arise if unobserved factors that affect a household's decision to use a particular farm implement for land preparation are correlated with outcome variables such as paddy yield and profit per hectare. To address this challenge, we apply the multinomial endogenous treatment effect (METE) model (Deb and Trivedi 2006a, 2006b). The model allows us to evaluate the impact of multiple farm implements used for land preparation (i.e., 4WTs, 2WTs, DAs, and HTs) and to correct for endogeneity in adoption decisions. We also follow the lead of Kim et al. (2019) and combine the METE model with the Mundlak-Chamberlain approach, where the over-time averages of household-level explanatory variables (MC device) are included in the estimation model as additional regressors. This allows further control for time-invariant unobserved household-level heterogeneity.

The estimation of METE involves two stages. In the first stage, the determinants for farmers' choice to use either 4WTs, 2WTs, DAs, or HTs are estimated, and the effects of using the implement of choice are estimated in the second stage. Our dependent variable for the first stage is a categorical variable, which takes 1 if the household uses 4WT for the preparation of the sample plot, 2 if 2WT is used, 3 if DA is used, and 0 if only hand-held tools are used. In our data set, few farmers use more than two means for land preparation, and thus, our categorization is mutually exclusive.[4] We denote this categorical variable as j, where $j = 0,1,2,3$ for hand-held tools, 4WTs, 2WTs, and DA, respectively. We let EV_{ij}^{*} denote the indirect utility a farmer would obtain by selecting to prepare their plot using implement j, which is expressed as follows:

$$\mathrm{EV}_{ij}^{*} = \mathbf{z}_i'\alpha_j + \delta_j l_{ij} + \eta_{ij} \tag{1}$$

where $\mathbf{z}_i$ is the exogenous covariate containing the household- and village level variables and a set of instrumental variables (IVs), as we explain later. η_{ij} is independent and identically distributed error term. l_{ij} denotes unobserved characteristics (latent factors) affecting household $i's$ decision on using j^{th} tool for land preparation, as well as the outcome variables such as paddy yield and labor productivity.

[4] There are a few cases where farmers use multiple means for land preparation. After close examination of the original data and questionnaire, we categorized these households under the DA category. We conducted Hausman test and confirmed that our specification does not violate the independence of irrelevant alternatives (IIA) assumption in multinomial logit model. For brevity, we did not include results of these tests in the manuscript, but they can be obtained from the corresponding author upon request.

Furthermore, let $\mathbf{d}_i$ denote a vector of binary variables, indicating whether the household used 4WTs, 2WTs, or DAs to prepare their rice plots (i.e., $\mathbf{d}_i = d_{i1}, d_{i2}, d_{i3}$). Also, let $\mathbf{l}_i = l_{i1}, l_{i2}, l_{i3}$, in which case, the probability of using either choice of j is expressed as:

$$\Pr(\mathbf{d}_i|\mathbf{z}_i, \mathbf{l}_i) = \mathbf{g}(\mathbf{z}_i'\alpha_j + \delta_j l_{ij}), \qquad j = 1, 2, 3. \tag{2}$$

where $\mathbf{g}$ is an appropriate multinomial probability distribution. We follow Deb and Trivedi (2006a and 2006b) and assume that $\mathbf{g}$ has a mixed multinomial logit (MMNL) structure which relaxes the independence of irrelevant alternatives (IIA) assumption. The mixed multinomial logit is presented as:

$$\Pr(\mathbf{d}_i|\mathbf{z}_i, \mathbf{l}_i) = \frac{\exp\,(\mathbf{z}_i'\alpha_j + \delta_j l_{ij})}{1 + \sum_{k=1}^{J} \exp\,(\mathbf{z}_i'\alpha_k + \delta_k l_{ik})} \tag{3}$$

The expected outcome for individual i can be written as:

$$E(y_i|\mathbf{d}_i, \mathbf{x}_i, \mathbf{l}_i) = \mathbf{x}_i'\beta + \sum_{j=1}^{J} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij} \tag{4}$$

where y_i denotes the outcome variable of interest, such as cultivated area, technology adoption, and land and labor productivity variables. $\mathbf{x}_i$ is a set of exogenous covariates associated with parameter vectors β, γ_j (for $j = 1,2,3$) denote the effects of using 4WTs, 2WTs, DAs relative to base category (i.e., HTs), and λ_j denotes the effects of latent factor l_{ij}, that is, unobserved characteristics that influence the decision on the type of implement used in preparing the farm, as well as outcome variables.

If λ_j is positive (negative), the implement choice and outcome variables are positively (negatively) associated with unobservable variables.[5]
The joint probability density of treatment and outcome variables conditional on the common latent factors can be written as

$$\begin{aligned} \Pr(y_i, \mathbf{d}_i|\mathbf{x}_i, \mathbf{z}_i, \mathbf{l}_i) &= f(y_i|\mathbf{d}_i, \mathbf{x}_i, \mathbf{l}_i) \times \Pr(\mathbf{d}_i|\mathbf{z}_i, \mathbf{l}_i) \\ &= f(\mathbf{x}_i'\beta + \mathbf{d}_i'\gamma + \mathbf{l}_i'\lambda) \times \mathbf{g}(\mathbf{z}_i'\alpha_1 + \delta_1 l_{i1}, \dots, \mathbf{z}_i'\alpha_J + \delta_J l_{iJ}). \end{aligned} \tag{5}$$

The problem in this estimation, however, is that l_{ij} are unknown. Assuming l_{ij} are independently and identically distributed and are drawn from the standard normal distribution, their joint distribution h can be integrated out of the joint density as follows:

$$\Pr(y_i, \mathbf{d}_i|\mathbf{x}_i, \mathbf{z}_i) = \int \{ f(\mathbf{x}_i'\beta + \mathbf{d}_i'\gamma + \mathbf{l}_i'\lambda) \times \mathbf{g}(\mathbf{z}_i'\alpha_1 + \delta_1 l_{i1}, \dots, \mathbf{z}_i'\alpha_J + \delta_J l_{iJ}) \}\, \mathbf{h}\,(\mathbf{l}_i) d\mathbf{l}_i \tag{6}$$

[5] For brevity, values of λ_j are not reported in the manuscript but they can be obtained from the corresponding author upon request.

This integral does not have, in general, a closed-form solution. Therefore, we use a simulation-based estimation denoted as:

$$\ln L(y_i, \mathbf{d}_i|\mathbf{x}_i, \mathbf{z}_i) = \sum_{i=1}^{N} \ln \left(\frac{1}{S}\sum_{s=1}^{S}[\mathbf{f}(\mathbf{x}_i'\beta + \mathbf{d}_i'\gamma + \tilde{\mathbf{l}}_{is}'\lambda) \times \mathbf{g}(\mathbf{z}_i'\alpha_1 + \delta_1\tilde{l}_{i1s}, \dots, \mathbf{z}_i'\alpha_J + \delta_J\tilde{l}_{iJs})]\right) \quad (7)$$

where $\tilde{l}_{is}$ is the s_{th} drawn from a total of S draws of pseudorandom numbers obtained from the density $\mathbf{h}$. The simulated-log likelihood function is given by:

$$\ln l(y_i, \mathbf{d}_i|\mathbf{x}_i, \mathbf{z}_i) \approx \sum_{i=1}^{N} \ln \left(\frac{1}{S}\sum_{s=1}^{S}\{f(\mathbf{x}_i'\beta + \mathbf{d}_i'\gamma + \tilde{\mathbf{l}}_{is}'\lambda) \times \mathbf{g}(\mathbf{z}_i'\alpha_1 + \delta_1\tilde{l}_{i1s}, \dots, \mathbf{z}_i'\alpha_J + \delta_J\tilde{l}_{iJs})\}\right) \quad (8)$$

We assume f follows the normal distribution and estimate the model using a maximum simulated likelihood approach, 500 quasi-random draws based on the Halton sequence. Furthermore, similar to the standard multinomial logit model, the parameters in the MMNL are identified only up to a scale.

Therefore, we assume δ_J= 0.5 and use the Stata command *mtreatreg* to implement the METE model.[6]

According to Deb and Trivedi (2006b), the METE is identified when $\mathbf{z}_i = \mathbf{x}_i$. However, it is preferable to include some instrumental variables (IVs) in $\mathbf{z}_i$ which are not included in $\mathbf{x}_i$, such that the model is identified via exclusion restriction. Therefore, we add in $\mathbf{z}_i$, a set of potential IVs, including the number of four-wheeled tractors (4WTs) and two-wheeled tractors (2WTs) in the village, population density, and the village-level variables indicating the risk of livestock becoming infested with tsetse fly, a vector that transmits sleeping sickness, or trypanosomiasis.

Although there is no direct way to test if our IV satisfies exclusion restrictions, we conduct falsification tests to examine the validity of our IVs, following (Di Falco, Veronesi, and Yesuf 2011). The basic idea is that if the IVs for mechanization satisfy the exclusion restriction, they should not have any significant effect on the outcome variables of the sample households that used only HTs (i.e., $j = 0$). We test this by including the candidate IVs as additional explanatory variables along with $\mathbf{x}_i$ in a regression involving only households that used hand-held tools. The tests are conducted for each dependent variable of interest (i.e., cultivated area, yield, etc.) using pooled OLS regression with the MC device.

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[6] δ_J is specified using factor scale option in *mtreatreg*. Although we assume that $\delta_J = 0.5$ in the main results, as a robustness check, we run similar models assuming $\delta_J = 1$, and $\delta_J = 0.3$.

If the potential IV is significantly associated with outcome variables in the falsification tests (regardless of the coefficient sign), they are not used in the second stage. Therefore, we use a different set of IVs for each dependent variable. We also examine whether the first stage estimation would remain relevant even after dropping some IVs that did not pass the falsification tests. For this purpose, we conduct the Wald test to examine the joint significance of different sets of IVs in the first-stage equation. The falsification results presented from Tables A3 to A5 in the Appendix show that including any set of IVs leads to a statistically significant improvement in the fit of the first-stage multinomial models.

5. Estimation Results

Table 4 presents the marginal effects of factors associated with the use of 4WTs, 2WTs, and DAs for land preparation. Column 1 shows the results for the use of 4WTs, while columns 2, 3, and 4 show the results for 2WTs, DAs, and HTs, which is a reference category. We found that the presence of 2WTs in the village increases the probability of them being used by farmers. Since only about 2 percent of farmers in our sample used their own 2WTs, the result suggests that access to the custom machinery hire market is among the driving factors of machinery use, as Diao et al. (2014) and Binswanger and Rosenzweig (1986) argue. We also found that moderate and high risks of trypanosomiasis are positively associated with the use of 4WTs and negatively associated with the use of DAs. These results suggest that farmers in areas infested with tsetse flies are likely to use the 4WTs as a substitute for DA power.

Furthermore, our estimates show that 4WTs are more likely to be used in plots with clay soils and less likely to be used in irrigated plots and plots surrounded with bunds. It is difficult for heavy and large 4WTs to be moved to the farm and maneuvered within a plot without destroying bunds and irrigation channels because there are no special roads for machinery to access paddy fields in Tanzania. Our estimations show that farmers with large plots are likely to use 4WTs and 2WTs. We also find that the amount of non-farm household assets increases the probability of using 4WTs and 2WTs, suggesting that wealthy farmers are more likely to use machinery.

The estimation results for the effects of mechanization are presented in Tables 5 to 7. The effects of mechanization are presented in two panels. Panel A shows the METE results estimated using a set of IVs in $\mathbf{z}_i$ as explained earlier. We also report *Chi*-squared values obtained in the likelihood ratio test for exogeneity, and their associated p-value.[7] In Panel B, we present the METE results estimated under the exogeneity assumption, without including IVs (i.e., $\mathbf{z}_i = \mathbf{x}_i$). Since likelihood ratio tests indicate that endogeneity is an issue for most dependent variables, our discussion focuses on Panel A. In each estimation, we report robust standard errors clustered at the village level in parentheses. As basic household and plot-level characteristics, we control for the number of working-age adults, years of schooling of household head, female-headed household (dummy), age of household head, total landholdings (ha), the value of non-farm household assets (million TShs), amount of credit received by the household ('00,000 TShs), size of the sample plot (ha), dummy variables indicating whether the sample plot is irrigated, has clay soil, or has bunds, district, and year dummies, as well as the MC device, although we only report the coefficients of main variables of interest for brevity.

Table 5 shows the effects of mechanization on the area cultivated within the sample plot and technology adoption. On average, the use of 4WTs is associated with an increase of cultivated area within the sample plot by 0.37 hectares compared to HT use. On the other hand, the coefficients of 4WT use for the adoption of transplanting in rows and MVs are negative and significant. One of the possible reasons is that labor- and care-intensive technologies are less likely to be adopted in large plots because they require high monitoring costs for hired labor (Hayami and Otsuka 1993). We also find that the use of 2WTs increases the cultivated area within sample plots by 0.12 hectares. As opposed to 4WTs, the use of 2WTs significantly increases adoption rates of transplanting in rows (by 7.7 percent) and increases chemical fertilizer application by about 37.3 kilograms per hectare. Regarding DA use, we did not find any significant effect on the cultivated area within the sample plot. Although DA use increases the adoption of transplanting, it has negative and significant coefficients for the adoption of MVs and chemical fertilizer use, for which we have no clear explanation.

The estimation results of the impact of mechanization on land productivity, area cultivated at the household level, and household income are presented in Table 6. The results show that the use of 4WTs is associated with a decrease in paddy yield of about 1 ton per hectare, resulting in a decrease in income per hectare by about 329,000 TShs.[8] On the other hand, we find that the use of 2WTs is positively associated with an increase in paddy yield of about 0.3 tons per hectare.

[7] In the likelihood ratio tests, the null hypothesis is that lambda parameters (λ_j) are jointly equal to zero. Where the test's p-value is less than 0.01, we reject the null hypothesis suggesting that choice of implements is endogenously determined and the results obtained under exogeneity assumption (Panel B) cannot be reliable.

[8] All the monetary values are adjusted for inflation using the 2009 value of Tanzanian Shillings (TShs). As of 2009, one USD was approximately equal to 1,300 TShs.

One of the potential reasons for the high adoption rate of intensive technologies and high yield for 2WT users is that the 2WT is relatively light and can be used for puddling, while the 4WT cannot. Efficient and timely puddling by using 2WTs may make the return to intensive technologies higher and enable farmers to achieve a high yield. Unfortunately, however, the income and profit per hectare of 2WT users are not statistically higher than that of HT users, perhaps because of increased machinery and labor hire costs. Similar to 4WTs, DA use is negatively associated with paddy yield and income per hectare.

Regarding the effects of mechanization on the area under rice cultivation at the household level and household income, it should be noted that machinery use here is based on observations from the sample plot since we do not have detailed data on machinery use in other rice plots. This may lead to measurement errors in machinery use at the household level as, on average, farmers cultivate 1.5 plots, and the results in Columns (4) and (5) of Table 6 should be interpreted with caution. We find that both 4WT and 2WT use in the sample plots increases the area under rice cultivation at the household level by 0.27 and 0.31 hectares, respectively, while we observe no significant impact from machinery use on household income. DA use has no significant coefficient for either area under rice cultivation at the household level or household income.

In Table 7, we present the effects of machinery use on labor and labor productivity. We observed mixed results on the impact of 4WT use on hired labor use. In panel A, when we assume endogeneity of machinery use, we observe a positive and significant coefficient, while the coefficient turned negative in panel B, where we assume exogeneity. In any case, however, we observe that 4WT use significantly reduces family and total labor use, resulting in an increase in labor productivity. Compared to hand-held tools, 4WTs increase labor productivity by 8.6 kilograms of paddy per person-days. One important finding is that 2WTs are positively associated with hired labor use, possibly because of the increased demand for the skilled labor required to adopt labor-intensive agronomic practices. This has an important implication for labor markets, suggesting that small-scale mechanization does not decrease the demand for labor. Consequently, however, we do not observe a significant impact of 2WTs on labor productivity despite the significant decrease in family labor use. DA use decreases both hired and family labor. However, it did not result in increased labor productivity.

To further understand how mechanized tillage affects labor use and labor productivity, we investigate the effects of machinery and draft animals on labor use by task. The results are presented in Table A5 in the Appendix. We found that, although the use of 4WTs and 2WTs has similar effects on labor use for various tasks, the use of 2WTs is associated with an increase in the use of hired labor for crop establishment, including sowing and transplanting, as well as weeding. This is consistent with our argument that 2WT use induces the adoption of labor-intensive technologies and careful management of the paddy field, probably because of its ability for efficient puddling.

For the robustness check, we estimated the METE by assuming the factor scales (δ_J) of 1 and 0.3. We also estimate the fixed effects (FE) and correlated random effects (CRE) using the same dataset and report these results in Table A6 to A9 in the Appendix. Although some coefficients of key variables of interest turn insignificant (or significant) depending on the estimation models, the direction of the coefficients is the same in most cases, suggesting the robustness of our results.

6. Conclusion

This study examined the impact of mechanization on rice production using three-year panel data collected in Tanzania, one of the major rice-producing countries in SSA. Specifically, we examined the effects of mechanization on the expansion of the area under rice cultivation, technology adoption, and land and labor productivity. Unlike previous literature, we compare the use of 4WTs, 2WTs, DAs and HTs for land preparation. We applied the multinomial endogenous treatment effect with Mundlak-Chamberlain devices to control for a possible endogeneity problem that arises from farmers' endogenous selection of cultivation methods.

In sum, our findings suggest that large-size machinery (4WTs) can contribute to the extensification and improvement of labor productivity while it does not affect paddy yield. On the other hand, small-size machines significantly contribute to the expansion of cultivated areas and the improvement of land productivity. We also find that DA use is associated with a low adoption rate of MVs and reduced application of chemical fertilizer, resulting in low yield and income per hectare, while it has no impact on labor productivity. Our results are partially consistent with previous empirical studies by Mano, Takahashi, and Otsuka (2020) and Houssou and Chapoto (2014), who report a positive relationship between agricultural mechanization and land productivity, although we do not observe such a tendency for 4WTs.

The most important findings of this study are twofold. The first is the different role of 2WTs and 4WTs in extensification, intensification, and the improvement of labor productivity. We find that 2WTs induce the adoption of yield-enhancing technologies, resulting to an increase in paddy yield. In examining types of land preparation activities carried out using 4WT and 2WT, we find that many 2WT users utilized them in puddling, while most of the 4WT users utilized them in plowing and hallowing. 2WTs are considered to be efficient for puddling and, thus for creating ideal conditions for crop establishment. Other benefits of puddling include enhancing nutrient and water uptake by the plant, water conservation, evenly distributing nutrients, and reducing weed intensity. While the evidence on this matter remains scant, the effect of 2WT on yield may be due to its effectiveness in performing puddling. In contrast, our results suggest that 4WTs contribute to the area expansion and the improvement of labor productivity by reducing labor use, but they decrease land productivity.

Second, we observe that both 4WTs and 2WTs reduce family labor use. However, 2WTs especially have a significant positive effect on the application of hired labor. One of the reasons that led to the decline of mechanization in SSA in the 1970s and 1980s was the concern that mechanization would lead to the displacement of hired laborers (Binswanger 1986). Our results show that, although mechanized tillage significantly reduces labor requirements in preparing the field, it also enables farmers to adopt labor-intensive technologies such as transplanting in rows and weeding and thus increases demand for hired labor. This has an important implication for the labor market, demonstrating that mechanization is not necessarily harmful to poor agricultural laborers.

Our results contribute to policy debates that promote appropriate mechanization by showing that 4WTs and 2WTs play different roles in ensuring food security in SSA (Diao et al. 2016; Diao, Takeshima, et al. 2020; FAO and AUC 2018). Namely, 4WTs can perform well in areas with expandable land, and labor is the limiting factor of production. They can also be used in areas with heavy, clay soil and where the use of draft animals is limited due to the prevalence of the tsetse fly. On the other hand, 2WTs may play a role in areas where it is difficult to expand the size of the land due to high population pressure or the presence of essential farm infrastructure such as irrigation systems. However, we refrain from claiming that these implications are generalizable, as the effects of mechanized tillage may be site- and crop-specific (Daum et al. 2022). The impact of small-scale machinery can differ, especially in upland and lowland crop cultivation, because puddling cannot be done in the uplands. This casts doubt on the external validity of our study in regard to upland cultivation. Further research could be beneficial in identifying the conditions under which agricultural mechanization is particularly effective for enhancing food production in SSA.

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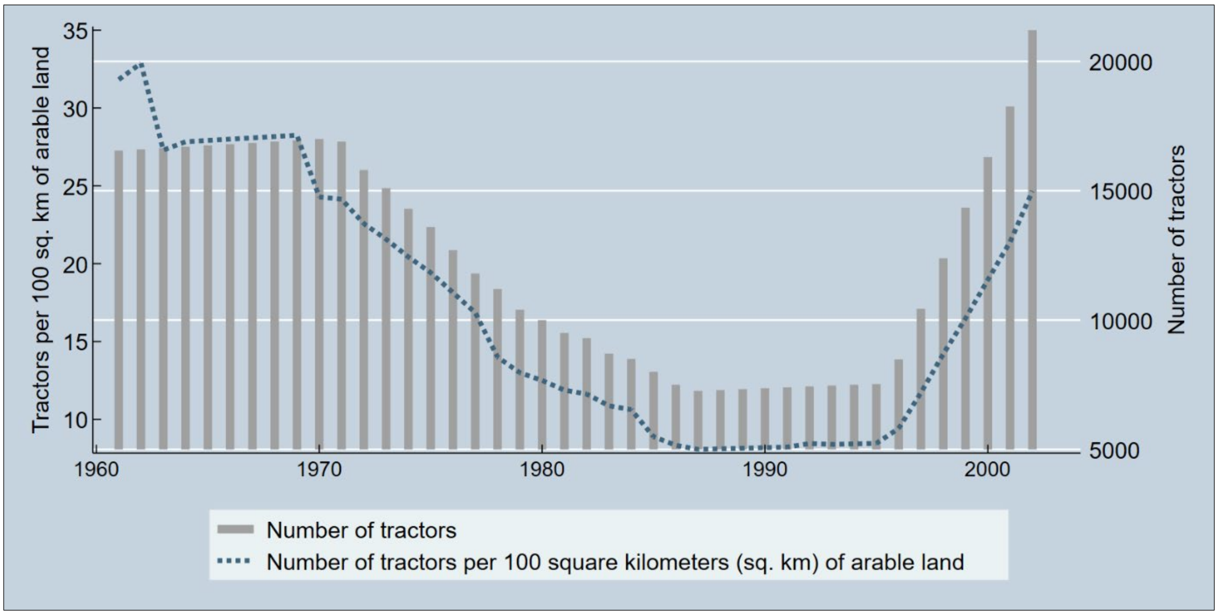

Figure 1: Mechanization trends in Tanzania (1961 to 2002)
Source: World Bank (2023)

Figure 2: Location of sample villages
Source: Authors

Table 1: Access to machinery and machinery use (2009–2018)

VARIABLES	(1) 2009	(2) 2012	(3) 2018
Panel A: Farm appliances used by the household to prepare rice plots:			
Four-wheeled tractors (4WT: %)	34.24	42.06	46.39
Power tillers (2WT: %)	7.58	14.33	22.29
Traction animals (DA: %)	18.48	17.76	14.16
Hand hoe (HT: %)	39.70	25.86	17.17
Panel B: Machinery access and population density at the village level:			
Number of four-wheeled tractors in the village	2.27	4.80	3.37
Number of two-wheeled tractors in the village	0.74	2.05	8.15
4WT hire fees ('000 TShs)	40.73	40.04	25.22
2WT hire fees ('000 TShs)	43.16	40.73	32.14
DA hire fees ('000 TShs)	38.12	33.99	22.72
Village population density ('00 people/km^2)	1.42	1.62	1.65
Number of observations (households)	330	321	332

Source: Authors

Notes: (i) *** denotes significant at 1%, ** significant at 5%, and * significant at 10% in *t*-test comparison between the labeled categories. (ii) All the monetary values are adjusted for inflation using the 2009 value of Tanzanian shillings (TShs). (iii) Since not all villages have machinery rental markets, 4WT and 2WT rental rates are based on villages where such markets exist

Table 2: Cultivated area, technology adoption, and paddy yield in irrigated and rainfed plots by machinery use for land preparation (2009–2018)

VARIABLES	*Irrigated plots*				*Rainfed plots*			
	4WT	2WT	DA	HT	4WT	2WT	DA	HT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cultivated area and technology adoption								
Area cultivated in sample plot (ha)	1.16***	1.11***	1.15***	0.53	1.21***	1.33***	1.30***	0.77
Adoption rate of transplanting in rows (%)	17.65***	38.75	22.09***	48.53	2.56***	33.85***	10.13	11.11
Adoption rate of MVs (%)	39.22***	43.75***	8.14***	78.68	20.51***	47.69	15.19***	37.78
Chemical fertilizer use (kg/ha)	65.97	88.22**	28.74***	57.29	19.99	86.23***	25.03	18.11
Panel B: Land productivity								
Paddy yield in sample plot (tons/ha)	3.83	4.42**	3.28*	3.72	2.12**	4.25***	2.36	2.53
Income from sample rice plot ('000 TShs/ha)	1,075.53	1,317.97**	1,038.78	1,039.05	471.25***	988.83**	572.22	711.61
Profit from sample rice plot ('000 TShs/ha)	877.65	1,072.50***	686.64	680.67	314.61	816.12***	286.84	327.62
Number of observations (Households)	51	80	86	136	351	65	79	135

Source: Authors
Notes: (i) 4WTs, 2WTs, DAs, HTs, respectively, denote the use of four-wheeled tractors, power tillers, draught animals, and hand-held tools for land preparation activities in sample rice plots. (ii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10% in *t*-test comparison between the use of four-wheeled tractors, power tillers, and draught animals against hand-held tools.

Table 3: Labor costs and labor productivity in irrigated and rainfed plots by machinery use for land preparation (2009–2018)

VARIABLES	*Irrigated plots*				*Rainfed plots*			
	4WT	2WT	DA	HT	4WT	2WT	DA	HT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Paid-out cost of hired labor ('000 TShs/ha)	374.39	426.87	299.23***	420.93	178.74***	276.39	192.01*	247.46
Imputed cost of family labor ('000 TShs/ha)	151.96***	166.72**	262.57*	338.83	133.49***	134.17***	233.07**	365.96
Total labor costs ('000 TShs/ha)	526.35***	593.59***	561.81***	759.76	312.23***	410.56***	425.08***	613.42
Hired labor use (person-days/ha)	72.61**	88.04	59.93***	91.22	42.37***	48.19**	40.27***	68.01
Family labor use (person-days/ha)	34.44***	38.56***	61.52	76.02	31.21***	26.60***	49.86***	80.68
Total labor use (person-days/ha)	107.05***	126.61***	121.45***	167.24	73.58***	74.79***	90.12***	148.70
Labor productivity (kg/person-days)	60.98***	43.82***	35.72**	27.52	39.22***	82.62***	36.84***	22.72
Number of observations (Households)	51	80	86	136	351	65	79	135

Source: Authors

Notes: (i) 4WTs, 2WTs, DAs, HTs, respectively, denote the use of four-wheeled tractors, power tillers, draught animals, and hand-held tools for land preparation activities in sample rice plots. (ii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10% in *t*-test comparison between the use of four-wheeled tractors, power tillers, and draught animals against hand-held tools. (iii) All the monetary values are adjusted for inflation using the 2009's value of Tanzanian Shilling (TShs).

Table 4: Marginal effects of factors associated with mechanization in rice cultivation (pooled multinomial logit estimates)

VARIABLES	(1) 4WT	(2) 2WT	(3) DA	(4) HT
Panel A: Potential IVs				
Number of 4WTs in the village	0.007	0.002	0.001	-0.010
	(0.005)	(0.003)	(0.005)	(0.007)
Number of 2WTs in the village	0.004	0.006**	-0.009***	-0.001
	(0.005)	(0.003)	(0.002)	(0.006)
Village population density (100 people/km^2)	-0.028	-0.008	0.018	0.019
	(0.040)	(0.019)	(0.018)	(0.030)
Moderate risk for trypanosomiasis (dummy)	0.344**	0.060	-0.113*	-0.291**
	(0.158)	(0.047)	(0.062)	(0.147)
High risk for trypanosomiasis (dummy)	0.511***	0.059	-0.261***	-0.309
	(0.198)	(0.115)	(0.095)	(0.205)
Panel B: Other exogenous variables				
Age of household head	-0.003**	0.001	-0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Years of schooling of household head	0.001	0.004	-0.006	0.000
	(0.005)	(0.003)	(0.004)	(0.004)
Number of working age adults	0.011	-0.017*	-0.000	0.006
	(0.009)	(0.010)	(0.009)	(0.010)
Female headed household (dummy)	0.052	-0.018	0.029	-0.062
	(0.039)	(0.040)	(0.043)	(0.042)
Value of non-farm household assets (mil. TShs)	0.079***	0.025**	-0.010	-0.094***
	(0.021)	(0.011)	(0.016)	(0.028)
Total landholdings (ha)	0.000	-0.004	0.001	0.003
	(0.006)	(0.003)	(0.003)	(0.005)
Amount of credit received (‘00000 TShs)	0.021**	0.003	0.007*	-0.031**
	(0.010)	(0.003)	(0.004)	(0.014)
Number of bulls owned	0.003	0.002	0.004	-0.009
	(0.007)	(0.003)	(0.004)	(0.010)
Bunded plot (dummy)	-0.209***	0.086**	0.039	0.084**
	(0.038)	(0.039)	(0.029)	(0.034)
Size of the plot (ha)	0.058***	0.019**	0.021	-0.097***
	(0.020)	(0.008)	(0.014)	(0.027)
Irrigated plot (dummy)	-0.254***	0.051	0.002	0.202***
	(0.045)	(0.035)	(0.027)	(0.038)
Sample plot has clay soil (dummy)	0.058**	0.009	-0.007	-0.060***
	(0.028)	(0.021)	(0.013)	(0.022)
Distance to district capital (km)	-0.002***	-0.001	0.003***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
District and year dummy variables	YES	YES	YES	YES
Mundlak & Chamberlain (MC) device	YES	YES	YES	YES
Joint significance test of IVs: Chi square= 39.53***				
Number of observations: 983 households				

Source: Authors
Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) The value for HT users is used as the base category. (iii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%.

Table 5: Effects of mechanization on cultivated area and technology adoption

VARIABLES	(1) Area cultivated in sample plot (ha)	(2) Transplanted in rows (dummy)	(3) MVs (dummy)	(4) Amount of chemical fertilizer used (kg/ha)
Panel A: METE (Assuming endogeneity, 500 replications, 0.5 factor scale)				
4WT use (dummy)	0.377***	-0.338***	-0.322***	-17.803***
	(0.106)	(0.004)	(0.074)	(6.748)
2WT use (dummy)	0.124*	0.077***	-0.053	37.493***
	(0.075)	(0.005)	(0.090)	(11.984)
DA use (dummy)	-0.034	0.097***	-0.366***	-25.084**
	(0.110)	(0.010)	(0.058)	(12.217)
LR test of exogeneity (Chi sq.)	8.812	85.504	13.415	12.171
LR test's p-value	0.032	0.000	0.004	0.007
Panel B: METE (Assuming exogeneity, 500 replications, 0.5 factor scale)				
4WT use (dummy)	0.387***	-0.112	-0.341***	-21.604***
	(0.108)	(0.121)	(0.065)	(6.227)
2WT use (dummy)	0.136*	0.058	-0.054	34.647***
	(0.075)	(0.108)	(0.078)	(12.236)
DA use (dummy)	-0.021	-0.073	-0.363***	-27.290**
	(0.111)	(0.076)	(0.063)	(13.037)
Number of observations	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) The HT user (i.e., j= 0) is the base category. (iii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%. (iv) We control for the number of working-age adults, years of schooling of household head, female-headed household (dummy), age of household head, total landholdings (ha), the value of non-farm household assets (million TShs), amount of credit received by the household ('00,000 TShs), size of the sample plot (ha), dummy variables indicating whether the sample plot is irrigated, has clay soil, or has bunds, as well as district and year dummies.

Table 6: Effects of mechanization on land productivity, area under recultivation at household level, and total household income

VARIABLES	(1) Paddy yield in sample plot (tons/ha)	(2) Income from rice cultivated in sample plot ('000 TShs/ha)	(3) Profit from rice cultivated in sample plot ('000 TShs/ha)	(4) Area under rice cultivation at household level (ha)	(5) Total household income (‘00000 TShs)
Panel A: METE (Assuming endogeneity, 500 replications, 0.5 factor scale)					
4WT use (dummy)	-1.046***	-329.759**	187.472	0.272***	2.428
	(0.077)	(150.686)	(181.475)	(0.097)	(2.537)
2WT use (dummy)	0.316***	-161.756	232.317	0.308*	1.052
	(0.119)	(282.336)	(149.378)	(0.169)	(3.436)
DA use (dummy)	-0.305**	-284.211***	-113.608	0.105	1.352
	(0.120)	(107.848)	(144.197)	(0.171)	(3.146)
LR test (Chi sq.)	86.928	3.267	0.874	4.614	0.752
LR test’s p-value	0.000	0.352	0.832	0.202	0.861
Panel B: METE (Assuming exogeneity, 500 replications, 0.5 factor scale)					
4WT use (dummy)	-0.955***	-365.334***	168.443	0.294***	2.814
	(0.042)	(69.811)	(154.062)	(0.098)	(2.829)
2WT use (dummy)	0.420***	-147.468	219.880	0.335**	0.403
	(0.036)	(111.608)	(142.496)	(0.168)	(3.507)
DA use (dummy)	-1.233***	-275.695***	-157.785	0.120	-0.017
	(0.052)	(102.994)	(164.669)	(0.172)	(3.930)
Number of observations	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table 5.

Table 7: Effects of mechanization on labor use and labor productivity

VARIABLES	(1) Paid-out cost of hired labor ('000 TShs/ha)	(2) Imputed cost of family labor ('000 TShs/ha)	(3) Hired labor use (person-days/ha)	(4) Family labor use (person-days/ha)	(5) Total labor use (person-days/ha)	(6) Productivity of total labor use (kg/person-days)
Panel A: METE (Assuming endogeneity, 500 replications, 0.5 factor scale)						
4WT use (dummy)	-52.307**	-280.717***	2.155***	-33.709***	-79.800***	8.634**
	(26.404)	(29.317)	(0.357)	(0.828)	(6.401)	(3.786)
2WT use (dummy)	-0.204	-182.243***	10.597***	-63.030***	-36.959***	9.059
	(34.993)	(37.691)	(0.385)	(1.002)	(13.357)	(7.150)
DA use (dummy)	-63.919***	-130.869***	-27.389***	-34.363***	-48.215***	-5.817
	(19.184)	(33.030)	(0.465)	(1.258)	(8.269)	(4.765)
LR test of exogeneity (Chi sq.)	3.967	4.543	102.099	58.181	5.017	2.099
LR test's p-value	0.265	0.208	0.000	0.000	0.171	0.552
Panel B: METE (Assuming exogeneity, 500 replications, 0.5 factor scale)						
4WT use (dummy)	-84.669***	-219.497***	-9.488***	-42.157***	-58.483***	7.162**
	(26.410)	(24.305)	(1.016)	(4.096)	(1.936)	(3.437)
2WT use (dummy)	-16.265	-256.502***	13.967***	-62.563***	-69.970***	10.327
	(41.455)	(42.380)	(1.140)	(6.146)	(1.365)	(7.069)
DA use (dummy)	-123.307***	-128.594***	-28.836***	-27.904***	-52.693***	-8.004*
	(23.414)	(36.200)	(1.065)	(7.316)	(1.875)	(4.799)
Number of observations	983	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table 5.

Online Appendix Tables

A1: Summary Statistics

VARIABLES	(1) Mean	(2) Min	(3) Max
Area cultivated in sample plot (ha)	1.05	0.10	8.09
Share of leveled plot (%)	46.59	0.00	100.00
Share of bunded plot (%)	50.66	0.00	100.00
Adoption rate of transplanting in rows (%)	18.21	0.00	100.00
Adoption rate of MVs (%)	34.08	0.00	100.00
Chemical fertilizer use (kg/ha)	38.38	0.00	370.64
Insecticide and herbicide use (liter/ha)	1.88	0.00	9.88
Paddy yield in sample plot (tons/ha)	2.94	0.00	9.34
Income from rice cultivated in sample plot ('000 TShs/ha)	775.07	-1,352.71	3,867.77
Profit from rice cultivated in sample plot ('000 TShs/ha)	521.41	-2,258.03	3,549.37
Paid-out cost of hired labor ('000 TShs/ha)	270.10	0.00	2,349.44
Imputed cost of family labor ('000 TShs/ha)	216.83	0.00	2,179.71
Total labor costs ('000 TShs/ha)	486.92	0.00	2,634.69
Total labor use (person-days/ha)	108.50	0.00	403.44
Productivity of total labor use (kg/person-days)	39.21	0.00	452.83
Total paid-out cost of hired labor ('000 TShs/ha)	270.10	0.00	2,349.44
Paid-out cost of hired labor for preparing rice plot ('000 TShs/ha)	57.51	0.00	587.36
Paid-out cost of hired labor crop establishment ('000 TShs/ha)	48.23	0.00	320.38
Paid-out cost of hired labor for manual weeding ('000 TShs/ha)	51.08	0.00	398.16
Paid-out cost of hired labor for harvesting ('000 TShs/ha)	113.29	0.00	1,797.68
Total imputed cost of family labor ('000 TShs/ha)	216.83	0.00	2,179.71
Imputed cost of using family labor for preparing rice plot ('000 TShs/ha)	56.91	0.00	828.16
Imputed cost of family labor for crop establishment ('000 TShs/ha)	34.97	0.00	457.08
Imputed cost of family labor for manual weeding ('000 TShs/ha)	52.53	0.00	689.28
Imputed cost of family labor for harvesting ('000 TShs/ha)	72.41	0.00	1,011.11
Total hired labor use (person-days/ha)	59.69	0.00	250.00
Hired labor use for preparing rice plot (person-day/ha)	12.68	0.00	103.75
Hired labor use for crop establishment (person-day/ha)	10.61	0.00	55.50
Hired labor use for weeding (person-day/ha)	15.85	0.00	80.00
Hired labor use for harvesting (person-day/ha)	20.55	0.00	69.19
Total family labor use (person-days/ha)	48.81	0.00	331.67
Family labor use for preparing rice plot (person-day/ha)	10.93	0.00	119.17
Family labor use for crop establishment (person-day/ha)	6.22	0.00	71.88
Family labor use for weeding (person-day/ha)	15.72	0.00	100.00
Family labor use for harvesting (person-day/ha)	15.93	0.00	112.50
Area under rice cultivation at HH level (ha)	1.42	0.10	19.02
Total household income (‘00000 TShs)	17.79	-26.51	253.81
Income from sample plot (‘00000 TShs)	6.92	-32.92	134.39
Rice income from other plots (‘00000 TShs)	3.10	-3.48	119.86
Crop income from other plots (‘00000 TShs)	3.86	-8.03	119.86
Income from livestock production (‘00000 TShs)	1.12	-7.49	65.37
Income from business and wage activities (‘00000 TShs)	2.79	-10.81	164.23
Number of four-wheeled tractors in the village	3.46	0.00	23.00
Number of two-wheeled tractors in the village	3.67	0.00	34.00

Village population density (100 people/sq.km)	1.56	0.17	5.16
Moderate risk for trypanosomiasis (dummy)	0.21	0.00	1.00
High risk for trypanosomiasis (dummy)	0.62	0.00	1.00
Age of household head	47.93	19.00	100.00
Years of schooling of household head	6.34	0.00	14.00
Number of working-age adults	3.16	0.00	11.00
Female-headed household (dummy)	0.11	0.00	1.00
Total landholdings (ha)	3.24	0.00	35.61
Value of non-farm household assets (mil. TShs)	0.76	0.00	14.75
Landholdings in upland area (ha)	0.68	0.00	19.43
Landholdings in lowland area (ha)	2.56	0.00	25.90
Amount of credit received by the household ('00000 TShs)	0.52	0.00	30.00
Number of bulls owned	0.63	0.00	55.00
Plot size (ha)	1.42	0.10	33.99
Irrigated plot (dummy)	0.36	0.00	1.00
Sample plot has clay soil (dummy)	0.44	0.00	1.00
Distance to district capital (km)	66.87	4.80	187.00
4WT rental fee ('000 TShs)	34.26	20.79	60.00
2WT rental fee ('000 TShs)	38.08	10.40	62.37
DA rental fee ('000 TShs)	31.52	15.59	50.00
Village has irrigated area (dummy)	0.58	0.00	1.00
Observations: 983 households			

Source: Authors

Table A2: Falsification tests of instrumental variables for cultivated area and technology adoption variables

VARIABLES	(1) Area cultivated in sample plot (ha)	(2) Transplanted in rows (dummy)	(3) MVs (dummy)	(4) Amount of chemical fertilizer used (kg/ha)
Number of 4WTs in the village	0.011			1.087
	(0.008)			(2.231)
Number of 2WTs in the village	0.003	0.003	0.018	-0.000
	(0.006)	(0.006)	(0.011)	(1.277)
Village population density (100 people/km^2)	-0.037	-0.010	0.034	
	(0.027)	(0.051)	(0.033)	
Moderate risk for trypanosomiasis (dummy)		-0.332		
		(0.260)		
High risk for trypanosomiasis (dummy)				
Constant	-0.944*	-1.025*	-0.865	-161.584**
	(0.511)	(0.553)	(0.579)	(64.760)
Observations	271	271	271	271
Adjusted R-squared	0.650	0.330	0.464	0.451
Wald test of selected IVs (F-statistic)	1.625	0.972	1.833	0.119
Wald test of selected IVs (*p*-value)	0.204	0.419	0.177	0.888

Source: Authors
Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%.

Table A3: Falsification tests of instrumental variables for land productivity, area under rice cultivation at household level, and household income

VARIABLES	(1) Paddy yield in sample plot (tons/ha)	(2) Income from rice cultivated in sample plot ('000 TSh/ha)	(3) Profit from rice cultivated in sample plot ('000 TSh/ha)	(4) Area under rice cultivation at household level (ha)	(5) Total household income (‘00000 TSh)
Number of 4WTs in the village	0.056		26.397	0.007	0.495
	(0.046)		(17.143)	(0.016)	(0.517)
Number of 2WTs in the village		26.068*		-0.001	0.486
		(13.568)		(0.012)	(0.329)
Village population density (100 people/km^2)	0.019	60.905	57.352	-0.080	2.152
	(0.171)	(63.052)	(72.997)	(0.060)	(1.993)
Moderate risk for trypanosomiasis (dummy)					
High risk for trypanosomiasis (dummy)				0.159	-19.742*
				(0.442)	(9.972)
Constant	2.299	-416.318	-526.793	0.957	-9.598
	(1.808)	(742.929)	(860.780)	(0.908)	(27.694)
Observations	271	271	271	271	271
Adjusted R-squared	0.267	0.187	0.182	0.493	0.237
Wald test of selected IVs (F-statistic)	0.769	1.962	1.283	0.628	1.698
Wald test of selected IVs (*p*-value)	0.472	0.158	0.292	0.646	0.176

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%.

Table A4: Falsification tests of instrumental variables for labor costs and labor productivity

VARIABLES	(1) Paid-out cost of hired labor ('000 TSh/ha)	(2) Imputed cost of family labor ('000 TSh/ha)	(3) Hired labor use (person-days/ha)	(4) Family labor use (person-days/ha)	(5) Total labor use (person-days/ha)	(6) Productivity of total labor use (kg/person-days)
Number of 4WTs in the village	4.292	7.784	0.167	0.361	0.528	-1.067
	(9.001)	(7.889)	(1.278)	(1.600)	(1.411)	(0.719)
Number of 2WTs in the village	-2.895		-0.190			
	(4.332)		(1.068)			
Village population density (100 people/km^2)	-29.307				-0.484	1.594
	(26.414)				(4.507)	(2.684)
Moderate risk for trypanosomiasis (dummy)					19.017	
					(20.912)	
High risk for trypanosomiasis (dummy)		319.397*	-2.011	49.201	47.190	
		(183.757)	(27.595)	(29.740)	(37.508)	
Constant	-12.296	73.221	-17.687	104.950	87.262	47.758
	(422.339)	(432.197)	(66.890)	(82.480)	(91.816)	(48.406)
Observations	271	271	271	271	271	271
Adjusted R-squared	0.206	0.134	0.217	0.162	0.276	0.405
Wald test of selected IVs (F-statistic)	0.420	2.122	0.0229	1.370	0.594	1.521
Wald test of selected IVs (*p*-value)	0.740	0.137	0.995	0.269	0.670	0.234

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%.

Table A5: Effects of machinery use on labor use (decomposition by tasks)

VARIABLES	(1) Hired labor use for preparing rice plot (person-day/ha)	(2) Hired labor use for crop establishment (person-day/ha)	(3) Hired labor use for weeding (person-day/ha)	(4) Hired labor use for harvesting (person-day/ha)	(5) Family labor use for preparing rice plot (person-day/ha)	(6) Family labor use for crop establishment (person-day/ha)	(7) Family labor use for weeding (person-day/ha)	(8) Family labor use for harvesting (person-day/ha)
Panel A: METE (Assuming endogeneity, 500 replications, 0.5 factor scale)								
4WT use (dummy)	-21.915***	3.025***	-2.829***	7.576***	-19.037***	-3.617***	-11.946***	-15.244***
	(2.654)	(0.289)	(0.322)	(0.268)	(2.238)	(1.055)	(3.430)	(3.506)
2WT use (dummy)	-10.763***	2.566***	15.198***	6.847***	-20.026***	-7.895***	-14.339***	-6.457
	(2.390)	(0.228)	(0.393)	(0.338)	(3.368)	(1.683)	(2.498)	(4.763)
DA use (dummy)	-16.650***	-3.056***	-3.717***	1.064***	-11.309***	-3.747**	-1.577	-9.409
	(2.601)	(0.338)	(0.429)	(0.340)	(3.299)	(1.482)	(4.734)	(6.806)
Panel B: METE (Assuming exogeneity, 500 replications, 0.5 factor scale)								
4WT use (dummy)	-18.012***	-9.377***	1.132*	9.110***	-18.785***	-3.977***	-12.307***	-8.554***
	(2.158)	(0.496)	(0.580)	(0.128)	(2.210)	(1.135)	(2.284)	(2.267)
2WT use (dummy)	-12.796***	2.915***	15.537***	13.789***	-20.084***	-7.962***	-15.187***	-15.969***
	(2.489)	(0.447)	(0.612)	(0.171)	(3.380)	(1.715)	(2.389)	(3.159)
DA use (dummy)	-20.563***	-4.884***	-0.627	-0.846***	-11.536***	-3.788**	0.076	-3.125
	(2.843)	(0.536)	(0.558)	(0.128)	(3.579)	(1.521)	(2.959)	(3.277)
Observations	983	983	983	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) The HT user (i.e., j= 0) is the base category. (iii) *** denotes significant at 1%, ** significant at 5%, and * significant at 10%. (iv) We control for the number of working-age adults, years of schooling of household head, female-headed household (dummy), age of household head, total landholdings (ha), the value of non-farm household assets (million TShs), amount of credit received by the household (‘00,000 TShs), size of the sample plot (ha), dummy variables indicating whether the sample plot is irrigated, has clay soil, or has bunds, as well as district and year dummies.

Table A6: Effects of mechanization on cultivated area and technology adoption (robustness check)

VARIABLES	(1) Area cultivated in sample plot (ha)	(2) Transplanted in rows (dummy)	(3) MVs (dummy)	(4) Amount of chemical fertilizer used (kg/ha)
CRE				
4WT use (dummy)	0.218***	-0.156***	-0.223***	-9.517*
	(0.070)	(0.048)	(0.057)	(5.477)
2WT use (dummy)	0.123*	0.130**	-0.023	23.337*
	(0.073)	(0.064)	(0.062)	(13.061)
DA use (dummy)	0.009	0.017	-0.254***	-10.824
	(0.105)	(0.054)	(0.053)	(11.137)
FE				
4WT use (dummy)	0.189**	-0.075	-0.154**	-2.816
	(0.071)	(0.054)	(0.071)	(8.181)
2WT use (dummy)	0.174	0.150**	0.022	28.324**
	(0.104)	(0.065)	(0.057)	(13.815)
DA use (dummy)	0.007	0.020	-0.179***	-2.805
	(0.107)	(0.049)	(0.065)	(13.563)
METE: Assuming endogeneity (500 replications, 1 factor scale)				
4WT use (dummy)	0.502***	-0.382***	-0.429***	-33.992***
	(0.145)	(0.055)	(0.012)	(9.056)
2WT use (dummy)	0.138*	0.067	-0.048***	8.458
	(0.082)	(0.076)	(0.019)	(19.745)
DA use (dummy)	-0.055	0.058	-0.484***	-28.220*
	(0.116)	(0.074)	(0.008)	(16.416)
Observations	983	983	983	983
METE: Assuming endogeneity (500 replications, 0.3 factor scale)				
4WT use (dummy)	0.328***	-0.302***	-0.289***	-14.309**
	(0.092)	(0.013)	(0.082)	(6.625)
2WT use (dummy)	0.119	0.099***	-0.045	33.369***
	(0.075)	(0.023)	(0.124)	(12.588)
DA use (dummy)	-0.017	0.045	-0.323***	-20.681*
	(0.107)	(0.031)	(0.071)	(10.996)
Observations	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table A5.

Table A7: Effects of mechanization on land productivity and household-level variables (robustness check)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Paddy yield in sample plot (tons/ha)	Income from rice cultivated in sample plot ('000 TShs/ha)	Profit from rice cultivated in sample plot ('000 TShs/ha)	Area under rice cultivation at HH level (ha)	Total household income (‘00000 TShs)
CRE					
4WT use (dummy)	-0.447***	-189.924***	13.899	0.161*	0.723
	(0.139)	(65.200)	(67.379)	(0.095)	(1.815)
2WT use (dummy)	0.293	64.233	225.154**	0.293*	1.767
	(0.268)	(118.960)	(112.997)	(0.170)	(3.079)
DA use (dummy)	-0.615***	-159.063	-54.716	-0.009	0.175
	(0.190)	(97.157)	(90.671)	(0.198)	(2.738)
FE					
4WT use (dummy)	-0.482**	-116.398	16.610	0.087	0.331
	(0.199)	(91.363)	(94.593)	(0.105)	(3.243)
2WT use (dummy)	0.364	140.780	220.745*	0.400	6.174
	(0.234)	(123.801)	(119.434)	(0.249)	(3.896)
DA use (dummy)	-0.567*	-30.599	40.749	-0.114	2.109
	(0.297)	(135.304)	(127.657)	(0.259)	(4.095)
METE: Assuming endogeneity (500 replications, 1 factor scale)					
4WT use (dummy)	-1.537***	-535.249***	320.128	0.370***	5.015*
	(0.018)	(131.896)	(347.418)	(0.113)	(2.824)
2WT use (dummy)	0.387***	-155.237	229.715	0.368**	2.552
	(0.016)	(184.813)	(184.004)	(0.170)	(3.262)
DA use (dummy)	-0.368***	-204.284	-107.989	0.168	3.654
	(0.030)	(212.446)	(159.010)	(0.171)	(3.203)
Observations	983	983	983	983	983
METE: Assuming endogeneity (500 replications, 0.3 factor scale)					
4WT use (dummy)	-0.988***	-300.928***	128.557	0.234**	1.529
	(0.044)	(66.708)	(109.765)	(0.095)	(2.244)
2WT use (dummy)	0.377***	-107.384*	246.390**	0.292*	0.729
	(0.025)	(56.324)	(124.559)	(0.168)	(3.335)
DA use (dummy)	-0.799***	-218.776**	-114.313	0.076	0.681
	(0.046)	(92.806)	(143.704)	(0.173)	(2.665)
Observations	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table A5.

Table A8: Effects of mechanization on labor and labor productivity (robustness check)

VARIABLES	(1) Paid-out cost of hired labor ('000 TShs/ha)	(2) Imputed cost of family labor ('000 TShs/ha)	(3) Hired labor use (person-days/ha)	(4) Family labor use (person-days/ha)	(5) Total labor use (person-days/ha)	(6) Productivity of total labor use (kg/person-days)
CRE						
4WT use (dummy)	-52.178**	-203.078***	-17.315***	-39.778***	-59.985***	8.527**
	(25.603)	(24.923)	(4.442)	(4.884)	(4.787)	(3.721)
2WT use (dummy)	-38.833	-163.744***	-2.398	-32.564***	-37.621***	6.566
	(38.396)	(41.098)	(7.665)	(8.063)	(8.400)	(7.514)
DA use (dummy)	-101.395***	-123.207***	-21.540***	-24.803***	-47.124***	-5.835
	(21.489)	(30.983)	(4.821)	(6.957)	(6.574)	(4.687)
FE						
4WT use (dummy)	-73.560**	-143.000***	-19.918***	-27.829***	-47.747***	2.867
	(35.563)	(29.154)	(5.738)	(6.518)	(7.493)	(5.452)
2WT use (dummy)	-69.706*	-90.471*	-9.213	-18.565**	-27.778***	2.504
	(40.805)	(46.418)	(6.833)	(8.818)	(6.487)	(9.405)
DA use (dummy)	-124.975***	-93.046***	-21.466***	-21.598***	-43.064***	-11.455
	(26.101)	(25.941)	(4.887)	(6.280)	(4.724)	(8.960)
METE: Assuming endogeneity (500 replications, 1 factor scale)						
4WT use (dummy)	-56.555*	-332.478***	9.228	-38.188***	-85.604***	4.772
	(31.886)	(40.872)	(11.309)	(1.237)	(12.593)	(4.087)
2WT use (dummy)	26.079	-192.511***	-9.307	-89.625***	-45.012	0.634
	(36.471)	(38.219)	(13.730)	(0.904)	(42.438)	(7.567)
DA use (dummy)	-34.180*	-126.436***	-33.540***	-37.218***	-63.602***	-9.445*
	(20.305)	(33.686)	(9.199)	(1.499)	(15.617)	(5.368)
Observations	983	983	983	983	983	983
METE: Assuming endogeneity (500 replications, 0.3 factor scale)						
4WT use (dummy)	-51.333**	-257.430***	-2.463***	-35.345***	-72.970***	9.788***
	(25.730)	(26.348)	(0.940)	(1.567)	(5.787)	(3.753)
2WT use (dummy)	-13.863	-178.947***	6.367***	-53.554***	-37.701***	8.058
	(35.798)	(37.833)	(0.889)	(2.278)	(8.770)	(7.284)
DA use (dummy)	-77.869***	-134.687***	-27.057***	-32.109***	-48.835***	-4.490
	(19.814)	(33.285)	(0.672)	(3.649)	(7.060)	(4.406)
Observations	983	983	983	983	983	983

Source: Authors
Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table A5.

Table A9.1: Effects of machinery use on labor use (decomposition by tasks: robustness check)

VARIABLES	(1) Hired labor use for preparing rice plot (person-day/ha)	(2) Hired labor use for crop establishment (person-day/ha)	(3) Hired labor use for weeding (person-day/ha)	(4) Hired labor use for harvesting (person-day/ha)	(5) Family labor use for preparing rice plot (person-day/ha)	(6) Family labor use for crop establishment (person-day/ha)	(7) Family labor use for weeding (person-day/ha)	(8) Family labor use for harvesting (person-day/ha)
CRE								
4WT use (dummy)	-18.716***	-3.571***	2.330*	2.453	-18.437***	-4.637***	-9.461***	-8.996***
	(2.197)	(1.145)	(1.215)	(2.091)	(2.307)	(1.102)	(2.138)	(1.801)
2WT use (dummy)	-14.585***	1.070	4.904*	6.305*	-14.924***	-4.983***	-8.164***	-6.379**
	(2.353)	(1.996)	(2.681)	(3.289)	(3.224)	(1.410)	(2.419)	(2.728)
DA use (dummy)	-16.283***	-2.737	-1.870	-0.573	-12.933***	-3.718**	-5.261**	-2.966
	(2.284)	(1.923)	(1.490)	(2.111)	(3.003)	(1.519)	(2.140)	(2.888)
FE								
4WT use (dummy)	-18.170***	-3.718**	1.519	0.451	-15.094***	-3.650**	-6.106**	-2.979
	(2.730)	(1.669)	(2.367)	(2.916)	(3.498)	(1.635)	(2.948)	(2.172)
2WT use (dummy)	-15.275***	0.006	4.305	1.751	-12.733***	-2.607	-2.928	-0.298
	(2.909)	(2.916)	(3.190)	(3.349)	(4.528)	(1.612)	(2.793)	(3.294)
DA use (dummy)	-17.723***	-2.557	-0.383	-0.803	-14.508***	-4.483***	-2.878	0.270
	(2.695)	(1.889)	(2.287)	(2.309)	(3.054)	(1.596)	(2.179)	(3.332)
Observations	983	983	983	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table A5.

Table A9.2: Effects of machinery use on labor use (decomposition by tasks: robustness check)

VARIABLES	(1) Hired labor use for preparing rice plot (person-day/ha)	(2) Hired labor use for crop establishment (person-day/ha)	(3) Hired labor use for weeding (person-day/ha)	(4) Hired labor use for harvesting (person-day/ha)	(5) Family labor use for preparing rice plot (person-day/ha)	(6) Family labor use for crop establishment (person-day/ha)	(7) Family labor use for weeding (person-day/ha)	(8) Family labor use for harvesting (person-day/ha)
METE: Assuming endogeneity (500 replications, 1 factor scale)								
4WT use (dummy)	-25.376***	7.686***	-2.405***	12.274***	-19.655***	0.855	-14.531***	-22.692***
	(3.105)	(0.131)	(0.396)	(0.138)	(2.540)	(1.105)	(2.665)	(4.732)
2WT use (dummy)	-7.012***	2.636***	18.947***	15.309***	-23.698***	-5.511***	-19.312***	4.386
	(2.491)	(0.175)	(0.407)	(0.195)	(4.187)	(1.978)	(2.347)	(3.144)
DA use (dummy)	-18.245***	-1.900***	-6.689***	0.965***	-9.954**	-4.525**	3.259	-6.730*
	(3.158)	(0.254)	(0.436)	(0.176)	(3.932)	(1.815)	(2.884)	(3.966)
Observations	983	983	983	983	983	983	983	983
METE: Assuming endogeneity (500 replications, 0.3 factor scale)								
4WT use (dummy)	-18.174***	1.791***	-2.468***	4.901***	-18.956***	-4.102***	-10.026***	-13.242***
	(2.165)	(0.186)	(0.813)	(0.167)	(2.214)	(0.953)	(2.892)	(1.944)
2WT use (dummy)	-12.461***	3.013***	6.022***	5.672***	-18.105***	-6.875***	-11.885***	-7.026**
	(2.210)	(0.270)	(0.991)	(0.262)	(3.234)	(1.495)	(2.652)	(2.902)
DA use (dummy)	-19.059***	-2.692***	-4.664***	-1.408***	-11.853***	-3.627**	-4.745	-7.917**
	(2.739)	(0.203)	(0.495)	(0.296)	(3.185)	(1.453)	(3.033)	(3.575)
Observations	983	983	983	983	983	983	983	983

Source: Authors

Notes: (i) Robust standard errors clustered at village level in parentheses. (ii) Model specification and control variables are as in Table A5.

Abstract (in Japanese)

要　　約

近年、サブサハラ・アフリカにおいて農業機械化に注目が集まっている。しかし、農業機械化が小規模農家に与える影響については十分な研究がなされていない。特に、これまで大型トラクターと小型トラクターの比較は行われてこなかった。本研究ではタンザニアの3時点のパネルデータを用いて、大型トラクター、小型トラクター、及び牛耕が稲作の技術採用、土地生産性、労働投入及び労働生産性に与える影響を検証する。分析には Multinominal endogenous treatment effect model 及び Mundlak-Chamberlain devices を用いて、可能な限り農家による機械利用の内生性をコントロールした。その結果大型トラクターは耕作面積の拡大と労働生産性の向上に寄与するが、土地生産性を減少させることが明らかになった。他方、小型トラクターは耕作面積の拡大と労働集約的な技術の採用、単位面積当たりの収量を向上させるが、労働生産性には影響がないことが明らかになった。これらの結果は大型トラクターと小型トラクターが稲作生産向上に対して別の役割を果たしうることを示唆している。

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