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Mechanization Enhances Wheat Yield and Technical Efficiency: Evidence from Smallholder Farmers in the Arsi Zone, Oromia Region, Ethiopia.

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Abstract

Wheat, a vital staple crop in Ethiopia, plays a key role in ensuring food security due to its widespread consumption, adaptability to diverse agro-ecological zones, and significant contribution to food availability. Recent national efforts to increase wheat production have included expanding the use of agricultural machinery; however, the effects of mechanization, especially among smallholder farmers, on wheat yields and efficiency remain insufficiently studied. To address this gap, this study applies a Stochastic Frontier Model (SFM) with selection correction alongside a Multinomial Endogenous Switching Regression (MESR) model to estimate technical efficiency and evaluate the impact of mechanization. Using data from 409 wheat farmers in the Arsi Zone, Oromia Region, results reveal substantial variation in technical efficiency across mechanization groups, with farmers using both tractors and combine harvesters achieving the highest efficiency scores (.95). Additionally, the Stochastic Production Frontier analysis shows that fertilizer inputs (DAP and urea) positively influence wheat output regardless of mechanization status. The MESR findings indicate that adopting machinery, whether tractors, combine harvesters, or both, significantly improves technical efficiency and yields. These outcomes highlight the need to improve farmers' access to mechanization services, strengthen extension support, and enhance information dissemination to increase adoption rates and boost wheat production among smallholder farmers in Ethiopia.

Key terms: Agricultural machinery, Technical efficiency, Stochastic Frontier Model with selection correction, Multinomial endogenous switching regression, Impact

1. Introduction

Wheat is the most important staple crop and has played an important role in feeding billions of people worldwide for over 8,000 years [1]. It is still one of the most widely cultivated cereals and is second only to maize in global production [2]. Ethiopia, one of the main producers of wheat for thousands of years, is also the second-largest wheat producer in Africa [3]. Despite the high contribution of wheat to food security, the production and productivity of wheat are not satisfactory compared to the increasing demand. This is due to factors such as the low penetration of technologies, fertilizers and wheat varieties [4-7]. Technical inefficiency is also attributed to the unsatisfactory wheat yield globally. For instance, according to Moersdorf, et al. [8], damage to electrical grids has contributed to a decline in production, in many countries, including India and China, experiencing reductions of up to 75% in crop yields. Furthermore, climate change is a significant challenge for wheat production worldwide. Pequeno, et al. [9] project that climate change will lead to an average global yield reduction of 1.9% by 2050. This impact is expected to be particularly severe in developing countries, especially those in the tropics, where food security is already precarious. Specific models forecast substantial yield losses by 2050, with declines of 15% in African nations and 16% across Southern Asia, further threatening food supplies. Therefore, using technology that increases production and technical efficiency is very important to fill the demand gap for wheat and outweigh the negative effects of climate change [10]. However, simply increasing inputs or introducing new technologies alone may not achieve the desired level of wheat productivity. Hence, farmers should utilize these inputs efficiently to maximize their production [11, 12].

In Ethiopia, inefficiencies, low technology adoption, and climate change have contributed to low wheat yields [13-18]. Furthermore, policy effects also exacerbate this situation [19]. According to Shikur [19], Ethiopia's current wheat supply-demand gap of 44% could potentially be reduced to 7% with the implementation of appropriate policies, such as price supports, input subsidies, market-oriented reforms, and integrated wheat development strategies—which boost yields by encouraging investment, improving access to inputs, and aligning production with market demand, as demonstrated by Egypt’s experience. Due to these and other problems, the country's wheat self-sufficiency decreased from 99% in the 1960s to 70% by 2020 [3]. The country's yields are currently below both the global average and that of Egypt. For instance, during the 2023-2024 season, Ethiopia's average wheat yield was 3.05 tons per hectare, falling below the global average of 3.55 tons per hectare and considerably lower than Egypt’s yield of 6.57 tons per hectare [20]. Despite this, Ethiopia is the largest wheat producer in Sub-Saharan Africa, and millions of people rely on wheat for their livelihoods and food security. Therefore, improving wheat productivity is crucial for the country’s national development and long-term food security [21].

The Arsi Zone is a key wheat-producing area in Ethiopia. According to ESS [22], it contributes significantly to the nation's wheat supply, representing over 11% of wheat coverage and nearly 12.5% of total production. However, despite its potential, wheat productivity in the Arsi Zone is also 3.31 t/ha [23], which is higher than the national average of 3.06 t/ha but significantly lower than the global average and far from the potential wheat yield of 5 t/ha [24, 25]. This gap exists because of the wheat farming system in Ethiopia, which is carried out by small-scale farmers who lack access to modern technology, leading to operational inefficiencies [10, 18, 26-28]. In Ethiopia, smallholders operating on less than 2.5 hectares are the backbone of the sector, with 4.5 million farmers producing 95% of Ethiopia's wheat across 1.7 million hectares. This demographic manages approximately 84% of both national wheat acreage and total output, while also relying on the crop for vital rural employment. As a pillar of the national economy, wheat accounts for 20.2% of total cereal production and 12.2% of the country's harvested area. Production is heavily concentrated in the Oromia (57–58%) and Amhara (28–32%) regions [29]. Consequently, given Oromia's primary role in national output, addressing the technical and socio-economic constraints within high-potential hubs like the Arsi Zone is essential for closing the yield gap and achieving national wheat self-sufficiency.

To address the shortage, the Ethiopian government is prioritizing wheat production through off-season farming, utilizing available water resources and technology. However, while production has increased, this growth has mainly come from farmland expansion into lowland areas rather than productivity improvements. As a result, Ethiopian wheat remains expensive, forcing private traders to rely on cheaper imports, particularly from Eastern Europe. For instance, from January to May 2024, around 400,000 metric tons of wheat were imported [30]. Enhancing smallholder productivity through efficient resource use is key to sustainable wheat production. Utilizing machinery like tractors and combine harvesters boosts productivity, resource management, and farmer livelihoods [31-34]. The integration of agricultural machinery in wheat production has not only improved the speed and scale of wheat farming but also reshaped labor dynamics and rural economies [35-38]. Globally, the use of tractors has demonstrated a positive impact on wheat yields through deep ploughing and the restoration of soil fertility [39], and combine harvesters also play a significant role in increasing wheat yields by reducing post-harvest losses [40]. In Ethiopia too, the adoption of tractors and combines harvester shows a positive correlation with increased yields [33, 41]. Furthermore, using this machinery has great potential to reduce the negative climate effect on the production of different crops [42, 43]. This underscores the potential of machinery's contribution to wheat productivity. While boosting wheat yields remains a primary goal, achieving technical efficiency is equally crucial, particularly for small-scale farming, where optimizing resource utilization is vital for profitability and sustainability [44, 45]. A substantial body of literature has explored technical efficiency in wheat production. For instance, researchers such as Singh, et al. [46], Aamir, et al. [47], and Solomon, et al. [48] used to analyze the technical efficiency of wheat using Data Envelopment Analysis (DEA), while studies like Gebiso, et al. [28], Girma, et al. [10], Alemayehu, et al. [49], Chen, et al. [50] have utilized Stochastic Frontier Analysis (SFA), their result shows that using different technologies also improve technical efficiency of wheat, particularly study like Gebiso, et al. [28], which specifically analyzed the impact of mechanization, revealed that the utilization of machinery—such as tractors and combine

harvesters—contributes positively to technical efficiency while simultaneously boosting overall productivity.

Despite the potential of agricultural machinery to bolster production and technical efficiency, its adoption in Ethiopia remains low, particularly when compared to other Sub-Saharan African (SSA) nations. This stagnation is attributable to several factors, foremost among which are policy biases and entrenched perceptions. Historically, mechanization has been associated almost exclusively with large-scale farming; consequently, it was largely omitted from policy agendas, leaving smallholder farmers chronically underserved. Furthermore, socio-cultural considerations significantly influence adoption decisions. Kuto, et al. [51] document how mechanized farming and industrialization can disrupt traditional livelihood systems, indigenous knowledge, and communal labor-sharing arrangements. In many rural communities, agriculture is deeply embedded within social institutions that regulate labor exchange and social cohesion; therefore, mechanization may be perceived as a threat that weakens local employment opportunities and erodes culturally significant practices.

Beyond these social shifts, mechanization may promote specialization [52], which can disrupt local food systems [33, 53-55]. Additionally, it is often bundled with inorganic fertilizer packages that may negatively impact long-term soil fertility [56] and contribute to environmental degradation, including the loss of cropland, pastures, forests, and water resources [51]. Notwithstanding these potential negative externalities, a scholarly consensus persists that adopting agricultural mechanization—when combined with a diversified income portfolio—is a vital mechanism for mitigating poverty and enhancing the welfare of vulnerable households [33, 57-62].

In this context, our study investigates the specific contribution of mechanization to wheat productivity and technical efficiency. While a vast body of literature has explored the impact of inputs such as improved seeds and fertilizers [63-69]. The role of mechanization in enhancing technical efficiency remains a comparatively under-researched area. Furthermore, existing studies often fail to address a critical econometric challenge: selection bias. Many researchers frequently assume that farmers who adopt mechanization are homogeneous with those who do not—an assumption that, as noted by González-Flores, et al. [70], can lead to biased and unreliable estimates.. A notable example is the work of Gebiso, et al. [28], which categorizes mechanization levels without correcting for endogenous adoption decisions. This omission risks biased estimates that may overstate mechanization benefits while ignoring differences between adopters and non-adopters.

To overcome these limitations and provide a more robust analysis, this study employs a sophisticated econometric framework. We utilize a Cobb-Douglas stochastic frontier selection

biased approach, as outlined by Greene [71], specifically to estimate farmer technical efficiency. Crucially, this is embedded within a Multinomial Endogenous Switching Regression (MESR) model. This integrated approach is our key methodological contribution; it allows us to explicitly account for both observed and unobserved differences between mechanization users and non-users, thereby correcting for selection bias and providing unbiased impact estimates. Using this framework, our study investigates the individual and combined effects of tractor plowing and combine harvesting on the wheat yield and technical efficiency of farmers in the Arsi Zone of Ethiopia. The findings are intended to provide crucial, evidence-based insights for designing policies that effectively promote mechanization, enhance farmer efficiency, and ultimately improve food security and livelihoods for smallholders.

The rest of the paper is structured as follows. Section 2 provides a description and the method of analysis, presenting the conceptual framework and econometric strategy used in the study. Section 3 contains information on the data and descriptive results and presents the econometric findings, while Section 4 presents the conclusions of the study.

2. Methodology

2.1 Description of the Study Area

This study was conducted in the Arsi Zone, located in the Oromia National Regional State of Ethiopia, which covers 21,008 km². The zone is bordered by several other zones and regions, and its capital, Assela, is situated 175 km from Addis Ababa. The research specifically focused on four districts within the Arsi Zone—Hetosa, Lude Hetosa, Dodota-Dera, and Sire (see Figure 1 below). These districts are characterized by varying agro-ecological conditions: Sire has an altitude range of 1200-2700 meters, mean temperature of 15-30°C, and 500mm average annual rainfall; Dodota-Dera has an altitude range of 1400-2500 meters, mean temperature of 20-25°C, and 1000mm average annual rainfall; Hetosa has an altitude range of 1500-4170 meters, mean temperature of 5-28°C, and 1000mm average annual rainfall; and Lude Hetosa has an altitude range of 1800-2500 meters, mean temperature of 10-27°C, and 800-1000mm average annual rainfall. The primary crops cultivated in these districts include wheat, barley, teff, beans, and onions [72, 73].

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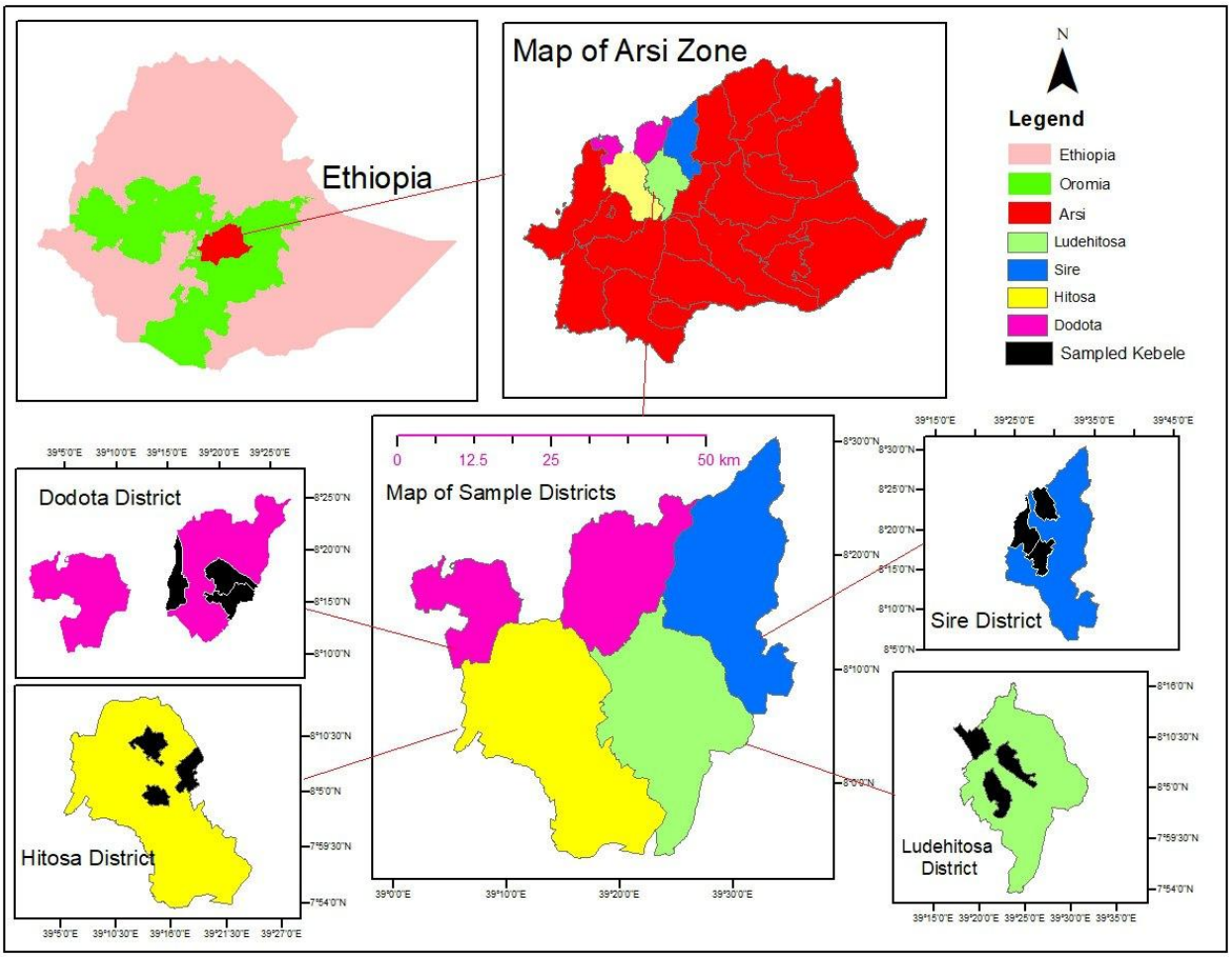


Figure 1 presents a map of the study area prepared by the authors. The map was created using [Software Name] (version 10.8; available at: https://igetintopc.com/esri-arcgis-desktop-10-8-free-download/).

2.2 Data Sources, Types, and Collection

This study employed both primary and secondary data. Primary data were collected from 413 rural households across four selected districts using a semi-structured questionnaire, refined based on pre-testing feedback and administered by trained enumerators. Secondary data were gathered from the Arsi Zone and district offices of agriculture and rural development, along with published and unpublished documents, to provide a comprehensive context and validate primary findings.

2.3 Sampling technique and sample size

To ensure representativeness and reliability, this study employed a multi-stage sampling technique combining purposive and simple random methods. The study population comprised rural farm households in four selected districts (Woreda) of the Arsi Zone, Ethiopia. First, the Arsi Zone was purposefully chosen for its significance in wheat production and relatively high machinery adoption. Second, four districts (Sire, Dodota, Lode Hetosa, and Hetosa) were selected randomly.

Third, three kebeles were randomly selected from each district after excluding those not suitable for machinery use. Finally, sample farmers were randomly selected from these 12 kebeles. The sample size was calculated using the Krejcie and Morgan [74] formula, considering a 95% confidence interval, population size and proportion, and a desired degree of accuracy, resulting in a base sample of 374 households. This was adjusted by 10% to account for potential sampling error, resulting in a final sample of 413 households. Subsequently, adopters and non-adopters of each machinery type were identified, followed by a rigorous analysis of the impacts of adoption on wheat productivity and efficiency. From the sample, 4 farmers did not produce wheat, hence, in this study we exclude them.

$$s = \frac{X^2 NP(1-P)}{d^2(N-1) + X^2 P(1-P)} = \frac{3.84 * 13,661 * 0.5(1-0.5)}{0.05^2(13,661-1) + 3.84 * 0.5(1-0.5)} = 374 \quad (1)$$

2.4 Data collection

Quantitative data was collected using structured questionnaires administered to the sample households (farmers). These questionnaires were initially prepared in English and carefully translated into Afaan Oromo. Data collectors were used for distributing and filling out the questionnaires. Before the formal data collection process began, the questionnaire underwent a pretesting phase to fine-tune its content and format. Additionally, an orientation session was conducted for enumerators to ensure they had a common understanding of the data collection instrument and procedures. Alongside this primary data collection, secondary data was gathered from published sources such as books, proceedings, journals, and unpublished documents like annual reports from various Woreda and kebele.

2.5 Data Analysis

Data analysis for this study was performed using NLOGIT 5 and STATA 18 software. A combination of descriptive statistics, inferential statistics (including t-tests for mean differences), and econometric models such as the stochastic frontier model and multinomial endogenous switching regression were used to analyse the efficiency and impact of agricultural machinery on the efficiency and productivity of wheat. The detailed information about the model is presented below.

2.5.1 Stochastic Frontier Model

Technical efficiency fundamentally encapsulates a producer's ability to optimize output given the available resources, reflecting the proficient allocation and utilization of inputs within the production process. Any deviation from the maximum attainable output signifies inefficiency in resource utilization [75, 76]. To investigate technical efficiency in wheat production in this study, we employ the SFM.

Both SFM and DEA are well-established methodologies in agricultural economics for efficiency measurement [77]. However, these approaches are grounded in distinct analytical paradigms. SFM, a parametric tool pioneered by [78] and [79], adopts a pre-specified functional form and explicitly acknowledges the presence of stochasticity in production. A key advantage of the SFM

is its ability to separate the error term into two distinct components: one representing inefficiency and the other capturing random error. This decomposition enables a clearer distinction between actual inefficiency and random variations in empirical data. On the other hand, DEA, a non-parametric approach developed by Charnes, et al. [80] and later applied by Sakouvogui [81], utilizes mathematical programming without assuming a specific functional form. This flexibility allows DEA to efficiently handle multiple inputs and outputs, making it a valuable tool for performance evaluation [82].

However, the flexibility of DEA also makes it more susceptible to outliers, which can distort efficiency estimates [83, 84]. Additionally, DEA assumes that all deviations from the efficiency frontier are solely due to inefficiency, an assumption that may not hold in smallholder agriculture, where farmers often face exogenous factors beyond their control [85, 86]. The model's reliance on the assumption of operational homogeneity across farmers further limits its applicability, particularly in developing countries where farming practices are highly diverse and smallholders exhibit significant heterogeneity [21].

Given these limitations, SFM provides a more robust and nuanced approach for analyzing technical efficiency in this study. By accounting for both inefficiency and random variation, SFM offers a more realistic representation of the challenges faced by wheat producers in the Arsi Zone. The production efficiency function is defined as follows.

$$\boldsymbol{Y_i = \beta_i X_i + \varepsilon_i} \qquad 2$$

where Y_i denote the actual wheat output of the ith farmer, $X_{i,}$is a vector of inputs, while β is a vector of unknown parameters to be estimated, and ε_i is composite error term, consisting of two parts: a symmetric, normally distributed disturbance term $vi \sim N(0, \sigma_v^2)$, which captures measurement errors and random shocks beyond the farmer's control, and a one-sided non-negative term disturbance term (ui), which represents technical inefficiency and is assumed to follow a half-normal distribution, i.e. $(U \sim |N(0, \sigma_u^2)|)|$. This stochastic frontier model framework follows the specification introduced by (Aigner et. al., 1977). Equation 2 is redefined as follows:

$$\boldsymbol{Yi = f(Xi, \beta) exp(vi - ui)} \qquad \mathbf{3}$$

The Cobb-Douglas production function used in this study to analyze the transformation of input to output following [76], which is mostly used in many agricultural research, primarily because of simplicity and interpretability, particularly when juxtaposed with the more complex Trans log

function [28, 87-89]. Although the translog function provides greater flexibility, it also presents considerable practical difficulties. Its complexity frequently results in multicollinearity issues and less efficient outcomes [75, 90], which become particularly acute when dealing with many parameters. In practice, applying the translog function with more than three input variables can result in computational difficulties [28, 91]. Additionally, the inclusion of second-order terms in the translog function complicates the direct interpretation of parameters, making it necessary to perform additional calculations to derive partial output elasticities. This added computational burden obscures key insights and increases the complexity of the analysis [89].

Given these challenges, the Cobb-Douglas production function emerges as a more suitable choice for this study. Its computational tractability and straightforward interpretability make it a preferred functional form in agricultural economics research [92, 93]. Accordingly, this study adopts the Cobb-Douglas production function for estimation of wheat output, which is defined as follows:

$$\boldsymbol{lnYi = lnβ0i + βlnland + βlnlabor + βlnseed + βlnfertilizer + βlnpesticiede + βlnoxen + βlntractor + βlncombiner + (vi - ui)} \quad \textbf{4}$$

In this model, $lnYi$ represents the wheat output in quintals, while the other variables include lnland, which denotes the area of land used for wheat cultivation (in hectares), lnlabor representing the labor input in days, lnseed for the amount of seed used (in kilograms), lnfertilizer for fertilizer used (in kilograms), lnpesticide for pesticide usage (in liters), lnoxen for oxen labor (in days), lntractor for the area ploughed by tractor, and lncombine for the area harvested by a combine harvester. The parameters β are to be estimated from the data.

Furthermore, random variability in the production process is captured by Vi, a normally distributed term that is unrelated to inefficiency. The term ui, representing technical inefficiency, is also assumed to be non-negative and independently and identically distributed, following a half-normal distribution denoted as$N\ (0, \sigma_u^2)$.

Given the level of input, the production efficiency of the ith wheat farmers is the ratio of available input to frontier output.

$$\boldsymbol{TE = \frac{f(Xi,β)exp(vi-ui)}{f(Xi,β)exp(vi)} = exp(-ui)} \quad \textbf{5}$$

However, this approach does not account for selection bias arising from unobserved factors. To address this issue, Greene [71] developed a model that corrects for sample selection bias. In the stochastic frontier sample selection model, the unobserved characteristics in the selection equation are correlated with the random error term in the stochastic frontier model, allowing for a more accurate estimation of efficiency [94]. Then, the selected equation is formulated as follows:

Selection equation:

$$\boldsymbol{A_{im} = 1[\alpha Z_{im} + \theta_{im} > 0],\ \theta_{im} \sim N(0,1)} \quad \textbf{6}$$

$Y_i = \beta_i X_i + \varepsilon_i$ (Y_i , X_i)are observed only when A_{im} =1 7

The error structure is specified as follows:

$\varepsilon_i = vi - ui$

$$\boldsymbol{ui = |\sigma_u U_i| = \sigma_u |U_i| \text{ where } U_i \sim N(0,1)} \quad \textbf{8}$$

$vi = |\sigma_v V_i|$ where $V_i \sim N(0,1)$

$(\theta_{im}\ vi) = N_2 \sim [(0,0), (1, \rho\sigma_{v,}\sigma_v^2)]$

In this model, A_{im} is a binary variable representing different combinations of agricultural machinery, while Z_{im} is a set of explanatory variables included in the binary sample selection model. The term θ_{im} represents the unobserved error component. The output of wheat farmers is denoted by y, and x represents the vector of inputs in the production frontier. The composed error term is given by ε.

The parameters α and β are estimated coefficients, and the error structure follows the standard components used in stochastic frontier analysis. Sample selection bias occurs when the noise term in the stochastic frontier model, vi, is correlated with the unobserved factors in the sample selection equation, θ_{im} [71]. A statistically significant ρ\rho indicates the presence of selectivity bias due to unobserved characteristics.

2.5.2 Multinomial Endogenous Switching Regression

Another key objective of this study is to examine the effect of agricultural machinery on the technical efficiency and productivity of wheat farming. Given the non-random nature of the dataset and the likelihood of self-selection influenced by both observable and unobservable factors, the application Ordinary Least Squares (OLS) would lead to biased and inconsistent estimates [95]. To mitigate this selection bias, this study adopts the MESR model, as developed by Bourguignon, et al. [96].

The analysis proceeds in two stages. In the first stage, the decision to adopt agricultural machinery whether individually (single) or jointly is modelled using a multinomial logit selection model. This step accounts for the self-selection process by identifying factors influencing farmers' choices regarding machinery adoption. In the second stage, the impact of agricultural machinery on key outcome variables, including wheat production efficiency and productivity, is estimated using OLS with selectivity correction terms.

Households' adoption decisions are modelled using random utility theory, which assume that the farmer's goal is to maximize the productivity, and efficiency of wheat. In deciding to select one agricultural package over another, the farmer evaluates the utility derived from each option. If the utility from a particular package "j" exceeds that of another option, "m", the farmer is more likely to adopt package "j".

$$\boldsymbol{Uij = Uim\ if\ j \neq m} \qquad \mathbf{9}$$

The farmer's expected profit from adopting a specific agricultural package is influenced by both observable and unobservable factors. Observable factors include household characteristics, plot attributes, and proximity to essential resources, while unobservable factors are captured in a latent variable. These elements collectively shape the farmer's decision-making process, where the final choice is based on the highest perceived utility. The error terms in this decision framework are assumed to follow an independent and identically distributed (iid.) Gumbel distribution [96]. To model the probability of a farmer (i) selecting a specific machinery package (j), a MNL[1] model is employed. This model accounts for various factors such as farm size, fertility and socioeconomic conditions, which influence the adoption decision. The MNL specification is given as follows:

$$\boldsymbol{P_{ij}=\eta_{ij}<0|X_i=\frac{expX_i\beta_j}{\sum_{n=1}^{J} expX_i\beta_n}} \qquad 10$$

Were P_{ij} represents the probability that a farmer i chooses to adopt agricultural machineries. X_i Is vector of exogenous variable, and β_j is a vector of parameters to be estimated, respectively.

[1] To save space, we did not analyze the determinants of machinery adoption in detail; however, the results are presented in Appendix Table 6A.

In the second stage of the MESR[2] framework, the study employs an OLS regression with selectivity correction to analyze the relationship between the outcome variable and a set of explanatory variables Z_i, estimated for each agricultural machinery regime)1=non-adoption,2= tractor only, 3=combine only and 4=joint adoption). The outcome equation for each potential regime *j* is given as:

$$\begin{cases} \boldsymbol{regime1\ Yi1 = Z_i\beta_1 + u_{i1}\ if\ T = 1} \\ \vdots \\ \boldsymbol{regimeJ\ YiJ = Z_i\beta_j + u_{ij} if\ T = j = 2,3,4} \end{cases} \quad \textbf{11}$$

Where *T* is an index that denotes the farmer *i*'s choice of adopting a type of Agricultural machinery technology; Yi is the outcome variables for the *i*-th farmer; Zi is a vector of exogenous variables; β_1 and β_j are parameters to be estimated; $ui1$ and uiJ are the error terms. Equation (11) addresses selection bias using observed covariates (Zi). However, unobserved factors that affect both the adoption of agricultural machinery and the outcome variables lead to unobserved selection bias, as the error terms of Equations 11s) would be correlated. This bias results in inaccurate and biased estimates. Thus, we use the MESR framework to determine the selectivity correction terms from the estimation of Equation (10), and those terms are included in Equations 11s to solve the unobserved selection bias. Following Amankwah and Gwatidzo [97], and Setsoafia, et al. [98] the second stage of the MESR is estimated as follows, including the correction.

$$\begin{cases} \boldsymbol{regime1\ Yi1 = Z_i\beta_1 + \delta_1\lambda_1 + \varepsilon_{i1}\ if\ I = 1} \\ \vdots \\ \boldsymbol{regimeJ\ YiJ = Z_i\beta_j + \delta_j\lambda_j + \varepsilon_{ij} if\ I = j} \end{cases} \quad \textbf{12}$$

Where δ_1 and δ_j are covariance between error terms in Equations (**11**s), $\lambda 1$ and λJ are correction factors introduced to address potential biases from unobserved selection. These correction factors are calculated using the estimated Inverse Mills Ratios (IMR), which are derived from the predicted probabilities obtained from the multinomial logit model in Equation 10 . The IMR is provided as:

$$\boldsymbol{\lambda_j = \sum_{k \neq J}^{J} \Upsilon_j \left(\frac{P_{ik} \ln (P_{ik})}{1 - P_{ik}} + \ln (P_{ij}) \right)} \quad \textbf{13}$$

Where Υ is the correlation between *eij* and *εij,* in the multinomial choice setting, there are $J - 1$ selectivity-correction
term for each alternative agricultural machinery option being considered. The standard errors in Equation 12 are bootstrapped to account for the heteroscedasticity arising from the generated regressor (λj) in the second stage.

[2] The econometric results for technical efficiency and wheat productivity are presented in Appendix Table 7 and Table 8 respectively.

Following Di Falco, et al. [99], and Shiferaw, et al. [100] we incorporated selection instruments to address unobserved heterogeneity in estimating the technical efficiency and productivity of wheat effects of the agricultural machinery and conducted a falsification test to ensure the integrity of the model (see Table 5A in appendix). Mobile ownership was used as an instrumental variable (IV), following prior impact studies[101] and [102].

A valid IV must satisfy relevance and exclusion restriction**.** Mobile access meets these criteria as it significantly influences machinery adoption by enhancing farmers' access to information, reducing uncertainty, and improving decision-making. The joint test results in the MNLR confirm its significance in technology adoption, while falsification tests indicate no direct effect on technical efficiency or wheat yields, validating the exclusion restriction.

We estimate the expected actual and counterfactual productivity and efficiency and compare them pairwise. Specifically, we first derive the expected outcomes of the treated households, which in our study means *j*=2, 3 and 4 (*j*=1 is the reference, i.e. non-adoption). From equation (**11**), the conditional expectations for each outcome variable based on practice can be derived as follows:

For adopters with actual adoption, the expected value of the outcome variable is

$$\mathbf{E}\ (\mathbf{YiJ}|\mathbf{T}=\mathbf{J}) = \mathbf{Z_i\beta_j} + \boldsymbol{\delta_j\lambda_1}\ \textbf{if T=J} \qquad \textbf{14}$$

And for adopters, had they not adopted (counterfactual)

$$\boldsymbol{E}\ (\boldsymbol{Yi1}|\boldsymbol{T}=\boldsymbol{J}) = \boldsymbol{Z_i\beta_1} + \boldsymbol{\delta_1\lambda_j}\ \textbf{if T=J} \qquad \textbf{15}$$

The impact of adopting agricultural machinery *j* is denoted as the average treatment effect on the treated (ATT), which is calculated by subtracting from equation 14 and 15 .

$$\boldsymbol{ATT}= \boldsymbol{E}\ (\boldsymbol{YiJ}|\boldsymbol{T}=\boldsymbol{J})\text{- }\boldsymbol{E}\ (\boldsymbol{Yi1}|\boldsymbol{T}=\boldsymbol{J})= \boldsymbol{Z_i}(\boldsymbol{\beta_j}-\boldsymbol{\beta_1})+\boldsymbol{\lambda_j}(\boldsymbol{\delta_j}-\boldsymbol{\delta_1}) \qquad \textbf{16}$$

3. Result and Discussion

3.1 Characteristics of sampled household

Table 1 below presents the description of sampled farmers' characteristics with respect to adoption status and compares them, which provides insight into the effect of adoption on the efficiency and productivity of wheat. The table indicates that, on average, farmers cultivate 1.5 hectares of wheat land, using 32 person-days of labor, 275 kg of seed, 241 kg of fertilizer, 12 days of oxen labor,

0.89 hectares of land ploughed by tractor, 1 hectare of wheat harvested by combine, and 1.92 liters of pesticide to produce 43 quintal of wheat.

The average wheat yields in the area is 28.5 quintal per hectare. The descriptive mean difference test results in Table 1 shows that the adoption of combine harvesters, both independently and in conjunction with tractors, significantly increases wheat yields. Furthermore, the table reveals that mechanization adopters have greater access to credit, which likely facilitates the financing of machinery services or rentals. In addition, distance from main markets plays an important role in adoption decisions. For example, farmers who live farther from main markets are significantly more likely to adopt combine harvesters than those who live closer (average distance difference = -0.683 km, $p < 0.05$). This may be because farmers in remote areas often face labor shortages, especially during the peak harvest season. These farmers tend to use combine harvesters to avoid delays and crop loss. On the other hand, farmers who live closer to market centers usually have better access to seasonal labor, since workers often gather in these more connected and populated areas. As a result, they may not need to rely as much on machines for harvesting. This result is consistent with Paudel, et al. [103], who identified labor constraints as a key factor driving the adoption of mechanization in African agriculture. Proximity to cooperatives and all-weather roads also appears to be a factor, with farmers located closer to cooperatives exhibiting a higher propensity to adopt both tractors and combines. This finding aligns with Zhang, et al. [104], who demonstrated the positive influence of cooperatives on technology adoption. Consequently, shorter distances between cooperative offices and farmer households are associated with increased farmer participation, ultimately contributing to higher adoption rates. Mobile phone ownership is significantly higher among all adopter groups, particularly combine-only adopters this because mobile phones improve access to information, enabling farmers to make informed decisions about technology adoption see for instance [105, 106].

Table 1 Descriptive Statistics, Measurement, and T-Statistics of Study Variables

Variables	Unit measurement	Pooled Mean	Tractor Only (Δ vs. Non-Adopters)	Combine Only (Δ vs. Non-Adopters)	Joint Adoption (Δ vs. Non-Adopters)
Outcome variable					
Wheat yields	Quintal per Hectare	28.55	2.316	3.451***	9.617***
Technical efficiency	Continuous	.855	0.006	0.010	0.007
Inputs					
Output of wheat	Per quintal	43.13081	8.839***	15.464***	40.485***
Labor	Man in days	32.2445	6.665*	-9.129***	-4.582*
Land	Hectare	1.514792	0.184	0.441***	0.897***
Seed	Kg	274.9389	40.341	63.982***	162.265***

Fertilizer (DAP and Urea)	Kg	241.1858	47.087*	55.029**	112.596***
Oxen	Oxen in days	12.10758	-6.039***	6.247***	0.561
Tractor	Area ploughed by tractor	.8952193	1.187***	0.000	1.857***
Combiner	Area harvested by combine	1.010432	0.000	1.436***	1.808***
Pesticide	Liter	1.92555	-0.211	0.141	0.777***
Socio-economic variables					
Sex	Dummy(1=male)	.8459658	0.027	0.047	-0.061
Age	Years	46.62592	-0.273	2.748*	3.886***
Education	Years of schooling	5.430318	0.831	-0.708	0.619
HHS	In number	5.550122	0.264	-0.121	0.636**
Credit access	Dummy (1=yes)	.2298289	0.048	-0.050	0.186***
Distance from main markets	Kilometer	4.283619	0.329	-0.683*	0.654
Distance from cooperative	Kilometer	2.20379	-0.788***	-0.485**	-0.897***
Distance from all-weather road	Kilometer	1.573778	0.785*	-0.643**	-0.272
Mobile ownership	Dummy(1=owned)	.7286064	0.225***	0.283***	0.199***
Livestock holding	TLU	3.972518	-0.205	-1.283***	-0.247
Dependency ratio	In number	.5252202	0.165*	-0.102	-0.136**
Fertility	Dummy (1=fertile)	.6797066	0.023	0.070	0.068
Land size (overall)	Hectare	2.294743	0.800***	0.166	0.896***

Source: own survey (2023)

Non adopter is reference category, ***, **, * represent 1%, 5%, and 10% significance level, respectively.

3.2 Estimation of Stochastic Frontier Selection Bias Model

Table 2 shows the selectivity of the stochastic frontier model, with significant Rho values for Tractor, and Joint Adopter, indicating the presence of selection bias. This justifies the use of a sample selection framework to estimate separate SPFs for adopters of each type of farm machinery. This approach, which accounts for selection bias, has been used in previous studies on technology adoption and agricultural productivity [49, 107].

Across the entire sample (pooled model), all inputs significantly and positively influence wheat output; similar previous findings in Ethiopia demonstrate this [21, 108]. According to SPF sample selection, labor, seed, pesticide, and fertilizer are the main wheat output drivers in the non-adopter group. For the tractor-only adopters, labor, fertilizer, and pesticide have a significant positive impact on production, whereas seed and oxen have a negative impact on production. Lastly, for those who adopted both technologies, land, seed, fertilizer, and oxen significantly and positively affect wheat production. The contrasting effects of seed usage across different mechanization categories can be explained through agronomic and operational differences. Among tractor adopters, land is typically well-prepared, which enhances seed-soil contact and promotes uniform germination. However, when excessive seed is applied in these optimally prepared fields,

overcrowding can occur, leading to increased intra-plant competition for sunlight, water, and nutrients. Studies have shown that high seeding rates reduce individual plant biomass, tillering, and panicle length ultimately diminishing yield per plant [109]. This explains the negative association between seed use and production in tractor-adopting farms. In contrast, non-adopter farmers, who often rely on oxen for ploughing, tend to experience uneven land preparation and greater weed pressure. To compensate, they typically use higher seed rates, especially under broadcasting methods, which are imprecise and prone to seed loss. This strategy is supported by [110], who observed a 40% yield increase at a seeding rate of 150 kg/ha in no-till systems. Likewise, [111] reported that increasing the seeding rate to 300 kg/ha led to a 6–18% yield improvement, highlighting the potential of higher seed rates in suboptimal field conditions.

Finally, in systems where both tractors and combine harvesters are used, tractor adoption facilitates more effective land preparation and weed control, creating favorable conditions for the germination of a higher number of wheat plants. This leads to denser crop stands, where increased plant competition may reduce the size of individual wheat heads. While this could negatively affect yield, the efficiency of combine harvesters in collecting even small and loosely attached grains helps offset such losses. As a result, farmers may still benefit from higher total output despite increased plant density. This interaction helps explain the observed positive relationship between seed rate and the joint adoption of tractors and combine harvesters, as mechanization enables both higher planting intensity and more effective harvest recovery. In addition to seed rate, land size, labor, fertilizer use, and combine-harvested land area positively contribute to wheat output. For combine harvester-only adopters, land size and fertilizer use are positively related to output, while seed rate is positively related but not statistically significant.

Table 2 Cobb–Douglas SPF with correction for selectivity bias model estimation results

Variable	Pooled	Non-adopter	Tractor only	Combiner only	Both Adopter
Constant	.99544*** (.249)	-1.41474*(.736)	2.40879***(.090)	2.47(0.6776) ***	0.7579 (0.439) *
Lnlabor	.16442*** (.029)	.18579***(.065)	.14121***(.007)	0.04924(0.06644)	0.1049 (0.061) *
Lnland	.38804*** (.047)	.04493(.148)	.65854 (.803)	1.005(0.344) ***	0.237 (0.116) **
Lnseed	.25363*** (.045)	.64150***(.153)	-.12007***(.017)	0.0800(0.07389)	0.257 (0.06) ***
Lnfertilizer	.15751*** (.024)	.17022***(.057)	.23807***(.004)	0.1131(0.048) **	0.22 (0.046) ***
Lnpesticide	.12106*** (.027)	.22093***(.055)	.36529***(.004)	0.0141(0.06792)	0.051 (0.048)
Lnoxen	.02545*** (.007)	-.02597(.082)	-.03618***(.002)	-0.0195 (0.13416)	0.029 (0.012) **
Lncombiner	.03070*** (.003)			-0.28026(0.3258)	0.15 (0.08092) *
Lntractor	.01982*** (.003)		.20810(.803)		0.020 (0.09795)
Lambda	1.4861*** (.177)				
Sigma	.37118*** (.001)				
Sigma(u)		.35743***(.106)	.64373***(.007)	0.198(0.1089) *	0.059(0.34412)
Sigma(v)		.21423***(.061)	.00902** (.004)	0.184(0.064) ***	0.27(0.034) ***
Rho(θ,v)		-.45791(.352)	-.91940***(.169)	-0.606(0.37246)	-0.437 (0.19) **
RTS	1.16	1.24	1.46	0.96	1.07

Source: own survey (2023)

***, **, * represent 1%, 5%, and 10% significance level, respectively.

3.3 Technical efficiency of Wheat farmers

According to Table 3, the overall technical efficiency of wheat production in the study area is 85.4%, ranging from 17.6% to 98.6%. This result implies that, on average, farmers could increase their wheat production by approximately 15% through more efficient use of existing resources and technology.

The highest level of technical efficiency is observed among farmers who have adopted both tractor and combine harvester technologies, with a mean efficiency of 95.3%. This group clearly outperforms non-adopters (76.4%), tractor-only adopters (71.3%), and combine harvester-only adopters (85.8%). While combine harvester adopters are notably more efficient than both non-adopters and tractor-only adopters, their efficiency still falls short of those adopting both technologies.

These results suggest that a comprehensive mechanization strategy, involving the combined use of multiple technologies, offers the most significant gains in production efficiency. Moreover, the wide range of efficiency scores, particularly among non-adopters and tractor-only users, underscores the need to understand the constraints or conditions that lead to such variations in performance.

Compared to previous studies, the results of this study indicate a relatively higher level of technical efficiency (TE), particularly among joint adopters of mechanization technologies. The overall mean technical efficiency in this study was 0.854, which exceeds the 0.82 reported by Girma, et al. [10] in West Shoa and the 0.80 reported by [21]. Notably, farmers who adopted both tractors and combine harvesters achieved the highest technical efficiency, with a mean TE of 0.953, while those who used only combine harvesters had a TE of 0.858. In contrast, tractor-only users had the lowest TE (0.713), even lower than non-adopters (0.764). This pattern is consistent with the findings of Alemayehu, et al. [49], who observed that joint adoption of climate-smart agricultural practices resulted in higher efficiency compared to single or non-adoption. These findings underscore the importance of integrated mechanization—using both tractors and combine harvesters, in enhancing technical efficiency in wheat production, as single-technology adoption may not yield the same productivity gains.

Table 3 Mean technical efficiency of Wheat farmers

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Non-adopter	121	.7639223	.1111451	.4369558	.9181423
Tractor	44	.7127348	.1733018	.1763874	.9861447
Combine harvester	75	.8577313	.0616963	.6684169	.9442873
Both tractor and combine adopter	169	.9529032	.0057423	.9330715	.9663094
Overall mean of technical efficiency	409	.8537052	.126946	.1763874	.9861447

Source: own survey (2023)

***, **, * represent 1%, 5%, and 10% significance level, respectively.

3.4 Impact of agricultural machinery adoption on technical efficiency and wheat productivity

The Table 4 below presents the analysis of Average Treatment Effects on the Treated (ATT), comparing the technical efficiency and wheat productivity of farmers who adopted agricultural machinery with their estimated outcomes had they not adopted these technologies (the counterfactual). The results demonstrate that adopting mechanized technologies has significant positive effects on both technical efficiency and productivity in the study area.

Specifically, the data show that farmers who adopted combine harvester technology alone experienced the largest improvement in technical efficiency, with an increase of 9.41 percentage points (12.32%) compared to the counterfactual. Those who adopted both tractor and combine harvester technologies also achieved substantial efficiency gains, improving technical efficiency by 20.03 percentage points (26.61%). In contrast, farmers who adopted only tractor technology had a slight decrease of 1.53 percentage points (-2.10%) in technical efficiency compared to their counterfactual, but not statistically significant.

Turning to wheat yields, the results indicate that adoption of these technologies generally boosts yields. Tractor adoption alone increased wheat yields by 3.30 quintals per hectare (14.54%), while combine harvester adoption increased yields by 3.47 quintals per hectare (14.68%). Notably, the joint adoption of both tractor and combine harvester technologies led to a significant yields increase of 9.39 quintals per hectare (39.29%) compared to non-adopters, highlighting the complementary benefits of combined mechanization.

These findings align with previous studies in Ethiopia [28] and from other countries [112-114], which document positive impacts of mechanization on efficiency and yields. The substantial yeilds gains from joint adoption also resonate with results from studies that found farmers with higher mechanization indices exhibited greater economic efficiency and wheat yields. Additional studies globally support the conclusion that mechanization significantly enhances agricultural productivity e.g. [35, 36, 115-118]. This result is further supported by the kernel density estimation presented in the figure below (Figure 2 and Figure 3), which shows that the distribution of non-adopters is concentrated to the left. The wheat yields results indicate that households would have obtained lower yields had they not used these agricultural machineries in production, especially when using tractors and combine harvesters jointly.

Furthermore, the results are consistent with those presented in Appendix Table 10, which estimates the treatment effects of different mechanization levels on technical efficiency and wheat yields using counterfactual analysis. As shown, farmers with a middle level of mechanization adoption have an actual technical efficiency of 0.8525 compared to a counterfactual efficiency of 0.7835, yielding a significant treatment effect of 0.0690 (8.81% increase). For high-level adopters, technical efficiency rises to 0.9371 versus a counterfactual of 0.7578, with a treatment effect of

0.1793 (23.66% increase). Similarly, wheat productivity for middle-level adopter's increases by 4.29 quintals per hectare (16.81%) compared to the counterfactual, while high-level adopters experience a 6.45 quintals per hectare increase (26.10%). All treatment effects are statistically significant at the 1% level, underscoring the strong positive impact of higher mechanization levels on both efficiency and productivity.

Table 4 The impact of agricultural machinery on technical efficiency and wheat productivity

Outcome	Technologies	Adopter	Non-adopter (counterfactual)	Treatment Effect	% Change
Technical Efficiency of Wheat	Tractor only	0.7127	0.7281	-0.0153	**-2.10%**
	Combine only	0.8577	0.7636	0.0941 ***	**12.32%**
	Tractor and combine	0.9529	0.7526	0.2003 ***	**26.61%**
Wheat yields	Tractor only	26.0118	22.7093	3.3025 ***	**14.54%**
	Combine only	27.1472	23.6725	3.4747 ***	**14.68%**
	Tractor and combine	33.3128	23.9180	9.3948 ***	**39.29%**

Source: own survey (2023)

***, **, * represent 1%, 5%, and 10% significance level, respectively.

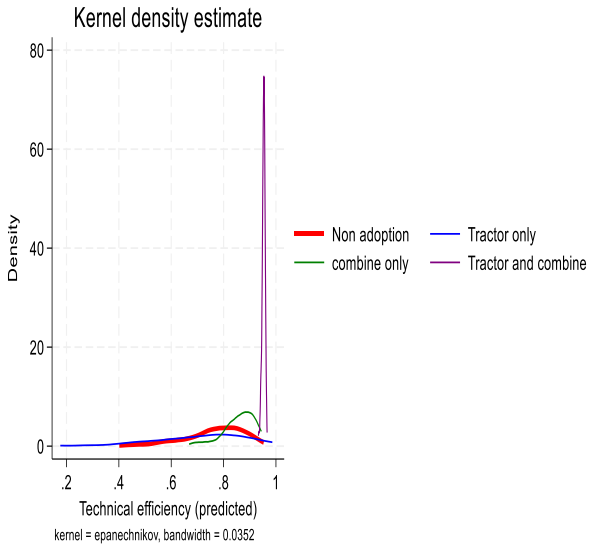


Figure 2 Kernel density of technical efficiency of wheat. Most farms exhibit relatively high predicted technical efficiency (~0.7–1.0), but adoption patterns differ. Tractor and combine adopters show a sharp peak near 1.0, indicating many farms achieve near-maximum efficiency. Non-adopters and combine-only users display broader, lower peaks, reflecting more variable efficiency, while tractor-only users show a flatter distribution, suggesting limited gains. These patterns highlight that promoting combined mechanization could substantially enhance both efficiency levels and consistency across farms in the study area.

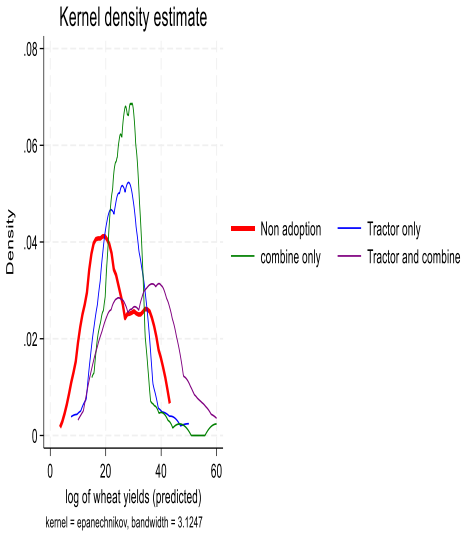


Figure 3 Kernel density estimates of predicted log wheat yields by adopter group. Predicted log wheat yields cluster between ~5–60. Combine-only farms (green) achieve the highest and most consistent yields. Tractor-only (blue) and tractor+combine (purple) farms show moderate yields with more variation. Non-adopters (red) have the lowest and most variable yields, reflecting less consistent performance. This suggests that promoting mechanization, could improve both yield levels and stability across farms in the study area.

4. Conclusion

This study set out to examine the role of agricultural mechanization—specifically the use of tractors and combine harvesters—on wheat yields and technical efficiency in Ethiopia's Arsi Zone, using cross-sectional data from 409 wheat-producing households. Despite national efforts to scale up mechanization and reduce wheat imports, there has been limited empirical evidence on how machinery adoption affects farm performance. By employing a Multinomial Endogenous Switching Regression (MESR) model and a Stochastic Frontier Analysis (SFA) with sample selection correction, the study addressed potential endogeneity and selection bias to derive robust insights. The results show that key production inputs, including land, labor, DAP and urea fertilizers, and pesticides, significantly influenced wheat output across all adoption categories. Additionally, increasing returns to scale were observed for all groups except for combine-only users, suggesting that expanding input use—especially for joint adopters and tractor users—can yield proportionally higher output.

The substantial variation in technical efficiency across adoption groups is one of the most revealing findings of this study. The central conclusion is not merely that mechanization enhances yield, but

that its adoption follows a distinct, tiered pattern shaped by farmers' pre-existing characteristics. The evidence shows that the least efficient farmers tend to adopt tractors as a critical intervention to overcome production constraints, whereas the most efficient and progressive farmers adopt both tractors and combine harvesters to optimize already high-performing operations. Moreover, the MESR counterfactual analysis confirmed the presence of positive and statistically significant treatment effects of machinery adoption on both wheat productivity and efficiency. For instance, joint adopters experienced a technical efficiency gain of 0.1793 (approximately 23.66%) and a yield improvement of 6.45 quintals per hectare—equivalent to a 26.1% increase compared to non-adopters. Middle-level adopters also saw meaningful gains, with a 0.0690 (8.81%) increase in efficiency and 4.29 quintals per hectare (16.81%) rise in yields. These results were further supported by econometric models showing that both binary adoption and intensity of machinery use (measured by the mechanization index) had strong positive effects on yields and technical efficiency. This highlights that not only the decision to adopt but also the extent of use plays a critical role in enhancing farm performance.

Given these findings, several policy recommendations emerge. First, promoting the joint adoption of tractors and combine harvesters through rental services, cooperatives, or group ownership arrangements can yield the highest productivity and efficiency gains. Second, strengthening mechanization service providers by improving their access to credit, spare parts, and technical training would enhance the reliability and accessibility of services for smallholders. Third, encouraging mobile phone ownership and digital platforms can improve access to mechanization information and extension services, as digital connectivity was found to facilitate adoption. Fourth, designing targeted financial support mechanisms, such as credit schemes or subsidies, especially for resource-constrained farmers, would help overcome adoption barriers. Lastly, reinforcing the input delivery system—particularly for fertilizers and pesticides—would ensure complementary gains alongside mechanization.

Moreover, sustaining the long-term benefits of mechanization is crucial. This requires promoting environmentally sustainable and socially inclusive mechanization pathways, including the introduction and use of machinery that minimizes ecological degradation and does not disrupt local farming systems and rural livelihoods. Accordingly, while mechanization improves technical efficiency and crop yields, its potential social and ecological implications should not be overlooked.

Authors' Contributions: GMA prepared the first draft of the manuscript and conducted the data analysis. Furthermore, GMA was responsible for the day-to-day oversight and coordination of data collection. WMD and MCZ read and revised the paper. All authors participated in the interpretation of the results and contributed to the revisions of the manuscript. All authors have read and approved the final manuscript.

Declarations

Ethics Approval: The study received ethical approval from Bahir Dar University, Bahir Dar, Ethiopia, and was authorized by the Research and Community Services Office in August 2023, under reference number RCS/121/2023. All procedures involving human participants and data collection were conducted in accordance with established ethical guidelines and regulations.

Consent to Participate: All participants in this research were fully informed about the study's aims and procedures. They provided their consent to participate voluntarily.

Consent to publish: Research participants consented to the use of the study's findings for academic purposes, including presentation at conferences and publication.

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Availability of data and materials: The dataset supporting this paper will be provided upon request

Appendix

Table 5A Simple falsification test of excluded instruments.

Outcome	Technology type	F-stat.	P-value
Technical efficiency	Non-adoption	1.193604	.2770575
	Tractor only	.8714468	.3580082
	Combine only	.0025012	.9602762
	Tractor and combine	.1603804	.689358
Wheat yields	Non-adoption	.0674936	.7955209
	Tractor only	.3554365	.5555238
	Combine only	.4292956	.5147982
	Tractor and combine	1.193604	.2770575

Table 6A Determinants of machinery adoption- multinomial logit model results (First-stage)

Variables	Tractor only	Combine only	Joint adoption
Sex	-.301829	.5308349	-.9739573**
	(.6313545)	(.593983)	(.4108051)
Age	-.0057293	.0117745	.0230093
	(.0250169)	(.0190186)	(.0200907)
Education	.0538639	-.0734792	.0926482*
	(.0617653)	(.0509691)	(.0513709)
HHS	-.0728258	-.008255	.0637736
	(.1166178)	(.0980861)	(.1020931)
Credit access	.9547353*	-.1944509	1.669425***
	(.5468925)	(.4775667)	(.3662072)
Distance from main markets	.2321843***	-.0695713	.2686869***
	(.0704376)	(.0728435)	(.0625395)
Distance from cooperative	-.812006***	-.2216137*	-.8447127***
	(.1733089)	(.1312284)	(.1382534)
Distance from all-weather road	.2584957***	-.3209143***	.032099
	(.0917155)	(.0910921)	(.0788374)
Mobile ownership	1.115049**	1.520166***	.773331**
	(.4375158)	(.3907293)	(.3320632)

Livestock holding	-.241086***	-.3192176***	-.2931394***
	(.0812503)	(.0715799)	(.0664233)
Dependency ratio	.6054708*	-.0924507	-.4088178
	(.3281665)	(.2946593)	(.3070959)
Fertility	-.2451767	.0476958	-.072728
	(.4936954)	(.4516787)	(.365472)
Land size	1.210917***	.4768519**	1.287807**
	(.2521921)	(.201395)	(.19546)
Constants	-2.814393*	-.623926	-2.357816
	(1.493278)	(1.353708)	(1.263198)
Number of obs = 409	Wald chi2(51) = 186.68	Prob > chi2 = 0.0000	
	Log LR= -390.37595	Pseudo R2 = 0.2522	

Notes: Robust standard errors in parenthesis; non-adoption is the reference category. *, ** and * represent significance levels at 1 %, 5 %, and 10 % respectively.**

Table 7A Selectivity correction based on multinomial logit Second step regression Bootstrapped standard errors (100 replications) for technical efficiency

Variable	Non-adopter	Tractor only	Combine only	Joint adoption
Sex	–0.0661 (0.0491)	–0.1082 (0.2843)	–0.0498 (0.0733)	0.0006 (0.0016)
Age	0.0015 (0.0017)	0.0060 (0.0116)	0.0032 (0.0021)	0.00003 (0.00007)
Education	0.0106** (0.0048)	0.0004 (0.0249)	0.0095 (0.0076)	0.0001 (0.0002)
Household size	–0.0024 (0.0067)	–0.0247 (0.0464)	0.0062 (0.0092)	–0.0001 (0.0003)
Credit access	0.0898** (0.0451)	0.1750 (0.3139)	0.1226 (0.0853)	0.0001 (0.0016)
Dist. to market	0.0022 (0.0086)	–0.0218 (0.0414)	0.0073 (0.0138)	0.0001 (0.0003)
Dist. to coop.	–0.0370** (0.0183)	0.0544 (0.1068)	–0.0245 (0.0300)	–0.0008 (0.0008)
Dist. to road	0.0050 (0.0100)	–0.0574 (0.0647)	–0.0128 (0.0192)	0.0002 (0.0005)
Livestock (TLU)	–0.0050 (0.0076)	0.0072 (0.0378)	–0.0092 (0.0123)	0.0000 (0.0002)
Dependency ratio	0.0049 (0.0349)	–0.0429 (0.2168)	–0.0637 (0.0400)	–0.0001 (0.0017)
Fertility	0.0738** (0.0326)	0.1943 (0.1880)	–0.0273 (0.0268)	0.0065*** (0.0015)
Land size	0.0359 (0.0259)	–0.0007 (0.1463)	0.0338 (0.0456)	–0.00001 (0.0011)
_m0	—	–0.2944 (0.5618)	–0.0362 (0.1111)	–0.0027 (0.0040)
_m1	0.1784 (0.1857)	—	–0.3269* (0.1769)	–0.0001 (0.0065)
_m2	–0.0962 (0.0980)	0.1423 (0.4729)	—	0.0006 (0.0046)
_m3	–0.0228 (0.1505)	0.3075 (0.6796)	0.3550* (0.1903)	—
_cons	0.7303*** (0.1046)	1.0695 (0.6566)	0.7886*** (0.1147)	0.9447*** (0.0052)
Sigma2	0.0300 (0.0650)	0.1725 (0.8888)	0.1596 (0.0997)	0.00003 (0.00008)
rho0	—	–0.9092 (0.8079)	–0.1161 (0.5832)	–0.6833 (0.4878)
rho1	1.3219 (0.8993)	—	–1.0497 (0.7942)	–0.0321 (0.8011)
rho2	–0.7125 (0.5799)	0.4396 (0.7702)	—	0.1465 (0.6719)
rho3	–0.1687 (0.8015)	0.9496 (0.8990)	1.1397 (0.7876)	—

Table 8 Selectivity correction based on multinomial logit Second step regression Bootstrapped standard errors (100 replications) for wheat productivity

Variables	Non-adopter (wp0)	Tractor only (wp1)	Combine only (wp2)	Joint adoption (wp3)
Sex	-3.4249 (3.3961)	0.6876 (14.5847)	-1.3108 (7.1360)	1.2354 (2.7335)
Age	0.0771 (0.1207)	0.5009 (0.4124)	0.3918 (0.2412)	0.1901 (0.1023)
Education (years)	0.7729** (0.3483)	-0.0495 (1.3751)	0.7101 (0.8957)	0.5698 (0.3395)
HHS	0.0104 (0.4461)	-1.1523 (1.8125)	1.0227 (0.9064)	0.5282 (0.3810)
Credit Access	10.276*** (3.8277)	5.6350 (11.6350)	9.6481 (10.9897)	3.1020 (2.2102)
Distance to Market (km)	-0.0109 (0.6428)	-0.5827 (1.9044)	0.0690 (1.4996)	0.9659*** (0.3565)
Distance to Coop (km)	-3.5762** (1.4326)	3.7353 (4.7304)	-0.7756 (3.4903)	-2.7612** (1.1636)
Dis.to land to road (km)	0.1510 (0.7767)	-1.7157 (3.8393)	-3.0116 (2.1732)	1.5911 (0.9649)
TLU	0.4039 (0.6354)	0.5132 (1.3316)	-0.2652 (1.4897)	-0.4669 (0.3313)
Dependency Ratio	-0.2139 (2.3895)	1.5688 (11.1300)	-10.0967* (5.2444)	-2.1820 (2.4660)
Fertility	4.8898** (1.9835)	7.6065 (9.6533)	0.6898 (3.0624)	13.3324*** (2.4816)
Total Crop Area	1.6273 (2.1885)	-2.3614 (5.8869)	-1.8341 (5.6109)	0.1014 (1.3621)
_m0	4.8103 (12.6972)	0.8020 (20.4336)	7.0686 (14.2120)	-5.6566 (5.5729)
_m1	-7.3559 (6.9564)	—	-53.7945** (24.4507)	2.2757 (11.6172)
_m2	5.3007 (11.2757)	2.7840 (19.7555)	—	0.1775 (7.8633)
_m3	—	1.1303 (22.8773)	44.1337* (23.7759)	—
_cons	22.163*** (7.0573)	16.9878 (45.2223)	23.2309 (15.3485)	3.9472 (7.9210)
Sigma²	103.439 (268.926)	38.7605 (1298.06)	3128.891** (1521.3510)	74.8058 (196.4340)
rho0	—	0.1652 (0.7897)	0.1621 (0.5568)	-0.8388** (0.3983)
rho1	0.6066 (0.8711)	—	-1.2334* (0.6613)	0.3375 (0.8429)
rho2	-0.9276* (0.5481)	0.5735 (0.8100)	—	0.0263 (0.6456)
rho3	0.6684 (0.7918)	0.2329 (0.8919)	1.0119 (0.7052)	—

Table 9 Variance inflation factor

Variable	VIF	1/VIF
d_mmkms	2.38	0.420244
d_fcokms	2.10	0.476004
Fertility	2.04	0.489161
Age	2.00	0.500479
Hhs	1.89	0.529176
education_~s	1.78	0.561275
d_mainroadkm	1.77	0.563382
totalareac~p	1.60	0.626640
Tlu	1.51	0.663482
depedencyr~o	1.41	0.708231
credit_acc~s	1.25	0.798995
assets_mob~e	1.24	0.804451
Sex	1.11	0.900904

Mean VIF	1.70

Table 10: Estimated Treatment Effects of Mechanization Level on Technical efficiency and Wheat productivity: Using Counterfactual Analysis

Outcome	Level of Adoption	Actual	Counterfactual	Treatment Effect	t-value	% Change
Technical Efficiency	Middle level of adoption	0.8525	0.7835	0.0690***	15.2682	8.81%
	High level of adoption	0.9371	0.7578	0.1793***	24.1428	23.66%
Wheat yields	Middle level of adoption	29.8352	25.5415	4.2937***	7.8406	16.81%
	High level of adoption	31.1665	24.7147	6.4518***	9.3421	26.10%

Note: The percentage change is calculated relative to the counterfactual (low-level adoption). *** indicates statistical significance at the 1% level.

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