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Of trackers and tractors. Using a smartphone app and compositional data analysis to explore the link between mechanization and intra-household allocation of time in Zambia

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Abstract

Digital tools may help to study socioeconomic aspects of agricultural development that are difficult to measure such as the effects of new technologies, policies and practices on the intra-household allocation of time. As new technologies, policies and practices may target different crops and tasks, they can affect time-use of men, women, boys and girls differently. Development strategies that overlook such effects can fail or have negative consequences for vulnerable household members. In this paper, the effects of agricultural mechanization on time-use in smallholder farming households in Zambia were investigated. For this, a novel data collection method was used: a pictorial smartphone application that allows real-time recording of time-use to eliminate recall bias. Existing studies analyzing intra-household allocation of resources often focus on adult males and females. This study paid particular attention to boys and girls. The study also addressed seasonal variations. For data analysis, compositional data analysis was used, which yields higher accuracy than univariate analysis by accounting for the co-dependence and sum constraint of time-use data. The study found that women benefit relatively more from mechanization with regard to time-use during land preparation, which leads to gender differentiation; for households using manual labor, such differentiation was not found. There was some evidence that the time "saved" is used for off-farm and domestic work. No negative second-round effects (such as higher labor burdens) during weeding and harvesting/processing and no negative effects on children were found. The study debunks some myths related to gender roles in African smallholder agriculture, opens the field to more studies on technology adoption and time-use and suggests that gender roles are changing with agricultural transformation.

Keywords: Agricultural mechanization, agricultural transformation, labor division, gender, child labor, time-use, Africa

JEL classification: J16, J22, O12, O33, Q12, Q16

1 Introduction

During the last years, various researchers have used digital tools to enhance data accuracy in the field of applied agricultural economics. For example, researchers have used GPS devices to measure plot sizes (Carletto et al., 2015a), fitness-trackers to capture energy expenditure (Zanello et al., 2017) and satellites to assess yields (Lobell et al., 2018). However, for socioeconomic data, researchers still largely rely on household surveys, which are prone to recall bias (Arthi et al., 2018; Bell et al., 2019; Fraval et al., 2018). The lack of reliable data collection methods for socioeconomic aspects that are difficult to recall has led to data suffering from poor quality and the neglect of potentially highly relevant research areas (Carletto et al., 2015b). One such research area is the effects of technology adoption (such as tractors or herbicides) or the exposure to new policies on the time-use within smallholder farming households in developing countries.

The need to monitor intra-household time-use effects when promoting technologies and designing policies is widely acknowledged (Blackden & Wodon, 2006; Bryceson, 2019; Doss, 2013; Theis et al., 2018). Since smallholder farming is often associated with a gender-division of labor, which can be based on crops, tasks or both, new technologies and policies can affect adult men and women as well as boys and girls differently (Blackden & Wodon, 2006; Doss et al., 2001; Quisumbing et al., 1995). Development strategies that overlook these dynamics can fail or have negative consequences for vulnerable household members. For example, promoting conservation agriculture may lead to more labor for women because of the increased weeding required (Farnworth et al., 2015); and the exacerbated need for bird scaring associated with the new rice variety NERICA has been shown to prevent children from going to school (Bergman-Lodin et al., 2012). There are concerns that such time-use changes have negative consequences on nutrition and childcare (Johnston et al., 2018). In this paper, the time-use effects of agricultural mechanization during land preparation are explored. Mechanization is unfolding rapidly in various Asian countries (Takeshima, 2017; Wang et al., 2016) and has received growing attention in Africa (Daum & Birner, 2017; Benin, 2015; Diao et al. 2014). Notwithstanding some anecdotal evidence, the effects of mechanization on intra-household time allocation have not been examined.

While the need to carefully monitor time-use effects of new technologies and policies is widely acknowledged, studying such effects empirically has been hampered by a lack of suitable data collection methods. Post-harvest questionnaires and 24-hour recall questions are prone to recall bias; time-use diaries require literacy and a familiarity with clock-based concepts of time; direct observations are expensive and associated with observer bias (Arthi et al., 2018; Daum et al., 2019). In this study, therefore, a smartphone application called Timetracker is used, which is based on visual tools. It allows real-time recording of time-use to reduce recall bias. The Timetracker was used to collect 2790 days of time-use data in Zambia during different seasons to capture seasonality. The Timetracker has the advantage of allowing data recording by children. This is a unique contribution, as existing studies analyzing intra-household allocation of resources - and time-use, which are far fewer in number and often qualitative in nature - focus mainly on adults (Doss, 2013). This is despite that 60% of all child labor is in agriculture, affecting around 100 million girls and boys (ILO, 2019).

Researchers studying gender differences in time-use have often studied time spent on different activities in isolation of each other (Arora, 2015). This can be misleading since total time-use always sums up to 24 hours. Also, time-use is intrinsically collinear and codependent: an increase in time spent on one activity reduces the time available for other activities (Chastin et al. 2015; Gupta et al., 2018). Standard statistical techniques fail to account for this and result in spurious correlations (Pearson, 1897). To address these challenges, compositional data analysis is used in this paper (Atchinson, 1986; Bacon-Shone, 2011). Compositional data analysis has been used in different disciplines such as soil science, biology, geochemistry and medicine (Bacon-Shone, 2011) but has not been applied within the agricultural economics field.

In addition to finding a reliable data collection method and dealing with the structure of time-use data, the third challenge when studying the effects of mechanization on time-use is establishing causality. Ideally, a randomized control trial would take place. In the context of agricultural mechanization, which is adopted ad-hoc, a randomized control approach is difficult to implement. An alternative would be to use propensity score matching (PSM). In this study, the data collection method was novel and aiming for a sample size large enough for PSM was considered risky. Hence, cross-sectional data was used to compare time-use across differently mechanized households. The study uses multiple linear regression models to account for covariates and builds on economic theory but the use of cross-sectional data remains a limitation. Thus, the study concentrates on the first two challenges related to time-use data, data collection and analysis, and should be understood as a proof-of-concept case study. The paper has three major objectives: 1) providing a proof-of-concept that using digital tools can help to collect more reliable socioeconomic data; 2) introducing compositional data analysis to agricultural economics; 3) exploring how time-use differs by levels of mechanization, paying particular attention to gender, child labor and seasonality.

In section 2, the potential effects of agricultural mechanization on the intra-household allocation of time-use are discussed and four research hypotheses are derived. In section 3, study site and sampling procedure are described and the ‘’Timetracker’’ is presented. In addition, the section discusses how the challenges of time-use data can be addressed using compositional data analysis. In section 4, the hypotheses are answered. Section 5 discusses and concludes.

2 Background and research hypotheses

In many African smallholder farming households, men and women have different workloads and duties (Arora, 2015; Blackden & Wodon, 2006; Quisumbing et al., 1995). For example, ploughing tends to be done relatively more by men and weeding and processing by women (Alesina, 2011; Baanante et al., 1999); however, such gender roles can clearly vary across space and time (Lambrecht et al., 2017) and have also been questioned (Palacios-Lopez et al., 2017). Little is known about the different roles of children in farm households – although numbers form the ILO suggest that 60% of child labor is in agriculture boys (ILO, 2019) and literature suggest that they vital for farm income (Bhalotra and Heady, 2003; Koomson and Asongu, 2016). As new technologies target different crops and tasks, they may affect men and women, boy and girls differently. As there is evidence that households favor technologies that can be directed to male crops and activities (Evers, 2001), there are various examples where the introduction of a new technology increased women's burden (Agarwal, 1985; Bergman-Lodin et al., 2012; Kumar, 1994; Doss, 2001; Quisumbing et al., 1995). Bergman-Lodin et al. (2012) also found negative effects on children; however, most studies do not focus on children. An increase in women's time-use may likely come from where women do not have the bargaining power to reject more labor-intense technologies or to demand a re-allocation of activities (Fisher et al., 2000).

The time-use effects of mechanization depend on which tasks or crops are mechanized, how accompanying inputs such as herbicides and hired labor are used, what the original labor allocation was, and how this allocation can be re-negotiated. For understanding how time-use allocation may be re-negotiated, both unitary and bargaining models have been proposed (Alderman et al., 1995; Doss, 2013) but this is not the focus of this paper. Typically land preparation is mechanized first because land preparation tends to be a labor bottleneck. However, it may also reflect preferences to adopt technologies which can be directed to male-focused activities (Evers & Walters, 2001). With land preparation being mechanized, household may cultivate additional land, which may increase the need for weeding, harvesting/processing or the time spend collecting firewood once forests are cleared, which are tasks often performed by women and children (Arora, 2015; Blackden & Wodon, 2006; Doss, 2001). This was observed in India on anecdotal basis by Mukhopadhyay (1984) who found that the mechanization of ploughing (which was a male activity) led to more land cultivated and a higher workload for women since they were then "dealing with bigger crops over a larger acreage without mechanization of any of the operations they control" (p.58). A similar phenomenon may be observable in Zambia since there is evidence on mechanization increasing the area under cultivation (Adu-Baffour et al., 2018). In more land-constrained countries, such a land expansion may not be possible and labor needs for activities such as weeding may drop but potentially higher yields may still translate to higher workloads for farming steps such as harvesting and processing.

Based on the theoretical framework sketched above, four research hypotheses can be derived, which will be tested in section 4.

H1: Land preparation is predominantly a male activity.

H2: Mechanized land preparation benefits males relatively more than females.

H3: The time "saved" by mechanized land preparation is used differently by gender.

H4: On mechanized farms, females spend more time on weeding and harvesting/processing compared to females on non-mechanized farms.

3 Study site, data collection method and sampling

3.1 Study Site

The study was conducted in the Eastern Province, which is one of Zambia's most important smallholder agricultural regions. The average size of land cultivated is 2.3 hectares - mainly maize, cotton, sunflower, groundnuts, and tobacco are grown (IAPRI, 2016). Farming is rain-fed and constrained by an extensive dry season. The emergence of medium-scale farmers as observed by Jayne et al. (2016) has led to more farmers owning tractors and providing services to neighboring farmers but the access to mechanizations remains low: 1% of the households use their own or hired tractors for land preparation and 57% of the farmers use their own or hired animal traction on a least one plot (IAPRI, 2016).

3.2 Data collection methods and sampling

As outlined above, time-use is difficult to measure, especially in developing countries. To address this challenge, a smartphone application called Timetracker was used, which is based on visual tools and allows real-time recording of 88 time-use categories (see figure 1; Daum et al., 2018 and Daum et al., 2019). The app allows to record up to three activities at a time but the focus here is on primary activities.

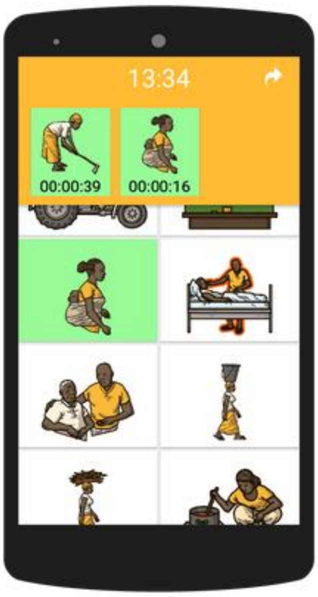

Figure 1: The Timetracker.

The Timetracker was used to collect data from 62 households: 20 used manual labor, 20 used animal power and 22 used mechanical traction for land preparation, which are henceforward abbreviated with “manual”, “animal” and “tractor” households. Based on the nationally representative Rural Agricultural Livelihood Survey, households were selected using a two-stage random sampling procedure. First, four communities were sampled based on the criteria that more than five households used manual labor, more than five households used animals, and more than five used tractors for land preparation. Second, five manual-, five animal-, and five to six tractor-households were randomly selected, who in each household had at least one adult male, one adult female, and one child. If not enough households could be identified based on these criteria, missing households were randomly added from lists of the District Agriculture and Cooperatives Offices. In each household, household head, spouse and the oldest child used the Timetracker for three days at five different points of the 2016/2017 cropping season. This resulted in 2790 data days. Since the smartphone app was used in rotation in four different communities, data was collected on 60 different days. This paper focuses on land preparation, weeding and harvesting/processing season. At the end of the season, a household survey was conducted. Table 1 provides descriptive statistics about the selected households – the amount of labor provided by male and female household members will be presented separately in the subsequent chapter.

In addition, six focus groups discussions were conducted (three with men and three with women). FDG were conducted separately for men and women to allow both to speak freely. Participants were randomly chosen for the households participating in the study. Visual tools were used to facilitate discussion. For example, respondents were asked to judge activities according to the perceived work toil and enjoyableness. For this, a large sheet of paper with two crossing axes indicating work toil (from hard work to no work) and enjoyableness (from enjoyable to not enjoyable) was used. Respondents were given stickers representing different activities. The stickers were placed within the framework once consensus was reached - after discussions.

Table 1: Sample characteristics

Variable	Manual-HHs	Animal-HHs	Tractor-HHs	Difference
Household characteristics				
Household size	6.6 (0.3)	7.8 (0.5)	6.7 (0.4)	
Gender head male (%)	95% (0.1)	100% (0)	95% (0.4)	
Age (years)	49.7 (3.8)	45.1 (2.5)	47.3 (2.9)	
Education level head (0-18)	6.8 (0.7)	8.5 (0.8)	10.5 (0.9)	***
Agronomic Characteristics				
Land cultivated (ha)	2.3 (0.2)	4.8 (0.9)	8.4 (1.3)	***
Land owned (ha)	2.5 (0.4)	5.9 (1.5)	19.8 (6.6)	***
Crop diversity	3.1 (0.2)	3.7 (0.2)	3.5 (0.2)	
Frequency of animal draught weeding	0.32 (0.1)	0.69 (0.12)	0.51 (0.1)	**
Maize yield (tons/ha)	1.9 (0.4)	2.6 (0.4)	3.6 (0.4)	***
Fertilizer per ha cultivated (kg)	110.5 (30.4)	190.3 (33.2)	216 (43.6)	
Pesticide per ha cultivated (l)	1.5 (1.0)	8.8 (3.3)	5.4 (2.5)	
Tropical livestock unit[1]	0.8 (0.2)	7.4 (1.8)	6.4 (1.7)	***
Hired labor (hours per cultivated ha)				
Land preparation	4.1 (2.8)	7.0 (5.6)	3.9 (2.1)	
Weeding	5.3 (5.3)	14.2 (10.9)	20.7 (10.0)	
Harvesting	8.8 (8.8)	7.6 (5.6)	16.7 (7.4)	
Child labor (hours per cultivated ha)				
Land preparation	38.3 (18.9)	29.1 (7.9)	11.8 (6.9)	
Weeding	45.4 (15.2)	59.9 (23,9)	16.6 (7.6)	
Harvesting	43.9 (15.8)	42.7 (12.4)	12.2 (4.6)	*
Socioeconomic Characteristics				
Log income	7.8 (0.36)	9 (0.28)	10.3 (0.21)	***
Share off-farm income	35% (13.2)	17% (7.1)	33% (6.6)	
Month with food shortage	2.4 (0.4)	1.5 (0.4)	1.2 (0.4)	*
Distance to nearest market (km)	6.7 (1.2)	6.6 (1.6)	4.4 (1.5)	
Extension contacts (p.a.)	1.9 (0.3)	2.6 (0.5)	2.2 (0.5)	
Access finance	10% (0.1)	10 % (0.1)	23% (0.1)	
Sample size	20	20	22	

Standard errors in brackets. Differences of means are obtained using analysis of variance (ANOVA) and are indicated with *, **, and ***, which denote differences at the 10 %, 5 %, and 1 % level. [1]The following weights were used: cattle=0.7, sheep=0.1, goats=0.1, pigs=0.2, chicken=0.01.

3.3 Statistical Analysis

The data collected always has positive numbers and sums up to fixed sum of 1440 minutes (24 hours) per day. Time spent on different activities is correlated and co-dependent: an increase in time spent on one activity reduces the time available for other activities. Such a data structure is known as compositional data (CoD) and requires special attention due to two features: sum constraint and correlation (Atchinson, 1986; Bacon-Shone, 2011). A simple series of univariate analyses, where each time-use category is analyzed separately is incapable to account for these features. A multivariate analysis, where all categories are analyzed simultaneously, can account for correlation but not for the sum constraint. The latter constraint can be addressed by fitting multivariate models to log-transformed ratios of the categories of a composition, so called log-ratios (lr), which are assumed to be logit-normal distributed (Bacon-Shone, 2011). Such methodology has been coined compositional data analysis (CoDA). CoDA yields higher accuracy than univariate analysis (e.g. Chastin et al. 2015; Gupta et al. 2018).

In this study, the values of single categories underwent an additive lr-transformation (alr), where each category is divided by a reference category and the resulting ratios were transformed by taking the natural logarithm (Bacon-Shone, 2011). A set of K=9 categories was constructed from the raw data, which resulted in $k=K$ - 1, i.e. k=8 lr. Table 2 shows the aggregated categories. The category 'personal care' was used as common reference category for log-ratio transformation. Atchison (1986) showed that conclusions about relations of compositions are independent of which category is chosen as reference.

Table 2: Aggregation of time-use activities to overall groups.

	Group	Sub activities
1	Crop farming	
1.1	Land Preparation	Land clearing, hoeing, plowing, harrowing, dibbling, potholing, ripping, ridging and raking (all with different power sources)
1.2	Weeding	Weeding by hand or using draught animals, knapsack sprayers, boom sprayers, and pest and disease control
1.3	Harvesting/processing	Harvesting, bundling, drying, storing, bagging, shelling, grinding, pounding, milling, winnowing (all with different power sources)
2	Crop farming (others)	Planting, applying fertilizer, applying manure, guarding of crops, watering as well as the activities that are not specifying the respective season (for example weeding and harvesting/processing activities during land preparation season)
3	Rural livelihood activities	Beverage preparation, marketing, animal husbandry, hunting, fishing, gathering food and grasses, charcoal making, maintaining/repairing, farm administration, vegetable garden, construction (household and community), meeting, cooking (community)
4	Off-farm and seasonal labor	Off-farm activities and the above mentioned farm activities as hired labor
5	Transportation	Walking, motorbike, bicycle, animal cart, car/van, bus, tractor (all of which can be loaded or unloaded)
6	Education	
7	Domestic	Care of children, sick and old, fetching water, collecting firewood, cooking (household), cleaning, washing pots and clothes, buying groceries
8	Leisure	Resting, media, religion, chatting, sports, dancing, making music
9	Personal care	Sleeping, being sick, eating, drinking, personal hygiene

A complication was that some activities were not done by every participant, resulting in zero values where a log-ratio transformation could not have been defined. Commonly, zeros in CoDA are subdivided into 'structural' or 'essential' zeros, where the category is truly empty or 'rounded' zeros, where the number is below a detection limit (Martin-Fernandez et al. 2003). Empty time-use categories could represent structural zeros as an activity may not have been performed by a participant. Martin-Fernandez et al. (2003) suggest analyzing the data separately for subjects performing and not performing a certain activity. However, the data recordings of the subjects' daily activities during three subsequent days are too short to conclude that subjects would come from different populations, one with a certain activity, the other one without. Moreover, it seems reasonable to consider zero values as being under a detection limit if e.g. an activity is performed for periods seemingly too short to be worth recording. Hence, multiplicative replacement - a method recommended for rounded zeros - was used and zeros were replaced by the small amount of one minute (ibid).

A multivariate model was used to study the dependence of alr of time consumption on mechanization and gender. As the sampling was stratified by communities with three different members of each household sampled, the multivariate model for analysis was extended to account for the possible correlations of observations within communities and households. The following multivariate linear mixed model was fitted to the alr-transformed data:

$$\begin{pmatrix} \log\left(\frac{y_{1ijml}}{y_{9ijml}}\right) \\ \vdots \\ \log\left(\frac{y_{8ijml}}{y_{9ijml}}\right) \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_8 \end{pmatrix} + \begin{pmatrix} c_{1i} \\ \vdots \\ c_{8i} \end{pmatrix} + \begin{pmatrix} \tau_{1j} \\ \vdots \\ \tau_{8j} \end{pmatrix} + \begin{pmatrix} \gamma_{1l} \\ \vdots \\ \gamma_{8l} \end{pmatrix} + \begin{pmatrix} (\tau\gamma)_{1jl} \\ \vdots \\ (\tau\gamma)_{8jl} \end{pmatrix} + \begin{pmatrix} h_{1ijm} \\ \vdots \\ h_{8ijm} \end{pmatrix} + \begin{pmatrix} e_{1ijml} \\ \vdots \\ e_{8ijml} \end{pmatrix}, \tag{1}$$

where the response vector contains the log-transformed ratios of time of 8 time-use categories divided by the reference category ‘personal care’. Each time-use category of each household member with gender *l* of each household *m* with mechanization level *j* from community *i* underwent this transformation. μ_1 to μ_8 are the fixed effects of time-use categories (tuc) 1 to 8, c_{1i} to c_{8i} are the random tuc-specific effects of the *i*-th community, τ_{1j} to τ_{8j} are the tuc-specific fix effects of the *j*-th mechanization type with the levels ‘manual, ‘animal’ and ‘tractor’. γ_{1l} toγ_{1l} are the tuc-specific fix effects of the *l*-th gender with levels: ‘female adult’, ‘male adult’, ‘girl’ and ‘boy’. $(\tau\gamma)_{1jl}$ to $(\tau\gamma)_{8jl}$ are the tuc-specific interaction terms of gender and mechanization type. h_{1ijm} to h_{8ijm} are the tuc-specific random household effects and e_{1ijml} to e_{8ijml} are the residual error terms. Time-use-category-specific random effects for community, household and residual error were assumed to have a multivariate normal distribution with mean zero and tuc-specific variances. Individual covariance parameters were estimated for all pairs of tucs, resulting in the following variance-covariance structure for communities:

$$\begin{pmatrix} c_{1i} \\ \vdots \\ c_{8i} \end{pmatrix} \sim MVN\left[\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{c1}^2 & \cdots & \sigma_{c1,8}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{c8,1}^2 & \cdots & \sigma_{c8}^2 \end{pmatrix}\right],$$

for households

$$\begin{pmatrix} h_{1ijm} \\ \vdots \\ h_{8ijm} \end{pmatrix} \sim MVN\left[\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{h1}^2 & \cdots & \sigma_{h1,8}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{h8,1}^2 & \cdots & \sigma_{h8}^2 \end{pmatrix}\right],$$

and for residual errors:

$$\begin{pmatrix} e_{1ijml} \\ \vdots \\ e_{8ijml} \end{pmatrix} \sim MVN \left[\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{e1}^2 & \cdots & \sigma_{e1,8}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{e8,1}^2 & \cdots & \sigma_{e8}^2 \end{pmatrix} \right],$$

resulting in a total of 108 variance-covariance parameters to estimate. Model (1) was fitted to the data of the three seasons separately.

Model parameters were estimated using the HPMIXED procedure of SAS (Version 9.4). Variance components were estimated by the method of restricted maximum likelihood (REML) and subsequently transferred to the MIXED procedure, which was used for inferences on fixed effects. Model assumptions of normal distribution of residuals and homogeneity of variance were graphically assessed. The presence of (multiplicatively replaced) zeros necessarily led to slight shortcomings in the fulfillment of assumptions. Normal distribution assumption was usually fulfilled; however, plots for homogeneity of variance showed some changes in the variance over the range of predicted values. Fixed effects were studied by partial Wald-type F-tests. The most appropriate method of Kenward and Roger (1997) to approximate the denominator degrees of freedom was relinquished because of disproportionately high computing time and the 'between-within-method' was used instead (Schluchter and Elashoff, 1990).

The influence of covariates such as household size and size of cultivated land was further studied in univariate models, where the time-use for the respective agricultural activities were regressed on different covariates. Hence, multiple linear regressions were performed where all regressors entered the model linearly without interaction. Fixed main effects for community, mechanization, gender and interaction of gender and mechanization, as well as random intercepts for households were constituent components of the model. The terms in the model were successively removed from by backwards-elimination. The criterion for keeping or removing a covariate was the p-value in a partial Wald-F-test at α=10%. All three response variables of the three multiple linear regression models, time spent on land preparation, weeding and harvesting/processing were square-root transformed to fulfill homogeneity of variance. The multiple linear regressions were fitted using the MIXED procedure.

4 Results

In this part, the research hypotheses will be tested. Section 4.1 addresses hypothesis 1 and 2, section 4.2 addresses hypothesis 3 and section 4.3 addresses hypothesis 4.

4.1 Are land preparation activities gendered? To which extent benefit different gender from mechanization?

In section 2, two hypotheses were developed: 1) land preparation is predominantly a male activity and 2) mechanized land preparation benefits males relatively more than females. The F-tests show a significant effect of gender and mechanization based on model (1). This means that the composition of overall time-use differs depending on gender and mechanization (Table 3). There is no significant interaction of mechanization and gender on the overall daily composition of time-use.

Table 3: Partial Wald-F-tests for fixed effects of model (1) during land preparation.

Effect	Description	Numerator DF	Denominator DF‡	F-value	p-value
μ_k	Effect of time-use category (tuc)	8	20	756.53	<0.0001
τ_{kj}	tuc-specific Effect mechanization (M)	16	48	1.90	0.0450
γ_{kl}	tuc-specific Effect of gender (G)	24	72	17.29	<0.0001
$(\tau\gamma)_{kjl}$	tuc-specific Interaction of M and G	48	136	1.15	0.2597

Tests are based on model (1); *k*=1 to 8 are 8 additive log-ratios of tuc with 'personal care' as common denominator

‡Denominator Degrees of freedom are adjusted according to the 'Between-Within-Method'

However, there is a significant interaction of gender and mechanization ($p < 0.0001$) for the single time-use activity 'land preparation on their own farm' based on model (1). This interaction was further studied in pairwise *t*-tests (see figure 2).

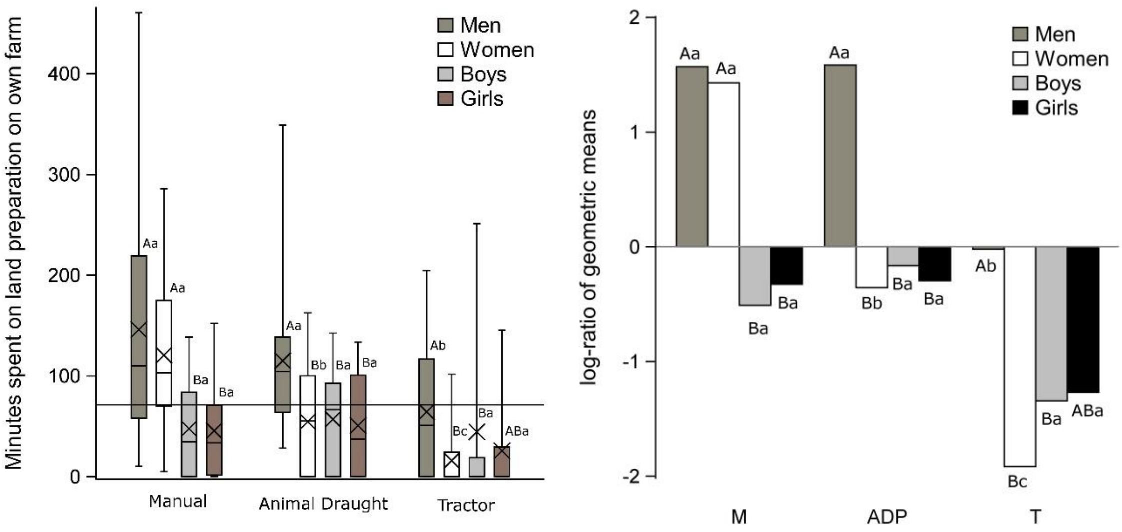

Figure 2: Boxplots (left) and descriptive log-ratios of geometric means (right) of minutes spent on land preparation on own farm by mechanization and gender

In the right figure, each bar represents the log-transformed ratio of the mean of each group compared to the overall mean of all 12 groups. Log-ratios larger or lower than zero represent above or below average time-use. Pairwise comparisons are based on estimates from model (1). Lower case letter refer to differences by mechanization within the same gender at α=10%. Capital letters refer to differences of different gender within the same mechanization type at α=10%.

In tractor-households, men spent significantly less time on land preparation (arithmetic mean of 64 minutes) compared to animal-households (115 minutes, p=0.0072) and manual-households (146 minutes, p=0.0081), the latter two did not differ significantly (p=0.9671). Women in manual-households spent 120 minutes on land preparation while their counterparts in animal-households (54 minutes, p=0.0040) and tractor-households spent significantly less time (16 minutes, p<0.0001). Time spent is significantly lower for women in tractor-households compared to animal-households (p=0.0063). The reduction of time-use can be observed despite tractor- and animal-households cultivating more land (see table 1), a factor that will be controlled for in table 4. Time spent did not differ significantly between mechanization types for boys and girls, potentially because no rigid agricultural gender roles exist for them yet. Within tractor and animal-households, men spent the significantly highest amount of time (64 and 115 minutes) compared to women (16 minutes, p=0.0005 for tractor-households and 54 minutes, p=0.0011 for animal-households) and children. However, in manual-households the contribution of men (146 minutes) and women (120 minutes) did not differ (p=0.8211) and both spent significantly more time than their children.

The numbers presented so far cannot prove causality (mechanization leading to less time spent on land preparation), although economic theory would suggest this. The difference between time-uses may also occur because households differ with regard to other variables (and differed already before some became mechanized). In table 4, some factors that might also be correlated with time spent on land preparation are controlled for using multiple linear regression. Controlling these factors, the interaction factor (gender*mechanization) remains highly significant. This suggests that mechanization has more influence on the time spent than factors such as cultivated land size, household size, or hired labor. However, many of these variables differ between the mechanization groups (table 1) and, consequently, a regression on these variables without mechanization shows significant slopes (for example, a negative slope for cultivated land size, data not shown).

Table 4: Multiple linear regression of covariates on time-use for land preparation, with parameter estimates for slopes and standard error in parentheses and F-tests

Effect	Estimate	DF	F-value	p-value
Community	- ‡	55.3	3.80	**0.0151**
Gender (M, F, B, G)	-	133	12.53	**<.0001**
Mechanization (M, A, T)	-	64.3	7.53	**0.0012**
Gender*mechanization	-	133	2.48	**0.0266**
Off-farm income	-0.00005 (0.000027)	54.5	3.45	**0.0687**
Costs per ha	0.000418 (0.000266)	53.4	2.47	0.1217
Pregnancy	1.2098 (1.0592)	52.5	1.30	0.2586
Household size	-0.1348 (0.1858)	53.7	0.53	0.4714
Tropical livestock unit	-0.03753 (0.06147)	51.3	0.37	0.5442
Distance market	-0.01339 (0.02223)	49.2	0.36	0.5498
Hired labour	-0.01016 (0.02537)	48.5	0.16	0.6906
Months with food shortage	0.07680 (0.2438)	50.4	0.10	0.7541
Education	0.02409 (0.1075)	46.2	0.05	0.8326
Crop diversity	0.06811 (0.3980)	45.4	0.03	0.8649
Land cultivated	-0.00992 (0.1181)	47.4	0.01	0.9334

Multiple linear regression on square-root transformed time spent in land preparation. Covariates were removed in back-wards elimination. Threshold of deletion were p-values below 10%. The model contains a random intercept for each household.

‡ Parameter estimates for qualitative factors are not shown for brevity.

The hypothesis that land preparation is a male activity can only partially be confirmed. In manual-households, men and women equally contribute to land preparation. A gender differentiation emerges only with the use of different forms of mechanization (by animal draught and tractors). In animal-households, women spend less time on land preparation activities compared to manual-households, while men spent a comparable amount of time. When using tractors, both men and women work less but men work more than women. In general, the time spent on land preparation is the lowest for all household members when tractors are used and children contribute less time irrespective of mechanization. The hypothesis that men benefit most from mechanization cannot be confirmed. Men do benefit from mechanization in terms of time-use but women benefit relatively more: they work significantly less. Children who spend less time on land preparation than their adults seem to be little affected by mechanization in terms of time-use.

4.2 Is time "saved" used differently by gender?

The previous section has shown that agricultural mechanization is associated with less time spent on land preparation. Clearly, this time must be spent on some other activities. In this section, the hypothesis is tested that males and females use this time differently. In the previous section, no time saving effects for (the sampled oldest) children were found, who are thus omitted in this section.

Table 5: Difference of time consumption relative to manual-households by mechanization type and gender

	Animal		Tractor	
	women	men	women	men
Crop farming (land preparation)	-65^a (0.004)	-31^a (0.967)	-105^b (< 0.0001)	-81^b (0.008)
Crop farming (others)	0^a (0.453)	8 (0.129)	-8^b (0.094)	-1 (0.617)
Rural livelihood activities	-10 (0.757)	-33 (0.631)	10 (0.779)	-30 (0.899)
Off-farm and seasonal labour	8^a (0.399)	1 (0.747)	39^b (0.087)	27 (0.664)
Transportation	-24 (0.677)	43 (0.398)	-19 (0.254)	43 (0.562)
Education	0 (0.983)	0 (0.893)	0 (0.923)	4 (0.534)
Domestic	114 (0.123)	-15^a (0.553)	28 (0.409)	3^b (0.131)
Leisure	-18 (0.613)	31 (0.216)	22 (0.828)	35 (0.473)

How to read the table, example row 'Crop farming (others)': Women in animal-households spent the same and women in tractor-households spent 8 minutes less time compared to manual-households. While the first difference is statistically not significant (p=0.453), the second is at α=10%. A pairwise comparison between time-use of women in animal- and tractor-households was significant at α=10%, therefore the two values carry different lower case letters a and b.

Estimates of time spent on different activities from model (1) were compared in pairwise t-tests between men and women and between the three mechanization categories. Table 5 presents the difference compared to manual-households. Table 5 suggests that women in animal-households spent significantly less time (65 minutes) on land preparation compared to manual-households. This was not the case for men who thus have no extra time that could be spent on other activities. It is not clear for which activities the additional time that women in animal-households have is used. Potentially, time is spent on domestic work, which is 114 minutes higher but the difference is slightly above significance. In tractor-households, both men and women spent less time on land preparation activities compared to manual-households. The extra time seems to be used for off-farm work by women. Men in tractor-households spent more time on domestic work compared to animal-households but this is compared to low base, and compared to manual-households, no significant difference was found. This suggests that additional time saved might be distributed across all other time-use categories such as leisure and transport, and therefore, stays below detection level. Still, the hypothesis that males and females in mechanized households use their extra time differently can be confirmed.

Figure 3 presents a framework of how different activities are perceived by respondents. Following this framework, animal- and tractor-households spent less time on hard and non-enjoyable activities but more on enjoyable activities (such as child care, cleaning and cooking). Thus, despite not finding a significant difference with regard to time spent on leisure, respondents seem to have a higher life quality with regard to these criteria. Figure 3 faces some limitations, however, as the perceptions of enjoy-ability and work may be socially constructed and differ by gender. For example, women may have learned to "enjoy" doing domestic chores.

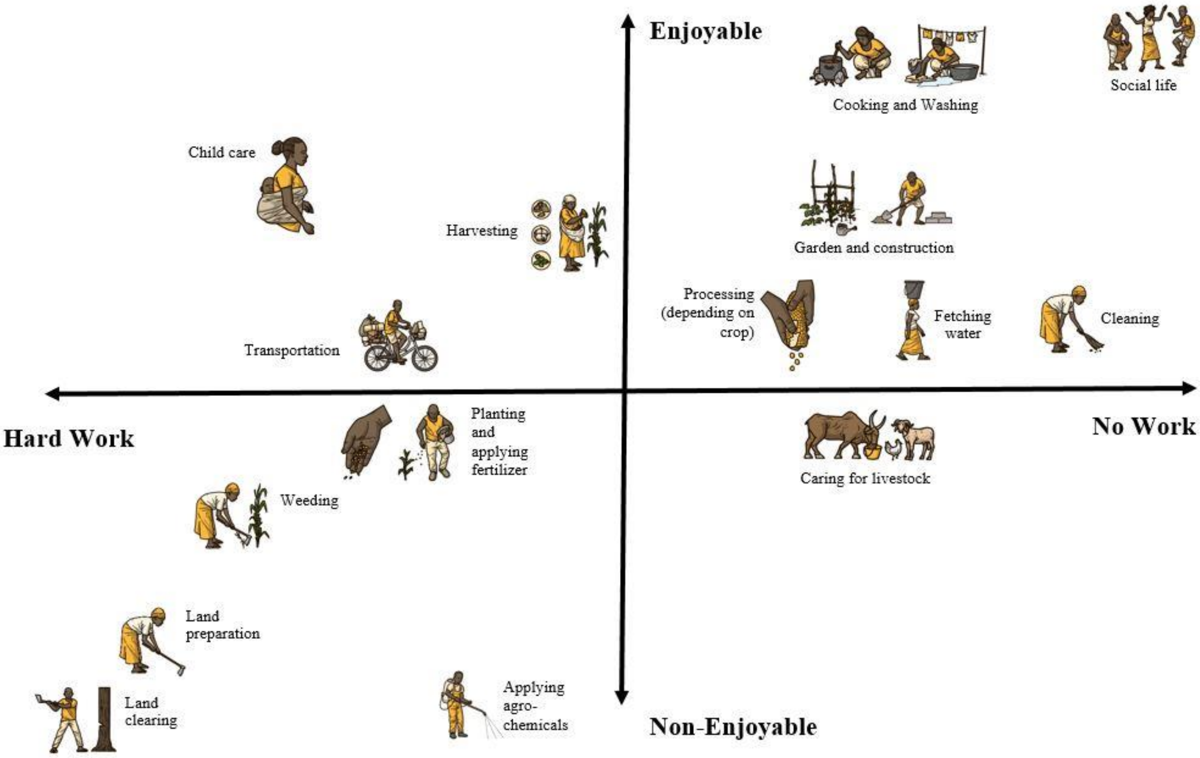

Figure 3: Matrix of activities by enjoyableness and drudgery.

4.3 What happens during the next farming steps?

In this section, the hypothesis is tested whether females spent more time on weeding and harvesting/processing on mechanized farms compared to non-mechanized farms. This could be the case when mechanized households cultivate more land, which increases the need for weeding and harvesting/processing, which might be primarily female tasks. The argument that mechanization leads to land expansion cannot be thoroughly analyzed in this study as it is based on cross-sectional data but seems plausible based on economic theory and previous studies. Adu-Baffour et al. (2018), for example, have shown that Zambian farm households mechanizing land preparation can double the amount of land cultivated. In this paper, the sampled tractor-households cultivated significantly (p=0.0053) more land (6.7 ha) than animal-households (3.9 ha); and animal-households cultivated significantly more land than manual-household (2.1 ha). The larger amount of land cultivated may be correlated with more time spent on weeding (and harvesting/processing). Indeed, table 6 suggests a significant effect of the interaction of mechanization and gender on the daily time-use composition during weeding based on model (1).

Table 6: Partial Wald-F-tests for fixed effects of model (1) at weeding

Effect	Description	Numerator DF	Denominator DF‡	F-value	p-value
μ_k	Effect of time-use category (tuc)	8	20	1313.09	<0.0001
τ_{kj}	tuc-specific Effect mechanization (M)	16	48	2.09	0.0249
γ_{kl}	tuc-specific Effect of gender (G)	24	72	83.82	<0.0001
$(\tau\gamma)_{kjl}$	tuc-specific Interaction of M and G	48	128	2.53	<0.0001

However, there is no significant gender differences in pairwise t-tests at α=10% between manual-households and animal-households for the single time-use category of 'weeding on the own farm' (figure 4). In tractor-households, men work significantly less than women and men and boys work significantly less compared to their counterparts in manual- and animal-households. This suggests that a gender differentiation for weeding activities only appears with the use of tractors and men especially benefit from this. However, neither girls nor women are negatively affected in terms of time-use.

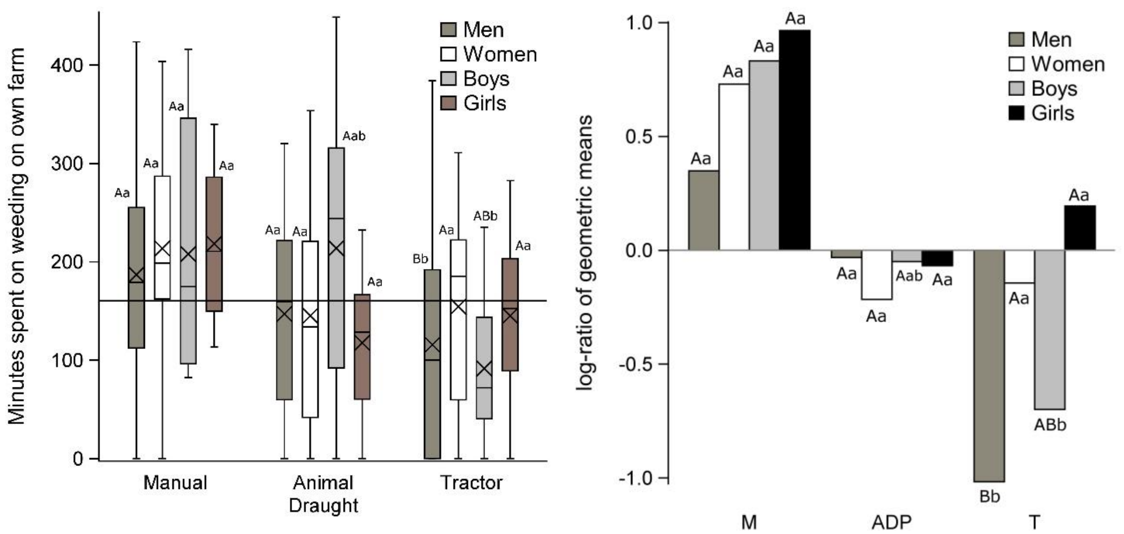

Figure 4: Boxplots (left) and descriptive log-ratios of geometric means (right) of time-use on weeding on own farm by mechanization and gender.

Despite cultivating more land, animal- and tractor-households do not spend more time on weeding. The time spent on weeding was highest for manual-households (204 minutes), significantly higher than animal-households (152 minutes, p=0.075). Time spent on weeding for animal-households did not differ significantly from tractor-households (130 minutes, p=0.308). However, time spent on weeding may also be influenced by other factors such as the use of herbicides and laborers, which are controlled for in table 7.

Table 7: Multiple linear regression of covariates on time-use for weeding, with parameter estimates for slopes, standard errors in parentheses and F-tests

Effect	Estimate	DF	F-value	p-value
Community	-	58.1	3.47	**0.0216**
Gender (M, F, B, G)	-	132	0.97	0.4103
Mechanization (M, A, T)	-	48.9	0.68	0.5133
Land cultivated	-0.4946 (0.09852)	57.5	25.20	**<0.0001**
Tropical livestock unit	-0.1130 (0.07136)	55.7	2.51	0.1191
Months with food shortage	-0.3685 (0.2661)	55.8	1.92	0.1717
Crop diversity	-0.4423 (0.4426)	54.0	1.00	0.3221
Off-farm income	-0.00004 (0.000038)	54.1	0.87	0.3550
Fertilizer per ha	-0.00323 (0.003439)	51.2	0.88	0.3516
Education	0.1128 (0.1302)	50.8	0.75	0.3905
Hired labour	-0.01037 (0.01338)	50.5	0.60	0.442
Pregnancy	-0.5667 (1.4045)	46.6	0.16	0.688
Household size	-0.06683 (0.2605)	46.8	0.07	0.7987
Distance market	-0.00840 (0.03059)	45.0	0.08	0.7848
Pesticides per ha	-0.01235 (0.05238)	43.7	0.06	0.8147
Gender * mechanization	-	122	0.44	0.8474
ADP weeding	-0.1296 (1.3958)	43.5	0.01	0.9265
Cost per land	0.000035 (0.000632)	40.8	0.00	0.9560

Multiple linear regression on square-root transformed time spent on weeding.

Table 7 shows that when controlling for covariates, the effect of mechanization on time spent on weeding becomes insignificant as the size of cultivated land has a larger influence on time spent on weeding. The relationship between cultivated land size and time-use for weeding is negative. For subsistence farming households with little land, weed control may be more essential than for households with large landholdings. Thus, the hypothesis that mechanization of land preparation is associated with increased female labor for weeding must be rejected.

However, this may still be the case for harvesting/ processing. Table 8 shows that there were no tuc-specific effects of mechanization and the interaction of mechanization and gender on the overall daily time-use composition during harvesting/processing.

Table 8: Partial Wald-F-tests for fixed effects of model (1) during harvesting/processing.

Effect	Description	Numerator DF	Denominator DF‡	F-value	p-value
μ_k	Effect of time-use category (tuc)	8	20	1659.88	<0.0001
τ_{kj}	tuc-specific Effect mechanization (M)	16	48	0.46	0.9560
γ_{kl}	tuc-specific Effect of gender (G)	24	72	14.88	<0.0001
$(\tau\gamma)_{kjl}$	tuc-specific Interaction of M and G	48	136	1.18	0.2251

In pairwise t-tests on the single time-use category of harvesting/processing no gender differences were found in manual-households based on model (1). In animal-households, girls work significantly less than all other household members, while boys work less in tractor-households (see figure 5).

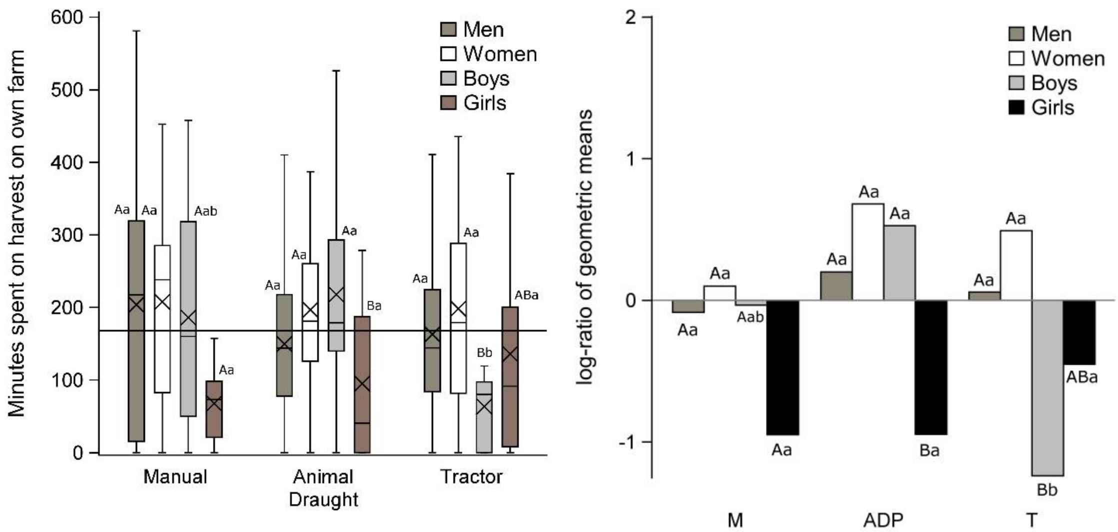

Figure 5: Boxplots (left) and descriptive log-ratios of geometric means (right) of time-use on harvesting/processing on own farm by mechanization and gender.

Table 9 shows that factors other than mechanization have a bigger influence on time spent on harvesting/processing. This includes livestock owned based on tropical livestock units – potentially, households with more livestock spend more time caring for animals and have less time for harvesting/processing. Another factor is the use of hired labor: households hiring more labor spent less time on harvesting/processing. Finally, households with more months of food shortage spent less time on harvesting/processing (even after yields were dropped from the regression), a phenomenon that may show that households who suffered food shortages consume most of the harvest directly rather than processing for sale or harvest more while green. It may also be that such households have less energy to work.

Table 9: Multiple linear regression of covariates on time-use for harvesting/processing with parameter estimates for slopes, standard errors in parentheses and F-tests

Effect	Estimate	DF	F-value	p-value
Gender (M, F, B, G)	-	132	4.70	**0.0037**
Tropical livestock unit	-0.1366 (0.07523)	55.6	3.30	**0.0748**
Hired labour	-0.03548 (0.01575)	56	5.07	**0.0282**
Months with food shortage	-0.7116 (0.3024)	56.2	5.54	**0.0221**
Community	-	53.1	1.61	0.1981
Pregnancy	-2.0299 (1.4822)	51.6	1.88	0.1768
Off-farm income	-0.00004 (0.000039)	53	0.99	0.3232
Mechanization (M, A, T)	-	48.9	0.05	0.9481
Gender*mechanization	-	125	0.99	0.4362
Cultivated land	0.1362 (0.1679)	49.5	0.66	0.4213
Crop diversity	-0.4907 (0.5282)	45.4	0.86	0.3578
Distance market	-0.02771 (0.03342)	45.3	0.69	0.4113
Education	0.07261 (0.1518)	45	0.23	0.6374
Fertilizer per ha	-0.00186 (0.004419)	42.9	0.18	0.6764
Cost per ha	0.000296 (0.000666)	42.3	0.20	0.6584
Household size	0.07607 (0.3025)	43.1	0.06	0.8026
Yield	0.000069 (0.000459)	41.5	0.02	0.8819

Multiple linear regression on square-root transformed time spent on harvesting/processing.

The hypothesis that agricultural mechanization during land preparation increases female labor needed for harvesting/processing has to be rejected.

5 Discussion and conclusion

New technologies, policies and practices can affect the intra-household allocation of time in smallholder farming households, which may put more vulnerable household members at a disadvantage. Understanding time-use effects is important to target policy interventions. However, exploring such effects has been difficult because 1) a lack of suitable data collection methods and 2) the structure of time-use data, which cannot be addressed with conventional statistical methods. This study showed that using a pictorial smartphone application called Timetracker provides sufficiently good and comprehensive data to study such concerns. Furthermore, the study has shown that compositional data analysis can be used to address the specific challenges of time-use data. Solving these two challenges, the study then explored the time-use effects of agricultural mechanization.

The results confirm existing literature that some farming activities such as land preparation are gendered (Alesina, 2011; Baanante et al., 1999). However, in this study the gender differentiation for land preparation activities (and weeding) only emerges with mechanization. No evidence could be found that harvesting/processing are gendered activities. This echoes findings from Doss et al. (2001) and Palacios-Lopez et al. (2017) who question stylized facts on the gender division of agriculture. The study finds that men and women benefit from agricultural mechanization with regard to time-use and that women benefit relatively more than men. It remains unclear whether this is a sign of empowerment or dis-empowerment as once they are not working on the fields, women may have less influence on farming, including farm income. This resonates with Alesina et al. (2011), who found that historically plough-based societies were less dependent on female labor compared to hoe-based societies and still have lower rates of female participation in work and society today. No significant evidence of time benefits for children during land preparation was found. However, Adu-Baffour et al. (2019), having a larger sample and focusing on the whole of Zambia, found that children benefit from agricultural mechanization. In general, surprisingly few gender differences between boys and girls were found, which may however be due to the sampling of the eldest children only. Future studies should study gender roles with regard to children more explicitly.

Time “saved” due to mechanization seems to be distributed across various activities, with some evidence that women in animal-households use the “saved” time on domestic chores, which may be a sign of dis-empowerment; women in tractor-households use the extra time for off-farm work, which may be a sign of empowerment. In tractor-households, men spent significantly more time on domestic work but this is compared to a very low base. No negative second-round effects of increased time-use for weeding by women was found, despite mechanized household cultivating more land. A reason might be that mechanized land preparation reduces weed pressure (Nyamangara et al., 2014). Also, households with more land spent less time on weeding as the intensity of labor use may decrease with farm size (Sen, 1952; Wineman and Jayne, 2017). During harvesting/processing, no effects of mechanization during land preparation on time-use were found.

As mentioned above, the study faces some limitations. Given that the focus has been on finding a reliable way to collect time-use data and how to analyze such data, the sample remained small. In subsequent studies, larger sample sizes should be envisaged. Ideally, future studies can find ways to use a randomized control trial (RCT) approach to establish causality. However, while using RCTs is not impossible, they would be challenging to set-up given the ado-hoc adoption of tractor service and the diversity of agronomic conditions of farmers. Future study should at least envision having a larger sample and using propensity score matching. Another limitation is that the extrapolation of the daily data to the entire farm season remains difficult. Given these limitations, the study remains cautious with regard to policy implications. While no evidence of agricultural mechanization negatively affecting woman and children was found, this may be different in other situations depending on the tasks and crops are mechanized, the use of accompanying inputs as well as the existing gender roles and how they can be re-negotiated (Alderman, 1995; Doss, 2013; Fisher et al., 2000).

The study provides proof-of-concept that using picture-based smartphone apps can help to collect data on research areas that are difficult to measure and analyze but that are potentially highly relevant. Thus, the study opens the field to more studies focusing on agricultural development and time-use in rural areas. For example, this study found a high share of time spent on mobility and transportation (see appendix), which is often neglected by studies focusing on time-use in agriculture, although reducing such time use may allow farmers to spend more time on their fields. Similarly, the time-use effects of technologies for home economics such as improved cook stoves, electronic household items and processed food, which may all help to reduce time poverty among women and loosen constraints to participate in paid work, may be interesting to study.

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Appendix

Table A1: Time-use by gender and mechanization across seasons.

Activities and Season	*Males*			*Females*			*Boys*			*Girls*		
Season	M	ADP	T	M	ADP	T	M	ADP	T	M	ADP	T
Land Preparation												
Crop farming (land preparation)	146	115	64	120	54	16	48	57	44	45	51	26
Crop farming (others)	38	46	38	56	56	48	30	9	36	41	23	45
Rural livelihood	166	133	136	44	34	55	21	81	25	26	37	55
Off-farm work and seasonal labour	5	6	32	0	8	39	4	1	7	9	5	0
Transportation	142	186	186	108	83	89	113	137	140	152	154	124
Education	0	0	4	0	0	0	46	138	60	105	74	71
Domestic	26	11	29	234	349	262	182	114	170	151	144	162
Personal care	597	589	596	590	585	622	657	607	638	588	623	621
Leisure	312	343	347	276	258	298	330	285	308	309	319	326
Weeding												
Crop farming (weeding)	187	147	116	213	145	154	208	214	92	218	118	145
Crop farming (others)	46	82	86	50	75	43	38	57	61	47	81	52
Rural livelihood	51	77	91	18	6	30	37	9	29	0	16	22
Off-farm work and seasonal labour	62	15	2	14	13	33	4	3	1	20	35	15
Transportation	117	220	223	107	100	108	126	118	169	114	144	147
Education	0	0	0	0	0	0	1	10	0	0	4	3
Domestic	19	12	19	200	290	185	121	138	103	169	110	136
Personal care	605	574	609	613	590	637	634	642	675	622	625	651
Leisure	345	305	288	216	212	241	264	238	303	242	297	264
Harvesting/processing												
Crop farming (harvesting/processing)	204	150	163	208	197	198	186	218	64	68	95	136
Crop farming (others)	18	9	1	6	1	1	0	0	3	1	4	1
Rural livelihood activities	69	58	69	17	15	14	6	11	34	10	16	7
Off-farm work and seasonal labour	0	21	36	0	0	10	0	0	0	5	68	0
Transportation	164	272	159	86	134	67	111	157	146	124	87	89
Education	0	0	0	8	3	1	78	41	85	103	52	55
Domestic	19	17	29	246	278	235	169	78	116	201	157	172
Personal care	656	618	651	630	654	655	659	600	701	641	627	661
Leisure	305	288	326	232	198	252	225	328	287	281	280	313