Food Policy 130 (2025) 102795

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Heterogenous correlates of mechanization use and rural livelihoods in Zimbabwe: A quantile regression analysis

Hambulo Ngoma[a,*], Billy Mukamuri[b], João Vasco Silva[a], Frédéric Baudron[a,c,d]

[a] International Maize and Wheat Improvement Center (CIMMYT), 12.5 Km Peg, Harare, Zimbabwe
[b] Department of Community and Social Development, University of Zimbabwe, Harare, Zimbabwe
[c] Centre de coopération Internationale en Recherche Agronomique pour le Développement (CIRAD), UPR AIDA, F-34398 Montpellier, France
[d] Agroécologie et Intensification Durable des cultures Annuelles (AIDA), Université de Montpellier, CIRAD, Montpellier, France

ARTICLE INFO

JEL Codes:
Q16
O33

Keywords:
Small-scale mechanization
Unconditional quantile regression
Small-scale farmers

ABSTRACT

The drive to mechanize and modernize African agriculture is in high gear, making the need for empirical evidence to guide mechanization investments critical. This paper assesses the heterogenous and distributional correlates of using mechanization and rural livelihoods in Chegutu and Zvimba districts of Zimbabwe, where a private sector company had the largest sales of different machinery across the country between 2019 and 2021. We used a quantile regression estimator and measured livelihoods using farm and household revenues. Based on survey data from 988 randomly selected households, we found that adoption was associated with rising land/labor ratio, market access and wealth. The use of mechanization was associated with a median annual increase of USD 262 in revenue with a wide range from USD 103 at the 25th percentile to USD 2,900 at the 95th percentile per year. The largest revenue gains were associated with post-harvest and irrigation equipment use, and in the upper percentiles of the revenue distribution. These findings call for (i) wealth agnostic promotional efforts to ensure equitable mechanization benefits, (ii) better targeting of mechanization types to farmer needs, and (iii) concerted efforts to strengthen mechanization service provision models.

1. Introduction

Feeding a growing world population and meeting dietary changes require improving efficiency in agricultural production. The United Nations Food and Agricultural Organization (FAO) and the African Union Commission (AUC) posit that agricultural mechanization offers such prospects (FAO and AUC 2019) and that mechanization can reduce the drudgery associated with prevalent human powered farming systems. Mechanization improves land and labor productivities (Pingali 2007; Pingali, Bigot, and Binswanger 1987; FAO and AUC 2019; Baudron et al. 2019a; Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020), and it is positively correlated with intensification (Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020). As such, agricultural mechanization has the highest endorsement at policy level as a key component for ending hunger by 2025.[1] Rising population and land prices, rural wages, and land-labor ratios in many parts of Africa (Daum and Birner 2020; Jayne et al. 2021; Diao, Silver, and Hiroyuki 2016), and declining animal draught herds in Zimbabwe and more generally in southern Africa (Baudron et al., 2019b), favor mechanization. This is buoyed by the emergence of better-endowed medium-scale farms (5 – 100 ha) who have the financial capacity to meet the required upfront investments in mechanization (Jayne et al. 2016). A supporting local manufacturing base is also on the rise in Africa, albeit with some challenges (Daum et al. 2023). On balance, these changes in labor and land markets, and the unfolding structural transformation of rural non-farm sectors present good prospects for mechanizing African agriculture (Houssou et al. 2013).

Efforts to mechanize agriculture date back to the post-second world war where the main focus was on making tractors available, also termed tractorization (Pingali 2007). In Zimbabwe, mechanization activities were initially skewed towards large commercial farmers, but the scope was broadened in the post-independence era as part of the land reform (Shonhe 2022; Zikhali 2008). Although the land reform program to redistribute land was well intentioned, it was associated with declining productivity and production, and engendered perceptions of land tenure insecurity (Zikhali 2008). It could also have unintended consequences

* Corresponding author.
E-mail address: h.ngoma@cgiar.org (H. Ngoma).

[1] 31247-doc-malabo_declaration_2014_11_26.pdf (au.int).

https://doi.org/10.1016/j.foodpol.2024.102795
Received 28 May 2024; Received in revised form 28 December 2024; Accepted 30 December 2024
Available online 11 January 2025

on mechanization uptake. For example, the transfer of farmers from unmechanized communal lands to mechanized A1 resettlement farms could result in losses in production efficiencies if not accompanied by strong capacity development of the newly resettled farmers. Land in Zimbabwe is divided into communal land (cultivating up to 2 ha), A1 (cultivating up to 6 ha) and A2 (cultivating over 12 ha) (Zikhali 2008). The land reform sought to decongest communal areas by re-allocating larger parcels to small-scale farmers, while A2 includes commercial resettlements for medium and large scale farmers (Zikhali 2008). Evidence on the uptake of mechanization and its impacts on a range of outcomes remains thin in the country. Yet there is an increase in the demand for appropriate-scale mechanization among smallholders and the use of mechanization has been found to be positively associated with the use of improved seeds and inorganic fertilizer, or intensification more broadly, and improves land and labor productivity (Amankwah and Gwatidzo 2024; Ngoma et al. 2023; Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020).

This paper contributes towards filling knowledge gaps on the associations of the current mechanization drive with rural livelihoods in Southern Africa. We assess the drivers of the uptake of the different types of mechanization options and their correlates with farm and household revenues. To the best of our knowledge, this is the first paper in the context of southern Africa to apply a quantile regression framework to assess distributional associations of the use of various mechanization options and rural livelihoods. We used survey data collected from Zvimba and Chegutu districts, mostly from A1 resettlement farms. We define farm revenue as the value of crops and livestock over a period of one year, and household revenue as the sum of farm and business revenue over a one-year period.[2]

We add to existing literature in two ways. First, unlike past studies that assessed the impacts of adopting mechanization at the mean, e.g., Adu-Baffour, Daum, and Birner (2019), we add by assessing the distributional correlates of the use of appropriate-scale mechanization and rural livelihoods in Zimbabwe. Second, we extend existing analyses focused on willingness to pay or invest, and potential returns to investments in mechanization (e.g.,Ngoma et al. 2023; Kotu et al. 2023) by assessing *ex post* the actual correlates of adopting mechanization.

In the spirit of what Baudron et al. (2015) termed "*appropriate-scale mechanization*", we focused on a broad range of mechanization options including land preparation, seeding, harvesting, post-harvest, processing, and transportation among other operations, to assess whether using any of these was associated with better livelihood outcomes in Zimbabwe. We define appropriate-scale mechanization in line with Baudron et al. (2015) to refer to a situation where different pieces of mechanization equipment are used as deemed fit by farmers. The core idea is to have a flexible approach where machines fit farmer contexts in terms of resources (affordability), land holding (farm size) and market orientation rather than the other way round. In this way, farmers use machines they deem appropriate for their scale of operations.

The decision to mechanize farm operations (i.e., primary agricultural production, harvesting, threshing, processing, storage, transportation) requires an in-depth understanding of the benefits of such mechanization to target users. Yet, despite the optimism towards mechanization, evidence remains sparse on the impacts of mechanization on smallholder's livelihoods, on the viability of different mechanization business models (Houssou et al. 2013), and on what can be done to enhance adoption of mechanization (Kotu et al. 2023). On the positive side, Adu-Baffour, Daum, and Birner (2019) found that farmers who accessed mechanization services from the AFGRI-John Deere tractor scheme in Zambia increased area cultivated, household incomes, and crop yield. Kotu et al. (2023) found that 65 % of smallholders in the study area in Tanzania were willing to invest in group business models for small (4-7hp) and large (16-20hp) engines and that such investments were profitable.

Using experimental auctions, Ngoma et al. (2023) found that at least 50 % of smallholders surveyed in Zambia and Zimbabwe were willing to pay above prevailing market prices for two-wheel tractor (2WT)-based ripping services. In addition, Tufa et al. (2023) found that smallholders in Malawi were willing to pay up to 11 %, 33 %, and 5 % more than prevailing market rates for land preparation, maize shelling and transportation services, respectively. Omulo et al. (2022) found that direct seeding and rip tillage resulted in higher yields and larger gross margins compared to disc harrowing in Zambia. In Zimbabwe, Amankwah and Gwatidzo (2024) found that the use of mechanization was positively associated with the use of improved seeds and fertilizer. Mechanization was found to enhance intensification and improve labor and land productivity in Côte d'Ivoire (Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020).

Not all results are positive. For example, Houssou et al. (2013) assessed the viability of subsidized government mechanization schemes and found that the agricultural mechanization service enterprise centers supported by the Government of Ghana were not a viable business model on account of underutilization and challenges related to frequent breakdowns, unavailability of spares, mechanics, and skilled operators. As can be seen from the foregoing, there are few studies that have evaluated the impacts or associations of mechanization use and livelihoods. Yet, farmers may only invest in mechanization if it confers positive returns. Understanding the impacts of mechanization is important to inform suppliers on the mechanization options that have the highest returns and to guide market segmentation. On the demand side, this information can help to select mechanization options with the highest return on investments for specific customers and spatial domains.

Zimbabwe makes an interesting case study given its long history of agricultural mechanization. Efforts to mechanize agriculture in the country initially focused on large four-wheel (i.e., two axles) tractors and targeted commercial farmers (Pingali, Bigot, and Binswanger 1987; Shonhe 2022). Mechanization was introduced to smallholders post-independence through group tractor hire schemes, district development funds, and the rural agricultural agencies (Shonhe 2022). At the same time, private-sector driven efforts such as those of AFGRI and John Deere tractor schemes, the Reserve Bank of Zimbabwe backed mechanization program, and the Belarus farm mechanization facility were being rolled out in the country (Ngoma et al. 2023). At policy level, the Zimbabwean government has developed a five-year mechanization implementation strategy to support appropriate-scale farm mechanization (Ngoma et al. 2023), although its implementation is yet to be fully realized. Moreover, Zimbabwe is one of several countries in southern Africa benefiting from an influx of mechanization programs supported by various international research and development partners (Ngoma et al. 2023).

Evaluating the effects of mechanization on given outcomes requires an understanding of the counterfactual outcomes. That is, the outcomes adopters of mechanization would have realized had they not adopted. This is challenging for two main reasons. First, outcomes can only be observed in one state of the world for either adopters or non-adopters. Second, even when the first concern is addressed, adoption is often non-random and endogenous. Thus, adopters may systematically differ from non-adopters such that even without adopting mechanization, the former would still be better off. We address the first empirical challenge using a control sample of farmers drawn from an area with no-known mechanization promotion efforts. While an instrumental variable identification strategy (Wooldridge (2010) would be preferable for the second challenge, finding credible instruments is challenging. As such, we used an unconditional quantile treatment approach (Firpo, Fortin, and Lemieux 2009) that allows us to use adoption as its own instrument to assess how adoption is associated with farm and household revenues, at different distribution points beyond the average. As a complement, we also used the inverse probability weighted regression adjustment

[2] The were captured through survey questions asked to respondents. The reference period was the last one year preceding the survey in 2022.

(IPWRA) that allows us to estimate the potential outcomes while considering counterfactual outcomes.

Without claiming causality, we found that adoption of mechanization was associated with rising land/labor ratio, market access and wealth. The use of mechanization was associated with a median increase of USD 262 in revenue with a wide range from USD 103 at the 25th percentile to USD 2,900 at the 95th percentile per year. The largest revenue gains were associated with post-harvest and irrigation equipment use, and in the upper percentiles of the revenue distribution.

2. Theoretical framework

Contemporary scholars have explained the evolution of mechanization, i.e., when to and not to mechanize agriculture using two classic theories: Ruttan and Hayami (1973)'s induced innovation and Boserup (1965)'s evolution of farming systems (Daum 2022, 2023; Daum and Birner 2020; Diao, Silver, and Hiroyuki 2016; Ngoma et al. 2023). The induced innovation theory postulates that changes in the prices of land, labor and capital, the main factors of production, dictate that innovations associated with cheaper and abundant factors substitute the more scarce and expensive ones. However, this regularity is not observed in all contexts. For example, Mano, Takahashi, and Otsuka (2020) found that mechanizing land preparation in fact led to higher labor use to support intensification. As such, authors argued that capital and labor in the context studied were complementary and not substitutes. Boserup's evolution of farming systems theory adds that shortage of land coupled with population pressure beyond a threshold will trigger changes to farming systems. As land becomes scarce, innovations that improve yields and reduce the need to expand cropland, e.g., mechanization and intensification, are expected to be taken up. Taken together, these theories have been used to explain agricultural mechanization in highly populated areas of south Asia, and Latin America with larger farm sizes, and to some extent in sub-Saharan Africa based on evolving non-farm rural sectors and related structural transformation (Daum 2023).

The two theories are necessary, but not sufficient, to unpack the effects of mechanization at household level as they cannot address why a given farmer would choose to adopt mechanization. Farmer decisions to adopt mechanization, like any other agricultural technology, are complex and driven by several factors including market access, labor, investment costs, transaction costs, and culture to name a few. As such, a complementary theory of investment is necessary. Following Houssou et al. (2013), consider farmer i with the choice of investing in mechanization (M) or an alternative business, including saving money in the bank (B). The goal of farmer i is to maximize profit (π) given the available mechanization technology, service prices, and all other variable costs. The level of π directly influences utility (μ) (Houssou et al. 2013). The π from each alternative investment over period T can be represented as: $\pi_m = \sum_{t=1}^{T} R_t G_t - C$ and $\pi_B = \sum_{t=1}^{T} R_t G_t - C$, where R is the discount factor which is a function of the interest rate r;$R = [(1+r)]^{-1}$ and given as $R = [(1+r)]^{-1}$; C is the initial cost of investment; G is the gross margin, i.e., realized revenues from operations minus variable costs. In this respect, a rational farmer will only invest in mechanization when $\pi_m > \pi_B$ and by extension, if the utility from investing in mechanization is larger than from investing in alternative businesses: $\mu_m > \mu_B$. Because utility is a function of profits from investments and other factors (λ) like leisure, $\mu_i = f(\pi_m, \pi_B, \lambda)$, e.g., Singh, Squire, and Strauss (1986), understanding the effects of adopting mechanization on specific livelihood indicators helps to shed light on returns to investments in mechanization. We focus on livelihood indicators which are inputs into π realized from mechanization.

Using the quantile treatment effect (QTE) approach allows us to assess the distributional correlates of adopting mechanization on farmers' livelihoods. This distributional analysis beyond the mean is important because farmers are heterogenous and can help to guide the design of better targeted policies for farmers in the different percentiles of the outcome distribution.

3. Materials and methods

3.1. Data sources and sampling strategy

A multistage sampling approach was followed. In the first stage, we purposively selected Chegutu and Zvimba districts, where a private sector company, Kurima Machinery, recorded the highest share of sales in appropriate-scale farm mechanization during the period 2019 – 2022 (Ngoma et al. 2022). In the second stage, we selected 13 wards/villages in Chegutu and 10 wards/villages in Zvimba based on advice from the Zimbabwean government's Agricultural Technical and Extension Services (AGRITEX). The selected wards comprised small (communal areas) and medium landholders (A1 farmers) and were purposively selected based on prevalence and/or absence of mechanization activities. We used ward/village lists obtained from AGRITEX and village heads to randomly select 42 households per ward. Due to various reasons, including logistical challenges, we ended up with samples that ranged from 38 to 48 households per ward and a total sample of 988 households. Data were collected using face-to-face interviews and a structured questionnaire programmed in Survey Solutions.[3]

3.2. Estimation strategy

Given that the main interests of the paper, we begin by estimating a probit model to assess factors associated with the use of mechanization. We specify this model as:

$$\Pr(y_i = 1|x_i) = \Phi(x_i\beta) + \varepsilon_i \quad (1)$$

where y_i is a binary variable indicating whether farmer i used any mechanization option, whether hired or owned, over the past one year from the time of the survey in 2022. We also measured y_i as the number of machine types used to assess the robustness of the results and in that case, we estimated Equation (1) using a linear probability model.[4] Φ is the cumulative standard normal density function, x_i are the explanatory variables including farmer and farm characteristics such as land-labor ratio, farm size, number of crops grown, livestock ownership (in tropical livestock units, TLU) computed following Jahnke (1982), gender, age and education of the household head, whether a household is beneficiary of the government land reform program, land ownership and location fixed effects. $\beta's$ are the estimable coefficients, and ε_i is the error term.

To address the second interest on the associations of mechanization use and revenue, an instrumental variable conditional quantile treatment effect (IVQTE) such as that of Abadie, Angrist, and Imbens (2002) would be preferable. This approach combines quantile regression, allowing to assess the distributional associations at different quantiles of the outcome variable, and an instrumental variable approach to control for the endogeneity of adoption. However, in the absence of credible instrumental variables that meet both the relevance and exclusion restriction criteria, we used the unconditional QTE version, where we assumed that use of mechanization is exogenous conditional on observable covariates, X. As such, the findings in this paper have no causal claims.

Let D be an indicator of mechanization adoption, and Y the outcome of interest. Then Y_i^1 and Y_i^0 represent outcomes with and without adoption, respectively. Conditional on a set of covariates X , outcome Y_i for household i can be modeled as:

[3] https://mysurvey.solutions/en/.

[4] Animal traction is not considered as mechanization.

$$Y_i = Y_i^1 T_i + Y_i^0 (1 - D_i). \quad (2)$$

Estimating Equation (2) requires that: (i) potential outcomes are orthogonal to D given X: $(Y^0, Y^1) \perp D|X$, and (ii) that the support for covariates meets $0 < Pr(D = 1|X) < 1$. Following Firpo, Fortin, and Lemieux (2009), the unconditional QTE for quantile τ, is $\Delta^\tau = Q^\tau_{Y^1} - Q^\tau_{Y^0}$ and can be estimated using a weighted quantile regression:

$$(\widehat{\alpha}, \widehat{\Delta^\tau}) = argmin_{\alpha,\Delta} \sum W_i^F x \rho_\tau (Y_i - \alpha - D_i \Delta) \quad (3)$$

$$where\ W_i^F = \frac{D_i}{Pr(D = 1|X_i)} + \frac{1 - D_i}{1 - Pr(D = 1|X_i)}$$

In this set up, D is its own instrument (Firpo, Fortin, and Lemieux 2009). Y captures farm and household revenues, and X's are the independent variables defined in Table 1.

An estimable form of Equation (3) can be specified as:

$$Q_\tau(Y_i|X_i) = \delta_0(\tau) + \delta_1(\tau) X_{1i} + \delta_2(\tau) X_{2i} + \ldots + \delta_m(\tau) X_{mi} \quad (4)$$

where $Q_\tau(Y_i|X_i)$ is the τ*-th* quantile of the distribution of Y given X_i as defined before, $\delta_0(\tau)$ is the intercept, $\delta_1(\tau)$ to $\delta_m(\tau)$ are estimable coefficients at corresponding τ*-th* quantiles, within the common support $0 < \tau < 1$. We used the 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles to capture the heterogeneity in the associations between the adoption of mechanization and revenue. For robustness checks, we used the inverse probability weighted regression adjustment (IPWRA) that allows us to estimate the potential outcomes while considering counterfactual outcomes.

The two outcome variables capturing livelihood indicators, farm revenue and household revenue, are complementary but differ in important ways. Farm revenue captures the correlates of mechanization and farm activities (both crop and livestock), while household revenue includes business activities, e.g., hire services mostly associated with transportation of goods, tillage, and shelling. Key independent variables include whether a household used any mechanization option and specific mechanization options grouped as (1) crop establishment[5] including two- and four-wheel tractors and their attachments for planting and land preparation, (2) harvest and post-harvest including shellers, threshers, processing and combine harvesters, and (3) irrigation including all irrigation equipment and associated stationary engines. In addition to measuring these as dummy variables, in other instances, we measured them as counts of the number of equipment used.

4. Results

4.1. Sample characteristics and descriptive statistics

About 75 % of the sampled households were headed by males. The average age of the household head was 49 years, with 73 % of them having completed secondary/tertiary education (Table 1). Heads of adopting households were significantly younger (48 years) compared with non-adopting households (51 years). With an average farm size of 5 ha, adopting households had more livestock with 4.9 TLU compared to 2.1 TLU among non-adopters, and 30 % of adopters were engaged in contract farming compared to 18 % among non-adopters (Table 1). Adopter households earned an equivalent of USD 3,275 and USD 3,675 in farm and total household revenues, respectively, compared to under USD 2,000 among non-adopters. Overall, there were significant differences in the key variables between machinery adopters and non-adopters. For example, based on t-tests, adopters had significantly higher revenues, larger farms, and were more educated and younger than non-adopters (Table 1).

4.2. Machinery use, ownership and access modes

Four-Wheel Tractors (4WTs) were used by 56 % of the surveyed households (Fig. 1A). Other land preparation equipment such as ploughs, disk ridger, disk harrow, ripper, and rotavator attached to 2WTs or 4WTs were used by 46 % of the respondents. Stationary engines used for irrigation such as diesel and petrol engines and electric motors were used by 41 % of the respondents while post-harvest equipment such as maize and groundnut shellers and threshers were used by 15 % of the respondents (Fig. 1A). Processing and planting equipment were used by about 3 – 4 % of the respondents, while less than 1 % of the respondents used dairy equipment. The distribution of equipment was found to be similar between the two districts, with post-harvest equipment more prevalent in Zvimba district compared to Chegutu (Fig. 1B).

Individual ownership was the most prevalent machinery ownership mode. About 55 % of the respondents in Chegutu and 60 % of the respondents in Zvimba district owned the machines used (Fig. 2). These pieces of equipment were purchased by individuals with cash. The second most popular mode to access machines was through renting, mentioned by at least 36 % of the sample. Other access modes such as group ownership, loan purchases, gifts, and NGO supported were largely absent (Fig. 2).

A bivariate analysis showed that farm and household revenues increased with the number of equipment owned up to about 7 pieces of equipment, beyond which both revenues declined or plateaued (Fig. 3). Suffice to mention that the uncertainty associated with the estimates widens with increasing number of pieces of equipment owned, as reflected in the wider confidence intervals. Albeit qualitatively, these results suggest that there is a positive correlation between revenue and the pieces of equipment owned, but with diminishing returns beyond a threshold.

When disaggregated by machinery type and without controlling for any other factors, harvest and post-harvest machinery and irrigation equipment contributed most to farm and household revenues in the sample (Fig. 4).[6] Farmers earned statistically and significantly higher revenue from harvest and post-harvest machinery and irrigation, compared to crop establishment equipment (Fig. 4, right panel). There was no significant difference in revenue from irrigation equipment, and harvest and post-harvest machinery. However, this analysis is bivariate and does not control for other factors.

4.3. Determinants of mechanization use

Several factors were associated with an increased likelihood of using mechanization. A higher land/labor ratio, farm size, number of crops grown (a proxy for intensification), livestock ownership (a proxy for wealth), market access (proxied by contract farming), owning the land under cultivation and having benefited from the land reform program were associated with an increased likelihood of using mechanization in the study districts (Table 2). As would be expected, households headed by older individuals were less likely to use mechanization. These results hold when considering the use of any machinery (columns 1, 2 and 4, Table 2) and the number of machineries used (columns 3 and 5, Table 2) as dependent variables. These results were also robust to whether we used land/labor ratio (columns 1 – 3) or its constituents, farm size and household size (columns 4 – 5).

We also found similar results on the correlates of the use of specific machinery. The main differences were that household size and membership to a farmer cooperative were now significantly associated with

[5] This terminology is similar to the one used by Mano et al (2020) in referring to crop establishment.

[6] This disaggregation was possible because every household that used machinery was asked the types used and for what activities during the survey.

Table 1
Variable definitions and mean differences between adopters and non-adopters of machinery in Chegutu and Zvimba districts, Zimbabwe.

Variable	Variable definition	Full sample (Mean)	Non-adopters (A_0), n = 500	Adopters (A_1), n = 488	Mean diff (A_0-A_1)
Farm revenue, USD	*Value of crops and livestock produced per year*	2218.06	1186.56	3274.92	−2088.36***
Household revenue, USD	*Value of crops and livestock produced per year plus revenue from business*	2433.81	1222.20	3675.21	−2453.02***
Land/labor ratio	*Ratio of farm size to household size*	0.77	0.60	0.94	−0.34***
Farm size (ha)	*Total land holding in hectares*	4.03	3.26	4.83	−1.56***
Household size	*Total number of regular household members*	7.05	7.14	6.96	0.18
Age, household head (years)	*Age of household head in years*	49.35	50.53	48.15	2.38***
Number of crops cultivated	*Number of crops cultivated per year*	1.38	1.26	1.51	−0.26***
Livestock ownership	*Tropical livestock units for different livestock*	3.49	2.08	4.92	−2.84***
Member coop, (yes = 1)	*At least one household member belongs to a cooperative*	0.55	0.53	0.57	−0.04
Male, household head (yes = 1)	*Male head of household*	0.75	0.72	0.78	−0.06**
Secondary/tertiary education, household head	*Household head has a secondary/tertiary education level*	0.73	0.68	0.79	−0.11***
Contract farming (yes = 1)	*Engaged in contract farming*	0.24	0.18	0.30	−0.12***
Land from government reforms (yes = 1)	*Obtained land from government reform program*	0.12	0.06	0.18	−0.12***
Owned the land (yes = 1)	*Owns the land cultivated*	0.74	0.78	0.69	0.09***

Notes: The last column shows differences in the means across the groups; ***, **, and * indicate significance at the 1, 5, and 10 percent critical level, evaluated using the student *t*-test.

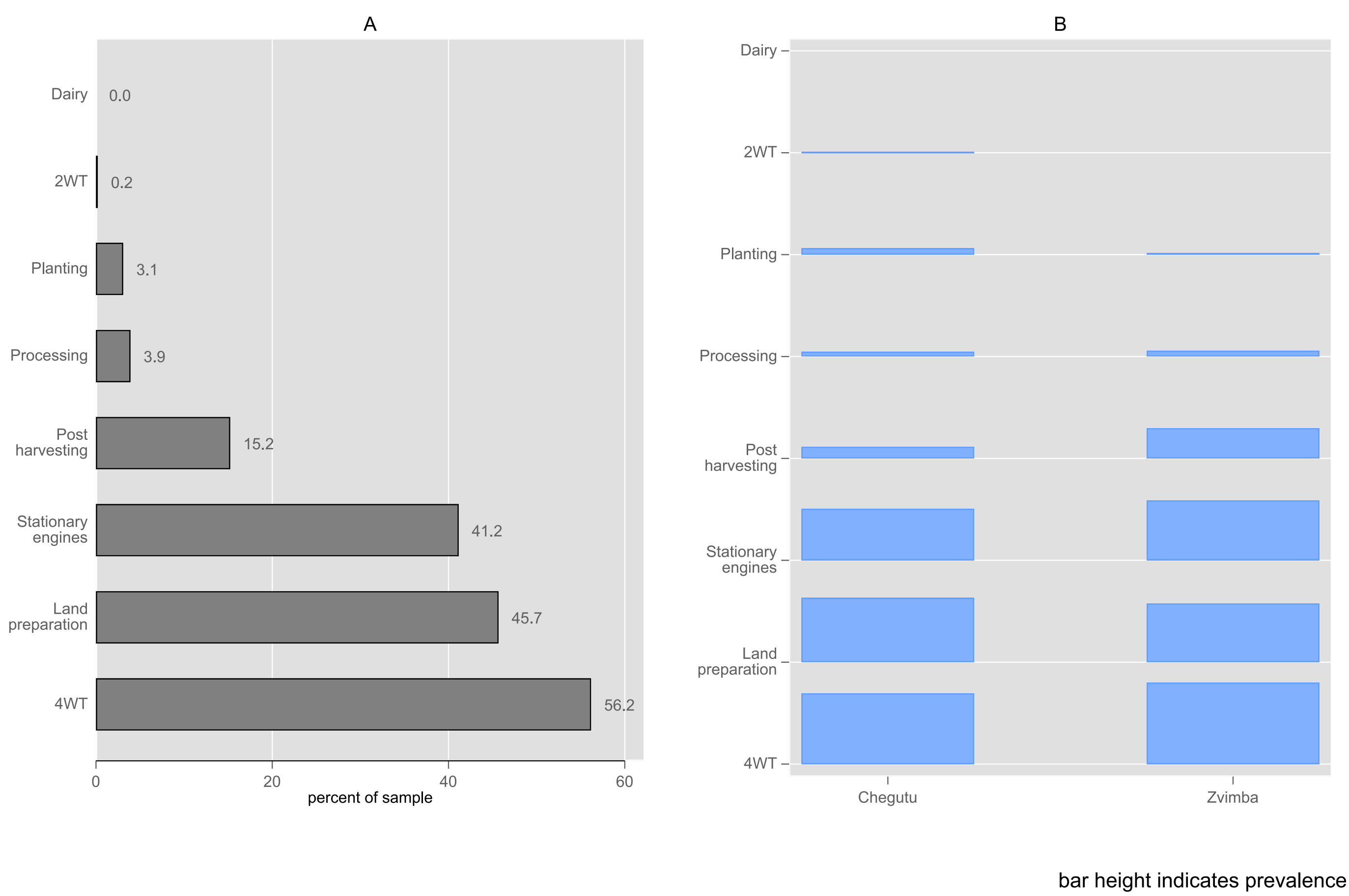

Fig. 1. Types of machinery used overall (A) and by district (B) in Chegutu and Zvimba districts, Zimbabwe. Notes: For the subsequent analysis, these were grouped into three groups: (1) crop establishment, (2) harvest and post-harvest, and (3) irrigation. Crop establishment includes two- and four-wheel tractors and their attachments for planting and land preparation; harvest and post-harvest includes shellers, threshers, processing and combine harvesters; irrigation includes all irrigation equipment and associated stationary engines.

increased use of crop establishment equipment but reduced with the use of irrigation equipment (Table 3). Being a male household head and education were associated with increased use of irrigation. Other results were like those in Table 2 except that most were only significant for crop establishment and irrigation equipment uptake. Only farm size, livestock ownership, number of crops grown and having benefitted from government land reform programs were associated with increased use of all three types of equipment (Table 3).

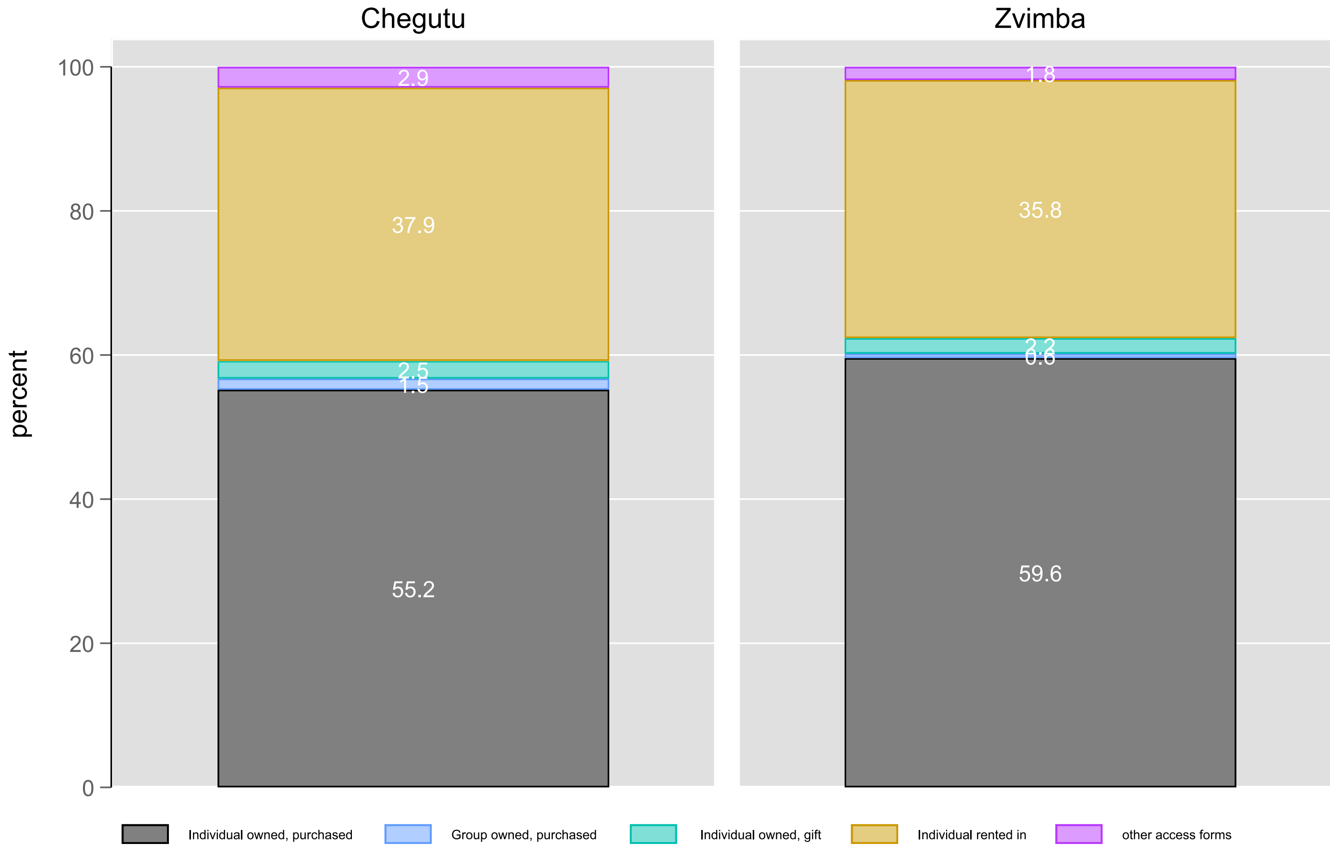

Fig. 2. Machinery access and ownership modes among machinery adopters in Chegutu and Zvimba districts, Zimbabwe.

4.4. Correlates of using mechanized equipment on livelihoods

The use of different pieces of machinery was associated with a median increase of USD 192 and USD 262 in farm and household revenues, respectively (Tables 4 and 5). These varied widely from USD 103 at the 25th percentile to USD 2,185 per year at the 95th percentile for farmer revenue (Table 4). Similarly, we found a wide range for household revenue from USD 135 at the 25th percentile to USD 2,873 per year at the 95th percentile (Tables 5). The correlates of farm and household revenues increased with increasing percentiles up to the 95th percentiles, with the largest associations at the 95th percentiles of farm revenue and household revenue distributions (Tables 4 and 5).

There were several other important factors associated with farm and household revenues in addition to using different pieces of machinery. Positive ones included wealth (proxied by livestock ownership), being a male-headed household, market access proxied by engaging in some form of forward marketing arrangements like contract farming, and the number of crops cultivated, an indicator of intensification (Tables 4 and 5). Being a male headed household was associated with increased revenues at all quantiles, except the 95th for household revenue, while the household head having a secondary/tertiary education was associated with increased farm and household revenue throughout except at 95th percentile for household revenue.

Because the preceding results are based on the use of any equipment, they mask any potential differential associations of the use of specific equipment types. For this reason, we re-ran the same models presented in Tables 4 and 5 for different machinery types and summarized the results in Fig. 5. Detailed results are not reported for brevity but are available in the Supplementary Materials, Tables A1-A6. After controlling for farm and household factors, we found that the use of irrigation and harvest and post-harvest equipment were associated with slightly more farm revenue and household revenue (Fig. 5, Tables A1-A6).

4.4.1. Robustness checks

Results from the IPWRA were similar to the main results in Tables 4 and 5 in that both sets of results showed that the use of mechanization was associated with higher farm and household revenues. On average and after controlling for potential confounders, farmers that used mechanization had USD 663 more farm revenue and USD 770 more household revenue per year than if they had not adopted (Table 6). The difference between the two sets of results is that the quantile regression allows us to model outcomes at different distribution levels while the IPWRA provides results at the mean only. The two are, however, complementary.

5. Discussion

Our results add to a nascent body of literature evaluating the drivers of adoption and the heterogeneous effects and/or associations of appropriate-scale farm mechanization and rural livelihoods of smallholders in southern Africa. On drivers, we found indicative evidence highlighting the associations of rising land/labor ratios and mechanization use. This is in line with the induced innovation hypothesis where more expensive factors of production are replaced with cheaper ones (Hayami and Ruttan 1971). In this case, as labor becomes scarce, due for example to outmigration, wages increase, it will be replaced by labor-saving technologies such as mechanization. These results are also consistent with Diao, Silver, and Hiroyuki (2016) who suggested that land/labor ratios are on the rise in sub-Saharan Africa and that this creates opportunities for mechanization.

Land and land tenure dynamics, market access, and wealth are important drivers of mechanization, but the results can vary depending on the context. Our results indicating a positive association of farm size and being a beneficiary of the land reform program in Zimbabwe with mechanization have important implications. First, they indicate that

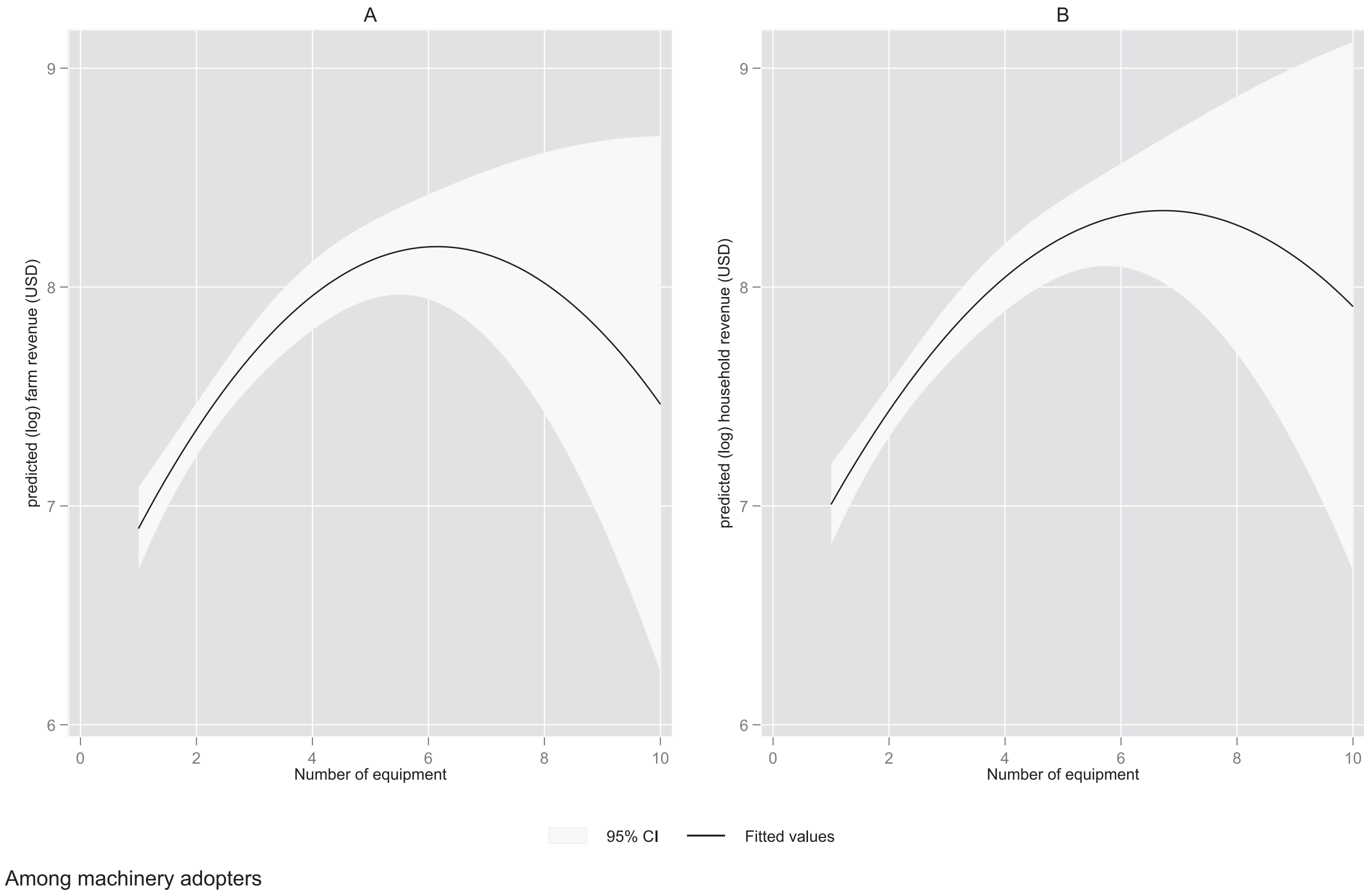

Fig. 3. Bivariate relationship between the number of machines owned and farm revenue (A) and household revenue (B) among machinery adopters in Chegutu and Zvimba districts, Zimbabwe.

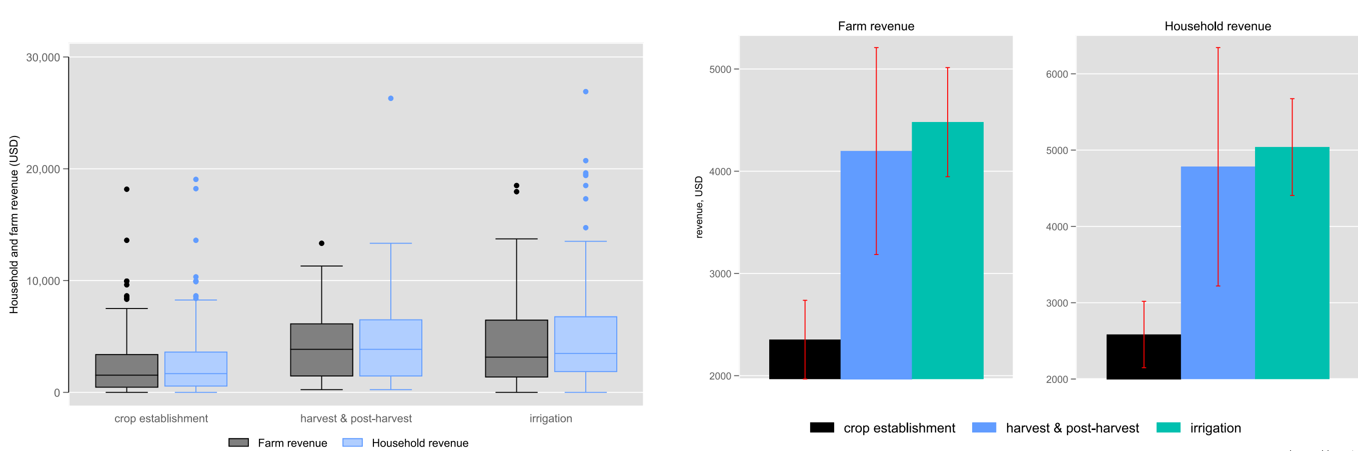

Fig. 4. Average annual farm and household revenues (USD) by machinery type in Chegutu and Zvimba districts, Zimbabwe. Notes: Crop establishment includes two- and four-wheel tractors and their attachments for planting and land preparation; harvest and post-harvest includes shellers, threshers, processing and combine harvesters; irrigation includes all irrigation equipment and associated stationary engines.

farmers with larger farm sizes are more likely to adopt mechanization. This is as expected because more than 70 % of the respondents in our surveys were A1 farmers operating about 6 ha on average. It is also not surprising that the most used mechanization option was 4WT among respondents (Fig. 1). These results also point to a possible positive correlation between the land reform program and mechanization. This is despite the fact that the program may have increased perceptions of tenure insecurity (Zikhali 2008). The positive association of wealth and the uptake of mechanization aligns with the notion that better resourced medium scale and emergent farmers are better able to engage in mechanization (Jayne et al. 2016). This result also agrees with Ngoma et al. (2023) who found that wealth was a significant driver of farmers' willingness to pay for 2WT-based mechanization in Zambia and Zimbabwe. Our results also point to the significance of market access as farmers engaged in contract farming were more likely to adopt mechanization. This result is aligned to the positive associations of mechanization and improved seeds and fertilizer use in Amankwah and Gwatidzo (2024). Further, this result also aligns to the findings

Table 2
Correlates of machinery use among farmers in Chegutu and Zvimba districts.

	(1)	(2)	(3)	(4)	(5)
	Use of any machinery	Use of any machinery	Number of machines used	Use of any machinery	Number of machines used
Land-labor ratio	0.059**	0.037***	0.152*	–	–
	(2.363)	(2.925)	(1.731)	–	–
Farm size (ha)	–	–	–	0.029***	0.155***
	–	–	–	(4.584)	(5.763)
Household size	–	–	–	0.003	−0.008
	–	–	–	(0.681)	(−0.443)
Age, household head	−0.003**	−0.003**	0.003	−0.003***	−0.003
	(−2.373)	(−2.295)	(0.613)	(−2.935)	(−0.486)
Number crops grown	0.093***	0.087***	0.282**	0.086***	0.255**
	(3.890)	(3.784)	(2.428)	(3.771)	(2.253)
Livestock ownership (TLU)	0.031***	0.026***	0.050***	0.022***	0.036**
	(6.416)	(8.358)	(3.467)	(7.139)	(2.361)
Member, cooperative	−0.017	−0.016	−0.094	−0.011	−0.121
	(−0.548)	(−0.498)	(−0.590)	(−0.356)	(−0.801)
Male, household head	−0.006	0.002	0.242	−0.012	0.212
	(−0.165)	(0.052)	(1.272)	(−0.323)	(1.188)
Secondary/tertiary education	0.038	0.048	0.217	0.048	0.086
	(0.986)	(1.246)	(1.140)	(1.237)	(0.468)
Contract farming	0.101***	0.097***	0.587***	0.077**	0.456***
	(2.694)	(2.615)	(3.199)	(2.136)	(2.660)
Government land reform (yes = 1)	0.220***	0.207***	0.507*	0.143**	0.325
	(3.703)	(3.546)	(1.957)	(2.452)	(1.318)
Owned land (yes = 1)	−0.027	−0.023	0.869***	−0.069	0.690***
	(−0.618)	(−0.510)	(4.117)	(−1.494)	(3.451)
Zvimba district	−0.047	−0.046	0.132	−0.048	0.133
	(−1.490)	(−1.442)	(0.858)	(−1.552)	(0.913)
Constant		0.349***	0.663	0.352***	0.854**
		(3.871)	(1.415)	(4.016)	(1.967)
Observations	926	926	458	947	470
R-squared		*0.165*	*0.141*	*0.182*	*0.201*

Notes: Column 1 was estimated using a Probit model while the rest used a linear probability model (LPM); z-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

suggesting a positive association between mechanization and land and labor productivities, and intensification more generally (Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020). The fact that most of the pieces of equipment were purchased by individuals with cash suggests that there are farmers willing to invest in mechanization and may only need technical support in maintenance and operation, and on the business side of hiring out. This is bolstered by the fact that the hire of equipment was the second most popular mode for accessing mechanization. Development practitioners can catalyze better linkages between machinery owners and users in ways that create sustainable mechanization service provision business models. That renting was the second most popular avenue for accessing mechanization highlights that there is a rise in the mechanization rental market in the study districts.

The overall results from our assessment indicating that using mechanization was associated with a median increase in revenues of USD 262 (USD 103 – 2,900 range) per year highlight the potential for mechanization to improve livelihoods. The findings also indicate that households in the higher quantiles are likely to benefit more in terms of farm revenue. The positive associations of using mechanization and revenue are in line with Adu-Baffour, Daum, and Birner (2019) who found that mechanization increased net-household income, expenditure, and productivity in Zambia. Our findings also buttress recent assessments showing that smallholders are willing to invest in mechanization in Tanzania (Kotu et al. 2023), Malawi (Tufa et al., 2023), and Zambia and Zimbabwe (Ngoma et al. 2023), and that such investments can be profitable (Baudron et al., 2019b; Kotu et al. 2023; Omulo et al. 2022). Results suggesting that wealth (proxied by livestock ownership) is an important driver of mechanization are in line with Ngoma et al. (2023), highlighting the need to deliberately design socially inclusive mechanization programs.

Our results showing that using harvest and post-harvest equipment use was associated with higher farm revenue are in agreement with Kotu et al. (2023), who found that using a maize sheller can potentially offer profits in the range of USD 3,400 – 3,900 per year in Tanzania. Even if we did not compute profit, the two results are reinforcing. Further, our findings that the use of harvest and post-harvest and irrigation equipment were associated with higher farm and household revenues can help to better define equipment packages, or 'starter packs' that can be offered to service providers to enable year-round income generating activities and to reduce on machinery idle time. While we were unable to verify the farm enterprises for which irrigation was used by farmers in the sample, we can conjecture that these are likely high value crops. Crop establishment equipment contributed the least to revenue, even if they were the most popular pieces of equipment used by respondents (Fig. 2). Again, this points to a need to enlighten farmers on machinery options with better returns. Retooling extension services and technical services branches that handle agriculture mechanization could be entry points.

Most farmers in the sample used a range of crop establishment equipment including disc ploughs, disc ridgers, disc harrow, rippers, and rotavators. Irrigation equipment used included stationary petrol and diesel engines and electric motors. Post-harvest equipment such as maize and groundnut shellers and threshers, dairy equipment, and processing and planting equipment were used by a smaller proportion of the sample. Using Pingali (2007)'s terminology, the distribution of the equipment types used shows that farmers invest in both 'power-intensive operations', such as land preparation, and 'control-intensive operations', such as planting and weeding. While the control intensive operations are limited for most farmers, there is a wide range of equipment for power intensive operations. This is as expected during the early stages of mechanization and in relative terms, conforms to the sequence of mechanization where farmers tend first to mechanize power-intensive operations before moving on to control intensive operations such as planting and weeding (Pingali 2007).

The breadth of equipment used and the positive associations of mechanization use and rural livelihoods also conforms to the assertion

Table 3
Correlates of the use of specific machinery among farmers in Chegutu and Zvimba districts.

	(1) Use of crop establishment equipment	(2) Use of irrigation equipment	(3) Use of harvest and post-harvest equipment
Farm size (ha)	0.038***	0.018***	0.011***
	(6.372)	(3.257)	(3.039)
Household size	0.009**	−0.009***	−0.001
	(2.088)	(−3.142)	(−0.391)
Age, household head	−0.003***	0.000	−0.000
	(−2.930)	(0.243)	(−0.730)
Number crops grown	0.052**	0.037*	0.063***
	(2.252)	(1.788)	(3.381)
Livestock ownership (TLU)	0.010***	0.024***	0.008***
	(2.935)	(8.127)	(2.830)
Member, cooperative	0.070**	−0.079***	0.006
	(2.250)	(−3.124)	(0.312)
Male, household head	−0.044	0.049*	−0.010
	(−1.294)	(1.789)	(−0.524)
Secondary/tertiary education	−0.013	0.073***	0.020
	(−0.372)	(2.636)	(1.079)
Contract farming	0.120***	0.096***	0.025
	(3.199)	(2.923)	(1.000)
Government land reform (yes = 1)	0.168***	0.087*	0.138***
	(2.873)	(1.772)	(2.875)
Owned land (yes = 1)	0.002	0.082***	−0.034
	(0.053)	(2.748)	(−1.383)
Zvimba district	−0.050*	−0.006	0.035*
	(−1.690)	(−0.226)	(1.851)
Constant	0.147*	−0.083	−0.070
	(1.767)	(−1.317)	(−1.584)
Observations	947	947	947
R-squared	0.154	0.181	0.161

Notes: All columns were estimated using LPM; z-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; we used farm and household sizes instead of the land/labor ratio.

that mechanization can be a key component to transform agri-food systems (Daum 2023). It also entails a need to rethink and broaden the scope of appropriate-scale farm mechanization to include power and control-intensive mechanization equipment such as 2WT and 4WT and their implements, dairy equipment, irrigation and post-harvest equipment depending on farm(er) needs and characteristics. Of course, there is need to ensure that such efforts are demand-driven to make them relevant to farmer needs and are market-led to ensure economic sustainability (Baudron et al., 2019a; Baudron et al. 2015).

In explaining the positive associations of mechanization and livelihood outcomes, we can conjecture that this is likely through productivity and intensification effects (Adu-Baffour, Daum, and Birner 2019; Omulo et al. 2022; Aihounton and Christiaensen 2024; Mano, Takahashi, and Otsuka 2020) and from freeing of labor for other non-farm income generating activities. Because mechanization is generally believed to improve operational efficiencies and outputs (Daum 2023; FAO and AUC 2019; Pingali 2007; Omulo et al. 2022; Amankwah and Gwatidzo 2024; Aihounton and Christiaensen 2024), its use is expected to raise productivity and facilitate investments in complementary inputs such as fertilizer and improved seeds (Adu-Baffour, Daum, and Birner 2019). We found a supportive association with intensification (proxied by the number of crops) and mechanization use. This is in line with Amankwah and Gwatidzo (2024) who found a positive association between the use

Table 4
Associations between the use of mechanization and farm revenue in Chegutu and Zvimba districts, Zimbabwe.

	(1) q.25	(2) q.50	(3) q.75	(4) q.95
Used farm machinery (yes = 1)	103.48***	192.72***	611.37***	2,185.45***
	(15.52)	(43.92)	(130.35)	(558.21)
Age, household head	1.52***	0.53	1.06	−7.43
	(0.43)	(1.03)	(1.91)	(6.51)
Number crops grown	169.27***	464.18***	975.83***	1,886.92*
	(31.40)	(92.29)	(259.86)	(1,011.89)
Livestock ownership (TLU)	373.78***	415.09***	444.54***	464.97***
	(4.78)	(9.61)	(15.06)	(27.24)
Member, cooperative	−30.19***	−68.68*	−186.48***	−89.15
	(8.31)	(35.00)	(69.90)	(113.98)
Male, household head	50.37***	109.34***	206.05***	307.94**
	(12.34)	(32.21)	(58.44)	(143.73)
Secondary/ tertiary education	51.96***	104.75***	174.37***	450.37*
	(11.68)	(34.72)	(65.22)	(230.96)
Contract farming	31.99	77.83	439.56*	2,654.33**
	(30.41)	(58.88)	(258.67)	(1,060.64)
Government land reform (yes = 1)	101.89	297.68***	891.86***	1,586.94***
	(68.62)	(80.65)	(188.29)	(225.86)
Owned land (yes = 1)	21.90	88.54***	196.11**	457.60***
	(18.20)	(34.09)	(87.74)	(114.25)
Zvimba district	107.37***	210.29***	335.09***	578.65***
	(18.77)	(40.76)	(69.57)	(113.19)
Constant	−323.16***	−676.58***	−1,284.19***	−1,779.90*
	(43.72)	(115.49)	(296.71)	(1,074.72)
Observations	949	949	949	949

Notes: Dependent variable is nominal farm revenue (USD); z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; q.25 – q.95 refers to the quantiles – 25th up to 95th.

of mechanization and improved seed and fertilizer in Zimbabwe, and Aihounton and Christiaensen (2024) and Mano, Takahashi, and Otsuka (2020) documenting positive associations between mechanization and intensification and labor and land productivity in Côte d'Ivoire.

While improvements in both land and labor productivity from mechanization is believed to free up labor to engage in other non-farm income generating activities, it varies depending on the agri-food value chain node. For example, Mano, Takahashi, and Otsuka (2020) found that while mechanizing land preparation freed up labor, it increased labor use in later nodes of the value chain, specifically at weeding stage, a key activity in support of intensification. This highlights the importance of context. However, in contexts where mechanization frees labor, such labor may be redeployed to other income earning opportunities. Income earned from such activities can then be re-invested to support mechanization. This may be feasible in many rural areas in sub-Saharan Africa because of the unfolding structural transformation associated with growing non-farm rural sectors and the rising land/labor ratios (Jayne et al. 2016; Sitko and Jayne 2014; Diao, Silver, and Hiroyuki 2016).

The value added of our study is to demonstrate through the distributional analysis, the need to better target mechanization to different types of farms. Recall the associations of mechanization use and livelihoods were highest in the 95th percentiles and that individual equipment ownership was the most prevalent followed by renting, findings underscored by Ngoma et al. (2023) and Baudron et al. (2019a). This is suggestive of effective demand for appropriate-scale farm mechanization in Zimbabwe. In addition, because about half of the farmers in the

Table 5
Associations between use of mechanization and household revenue in Chegutu and Zvimba districts, Zimbabwe.

	(1)	(2)	(3)	(4)
	q.25	q.50	q.75	q.95
Used farm machinery (yes = 1)	135.71***	262.30***	662.09***	2,873.27***
	(17.89)	(64.67)	(142.48)	(637.14)
Age, household head	1.44***	0.89	−0.64	−9.25
	(0.39)	(1.00)	(1.73)	(8.08)
Number crops grown	191.75***	461.57***	984.70***	2,007.66**
	(34.73)	(111.17)	(262.63)	(1,018.87)
Livestock ownership (TLU)	389.62***	431.21***	480.95***	554.26***
	(5.79)	(12.47)	(19.80)	(106.11)
Member, cooperative	−26.80***	−70.23**	−89.12	−130.47
	(10.32)	(31.64)	(70.79)	(228.39)
Male, household head	53.33***	98.84***	165.57***	162.62
	(9.93)	(28.81)	(53.02)	(294.84)
Secondary/ tertiary education	75.05***	120.26***	139.06**	372.96
	(11.50)	(30.82)	(59.77)	(269.93)
Contract farming	32.16	135.06	759.67**	2,420.43***
	(21.39)	(86.31)	(300.52)	(899.70)
Government land reform (yes = 1)	97.12	243.16**	636.47**	3,398.25***
	(64.41)	(123.17)	(277.55)	(744.40)
Owned land (yes = 1)	45.01***	106.77***	184.84**	399.60*
	(15.66)	(33.32)	(93.27)	(223.65)
Zvimba district	107.65***	232.84***	386.42***	522.49**
	(16.54)	(41.39)	(56.99)	(205.94)
Constant	−401.31***	−741.75***	−1,242.29***	−1,704.02
	(47.05)	(127.48)	(301.23)	(1,169.98)
Observations	949	949	949	949

Notes: Dependent variable is nominal household revenue (USD); z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; q.25 – q.95 refers to the quantiles – 25^{th} up to 95^{th}.

sample owned and purchased the machinery using own resources shows the importance of off-farm earnings. Such could be business owners and/or wage earners who stepped into mechanization because either they had the resources or they are seizing business opportunities, or both. Thus, there is need to find ways to support farmers to step up and graduate into mechanization service providers to avoid potential social differentiation.

Although the study was conducted in areas where Kurima Machinery had the largest sales, the breadth of equipment used that included 4WT goes beyond what the company deals in. As such, we do not think that our results are biased by targeting the sample in the two districts but rather, these results are typical of what would be expected in A1 farming areas in rural Zimbabwe. Overall, the findings in this paper are an important contribution to guide the drive towards sustainable mechanization in sub-Saharan Africa as espoused by FAO and AUC (2019).

There remain avenues for future research that were not addressed in this paper. First, there is a need to use stronger identification strategies that combine instrumental variables and panel data methods to determine the causal effects of mechanization. Second, because returns to investments in mechanization should be viewed as long-term, e.g., Mrema, Baker, and Kahan (2008), future studies can focus on quantifying returns to mechanization by length of adoption/use. Third, there is a need to further parcel out specific farm enterprises for which mechanization has the highest returns. This can help to target the most promising farm equipment to specific farm enterprises and value chains. Fourth, because profitability is critical to drive mechanization, there is a need for more studies assessing how profitable different pieces of equipment are, and the best-bet business models for service providers that promote equitable access to mechanization by smallholders. This is in line with the notion that demand should drive mechanization (Mrema, Baker, and Kahan 2008). In addition, our analysis only ended at revenue since cost data were not captured. This necessitates more work to capture the costs associated with mechanization to better assess profitability and returns to mechanization. And lastly, there is a need to build panel data surveys to better study mechanization adoption dynamics and impact over time. Nevertheless, these findings are an important first step given the data limitations on the economics of mechanization.

6. Conclusion and policy implications

The drive to mechanize and modernize African agriculture is in full gear for good reasons. African smallholders need to reduce drudgery, raise land and labor productivities, intensify production and invest in value addition of raw agricultural produce. There is a need for empirical evidence to guide the mechanization value proposition on the continent.

We applied a quantile regression framework to assess the correlates of adopting mechanization and farm and household revenues in two districts of Zimbabwe, where high sales of appropriate-scale farm mechanization equipment were recorded. This approach allowed us to evaluate the heterogenous and distributional correlates of mechanization use. Using survey data from 988 households, we found that adoption was associated with rising land/labor ratio, market access, and wealth. Farmers on average used three pieces of equipment with the majority being for crop establishment (four-wheel tractors and attachments), irrigation (stationary engines), and post-harvest (e.g., shellers and threshers). Most farmers purchased the machines they used on a cash basis, highlighting the prevalence of individual machinery purchases contrary to what is commonly stated. The second most common access mode was through hiring, signifying a growing machinery hire market.

The main results were also reinforcing as using mechanization was associated with higher farm and household revenues. Using different pieces of equipment was associated with a median annual increase of USD 262 in revenue with a wide range from USD 103 at the 25^{th} percentile to USD 2,900 at the 95^{th} percentile per year. When disaggregated by equipment types, post-harvest and irrigation equipment were associated with higher revenue. The distributional associations were larger in the upper percentiles of revenue, implying a need for wealth agnostic efforts to ensure equitable mechanization.

We draw three implications from the findings. First, there is a need to better target given types of mechanization to farmers in different wealth categories. To facilitate equitable mechanization, there is a need for deliberate efforts to enable low-income households to access mechanization. This could be through one-off catalytic mechanization subsidies or pre-arranged upfront mechanization services to be paid for after harvest if related to crop establishment, or through in-kind payments. Second, the breadth of machinery used by farmers in the sample entails a need to rethink and broaden the scope of appropriate-scale farm mechanization available to farmers to maximize benefits. These could include both power and control intensive mechanization equipment such as two-wheel tractors (2WTs) and four-wheel tractors (4WTs), and their attachments, post-harvest and irrigation equipment depending on farm(er) needs and characteristics. Third, because higher revenues were associated with post-harvest and irrigation, there is a need to rethink mechanization starter packs offered to mechanization service providers to ensure a broad range of services that enables all-year round business activities. Lastly, because there is a large proportion of farmers who owned different mechanization equipment that were bought without using credit, development interventions need to devote time and effort to identify such farmers and link them to potential users to develop sustainable mechanization service provision businesses and to reduce machinery idle time. On the research front, there is scope for more work

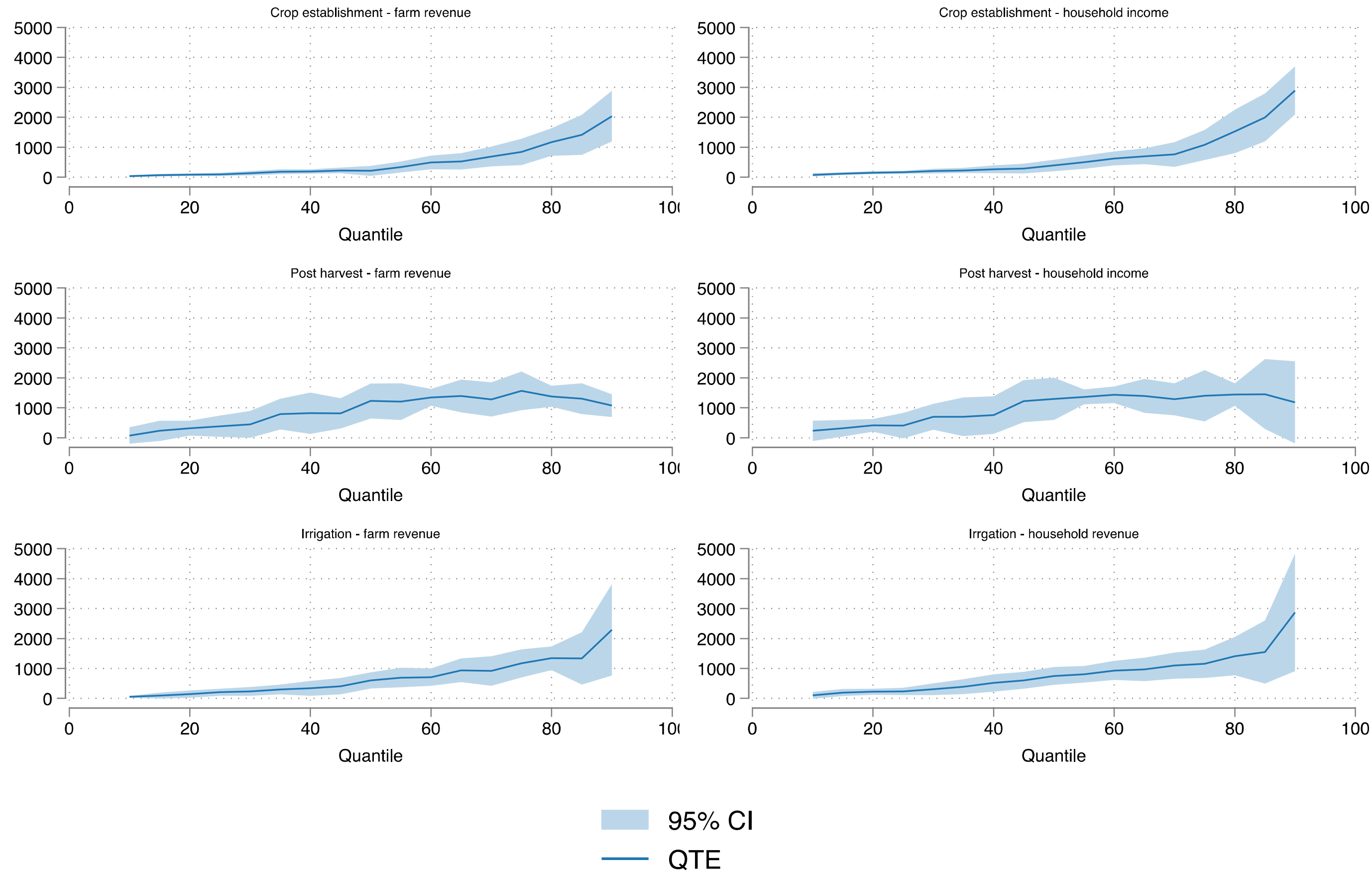

Fig. 5. Associations of using any machinery, crop establishment, irrigation, and harvest and post-harvest machines and annual farm revenue (left panel) and household revenues (right panel) in Chegutu and Zvimba districts, Zimbabwe. Notes: Full results are provided in Supplementary Table s A1- A6.

Table 6
Correlates of using mechanization and farm and household revenues based on the doubly robust inverse probability weighted regression adjustment (IPWRA).

	Farm revenue	Household revenue
Non-adopters	1963.12	2125.11
	[104.83]	[157.94]
Adopters	2625.82	2895.26
	[120.54]	[128.46]
Average Treatment Effect (ATE)	*662.70****	*770.15****
	[117.36]	*[165.58]*

Notes: Robust z-statistics in square brackets, *** $p < 0.01$.

on the profitability of mechanization, to identify farm enterprises and value chains for which mechanization is most promising, and to build long-term panel surveys to better assess adoption dynamics and impacts over time.

CRediT authorship contribution statement

Hambulo Ngoma: Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Billy Mukamuri:** Writing – review & editing, Writing – original draft, Project administration. **João Vasco Silva:** Writing – review & editing, Writing – original draft, Validation. **Frédéric Baudron:** Writing – review & editing, Writing – original draft, Validation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We acknowledge funding from the Australian Center for International Agricultural Research (ACIAR) to the HAFIZ (Harnessing Appropriate-scale Farm mechanisation In Zimbabwe) project (CROP/2021/166). We are grateful to the Zimbabwean Government officers, the University of Zimbabwe (UZ) and research assistants who facilitated fieldwork in Chegutu and Zvimba districts of Zimbabwe. The first author acknowledges additional financial support from the USAID funded Mechanization and Extension Activity, the CGIAR Regional Initiative, Ukama Ustawi and the CGIAR's Agroecology Initiative: Transforming Food, Land, and Water Systems Across the global south. We thank the Editor and three anonymous reviewers who provided detailed feedback over multiple rounds that helped improve the manuscript substantially. Authors are responsible for any errors and omissions.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2024.102795.

Data availability

Data will be made available on request.

References

Abadie, A., Angrist, J., Imbens, G., 2002. Instrumental Variables Estimates of the Effect of Subsidized Training on the Quantiles of Trainee Earnings. Econometrica 70 (1), 91–117. https://doi.org/10.1111/1468-0262.00270.

Adu-Baffour, F., Daum, T., Birner, R., 2019. Can small farms benefit from big companies' initiatives to promote mechanization in Africa? A case study from Zambia. Food Policy 84, 133–145. https://doi.org/10.1016/j.foodpol.2019.03.007.

Aihounton, G., Christiaensen, L., 2024. Does agricultural intensification pay in the context of structural transformation? Food Policy 122, 102571. https://doi.org/10.1016/j.foodpol.2023.102571.

Amankwah, A., Gwatidzo, T., 2024. Food security and poverty reduction effects of agricultural technologies adoption – a multinomial endogenous switching regression application in rural Zimbabwe. Food Policy 125, 102629. https://doi.org/10.1016/j.foodpol.2024.102629.

Baudron, Frédéric, Raymond Nazare, and Dorcas Matangi. 2019b. "The role of mechanization in transformation of smallholder agriculture in Southern Africa: Experience from Zimbabwe." In Transforming Agriculture in Southern Africa, edited by Richard A Sikora, Eugene R Terry, Paul L.G Vlek and Joyce Chitja. Stellenbosch: Routledge.

Baudron, F., Sims, B., Justice, S., Kahan, D.G., Rose, R., Mkomwa, S., Kaumbutho, P., Sariah, J., Nazare, R., Moges, G., Gérard, B., 2015. Re-examining appropriate mechanization in Eastern and Southern Africa: two-wheel tractors, conservation agriculture, and private sector involvement. Food Secur. 7 (4), 889–904. https://doi.org/10.1007/s12571-015-0476-3.

Baudron, F., Misiko, M., Getnet, B., Nazare, R., Sariah, J., Kaumbutho, P., 2019a. A farm-level assessment of labor and mechanization in Eastern and Southern Africa. Agron. Sustain. Dev. 39 (2), 17. https://doi.org/10.1007/s13593-019-0563-5.

Boserup, Ester. 1965. "The condition of agricultural growth." The Economics of Agrarian Change under Population Pressure, London, George Allen and Unwin.

Daum, T., 2023. Mechanization and sustainable agri-food system transformation in the Global South. A review. Agron. Sustain. Developm. 43 (1), 16. https://doi.org/10.1007/s13593-023-00868-x.

Daum, T., Birner, R., 2020. Agricultural mechanization in Africa: Myths, realities and an emerging research agenda. Glob. Food Sec. 26, 100393. https://doi.org/10.1016/j.gfs.2020.100393.

Daum, Thomas, Ygué Patrice Adegbola, Geoffrey Kamau, Alpha Oumar Kergna, Christogonus Daudu, Wahab Akeem Adebowale, Carine Adegbola, Charles Bett, Wellington Mulinge, Roch Cedrique Zossou, Abdoulaye Nientao, Oliver Kirui, and Fatunbi Abiodun Oluwole. 2023. "Made in Africa – How to make local agricultural machinery manufacturing thrive." Journal of International Development n/a (n/a). doi: Doi: 10.1002/jid.3845.

Daum, Thomas. 2022. Agricultural mechanization and sustainable agrifood system transformation in the Global South. Background paper for The State of Food and Agriculture 2022. In Agricultural Development Economics Working Paper 22-11. Rome, Italy: United Nations Food and Agriculture Organization (FAO).

Diao, Xinshen, Jed Silver, and Takeshima Hiroyuki. 2016. Agricultural mechanization and agricultural transformation. Washington, D.C.

FAO, and AUC. 2019. Sustainable agricultural mechanization: A framework for Africa – Synopsis. Addis Ababa, Ethiopia: Food and Agriculture Organization (FAO) and African Union Commision (AUC).

Firpo, S., Fortin, N.M., Lemieux, T., 2009. Unconditional Quantile Regressions. Econometrica 77 (3), 953–973.

Hayami, Yujiro, and Vernon W Ruttan. 1971. Induced innovation in agricultural development. Center for Economics Research, Department of Economics, University of Minnesota, Minneapolis, Minnesota 55455.

Houssou, N., Diao, X., Cossar, F., Kolavalli, S., Jimah, K., Aboagye, P.O., 2013. Agricultural mechanization in ghana: is specialized agricultural mechanization service provision a viable business model? Am. J. Agric. Econ. 95 (5), 1237–1244. https://doi.org/10.1093/ajae/aat026.

Jahnke, H.E., 1982. Livestock production systems and livestock development in tropical Africa, Livestock production systems and livestock development in tropical Africa. Kieler wissenschaftsverlag vauk, Kiel Germany.

Jayne, T.S., Chamberlin, J., Traub, L., Sitko, N., Muyanga, M., Yeboah, F.K., Anseeuw, W., Chapoto, A., Wineman, A., Nkonde, C., Kachule, R., 2016. Africa's changing farm size distribution patterns: the rise of medium-scale farms. Agric. Econ. 47 (S1), 197–214. https://doi.org/10.1111/agec.12308.

Jayne, T.S., Chamberlin, J., Holden, S., Ghebru, H., Ricker-Gilbert, J., Place, F., 2021. Rising land commodification in sub-Saharan Africa: Reconciling the diverse narratives. Glob. Food Sec. 30, 100565. https://doi.org/10.1016/j.gfs.2021.100565.

Kotu, B.H., Manda, J., Mutungi, C., Fischer, G., Gaspar, A., 2023. Farmers' willingness to invest in mechanized maize shelling and potential financial benefits: Evidence from Tanzania. Agribusiness 39, 854–874. https://doi.org/10.1002/agr.21801.

Mano, Y., Takahashi, K., Otsuka, K., 2020. Mechanization in land preparation and agricultural intensification: The case of rice farming in the Cote d'Ivoire. Agric. Econ. 51 (6), 899–908. https://doi.org/10.1111/agec.12599.

Mrema, G. C, D Baker, and D Kahan. 2008. Agricultural mechanization in sub-Saharan, Africa: Time for a new look. In Agricultural Management, Marketing and Finance Occasional Paper #22. Rome, Italy: Food and Agriculture Organization (FAO).

Ngoma, Hambulo, Joao Vasco, Joao Vasco Silva, Kudzai Makahamadze, Kush Sira, and Frederic Baudron. 2022. Understanding customer types for appropriate-scale machinery in Zimbabwe. CIMMYT Harare, Harnessing Appropriate-scale Farm mechanisation In Zimbabwe (HAFIZ) Project.

Ngoma, H., Marenya, P., Tufa, A., Alene, A., Lovemore Chipindu, Md., Matin, A., Thierfelder, C., Chikoye, D., 2023. Smallholder farmers' willingness to pay for two-wheel tractor-based mechanisation services in Zambia and Zimbabwe. J. Int. Developm. N/a 35 (7), 2107–2128. https://doi.org/10.1002/jid.3767.

Omulo, G., Birner, R., Köller, K., Simunji, S., Daum, T., 2022. Comparison of mechanized conservation agriculture and conventional tillage in Zambia: A short-term agronomic and economic analysis. Soil Tillage Res. 221, 105414. https://doi.org/10.1016/j.still.2022.105414.

Pingali, P., 2007. Chapter 54 Agricultural Mechanization: Adoption Patterns and Economic Impact. In: Evenson, R., Pingali, P. (Eds.), Handbook of Agricultural Economics. Elsevier, pp. 2779–2805.

Pingali, P., Bigot, Y., Binswanger, H.P., 1987. Agricultural Mechanization and the Evolution of Farming Systems in Sub-Saharan Africa. Johns Hopkins University Press, Baltimore.

Ruttan, V.W., Hayami, Y., 1973. Technology Transfer and Agricultural Development. Technol. Cult. 14 (2), 119–151. https://doi.org/10.2307/3102398.

Shonhe, T., 2022. The politics of mechanisation in Zimbabwe: tractors, accumulation and agrarian change. J. Peasant Stud. 49 (1), 179–199. https://doi.org/10.1080/03066150.2021.1918114.

Singh, I., Squire, L., Strauss, J., 1986. Agricultural household models: extensions, applications, and policy. Johns Hopkins University Press.

Sitko, N.J., Jayne, T.S., 2014. Structural transformation or elite land capture? The growth of "emergent" farmers in Zambia. Food Policy 48, 194–202. https://doi.org/10.1016/j.foodpol.2014.05.006.

Tufa, A., Alene, A., Ngoma, H., Marenya, P., Julius Manda, Md., Matin, A., Thierfelder, C., Chikoye, D., 2023. Willingness to pay for agricultural mechanization services by smallholder farmers in Malawi. Agribusiness 40, 248–276. https://doi.org/10.1002/agr.21841.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, 2nd ed. MIT Press, MA, Cambidge.

Zikhali, Precious. 2008. Fast Track Land Reform, Tenure Security, and Investments in Zimbabwe. Development Discussion Paper Series EfD DP 08–23. Environment for Development Initiative, Gothenburg, Sweden.