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# Adoption of Combine Harvester Custom Hiring and Its Impact on Crop Productivity and Farm Income: The Case of Smallholder Farmers in Northwestern Ethiopia.

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## COLLEGE OF AGRICULTURE AND ENVIRONMENTAL SCIENCES DEPARTMENT OF AGRICULTURAL ECONOMICS


# ADOPTION OF COMBINE HARVESTER CUSTOM HIRING AND ITS IMPACT ON CROP PRODUCTIVITY AND FARM INCOME: THE CASE OF SMALLHOLDER FARMERS IN NORTHWESTERN ETHIOPIA.

**M.Sc. Thesis**


**By**

**Tewodros Gete**



**February 2023**

**Bahir Dar, Ethiopia**

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**SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE (MSc.) IN AGRICULTURAL ECONOMIC**

**Adviser : Zemen Ayalew (PhD)**

**February 2023**

**Bahir Dar, Ethiopia**

## THESIS APPROVAL SHEET

As member of the Board of Examiners of the Master of Sciences (M.Sc.) thesis open defense examination, we have read and evaluated this thesis prepared by Mr. Tewodros Gete entitled "**Adoption of Combine Harvester Custom Hiring and Its Impact on Crop Productivity And Farm Income: The Case of Smallholder Farmers in Northwestern Ethiopia.".** We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Sciences (M.Sc.) in Agricultural Economics.

**Board of Examiners**

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Name of Internal Examiner: Zewdu Berhanie (PhD) Signature __________ Date 1/05/2023

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# DECLARATION

This is to certify that this thesis entitled "**Adoption of Combine Harvester Custom Hiring and Its Impact on Crop Productivity And Farm Income: The Case of Smallholder Farmers in Northwestern Ethiopia."** submitted in partial fulfillment of the requirements for the award of the degree of master of science in **"Agricultural Economics"** to the graduate program of **College of Agriculture and Environmental Sciences**, Bahir Dar university by Mr **Tewodros Gete** is an authentic work carried out his under our guidance. The matter embodied in this project work has not been submitted earlier for award of any degree or diploma to the best of our knowledge and belief.

Name of the Student: Tewodros Gete Signature____________________Date 17/ 2/2023

Name of the advisor: Zemen Ayalew (PhD) Signature ________________Date 17/2/2023

# DEDICATION

This thesis is dedicated to my Mother am the only son for her. Her love, prayers, and support have been the driving force that pushed me through this course of study.

# ACKNOWLEDGMENT

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# ABSTRACT

*Small holder farmers in Ethiopia can't increase their productivity and income due to lack of agricultural mechanization, even though agricultural mechanization has crucial socioeconomic benefits. The traditional method of harvesting makes it difficult to perform various farm operations in a timely manner, resulting in worsening loss of crops on farms during harvesting and threshing. The adoption and impact of agricultural mechanization on smallholder farmers' crop productivity and income have not been adequately studied. The major objective of this study was to assess the impact of combine harvester custom hiring on households' crop productivity and farm income. As well, the study examined the smallholder farmer's decision to hire a combine harvester and its financial profitability. Multi-stage sampling was used to gather data from 450 households in seven sample kebeles from Gozamin, Baso Liben, and Debre Elias districts in northwestern Ethiopia. Descriptive statistics, inferential statistics, binary logit model, truncated Poisson model, and an endogenous switching regression (ESR) model were used to analyze the data. The logistic result shows that the educational status of the household head, immediate access of the combiner, average field distance to the main road, fear of unseasonal rain, extension contact, and mobile phone possession had a significant positive effect on the hiring decision of combine harvester. On the other hand, the male household head and the active family labor force impacted the hiring decision of a mechanical harvester negatively. In the truncated regression, active family labor force, oxen, immediate access, type of combiner leaser, and straw waste suspicion were significant determinants of the intensity of custom hiring on the farmer's wheat plots. According to the ESR model results, adopters' crop productivity and farm income increased by 5.60 quintals per hectare and 12764.34 birrs as a result of hiring combine harvesters. Non-adopters would also gain 6.10 quintals per hectare and 8051.82 birrs if they had been hired. The hiring of combine harvester technology has an indispensable contribution to the improvement of smallholder productivity and income and it is financially profitable. The government, private stakeholders, and other concerned parties should facilitate the custom hiring of existing machinery; besides importing or manufacturing agricultural machinery that is well suited to the Ethiopian agricultural system perspective so as to separate farmers from oxen and change traditional agriculture practices.*

**Keywords:** Combine harvester; Custom hiring; Logit model; Truncated Poisson model; ESRM

# Table of Contents

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF APPENDICES

# ACRONYM AND ABBREVIATIONS

| | |
|---|---|
| ANRS | Amhara National Regional State |
| ATA | Agricultural Transformation Agency |
| ATT | Average Treatment Effect on the Treated |
| ATU | Average Treatment Effect on the Untreated |
| BCR | Benefit Cost Ratio |
| BLWOA | Baso Liben Woreda office of Agriculture |
| CDF | Cumulative Density Function |
| CSA | Central Statistics Agency |
| CADU | Chilalo Agricultural Development Unit |
| DA | Development Agent |
| DEWOA | Deber Elias Woreda Office of Agriculture |
| EGTE | Ethiopian Grain Trade Enterprise |
| ELAR | Ethiopian Institute of Agricultural Research |
| ESRM | Endogenous Switching Regression Model |
| FAO | Food and Agricultural Organization |
| FDRE | Federal Democratic Republic of Ethiopia |
| FIML | Full Information Maximum Likelihood |
| GWOA | Gozamin Woreda Office of Agriculture |
| HE | Heterogeneity Effect |
| IPW | Inverse Probability Weighting |
| LPM | Linear Probability Models |
| LR | Linear Regression |
| METEC | Metals and Engineering Corporation |
| MOANR | Ministry of Agriculture and Natural Resources |
| MPP | Minimum Package Program |
| NTAP | Nazareth Tractor Assembling Plant |
| OLS | Ordinary Least Square |
| PDF | Probability Density Function |
| PSM | Propensity Score Matching |

| | |
|---|---|
| PHL | Post-Harvest Loss |
| SD | Standard Deviation |
| SDG | Sustainable Development Goals |
| SIDA | Swedish International Development Agency |
| SSA | Sub-Saharan Africa |
| TLU | Total Livestock Unit |
| THS | Tractor Hiring Service |
| UNDESA | United Nations Department of Economic and Social Affairs |
| UNDP | United Nations Development Program |
| USAD | United States Academic Decathlon |
| USSR | United Socialist Soviet Republic |
| WADU | Wolaita Agricultural Development Unit |
| ZTPM | Zero Truncated Poisson Model |

# Chapter One: INTRODUCTION

## 1.1 Background

According to UNDESA (2019), Sub-Saharan African countries' populations are projected to double by 2050 G.C. The population growth rate of Ethiopia was ranked fifth globally. Also, a total of 133.5 million people lived in the country in 2032 G.C, which increased to 171.8 million in 2050 G.C (Alemayhu Bekele and Yihunie Lakew, 2014). It is expected that an additional billion tons of cereal grains would be required. So as to feed a growing population, the country needs to improve agricultural productivity (FAO, 2017).

UNDP estimates that 68.7 percent of Ethiopia's population (80,553 people) is multidimensional poor in 2022 G.C (https://www.undp.org/). It was estimated that an average smallholder farm in Ethiopia only earns a gross annual income of 1,246 USD. The smallholder agriculture in the country is subsistence-oriented, as only 21 percent of its production is sold (FAO, 2018). Improving income and reducing poverty can be realized by enhancing the productivity in agriculture that can be achieved through adoption of agricultural technologies (Mesele Belay *et al*., 2022; Tigist Mekonnen, 2017). However, the economy remains heavily dependent on rain-fed agriculture, which has very low productivity. Also, there are a number of factors that shrink crop productivity such as inadequate application of improved technology( inputs), vulnerability to climatic shocks, lack of farmland, fragmentation, and traditional farming methods (Gebissa Yigezu, 2021).

Changing patterns of precipitation and temperatures, recurring droughts, hailstorms, and erratic rainfall are the most common and frequent climate-related shocks in the country (Birtukan Atinkut and Abraham Mebrat, 2016). Thus, rural communities became increasingly dependent on foreign food aid and seasonal migration to meet growing food demands. Similarly, agricultural production would be adversely affected by climate change in the coming decades, and the severity would increase over time; among other commodities, production of teff, maize, sorghum, barley and wheat is expected to decrease in the coming decades by 25.4%, 21.8%, and 25.2% 30% and 25.5 %, respectively (Zerihun Yohannes *et al*., 2018).

Land fragmentation increase the amount of time spent moving from one parcel to another; it leads to a reduction in agricultural output (Knippenberg *et al*., 2020). Fragmented land hinders the use of agricultural machinery (Sui *et al*., 2022). Also the small farm size results in low yields and makes mechanization difficult. A majority of Ethiopia's agricultural production comes from small-scale farmers, who occupy more than 95% of the area under agricultural production (Diriba Welteji, 2018). Official data on landholding size in country were 38 % of households own less than 0.5 hectares, 23.65% own between 0.51 and 1.0 hectares, 24 percent own between 1 and 2 hectares, and 14 percent own more than 2 hectares of land (Asmamaw Mulusew and Mingyong, 2023; Gebissa Yigezu, 2021).

Smallholder farmers cannot increase their productivity and income due to lack of agricultural mechanization and technology. It is estimated that only 0.7% of Ethiopian farmers use mechanized agriculture for land preparation and less than 0.8% for crops threshers (Diriba Welteji, 2018). Similarly, only 3.7 percent of smallholder farmers have access to agricultural machinery (FAO, 2018). Mechanized harvesting and threshing has crucial socioeconomic impact, it helps to increase the efficiency of farm labor and reduce drudgery and workload, improve harvesting operation and reduce post-harvest losses. Also it minimizes production costs and allows farmers to earn more income. With the advent of mechanized harvesting and threshing, rural youth have more opportunities and women have more time for other activities during harvest time (Castelein *et al*., 2022). As a result of the adoption of alternative farming technologies, soil fertility, farmers' productivity, consumption, income, and overall farmers' welfare in Ethiopia have improved (Aryal *et al*., 2019).

In Ethiopia, the use of agricultural mechanization greatly varies among regions. Arsi-Bale areas of Oromia region have been high level of mechanization use due to the highly productive land in the region as well as the presence of commercial farms and large holder farms (Stickney et al., 1986). Nowadays, in major wheat growing areas, such as Arsi and Bale zones in Oromia region and West and East Gojam zones in Amhara region, wheat is harvested using combine harvester being operated on hire service arrangement (Yohannes Mekonnen, 2021).

Most small holder farmers can’t own farm machinery for self-use on their own farms due to small farm scale owned. Since combine harvester are not possible to utilize to their full capacity, they are forced to look for a collective use such as private contractors, machinery cooperative, national machinery hiring. Custom hiring companies of farm machinery are a unit comprising a set of farm machinery, implements and equipment for hiring to farmers. These companies give farm machinery on a rental basis to farmers who can’t afford to purchase high-end agricultural machinery and equipment. Due to the above mentioned reasons, farmers made decision to hire different agricultural machineries and equipment from service providers (Sukhpal and Kingra, 2013).

Cereals are the major food crops in terms of both the area planted (81.19%) and volume of production obtained (88.36 %). The major cereal crops produced in the country are teff, maize, sorghum and wheat that cover up to 22.56%, 19.46%, 12.94% and 14.62% of the grain crop area, respectively. Also, 474,813.86 quintals were harvested from 147,694.69 hectares of wheat crops, with an average yield of 32.12 quintals per hectare(CSA, 2021). The most suitable areas for wheat production fall between 1900m and 2700m in the highlands where rainfall distribution is bimodal and ranges between 600mm and 2000mm (Amare Aleminew and Merkuz Abera, 2020). East Gojjam has an altitude range of 1159 to 2600 meters above sea level and annual rainfall of 900 to 1800 mm on average, which is stable for wheat cultivation (Amare Gibru and Yihew Biru, 2022; Setotaw Ferede *et al*., 2020).

However, the country suffers from high on farm cereal post-harvest losses; grains are mostly lost at the farm level and the potential solutions need to be found there. Yet it hasn't received much attention until recently for the loss of quality and quantity of cereals (Sisay Debebe, 2022). The post-harvest losses had a significant impact on food security and income, showing that more than 23 million people could be fed through proper postharvest management. The economic loss of major food and cash crops experienced between 2009 and 2019 is 1.2 billion US dollars per annum. The amount represents 10% of the average annual national budget for the years 2018-2022 G.C (Tadesse Fikre, 2022).

Similarly to other districts of the Amhara region, the East Gojam zone has high wheat yield potential (Yirgalem Eshete *et al*., 2021). In spite of this, the East Gojam zone lost a substantial amount of wheat crops. There was approximately 203.1 kg ha-1 loss from harvesting, 105 kg ha-1 loss from threshing, and 63.6 kg ha-1 loss from cleaning of wheat yield. Also it is estimated that 12.9% to 17.5% of wheat is lost from the total production in Debre Elias district, with an average loss of 15.2% (Tadesse Dessalegn *et al*., 2017).

## 1.2 Statement of the Problem

Crop production and productivity is low to feed the growing population in Ethiopia (Mutimura *et al*., 2018). It made difficult to attain food self-sufficiency for the country. The average grain yield for main cereal crops is less than 1 ton per hectare. The magnitude of post-harvest losses of crops for cereals is about 15.5 to 27.2% for major grain crops and 23% average loss for all crops during harvesting season. The occurrence of rain and storms in peak harvesting season is considerable exacerbate the damage of standing crops (Samuel Gebreselassie *et al*., 2017).

In harvesting operations, time and harvesting methods are critical factors that determine losses (Kumar and Kalita, 2017). On-farm postharvest losses of crop are quite significant during traditional harvesting method (Mohammed and Tadesse, 2018). In Ethiopia mostly farm power is draft oxen and human muscle in the post-harvest operations. Trampling of grain, scattering and spoilage are common causes of crop losses during traditional threshing. The use of traditional methods makes it difficult to accomplish various farm operations in a timely manner, which is necessary for crop production. In addition, live animal and human threshing both results in significant quality and quantity losses, as well as being time consuming and arduous (Teha *et al*., 2020).

Also insufficient maturation and moisture content can cause a large number of losses during harvesting. The early harvest of crops with high moisture content increases the cost of drying, making it susceptible to mold growth and insects invading, resulting in broken grains and low grinding efficiency. However, leaving mature crops on the field causes large losses, including broken and fallen crops, exposure to pests ( bird, rodents and other animals) and natural disasters like unseasonal rain, hail, etc. (Banjaw, 2017).

Wheat grain yields in Ethiopia are significantly reduced during harvesting, drying, handling, and storage. The percentage of wheat post-harvest loss from the total product is maximum at harvesting 6.1 % and threshing 3.5 % (Tadesse Dessalegn *et al*., 2017). At farm level, wheat post-harvest loss during harvesting and threshing is a serious problem. Since postharvest losses significantly impact crop yields and income, it is important to identify remedial options (Dubale Befikadu, 2018).

Agricultural mechanization is an integral part of effective growth in agricultural productivity (Seife Ayele, 2022). However, it is still limited in Ethiopian agriculture despite its significant benefits for smallholder farmers (Muluken Gezahegn *et al*., 2021). The Ethiopian agricultural transformation agency (ATA) has introduced combine harvesters in the study area before the past ten years harvesting and threshing and yet a sizeable number of growers are still harvesting and threshing their wheat manually and/or threshing by animal trampling (Yohannes Mekonnen, 2021). A farmer's limited agricultural land holdings and high farm machinery costs make it impossible to purchase farm machinery for self-use (Yared Deribe and Bisrat Getnet, 2021). Nowadays, farmers are using custom hiring services of agricultural machinery for farm operations. It enables smallholder farmers to utilize the appropriate equipment for agricultural activity. However, the country does not yet have custom hiring service regulated policies and facilitation centers. The hiring decisions are based on several factors whose relative importance varies among farmers.

Ethiopia is the primary wheat producer in Sub-Saharan Africa (SSA) owing to the suitable agro-ecological conditions; it's demand has increased dramatically due to population growth, urbanization, and lifestyle changes (Minot *et al*., 2019). Moreover, wheat is an important cereal for Ethiopia's food security, poverty alleviation, and income generation. However, smallholder farmers have low wheat yields (Mulu Nigus *et al*., 2022). More than 1 million tons of wheat is imported into the country each year for domestic consumption. It has been recorded that wheat imports have grown significantly from time to time, causing the country to pay additional foreign currency (https://www.world-grain.com/).

It has been reported that the government has allocated $6 million towards improving irrigation, input supply, and machinery rental services (https://afriagrimagazine.com/). Apart from this, the government works hard to achieve the Malabo Declaration of the Africa Union's goals of halving post-harvest losses by 2025 and 2030 global targets of the SDGs of ending poverty and hunger. The country remains far below post-harvest loss targets and net importer of wheat despite such policy action (Sisay Debebe, 2022).

Also, the country have been working on developing a comprehensive mechanization strategy by collaboration with the Agricultural Transformation Agency (ATA) and the Ministry of Agriculture and Natural Resources (MoANR) and by setting ambitious targets on mechanization in the country's Growth and Transformation Plan. It aligned with the objectives of the country's industrialization strategy and its plans for the greening of the economy. Despite this, few smallholders own and use machinery in the country, and only 700 combine harvesters are active for farming operation (Guush Berhane *et al*., 2017).

The central question is: does the custom hiring of combine harvesters mechanization bring change on smallholder farmer's crop productivity and farm income in Ethiopian farming perspective? If yes, how much is the impact of this technology? There have been numerous studies regarding the adoption and the impact of improved agricultural technology on the well-being of smallholders farmers (yield, child nutrition, productivity, and income) (Bekele Wegi, 2020; Berhe Gebregewergs, 2016; Dawit Milkias and Abduselam Abdulahi, 2018; Demelash Abewa *et al*., 2020; Kassa *et al*., 2014; Menasbo Gebru, 2020; Mesele Belay and Markew Mengiste, 2021; Solomon Asfaw and Bekele Shiferaw, 2010; Solomon Estifanos *et al*., 2021; Workineh Ayenew et al., 2020; Zeng *et al*., 2017). Although studying the impact of improved agricultural technology is a good contribution, the issue of agricultural mechanization is needed to sustain the small holder farmer welfare.

Additionally, there have been studies undertaken on the adoption and willingness to adopt tractor and combine harvester hire services by (Aryal *et al*., 2019; Astewel Takele and Yihenew G.Selassie, 2018; Mishra and Satapathy, 2021; Owombo *et al*., 2012; Pingali, 2007; Praweenwongwuthi *et al*., 2010; Schmitz and Moss, 2015; Takeshima *et al*., 2020; Thakur *et al*., 2004; Wubamlak Ayichew *et al*., 2021; Xangsayasane *et al*., 2019; Yohannes Mekonnen, 2021). They hadn't measured the impact of these technologies on smallholder economic welfare in smallholder farming context. This motivated the researcher to investigate the barriers of smallholder farmers to hire the existing technology and to assess its change on crop productivity and income.

## 1.3 Objectives of the Study

### 1.3.1 General objective

The main objective of the study is to analysis the determinant and impact of combine harvester custom hiring on the smallholder farmers crop productivity and farm income.

### 1.3.2 Specific objective

- To examine the factor that affects the custom hiring decision of combine harvester
- To examine the factor that affects the intensity of combiner harvester custom hiring decision
- To estimate the impact of combine harvester custom hiring on wheat productivity
- To estimate the impact of combine harvester custom hiring on gross farm income
- To assess and compare the profitability of alternative wheat harvesting methods

## 1.4 Research Questions

1. What are the major factors affecting the farmers custom hiring decision of combine harvester?
2. What are the major factors affecting the intensity of combiner harvester custom hiring decision?
3. Does hiring of combine harvester bring change in the productivity of wheat crops on smallholder farming perspective?
4. Does hiring of combine harvester bring change in farm income on smallholder farming perspective?
5. What are the profitable methods of harvesting by small holder farmers?

## 1.5 Significance of the Study

Harvesting wheat by combine harvester is one aspect of mechanization in wheat farming. Thus, it is appropriate to conduct a study on the impact of combine harvester custom hiring on smallholder benefits. Due to the fact that the technologies were imported from overseas and sometimes not well fitted to our farming perspective, smallholder farmers had been unsatisfying and complaining.

These results may contain useful information that could be put to use in identifying and resolving the difficulties that farmers face when hiring combine harvesters. It is important to estimate mechanization's effect on reducing on-farm post-harvest loss as part of the Ethiopian government’s vision to become wheat self-sufficient in the future.

The study assists the condition for the custom hiring of combine harvesters, and thus, may help combine harvester owners to market their service to wheat farmers effectively. Similarly, farmers’ associations and cooperatives may use this funding to start up mechanization hiring service membership. Also apart from helping the government, this study could also help the private agricultural mechanization importer and producer realize the smallholder farmer’s feedback on the current wheat crop harvesting technology. Furthermore, it is essential to draw lessons and as baseline information for future studies.

### 1.6 Scope and Limitation

The study examines the impact of combine harvester custom hiring only on crop productivity and gross farm income among farmers only small geographical area. However, the impact of this technology on other economic and social aspects is beyond the scope of this work. Basically, the study focused only on one mechanization custom hiring service of combine harvester operation (big machine), not on the mini combine harvester (walking tractor) or other harvesters.

The findings of this research are based on the data available at the time, while the results of the study may have caution because of possible response bias. Further studies might be needed to enrich and investigate a more in-depth study on a wider geographical scale including for additional mechanization services and by using panel data, it possible to capture more time-variant effects.

### 1.7 Organization of the Thesis

The thesis consists of five chapters; in the remaining chapters, a review of various theoretical and empirical works of literature is provided in chapter two. The third chapter discusses the methodological aspects of study sampling and model specification. The fourth chapter of the study deals with the main findings of the study. Final conclusions and recommendations are discussed in the last chapter based on the major findings.

# Chapter Two: LITERATURE REVIEW

## 2.1 Concept and Definition

**On-farm postharvest losses:** These include losses incurred during reaping, hauling, and heaping, threshing, winnowing, drying, and storing grain on the field etc. (Arah et al., 2015).

**Off-farm postharvest losses:** The losses incurred during the transportation, storage, marketing, and processing of the grain away from the farm after harvest (Arah et al., 2015).

**Agricultural Mechanization**: The application of tools, implements, and machinery to achieve agricultural production. To mechanize means to use machines to accomplish tasks or operations, it could be simple hand tools, animal-drawn implements, or sophisticated mechanical machines (Clarke, 2000; Engineering, 1999).

**Combine harvester**: It is a machine designed for harvesting, threshing, separating, cleaning and collecting grains while moving through standing crops in a single operation.

**Custom hiring**: Custom hiring service is a farm machinery business that is managed by either a group or an individual to provide renting service for performing farm operations (Landers, 2000).

## 2.2 Theoretical Literature Review

### 2.2.1 Agricultural mechanization practice in Ethiopia

While Ethiopia has had a long history of agriculture, agricultural mechanization and farm implements were not developed until the late 1950 E.C (Guush Berhane *et al*., 2017). A history of animal power and hand tool-based agricultural practice has existed in the country since time immemorial. A farming technology that uses draught animals is more related to the highland culture, whereas hoe culture predominates in the fertile southern parts of the country (Friew Kelemu, 2015). Agroforestry is characterized by hand hoes as the most important farm implement, as opposed to cereal-based systems that use oxen-driven *Maresha* (Habtamu Muche *et al*., 2022). Despite this, mechanization is not a new concept in Ethiopia for improving agricultural productivity. Agricultural mechanization had been given different levels of emphasis during the last three governments.

In a feudal system during the emperor's time, smallholder farmers had limited land rights under the goodwill of their landlords (Tesfaye Desalegne, 2020). Agricultural development was not given adequate attention until food shortages shook the country in the 1950 E.C, when food imports were initiated for the first time. Since then, agricultural development strategies aimed at improving domestic production began emerging between 1950 E.C and 1960 E.C.

Agriculture mechanization education was first introduced at Alemaya College of Agriculture, Mechanization and Art in 1958 E.C (Dawit Alemu, 2014). In the 1960 E.C, the Chilalo Agricultural Development Unit (CADU) and Wolaita Agricultural Development Unit (WADU) were established with support from the Swedish International Development Agency (SIDA). The CADU and WADU demonstrated the use of agricultural mechanization in addition to improved seeds and chemical fertilizers. Moreover, the government designed a package of improved technologies for smallholder farmers in WADU and CADU under the Minimum Package Program (MPP) (Adugna Haile et al., 1991). However, these development strategies tended to focus mostly on supporting large-scale capital-intensive private farms primarily cereals producers, the Awash Valley were one of them (Cohen *et al*., 1987).

In 1976 E.C, when the Dergue seized power, the Agricultural Implements Research and Improvement Center was founded at Melkasa Agricultural Research Center. There were various farm implements developed and tested for tillage, planting, threshing, and crop storage *(*Sime *et al*., 2004). Nazareth Tractor Assembling Plant(NTAP) was established by the Dergue government in 1984 E.C under technical and economic cooperation agreements with the Soviet Union (Diao *et al*., 2016).

Plant workers assembled tractors using tractor parts imported from socialist countries, such as the Union of Soviet Socialist Republics (USSR). The tractors and their implements assembled at NTAP were sold to state farms. Agricultural mechanization focused mainly on state farms due to the socialist ideology that nationalized most of these large farms. Almost all development activities are planned centrally under the command economy, a proclamation of

1975 E.C that recognizes only large-scale mechanization on state farms except a fewer cereal-based cooperatives (https://www.globalsecurity.org/).

There was a relatively liberal market for agricultural technology under the federal democratic republic of Ethiopia (FDRE) periods, which involves both the public and private sectors. The tractor assembly plant established by the former government was renamed Adama Agricultural Machinery Industry (AAMI). This industry was transferred again in 2010 E.C to the Metals and Engineering Corporation (METEC), which manages a number of sister industries. It manufactures and assembles tractors, water pumps, agricultural combiner, and other products. Products from this corporation are used by the government, farm unions, and state owned enterprises for agricultural, and water irrigation related projects (www.metec.gov.et). As mechanization research gained significant attention, a directorate of agricultural mechanization research was established in 2000 E.C at the Ethiopian Institute of Agricultural Research (EIAR).

Since there hasn't been a clear policy that facilitates agricultural mechanization over the past three governments, the mechanization-related issues discussed above are mostly derived from agricultural development strategies and programs designed by the governments. Ethiopian agriculture heavily relies on traditional farm power sources in contrast to other parts of SSA, as the country has low access to farm machinery. Mechanization once implemented with much ambition and ultimate failure has resulted in unsuitability for Ethiopian conditions (Yared Deribe and Bisrat Getnet, 2021).

In addition to land holding, institutional and demography issues resulted on the idea and conclusion of mechanization is not work at all in Ethiopian. There are still many regions where agricultural machinery was practiced, but the technology is often outdated and low quality. Agriculture mechanization innovations are lacking and inaccessible to smallholder farmers. In contrast, the utilization of appropriate agricultural mechanization is expected to enhance the transformation of rural Ethiopia and lead to a middle-income country by 2025 G.C (Seife Ayele, 2022). Since the adoption of appropriate mechanization technologies has enabled smallholder farmers in Ethiopia to reduce drudgery and loss. Crops are produced, processed after harvest, and transported using human and animal power, with women and children that bearing the majority of the labor burden (Mupangwa *et al*., 2021).

### 2.2.2 Measurement of productivity

In general, productivity is the efficiency of the production of goods or services expressed by some metric. The rate at which aggregate output is compared to a single input or an aggregate input used in a production process is often used as a measure of productivity. In other words, this is how much output is produced per unit of input over a of set time frame (Rizov *et al*., 2018). Crop yield per hectare, production per worker, and the general output per unit of input are all ways of measuring agricultural productivity. It is also defined as a ratio between an output volume and an input volume (Schreyer and Pilat, 2001).

Individual products are usually calculated based on weight, known as crop yield. However, varying products make it difficult to calculate the total farm output. Comparing a single input, such as labor or land, with the final output is the most effective way to measure productivity (Nin *et al*., 2003). Such comparisons are called partial measures of productivity. The term partial productivity refers to measures of productivity that combine one class of input with one factor but not more than one. In practice, measures of partial productivity are used in production (Sumanth, 1997).

Therefore, In order to measure productivity the Diskin (1997) formula of harvested crop yield per hectare was employed.

$$\text{Wheat crop productivity} = \frac{\text{Total wheat output (qt)}}{\text{Total wheat planted area (ha)}}$$

### 2.2.3 Theoretical model of adoption

The adoption process, as described by Rogers *et al.* (2014), involves the decision-making process that individuals pass through from the moment they hear about innovation to the point they adopt it. An individual passes from first knowledge of an innovation to deciding to implement it or discard it (Van den Ban and Hawkins, 1996). Feder *et al*. (1985) define adoption as the decision to use a newly developed technology, method, practice, etc. whether by a firm, farmer, or consumer. The level of use of advancing technology in long-run equilibrium when a farmer has full information about the new technology and it's potential. Researchers have studied the process of adopting new innovations for over 30 years. One of the most popular adoption models is described by Rogers in his book, "Diffusion of Innovations" (Sahin, 2006).

According to Rogers *et al*. (2014), the innovation-decision process involves five steps:

**Knowledg**e: seeking information about innovation and knowing it exists. A key question in the knowledge phase is "what?", "how?" and "why? An individual tries to figure out what a particular innovation is and how and why it works.

**Persuasion**: occurs when an individual forms a favorable or unfavorable attitude toward an innovation, but it does not lead to its adoption or rejection.

**Decision**: during this step, individuals decide whether to adopt or reject the innovation. While adoption refers to the full use of an innovation as the most effective course of action available, rejection means not adopting an innovation.

**Implementation**: An innovation is put into practice, but innovation inevitably involves some uncertainty in diffusion (innovations can still be subject to uncertainty at this stage).

**Confirmation**: The innovation decision has already been made, but at the confirmation stage the individual looks for support for his or her decision. Later adoption of the innovation or discontinuation may occur during this stage depending on the attitude and support for the innovation.

In the adoption of technologies, the first thing is to consider whether adoption is a discrete state with binary variables or whether adoption is a continuous measure. There are several statistical and econometric methods that can be used in the analysis of adoption. They include frequency tables, contingency tables and correlation analysis. The use of tables helps to compare adopters and non-adopters of technology. By using binomial choice models, one can analyze accurately a qualitative response and regress variables that are related to the adoption of agricultural technologies.

**Limited dependent variable model**: In regression models, when the dependent variable is continuous, the linear regression model is probably the most commonly used statistical method. However, when the dependent variable is a discrete or categorical outcome, linear regression models are not appropriate(Wooldridge, 2010).

The qualitative variables usually indicate the presence or absence of a quality or an attribute such as adopter or non-adopter, combine harvester user or non-user etc. To quantify such attributes the presence and absence of the attribute take on values 1 or 0, and the variables that assume these values are called dummy variables (Gujarati *et al*., 2004). Therefore, in models where the dependent variable is qualitative, the objective is to find the probability of something happening, such as adoption of combine harvester. Quantitative response regression models are often called probability models (Maddala, 1992).

**Linear probability models**: The outcome variable (combine harvester custom hiring service) has a linear relationship with the independent variable. The use of a linear probability model in an adoption study has problems. Problems include non-normality of the error term or the assumption that normality cannot be assumed, the assumption of homoscedasticity is violated, and the null covariance of the independent variable and the disturbance term becomes correlative. There is a possibility that the estimated value of the qualitative dependent variable lies outside the 0-1 probability range. However, these problems can be overcome by the use of weighted least square to resolve the heteroscedasticity problem or by increasing the sample size to minimize the non-normality problem(Aldrich and Nelson, 1984; Dustan, 2010).

But the major problem with the linear probability model is that it assumes the probability or expected value of the dependent variable equal to one, given the independent variable, increases linearly with the independent variable, indicating the marginal effect of the independent variable remains constant (increases linearly with X, that is, the marginal or incremental effect of X remains constant throughout). The true relationship between Y and X, or more correctly, between the expected value of Y and X, is nonlinear (Wooldridge, 2010).

**Logit and Probit model:** The limitations of the LPM can be overcome by using more sophisticated binary response models. Logit model is a statistical model that models the probability of an event taking place by having the log-odds for the event be a linear combination of one or more independent variables. It estimates the probabilities of events as functions of independent variables; it appropriate whenever the total count has an upper limit and the initial growth is exponential. The logistic function converts a real number factors to a probability of Bernoulli distribution responses. In the log-odds scale, the unit of measurement is the logit, which comes from logistic function (Hosmer Jr *et al*., 2013; Tolles and Meurer, 2016). Likewise, the probit model is the inverse standard normal distribution of the probability modeled as a linear combination of the predictors. It is a probability unit or a convenient scale for normal deviates (Bliss, 1934; Cramer, 2002)

Various nonlinear functions have been suggested for the index function to make sure that the probabilities are between zero and one. The two models are used in the vast majority of applications (along with the LPM). In the logit model, the interest probability drives from the logistic function between zero and one for all real numbers X. The latent variable follows the cumulative distribution function for a standard logistic random variable. In the probit model the population distribution function is formulated from the standard normal density, it's that the probit model is more popular than logit (Wooldridge, 2015). The logistic distribution tends to have thicker tails than the normal distribution. As a result of properties of the normal distribution, many specification problems can be easily analyzed using probit. In practice many researchers choose the logit model because of its relative mathematical simplicity.

### 2.2.4 Theoretical model of adoption intensity

The intensity model was biased when using OLS regression. Since it does not account for the effect of truncating the sample at a certain point, the estimates of the coefficients are inaccurate. This can be viewed as a problem with the specification of the model (Heckman, 1979). It is also sometimes difficult to distinguish between truncation and censoring. Censored sample is possible to access the covariate observation from the larger random sample, but the exact value of the interest variable is unknown. In a truncated sample, impossible to have any observations from the larger random sample except those for which data on the interest variable is available(Heckman, 1976).

Using a censored regression model in our study would be inappropriate. Truncated regression models have the sample truncated for certain ranges of the dependent variable. This means that observations with dependent variable values below or above certain thresholds are excluded from the sample. A truncated regression reduces the variance of the outcome variable compared to a non-truncated regression(Breen, 1996).

In the case of non-negative integers, such as 0, 1, 2, etc., count data regressions provide an appropriate, rich, and flexible modeling tool (Winkelmann, 2015). Based on the Hurdle model, it is possible to differentiate between extensive margin effects (the probability that the count would be zero) and intensive margin effect (the probability that one or more counts would be counted). The range of the dependent variable is typically taken to be the set of natural number including zero. Slope coefficients indicate exponential conditional mean function; coefficients give the relative change in the expected count associated with a unit change of covariate (Winkelmann, 2015). A Poisson Regression model is a Generalized Linear Model (GLM) that is used to model count data. Response values (count) follow the Poisson distribution (https://www.dataquest.io). By modifying some unknown parameters, the logarithm of expected values (mean) can be transformed into a linear form (Frome, 1983).

A zero-truncated Poisson (ZTP) distribution is a discrete likelihood distribution that held a positive integer. This distribution is also known as the conditional Poisson distribution or the positive Poisson distribution (Cohen, 1960; Singh, 1978). In other words, ZTP is conditional probability distribution of a Poisson-distributed random variable that has a positive value. Count data without zero-category arise usually when the observational apparatus (device) is activated only when a case occurs or due to the reason that the number of individuals falling into the zero class cannot be determined, which makes it a missing data problem. The zero-truncated Poisson (ZTP) distribution is commonly utilized to investigate the relationship between the response counts and a set of covariates (Li *et al*., 2023).

2.2.5 Theoretical model of adoption impact

Impact evaluation assesses the changes caused by a particular intervention, such as a project, program or policy, both intended and unintended. Baker (2000) explains that an impact evaluation measures whether a program has caused desired or undesired changes in its intended users. Effects of development interventions, intended and unintended, both positive and negative, in the long run (Manning, 2010). A combination of facts and values (i.e., principles, attributes, qualities held to be appropriate, desirable and significant) is used to judge the merit of a particular intervention (Stufflebeam, 2001).

Asres (2003) point out that adoption of the latest technologies should aim at impacts or changes that are intermediate between livelihood outcomes and that have more to do with the income of the user. A change (monetary or non-monetary) faced by farmers when they switch to a variety that is worth keeping (adopting) is referred to as the impact of changing varieties due to the adoption of new technologies. In the farming community, high yielding varieties can play a significant role in determining the income status of beneficiaries (farmers), since the bargaining power of the farming household is largely related to the income derived from the use of the variety (Goldfeld and Quandt, 1973).

Different approaches have been suggested to undertake an impact evaluation. Estimating the impact of a program requires separating its effect from intervening factors which may be correlated with the outcomes, but not caused by the program(Chen and Rossi, 1983). This task of “netting out” the effect of the program from other factors is facilitated if control groups are introduced. Control groups is consist of a comparator group of individuals or households who did not receive the intervention, but have similar characteristics as those receiving the intervention, called the “treatment groups”. Identifying these groups correctly is a key to identifying what would have occurred in the absence of the intervention (Ezemenari *et al*., 1999).

However, two outcomes cannot be observed for the same individual. In other words, only the factual outcome is all that can be seen. Thus, the fundamental problem in any intervention evaluation is the missing data (Bryson *et al*., 2002; Ravallion *et al*., 2005). Estimating the impact of a program requires separating its effect from intervening factors which may be correlated with the outcomes, but not caused by the program. To ensure methodological rigor, an impact evaluation must estimate the counterfactual, that is, what would have happened had the intervention never taken place (Baker, 2000).

In a combine harvester custom hiring adoption, households may not be randomly distributed between the two groups (as adopters and non-adopters); instead, each household may assigned adopter or non-adopter based on the information we have, so the two groups may be systematically different. To address this, an endogenous switching regression (ESR) model is the most appropriate.

**Propensity score matching**: Inferences about the effects of treatments involve speculations about the effect one treatment would have had on a unit which, in fact, received some other treatment. In randomized experiments, the results in the two treatment groups may often be directly compared because their units are likely to be similar, whereas in nonrandomized experiments, such direct comparisons may be misleading because the units exposed to one treatment generally differ systematically from the units exposed to the other treatment. Balancing scores, defined here, can be used to group treated and control units. A balancing score, which is a function of the observed covariates, such that the conditional distribution of covariate given the score is the same for treated and control groups. The function of covariate that is balancing scores and identifies the coarsest function is called the propensity score (Rosenbaum and Rubin, 1983).

Propensity score matching (PSM) is a quasi-experimental technique, used to match based on the propensity score each treated unit with a non-treated unit that has similar characteristics so as to create an artificial control group. The conditional on some unobservable characteristics are balanced, untreated units and treated units, as if the treatment has been fully randomized. In this way, PSM seeks to mimic randomization to overcome issues of selection bias (https://dimewiki.worldbank.org/ ).

The goal of matching is to reduce imbalance in the empirical distribution of the pretreatment confounders between the treated and control groups. Lowering imbalance reduces, or reduces the bound on, the degree of model dependence in the statistical estimation of causal effects and, as a result, reduces inefficiency, and bias. If one’s data are so imbalanced that making valid causal inferences from it without heavy modeling assumptions is impossible. In this case, PSM would reduce imbalance, however, causal inference would not be possible based by that data (King and Nielsen, 2019).

Moreover, PSM allows estimation of mean impacts without arbitrary assumptions about functional forms and error distributions (Rizov *et al.*, 2018). If any crucial variables have been omitted, then the groups may remain unbalanced and the results of the study can be seriously biased. Biases may occur because of sample-selection or self-selection (endogeneity problem). Sample-selection bias involves the non-random selection of certain individuals, based on the availability of observable data(Titus, 2007).

**Endogenous switching regression model:** When both observable and unobservable characteristics are accounted, the endogenous switching regression model prevents a 'hidden bias' caused by neglecting unobservable variables. It would be incorrect to estimate parameters without considering the endogeneity of adoption on the outcome variable (Wabwile *et al*., 2016). PSM, for example, ignores unobservable factors that affect the adoption process, and assumes that the return (coefficient) to characteristics is the same for adopters and non-adopters. By solving the endogenity problem and considering both observable and unobservable factors, it can avoid the "invisible bias" caused by unobservable factors (Wu, 2022).

When we examine the impacts of new agricultural technologies, it can often be difficult to attribute yield differences and net returns between adopters and non-adopters to adoption alone. A randomized control trial would normally provide information on the counterfactual situation, which would resolve the causal inference problem(Miguel and Kremer, 2004). In contrast, when only cross-sectional data are available, as in the current study, there is no information about the counterfactual. It is an effective way of addressing the problem is to resort to an investigation of the direct effect of technology adoption by analyzing switching differences in outcomes among farm households (Abdulai and Huffman, 2014).

ESRM framework proceeds in two stages. In the first stage, the decision to adopt technology, which is estimated using a probit model; in the second stage, an Ordinary Least Squares (OLS) regression with selectivity correction is used to examine the relationship between the outcome variable and a set of explanatory variables conditional on the adoption choice (Khonje *et al*., 2015). In Monte Carlo experiments, maximum likelihood estimates of the endogenous switching model parameters were quite accurate (Kim *et al*., 2008).

## 2.3 Empirical Literature Review

2.3.1 Empirical studies of the determinants of agricultural mechanization adoption

**Sex of headed household:** it is common for men to make the majority of decisions and to have more access to and control over production resources than women (Sell and Minot, 2018). Further, technology use is strongly related to the availability of complementary assets like land, credit, education, and labor, all of which are significantly less accessible to women headed households than to men headed households (Appleton, 1996; Moshoeshoe *et al*., 2021; Nyanjong and Lagat, 2012; Smur *et al*., 2021). The factors contributing to these differences include traditions, culture, and institutional and economic constraints that limit access to productive resources (Demelash Abewa *et al*., 2020).

Combine harvesters are more commonly used by male headed households than by female headed households. It is difficult for female headed households to hire combine harvesters due to sociocultural reasons (Mohammed Hassena *et al*., 2000). Household head gender indicates that male household heads adopt agricultural technology more frequently than female household heads, and the difference is statistically significant (Berhe Gebregewergs, 2016).

However, Morris & Doss (1999) found no significant association between gender and the likelihood of adopting improved technology in Ghana. The researchers concluded that the accessibility of resources has more influence on technology adoption than gender. Tractor hiring services are negatively affected by the gender of households. Female farmers are more likely than male farmers to use tractor hiring services. This is because female farmers are incapable to plow their land on time Astewel Takele and Yihenew G.Selassie (2018), In addition, maleness in Bangladesh is negatively associated with tractor adoption (Mottaleb *et al*., 2016).

**Education:** most previous studies on the adoption of new agricultural technologies have considered education as an imperative determinant of the decision to adopt new technologies. Illiteracy is a significant barrier to adoption, as it limits a person's ability to understand, adopt, and think about new technologies. Combine harvesters are more likely to be used by farmers with elementary education compared to illiterate farmers. Furthermore, combining harvesters were more likely to be used by farm families with high school diplomas than by those without high school diplomas (Mohammed Hassena *et al*., 2000). The reason for this is that education affects the attitudes and thoughts of the respondents, making them more open and rational (Ghimire *et al*., 2015). It lets farmers analyze the benefits of the latest technology (Adebiyi and Okunlola, 2013).

Consequently, numerous study concludes that education has a positive and significant relationship with the adoption of agricultural mechanization technology (Barman *et al*., 2019; Guo *et al*., 2020; Houssou and Chapoto, 2015; Li *et al*., 2018; Owombo *et al*., 2012; Uematsu and Mishra, 2010; Vortia *et al*., 2021). However, the effect of the education level of household heads on improved technology was negative. In other words, a household head's education reduces their likelihood of adopting improved technology, contrary to what it would expect (Rahman *et al*., 2021).

**Age:** as farmers grow older, they begin to have more confidence in the ability to use traditional methods of production because as they gain experience, they are more likely to utilize these traditional methods. Older people prefer to stick with what they know over accepting new technology or adopting late unless they are given a substantial reason or the right incentive for doing so (Ayandiji and Olofinsao, 2015). Consequently, farmers often decline to accept tractor hiring service as their age increase (Astewel Takele and Yihenew G.Selassie, 2018).

Younger generations are more likely to open to farm mechanization; older farmers have more experience in farming accumulated through experimentation and observations. Because of this, they may find it difficult to abandon their traditional practices for new technologies. they may be less inclined to try new farm practices, younger farmers would have an increasing likelihood of agricultural technology adoption, as they become more aware of the benefits of agricultural technology and have the opportunity to adjust productive resources (Berhe Gebregewergs, 2016).

The young groups are prospective clients for thresher adoption, they are more interested in new technology and are more willing to accept the challenge of new innovation, which may motivate them to adopt (Rahman *et al.*, 2021). The higher the age of the household head is the lesser the probability of introducing the new technology (Workineh Ayenew *et al*., 2020). Moreover adoption analysis revealed that age had a negative effect on the likelihood of adoption (Beshir and Wegary, 2014; Hossain and Crouch, 1992; Teferi *et al*., 2015).

Nevertheless, other studies have found that the age of the farmer is a significant factor related to agricultural technology adoption decisions (Guo *et al*., 2015). The adoption of modern agricultural production technologies in Ghana found that age assumed a quadratic function. This means that the rate of adoption of technologies is low at both younger and older ages. They reported that this might imply that younger farmers do not have adequate resources to invest in technologies, especially those that are capital intensive (Akudugu *et al.,* 2012). The relationship between age and machinery usage has been found to be positive in some studies, especially when it is related to years of experience, older farmers are more likely to intensify machinery usage they may have saved enough money over the years to be able to afford the needed farming equipment (Kuwornu *et al*., 2017).

**Farm experience:** It appears that farmers with more experience are better able to evaluate the benefits of technology because they have more information and knowledge. Assuming that farming is a profitable revenue generator may have resulted in accumulated savings. These savings could be used to hire or purchase farming machinery and labor-saving technologies. Moreover, farmers may have developed more efficient methods of combining various technologies on their farms over time (Merga Challa and Urgessa Tilahun, 2014).

However, farm experience negatively influences adoption decisions. An increase in experience decreases the likelihood of adopting updated technology. Farmers with many years of farming experience may be reluctant to convert to more advanced technologies and stick to traditional farming methods instead (Yu *et al*., 2011).

**Family size:** Family size played an important role in influencing agricultural technology adoption. Family provides labor and management inputs, which affects the level of technology use in terms of the quality of management decisions and the availability of labor (Liberio, 2012). There is a positive and significant relationship between household size and the extent of technology adoption (Idrisa *et al*., 2012). The size of the family impacts access to information and credit that would facilitate the adoption of agricultural technology. New agricultural technology is more likely to be adopted by large families, especially if it involves a higher financial investment (Assefa Admassie and Gezahegn Ayele, 2010; Mekidelawit ayal, 2018). The hiring of combine harvester is positively related to an active family labor force. Due to their higher income levels, most farmers with large families can afford to hire combine harvesters (Yohannes Mekonnen, 2021).

However, it could be concluded that an increase in household size leads to a significant increase in labor availability (Mwangi and Kariuki, 2015). It may negatively affect farmers' decisions to adopt technologies. Due to this there is less of a need to adopt technologies that are commonly employed as a substitute for labor (Mariano *et al*., 2012; Mlenga and Maseko, 2015; Tolentino, 2017). The number of economically active labor forces in the household was found to have a negative relationship with tractor hiring decisions. Households with a higher number of economically active labor force are less likely to hire tractor mechanization services as the excess labor is used for carrying out field operations (Astewel Takele and Yihenew G.Selassie, 2018).

**Farm size:** Farm size was one of the key factors influencing technology adoption decisions (Akudugu *et al.*, 2012). Consequently, farmers with large farms are more likely to adopt new production techniques than farmers with small farms (Idrisa *et al*., 2012). Since they have limited holdings and are uncertain about the outcome of technology, small farmers practicing subsistence agriculture are highly risk averse (Mendola, 2007). It suggests that large farms are more efficient and as a result are more able to access mechanization services than smaller farms (Ghosh, 2010). The size of a farm is positively correlated with the number of technologies implemented (Sharma *et al*., 2011).

The size of the wheat area owned by a farmer significantly affected the method of wheat harvesting. Farmers with a larger area of wheat are more likely to use combine harvesters than those with a smaller area of wheat(Mohammed Hassena *et al*., 2000). Farmers who operate on larger farms are more likely to adopt new technologies. This is because they can afford to devote a part of their land to try and test its effectiveness (Mwangi and Kariuki, 2015). Also, certain technologies like mechanized equipment and animal traction require economies of scale to be profitable. However, it is not advisable to ignore all modern farming equipment.

Several economic benefits are available to small and medium-sized farmers when they adopt farm mechanization as they can increase their production level (Diao *et al*., 2016).

**Endowment of oxen:** Numerous studies have been conducted regarding the effect of oxen ownership on agricultural technology adoption. A positive influence of oxen ownership on adoption decisions has been found by (Gecho and Punjabi, 2011; Jaleta *et al*., 2013; Teferi *et al*., 2015; Tufa and Tefera, 2016). This variable has a statistically significant effect on the probability of adopting improved wheat technologies (Siyum *et al*., 2022). Furthermore, the variable was positively associated with the willingness to hire tractors because of the farmer's wealth class based on oxen ownership. As a result, rich farmers are more likely to start tractor hiring service (THS) businesses in the area than poor farmers. Among farmers with more than two oxen, THS was more likely to be hired than among those with many oxen or none (Astewel Takele and Yihenew G.Selassie, 2018).

As opposed to the above study, Beshir and Wegary (2014) found no significant difference between adopters and non-adopters with oxen ownership. There was a significant relationship between the number of oxen owned and the hiring decision of tractors, but the relationship was negative. In other words, hiring tractor plugging services becomes less likely as the number of oxen increases. More oxen-owning farmers tend to use their oxen instead of hired tractors (Yohannes Mekonnen, 2021).

**Credit availability:** The adoption of improved technology is more likely in farmers who have access to formal credit (Saleem, 2011). Modern agricultural technologies are adopted significantly and positively through credit. So as to modernize agriculture and increase productivity, farm credit is crucial, especially from formal sources. Credit enables farmers to purchase capital-intensive farm machinery by enhancing their purchasing power. Considering that mechanical technology is capital-intensive, a lack of access to such capital can limit its adoption (Akram *et al*., 2020; Foltz, 2004).

Access to credit encourages the adoption of risky technology by relaxing liquidity constraints and by boosting household risk-bearing capacities (Simtowe and Zeller, 2006). A significant positive impact of access to credit has been found on agricultural production technologies adoption (Akudugu *et al*., 2012).  Additionally, it is evident that farmers who face financial constraints adopt new technologies if they have access to credit from financial institutions in order to fill their financial gap. This implies that farmers are more likely to adopt more advanced technologies if they have access to credit (Workineh Ayenew *et al*., 2020).

**Off-farm income**: off-farm income refers to income earned by farmers outside of farm operations, such as the income earned from petty trading, charcoal sales, firewood sales, and others. It had a significant impact on technology adoption in Ethiopia's northeastern highlands (Beshir *et al*., 2012). Families that engage in off-farm activities are better able to purchase essential agricultural inputs, which enables them to produce more efficiently (Merga Challa and Urgessa Tilahun, 2014). Mechanization intensity is significantly correlated with nonfarm income. As non-farm income increases, a farmer has more funds to invest in and hire farm machinery and implement mechanization techniques (Aryal *et al*., 2019; Kuwornu *et al*., 2017; Owombo *et al*., 2012).

Liquid capital is provided by off-farm income to farmers for the purpose of purchasing inputs (Diiro, 2013; Evans and Ngau, 1991). Technology adoption can be enhanced by off-farm income, particularly for high-cost technologies. A household's off-farm income is a crucial factor in determining whether or not to hire a tractor. Farmers who earn additional income from other activities tend to be more involved in trading activities or employment opportunities, so they prefer to hire tractor services. Nonetheless, the results indicated that this variable was not statistically significant when it came to hiring a combine harvester (Yohannes Mekonnen, 2021).

**Extension Services:** Attending demonstrations and field days can help farmers adopt new technologies, if the DA visits more often and different extension teaching methods are used. Extension service is often credited with influencing farmers' adoption of modern technology as an effective source of knowledge. It is expected that farmers who receive better extension services adopt technologies than others (Maiangwa *et al*., 2010). Government agricultural extension services play a crucial role in lessening farmers' negative perceptions about combine harvesters and facilitating agricultural mechanization to offset the rapid rise in agricultural labor costs (Pullaila *et al*., 2018).

Farmers need to access agents who provide them with information about the latest technologies (Ayandiji and Olofinsao, 2015). The extension is seen to have a positive effect on the adoption of agricultural technologies. Access to extension services is essential in promoting modern agricultural production technologies because it can lessen the negative effect of low levels of formal education on the decision-making process of farmers (Mwangi and Kariuki, 2015).

Farm mechanization adoption in Nigeria is strongly influenced by access to extension agents. By increasing farmer access to extension agents, farm mechanization would be more widely adopted. This is because farmers would be aware of the importance of using farm machines to increase productivity and improve their lives in general. Extension agents serve as intermediaries for the dissemination of information to farmers and access to problems encountered by farmers and feedback to researchers (Owombo *et al*., 2012).

### 2.3.2 Empirical studies related to the impact of agricultural mechanization

The impact of mechanization on smallholder agricultural production in Ghana was investigated by Cossar (2019) using a Treatment Effect Regression Model (a two-step control function method). As a result of tractor use, some farms expand their cultivation area, use more labor for some operations, and engage more women in agricultural production. Furthermore, they found that mechanized plowing does not significantly reduce the amount of labor needed for land preparation, but actually increases it. The study did not, however, analyze the effects of tractor usage on farmers' economic welfare.

The impact of agricultural mechanization on crop production economies of scope in Nigeria was studied by Takeshima *et al*. (2020). To address the potential endogeneity of mechanical adoption, the inverse probability weighting method was used, along with primal and dual EOS estimation models. The adoption of mechanization technologies on rice farms is associated with a higher EOS between rice, but a lower EOS among non-rice crops (e.g., non-rice grains, legumes, and seeds). Although mechanical technologies may lower EOS among crops grown under relatively similar agro-ecological conditions, they can raise EOS for crops grown in heterogeneous environments. The study did not examine how agricultural mechanization affects farmer’s rice productivity.

A study by Benin (2015) analyzes the impact of Ghana's agricultural mechanization service centers. The difference-in-difference estimator is applied based on the estimated propensity scores as weights to the matched observations to estimate the average treatment effect on the treated (ATT) of the program. AMSEC's program has had varying effects on different outcomes. In addition to improving mechanization services, it reduced drudgery and increased yields. The study focused exclusively on tractor-based land preparation (specifically plowing).

Hasan *et al*. (2019) shows that combine harvesters have a significant impact on paddy production in Bangladesh. Compared to manual harvesters, combine harvesters saved 57.61% on paddy harvesting costs. Similarly, using a combine harvester saved 70% more labor than using a manual harvester. The average total harvesting losses (including harvesting, threshing and cleaning) were also found to be 1.61 % and 6.0% by a combine harvester and manual harvesting, respectively. Using a combine harvester reduced paddy losses by 4.47% over manual harvesting. The above results revealed that manual harvesting is a labor-intensive and expensive system. On the other hand, mechanical harvesters like combine harvesters are a time, labor and cost saving system along with reducing harvesting losses.

A study conducted by Ali *et al*. (2018), the role of mechanical rice harvesting in socioeconomic development of Bangladesh. The results indicated that manual rice harvesting cost 24400 BDT/ha, whereas mini-combine harvester and reapers cost 10123 BDT/ha and 13152 BDT/ha, respectively. A mini-combine and reaper can reduce rice harvesting loss by 5.12% and 2.14%, respectively, compared to a manual harvesting system. However, they didn't show the long term effects of adopting a technology on household livelihood (income, labor employment, etc.).

Januarti *et al*. (2018) analyzed the impact of using combine harvester technology on the social and economic conditions of swamp rice farmers and harvest workers in Sumatera by analyzing descriptive statistics. In swamp rice farming conducted by farmers employing combine harvesters, the amount of labor allocated is smaller than that of non-users. The productivity of swamp rice farming for the users is 4,543.56 kg per hectare per year in the form of dry grains whereas that of the non-users was 4, 423. 33 kg per hectare. Comparing the income of swamp rice farmers using combine harvesters with non-users, the income of users is 14, 942,737.16 rp per hectare per year and the income of non-users is 9, 954,095.76 rp per hectare per year.

However, the study uses only descriptive statistics to compare the labor allocation, income, and productivity of users and non-users of combine harvesters. They did not employ econometric models to measure the impact of the technology. In order to measure the partial effect of technology, we need to control the confounding factor of productivity and income, since the two regimes may be quite different.

## 2.4 Conceptual Frame Work

Different household characteristics could affect the smallholder farmer's custom hiring decision of combine harvester technology. These factors can be categorized as perception, socio-economic, demographic, farm and farming, technology supply and institutional factors. The variables included age, sex, farm experience, family labor force, education status, off farm income participation, number of oxen, slope of the wheat field, immediate access, average distance from the main road, having a mobile phone, extension contact, fee opinion, unexpected rain fear, straw wastage attitude, and type of combiner leaser.

Traditional harvesting methods require a lot of time, human labor, and oxen draft, which is an inefficient method. When the mature wheat crop is delayed in the field, it is vulnerable to unseasonal rain, pests (rodents, birds, animals, etc.), and shattering loss. Due to this suspicion, wheat was harvested too early with high moisture content, making it susceptible to mold growth and insects invading and resulting in broken grains and low grinding efficiency. During reaping, collecting, hauling, heaping, stacking and over-winnowing large amounts of the wheat grain are lost. When grain is stored in piles for a long period of time, it is susceptible to termites and other microorganisms. Traditional threshing leads to the low market value of wheat grain due to contamination with soil, dug, and urine, excessive striking, and incomplete separation of wheat from the chaff.

Mechanical harvesting of wheat reduces family labor burden and gives farmers more time in peak harvest season to collect another non-wheat crop at the right time. Additionally, it reduces animal drafting, which improves the efficiency and also allows oxen fitting activity. Combine harvesters can increase harvest efficiency and decrease losses associated with inefficient work during traditional harvesting and threshing. Therefore, custom hiring of combine harvesters would have a mixed effect on smallholder farmers' crop productivity and annual crop and livestock income along with the reduction of post-harvest loss.

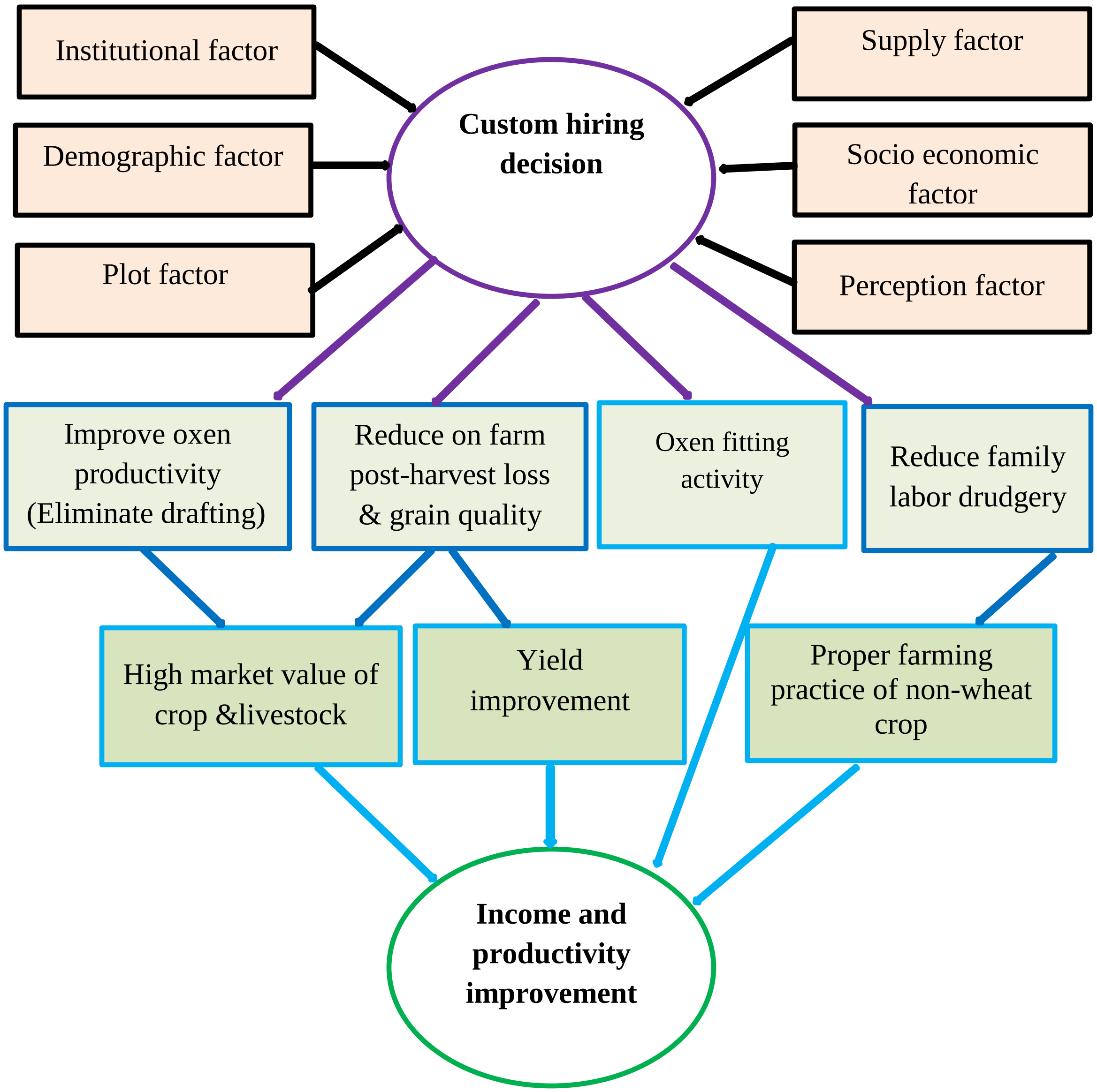


Figure 2. 1. Conceptual frame work

Source: Own computation

# Chapter Three: RESEARCH METHODOLOGY

## 3.1 Description of the Study Area

The study was conducted in Deber Elias, Baso Liben and Gozamin district, East Gojjam zone of Amhara region, northwestern Ethiopia. Small-scale mixed agriculture is the dominant source of livelihood for smallholder farmers. The study district has huge potential for wheat production; also teff and maize are dominant crops. Most of the farming in the district is done by traditional methods. Nevertheless, in the past decade mechanized agriculture tractors and combine harvesters have emerged in the three districts.

**Baso liben woreda:** It is located 307 km northwest of Addis Ababa, the capital city of Ethiopia, 292 km from the regional city Bahir Dar and 27 km from Debre Markos (Zone capital town). It alienated into two agro-ecological zones, woyina dega (46%) and kola (54%). A district consists of 22 rural kebele and 4 urban kebele. District area stretches between 10°37 - 10°38'N latitudes and 37°30 - 30°30'E longitudes, with a latitude range of 848-2417m above sea level. Rainfall is averaged at 900-1200 millimeters and annual temperatures are between 15.5 and 20°C. It is bordered on the south by a bend of the Abay River, the northwest by Guzamn, and the northeast by Aneded, and part of its western border is the Chamwaga River (BLWOA, 2022).

**Gozamin woreda:** is one of the Woredas of East Gojjam Zone in ANRS. It lies between 10.5° or 10° 30' N latitudes and 37.5° or 37° 30' E longitudes; a road distance of about 300 km northwest of Addis Ababa and at a road distance of about 250.8 km from Bahir Dar (the capital city of ANRS). Debre Markos is the capital of the district and it contains 25 rural-kebeles and 1 urban kebele. It is bordered in the east by Aneded and Debay Tilatgin, in the west by Machakel and Debre Elias, in the north by Sinan district, and in the south by Baso Liben district and Abay River. Above sea level, the altitude difference is 1200-3510 meters. As a result of these altitudinal differences, the district is divided into three agro-climatic zones: Dega, Woina-dega, and Kola. The southern part of the woreda has a Kola climate, while the northern and central parts have Woyna Dega agro climatic zones; the northern tips have Dega agro climatic zones. The average annual rainfall is between 1448 mm and 1808 mm with a mean annual evapotranspiration of 1500 mm. Temperatures range from 8.5°C at the minimum to 30°C at the maximum (GWOA, 2022).

**Deber Elias Woreda :** The district is also part of the East Gojjam Zone in Amhara Regional State of Ethiopia. The district is bordered on the south and west by the Abay (Blue Nile) River, separating it from the Oromia Region. The northwest is bordered by the West Gojjam Zone, the north by Machakel, and the east by Gozamin. Latitudes are 10°18'N and longitudes are 37°28'E, an altitude of 800-2200 meters. It is located about 340 km northwest of Addis Ababa and 41 km northwest of Debre Markos. A total of sixteen Kebele administrations exist in the area, including one urban kebele and fifteen rural kebele. It receives an average annual rainfall of 1150 mm and averages temperatures of 18-27°C (DEWOA, 2022).

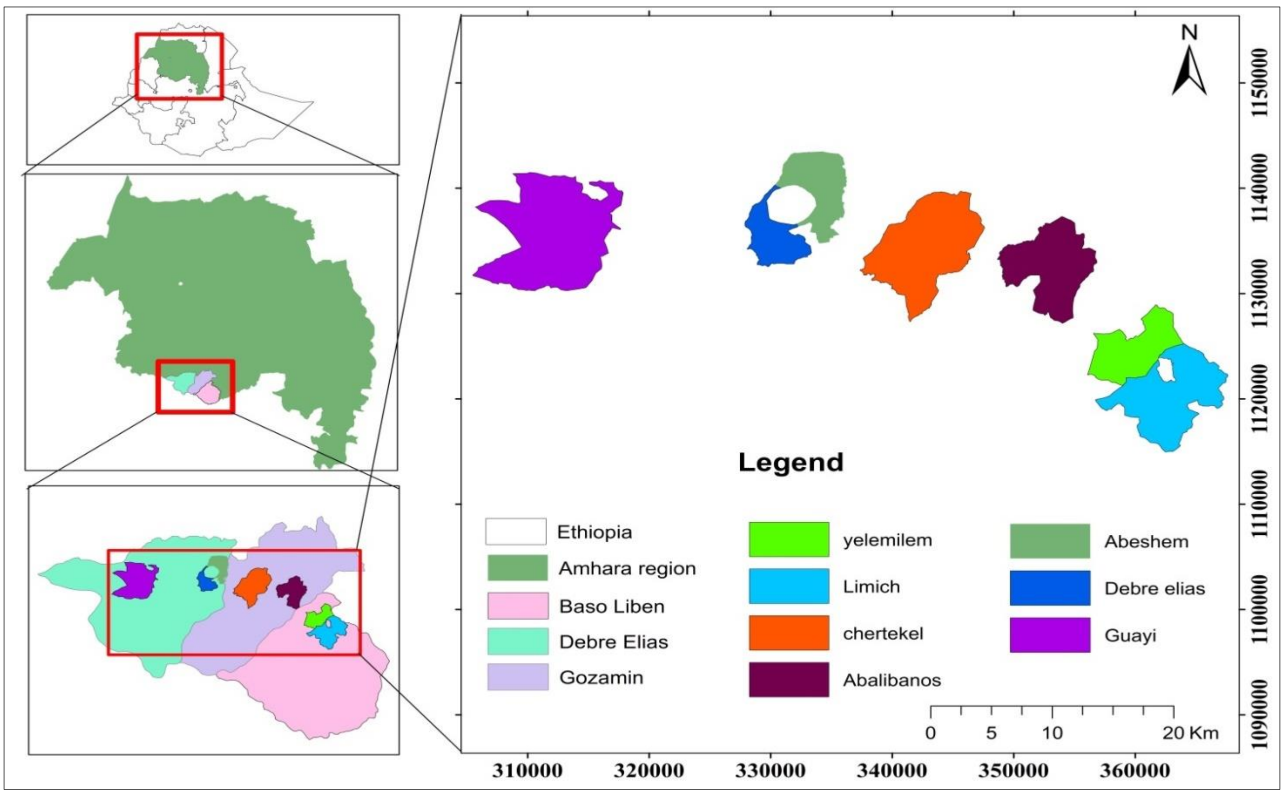

Figure 3. 1 Map of the study area

Source: Own computation

## 3.2 Sample Size and Sampling Method

A multistage sampling procedure with both purposive and random selection of villages and households was employed to get a well representative sample and to reduce sampling errors. First, three districts in the east Gojjam zone were selected Baso-Liben, Gozamin and Deber Elias, based on the potential of wheat production and combine harvester custom hiring service practiced in the past ten years. In the second stage from the frame of total kebele in each district purposively select wheat growing kebele. In the third stage from the frame of total wheat growing kebele the sample kebele was selected randomly by proportionate of the district. In the fourth stage stratified the household in two strata adopter and non-adopter based on agricultural development office data, and finally selected sample households were randomly from each stratum by proportionate of the kebele.

To determine an appropriate sample size Yemane (1967) formula was employed.

$$\mathrm{n} = \frac{N}{1 + N(e^2)} = \frac{39{,}385}{1 + 39{,}385(0.05)^2}$$

While the minimum required sample size was 396 households, 450 farm households were incorporated in the survey.

Table 3. 1. Selected kebeles and sample sizes

| District | Sample kebele | Total wheat producer household | | | Sample household |
|---|---|---|---|---|---|
| | | Male | Female | Total | |
| Deber Elias | Deber elias zuria | 1531 | 197 | 1728 | 75 |
| | Gaye | 1334 | 65 | 1399 | 61 |
| | Abeshem | 683 | 35 | 718 | 32 |
| Baso Liben | Yelemelem | 1061 | 181 | 1242 | 54 |
| | Lemech | 1412 | 71 | 1483 | 65 |
| Gozamin | Chertakel | 1964 | 232 | 2196 | 96 |
| | Aba Libanose | 1434 | 197 | 1531 | 67 |
| Total | | | | 10297 | 450 |

### 3.3 Type, Source and Method of Data Collection

Both primary and secondary data were used in this study to assess the impact of combine harvester adoption on smallholder farmers' economic welfare. The researcher collected data on perceptions and attitudes regarding mechanization, socio-economic, demographic, institutional, and farm and farming variables. A sample household was the main source of primary data. Website and reports from the Bureau of Agriculture, Woreda, and kebele level are secondary data that complement the primary data.

Focus group discussions were conducted with participants who had adequate knowledge and information about the study area, consisting of five individuals per kebele. We obtained general information about agricultural production and productivity, income, harvesting activity, post-harvest losses on farms, grain and byproduct prices, and custom hiring conditions in the study area. The researcher with trained enumerators collected data through face-to-face interviews using a structured questionnaire. Before the actual survey, the questionnaire was pretested. Tablet-assisted data collection with offline data entry kobo toolbox app was used.

### 3.4 Method of Data Analysis

3.4.1 Logit model specification

In a binary response model, interest lies primarily in the response probability $\mathrm{p}(\mathrm{y} = 1|\mathrm{x}) = \mathrm{G}(\mathrm{x}\beta)$, the index model (Wooldridge, 2015). Where, y is the household custom hiring decision and x is the covariate (sex, age, education, family labor, experience, off farm income, slope, distance to main roads, fee opinion etc.). The index of $\mathrm{G}(\mathrm{x}\beta)$ follows a sigmoid logistic function of the upper limits 1 and lower limits 0.

$$\mathrm{S} = \frac{1}{1 + \mathrm{e}^{-\mathrm{xi}}} = \frac{\mathrm{e}^{\mathrm{x}}}{1 + \mathrm{e}^{x}} \tag{1}$$

$$\lim_{x \to -\infty} \delta(x) = \lim_{x \to -\infty} \frac{1}{1 + e^{-x}} = \frac{1}{1 + \infty} = 0 \tag{2}$$

$$\lim_{x \to \infty} \delta(x) = \lim_{x \to \infty} \frac{1}{1 + e^{-x}} = \frac{1}{1 + 0} = 1 \tag{3}$$

Then the latent variable can be derived as,

$$y^* = \beta_0 + x\beta + e = y = 1(y^* > 0) = \mathrm{E}(\mathrm{Y} = 1 \ |X_i) \tag{4}$$

$$E(Y = 1 \ |X_i) = \frac{1}{1 + e^{-(\beta 0 + \beta 1x1 + \ \beta 2x2 + \beta 3x3 + \cdots + \beta kxk)}} \quad (5)$$

$$E(Y = 1 \ |X_i) = \frac{1}{1 + e^{-(X\beta)}} \quad (6)$$

$$E(Y = 0 \ |X_i) = 1 - \left(\frac{1}{1 + e^{-(X\beta)}}\right) \quad (7)$$

The likelihood of an observation,

$$L(\beta, y, x) = \prod_{i=1}^{n} (\frac{1}{1 + e^{-(X\beta)}})^{\ y_i}(1 - \frac{1}{1 + e^{-(X\beta)}})^{1-y_i} \quad (8)$$

The log-likelihood,

$$L(\beta, y, x) = lnL(\beta, y, x) \quad (9)$$

$$= \sum_{i=1}^{n} y_i \ln(\frac{1}{1 + e^{-(X\beta)}}) + (1 - y_i)ln1 - \left(\frac{1}{1 + e^{-(X\beta)}}\right) \quad (10)$$

$$\sum_{i=1}^{n} y_i \ln(\frac{1}{1 + e^{-(X\beta)}}) \ + (1 - y_i)ln\left(\frac{e^{-(X\beta)}}{1 + e^{-(X\beta)}}\right) \quad (11)$$

$$\sum_{i=1}^{n} \left(\frac{e^{-(X\beta)}}{1 + e^{-(X\beta)}}\right) + y_i\left(ln\left(\frac{1}{1 + e^{-(X\beta)}}) - ln\left(\frac{e^{-(X\beta)}}{1 + e^{-(X\beta)}}\right)\right)\right) \quad (12)$$

$$\sum_{i=1}^{n} \left(\frac{e^{-(X\beta)}}{1 + e^{-(X\beta)}} \frac{e^{(X\beta)}}{e^{(X\beta)}}\right) + y_i\left(ln\left(\frac{1}{1 + e^{-(X\beta)}}) - \left(\frac{e^{-(X\beta)}}{1 + e^{-(X\beta)}} \ \frac{1 + e^{-(X\beta)}}{e^{-(X\beta)}}\right)\right)\right) \quad (13)$$

$$\sum_{i=1}^{n} ln\left(\frac{1}{1 + e^{-(X\beta)}}\right) + y_i\left(ln\left(\frac{1}{e^{-(X\beta)}}\right)\right) \quad (14)$$

$$\sum_{i=1}^{n} \left[\ln(1) - \ln\left(1 + e^{-(X\beta)}\right) + yi\left(\ln(1) - \ln\left(e^{-(X\beta)}\right)\right)\right] \quad (15)$$

$$\sum_{i=1}^{n} \left[-\ln\left(1 + e^{(X\beta)}\right) + y_i x_i \beta\right] \quad (16)$$

So as to estimate the vector parameter of β , the Newton-raphson method is the best methods in this case (Jennrich and Sampson, 1976).

$$\beta^{t+1} = \beta^t - \frac{\nabla\beta L(\beta^t)}{\nabla\beta\beta L(\beta^t)} \quad (17)$$

Where, $\nabla\beta L(\beta^t)$ is the first order derivative $\nabla\beta\beta L(\beta^t)$ is the second order derivative and t is current iteration number. From the above equation the first order derivative ($\nabla\beta L(\beta^t)$ ) equals $\sum_i^n [y_i - p(x)] * x_i$ , since the parameter estimate is vector, the matrix follows $X^T$(Y-$\widehat{Y}$). Also the second order derivative is $\sum_{i=1}^n \nabla\beta p(x_i) * x_i$ the correspondence matrix is a hessian matrix, $-X^T P(1-P)X$. Finally $\beta^{t+1} = \beta^t + X^T$(Y-$\widehat{Y}$)$(-X^T P(1-P)X)^{-1}$. However, the regression coefficients in logistic regression are not directly meaningful. We need to reformulate the equation for the interpretation of odd ration,

$$\frac{e^{x\beta}/(1+e^{x\beta})}{1/(1+e^{x\beta})} = e^{x\beta} \tag{18}$$

3.4.2 Truncated Poisson model specification

When the research outcome is a count of a certain event, a Poisson distribution model would be the first choice to describe the phenomenon under study. A Poisson distribution with mean λ is denoted by Poisson (λ), which be called a standard Poisson distribution. Let Y be an integer-valued random variable that indicates the number of a certain event with probability mass function follows;

$$f(i) = \begin{cases} 0 & (y \le 0) \\ \dfrac{\lambda^y e^{-\lambda}/y!}{1-e^{-\lambda}} & (y \ge 1) \end{cases} \tag{1}$$

The probability function of the zero-truncated Poisson-lognormal model is given by,

$$p(y; \lambda \mid \ge 1, x, \varepsilon) = \frac{e^{-\lambda}\lambda^{yi}}{(1-e^{-\lambda})yi!} = \frac{(e^{(-x\beta+\varepsilon)})(-x\beta+\varepsilon^{yi})}{(1-e^{(-x\beta+\varepsilon)}yi!} \tag{2}$$

$$\int_{-\infty}^{\infty}\left[\frac{(e^{(-x\beta+\varepsilon)})(-x\beta+\varepsilon^{yi})}{(1-e^{(-x\beta+\varepsilon)}yi!}\right][f(\varepsilon_i)d\varepsilon_i] \tag{3}$$

However, there is no analytical solution for this integral even in gamma distribution and it has to be approximated using simulation or quadrature. The Gauss–Hermite quadrature get rid of the unobserved heterogeneity, and the likelihood function (Farbmacher, 2011).

$$p(y; \lambda \mid \ge 1, x, \varepsilon) = \frac{1}{\sqrt{\pi}}\int_{-\infty}^{\infty}(p\left(y; \lambda \mid \ge 1, x, \varepsilon, \sqrt{2\sigma v_i}\right) e^{-v_i^2})dv_i \tag{4}$$

$$L = \prod_{i=1}^{n}\frac{1}{\sqrt{\pi}}\sum_{r=1}^{r}(p\left(y; \lambda \mid \ge 1, x, \varepsilon, \sqrt{2\sigma v_i}\right)w_r \tag{5}$$

Hurdle models, first discussed by Mullahy (1986) are very popular for modeling count data. These measures may be determined by a two-part decision process. The hurdle model typically combines a binary model to model combiner hiring participation with a zero-truncated count-data model to model the extent of hiring participation for those participating (modeling the number wheat plot harvesting by combine harvester). There are many possible combinations of binary and truncated count-data models. An often-used model combines a probit or logit model with a zero-truncated negative binomial model (Winkelmann, 2004).

### 3.4.3 Endogenous switching regression model (ESRM) specification

We model the hiring of combine harvester technology and non-hiring. Suppose the farmer are risk neutral, the decision of farmer's based on the net benefit derived from the technology. The farmers are choose the technology that offer the maximum net benefit. Let the net benefit of the adopter is $\mathrm{Y_{iA}}$ and the net benefit for non-adopter is $\mathrm{Y_{iN}}$.

$$Y_{iA} = X_i\beta_A + \mu_{iA} \tag{1}$$

$$Y_{iN} = X_i\beta_N + \mu_{iA} \tag{2}$$

Where xi is a vector of variable household characteristics; $\beta_A \ and \ \beta_N$ are vector of parameter; $\mu_{iA} \ and \ \mu_{iN}$ are randomly distributed errors. A given farmer may hiring combine harvester technology if $Y_{iA} > Y_{iN}$. However, the two perceived net benefit is not observed for us the researcher only the characteristics of the farmer and the technology attribute are observed at the survey period. Now the possible way of observing the two net benefits is based on the latent variable, $A^*$ that is not observed but it can be expressed as a function of some observed characteristics as.

$$A^* = Z_i\gamma_i + \varepsilon_i, \qquad A_i = 1(A^* > 0) \tag{3}$$

Where, $A_i$ is a binary variable that equals 1 for framer that had hired the combiner and 0 otherwise. $\gamma_i$ Is the vector of parameter to be estimated, $\varepsilon_i$ is error term with mean zero and variance of sigma square. The Z variable includes the factors that affect farmers hiring decision of the technology, demographic, institutional, farm and socio economic characteristics.

The outcome equation on the impact of hiring combine harvester mechanization on wheat farmers' productivities is estimated through a production function, $Y = f(\ A, \beta, X)$.

$$y = \beta x + \delta A + \mu \tag{4}$$

Where Y is the wheat yield per hectare; A refers to custom hiring decision; β is a vector of parameters to be estimated; and X is a set of explanatory variables used in the model. Thus, in the switching regression approach, the farmers are partitioned according to their classification as adopters and no adopters in order to capture the differential responses of the two groups. Given that farmers choose to either adopt the technology or not adopt it, the observed net benefits take the following value.

Regime 1 (hiring participant); $Y_{iA} = X_i\beta_A + \mu_{iA}\,, \quad if\ A_i = 1$ (5)

Regime 2 (non -participant);$Y_{iN} = X_i\beta_N + \mu_{iA}, \quad if\ A_i = 0$ (6)

However, this model is subject to misinterpretation because the problem of self-selection biased. The farmers who would obtain below average net returns from the new technology, given the observed factor choose not hire and as such truncate the observed technology profit distribution. It is likely that the combiner adopter have systematically different characteristics from non-adopter. Thus, unobserved variables may influence both the combine harvester hiring decision and crop productivity, resulting in inconsistent estimates of the effect of hiring combine harvester mechanization on productivity.

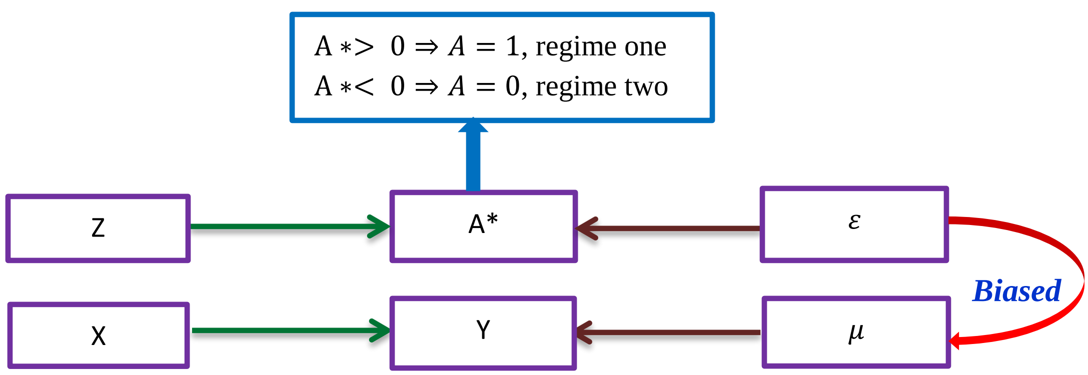


Figure 3. 2. Endogeneity problem

Source: Own computation

Self-selection into the adopter and non-adopter regime may lead to nonzero covariance between the error term of the adoption decision equation and the outcome equation. The three error term are assumed to have a trivariate normal distribution with mean vector zero;

$$cov\left(\mu_{A,}\mu_N, \varepsilon\right) = \sum\begin{bmatrix} \sigma_A^2 & ? & \sigma_{A\varepsilon} \\ ? & \sigma_N^2 & \sigma_{N\varepsilon} \\ \sigma_{\varepsilon A} & \sigma_{\varepsilon N} & \sigma_\varepsilon^2 \end{bmatrix} \tag{7}$$

Where $var\left(\mu_{A,}\right) = \sigma_A^2$. $var(\mu_N) = \sigma_N^2$, $var\ (\varepsilon) = \sigma_\varepsilon^2$ $cov\ \ \mu_{A,}\mu_N$ =? because of not observed simultaneously, $cov\left(\mu_{A,}, \varepsilon\right) = \sigma_{A\varepsilon}$ and $cov(\mu_N, \varepsilon)$ =$\sigma_{N\varepsilon}$ .

Thus, error terms in two outcome equations, conditional on the sample selection criterion, have nonzero expected values,

$$E(\mu_N\ \mid A = 0) = E(\ \mu_N\ \mid \varepsilon \leq\ -Z\gamma) \tag{8}$$
$$= \ \sigma_{N\varepsilon}\frac{-\varphi(Z\gamma/\sigma)}{1 - \Phi(Z\gamma/\sigma} = \sigma_{N\varepsilon}\lambda_N$$
$$E(\mu_A\ \mid A = 1) = E(\ \mu_A\ \mid \varepsilon >\ -Z\gamma) \tag{9}$$
$$= \sigma_{A\varepsilon}\frac{-\varphi(Z\gamma/\sigma)}{\Phi(Z\gamma/\sigma} = \sigma_{A\varepsilon}\lambda_A$$

Where $\Phi$ and $\varphi$ are the standard normal probability density function and the standard normal cumulative density function, respectively. The ratio of $\Phi$ and $\varphi$ evaluated at $Z\gamma$ is called the inverse mill ratio $\lambda_A\ and\lambda_N$ (selective term). This term incorporated into the two outcome equation to account for selection bias.

The expected value of the outcome $Y_{iA}$ is given as;$E(Y_{iA}\ \mid A = 1) = X_i\beta_A - \sigma_{A\varepsilon}\lambda_A$, sample selection is considered in the last term, because a given farmer that have hire combine harvester may have different from an average farmer with the same observed characteristics due to unobserved factor. The expected value of the same farmer had he doesn't hire the technology is given as; $E(Y_{iN}\ \mid A = 1) = X_i\beta_A - \sigma_{N\varepsilon}\lambda_A$.Thus, the estimated average treatment effect on the treated population is $ATT = E(Y_{iA}\ \mid A = 1) - E(Y_{iN}\ \mid A = 1) = (X_i\beta_A - \sigma_{A\varepsilon}\lambda_A) - (X_i\beta_A - \sigma_{N\varepsilon}\lambda_A\ )$.

The expected value of the outcome $Y_{iN}$ is given as; $E(Y_{iN}\ \mid A = 0) = X_i\beta_N - \sigma_{N\varepsilon}\lambda_N$ and expected value of a farmer if that had hire the technology give with the same characteristics is; $E(Y_{iA}\ \mid A = 0) = X_i\beta_N - \sigma_{A\varepsilon}\lambda_N$ finally the average treatment effect on the untreated population is equal to $ATU =\ (Y_{iA}\ \mid A = 0) - E(Y_{iN}\ \mid A = 0) = (X_i\beta_N - \sigma_{A\varepsilon}\lambda_N) - (X_i\beta_N - \sigma_{N\varepsilon}\lambda_N)$.

Full information maximum likelihood (FIML) estimation, as noted by Maddala (1986), is preferred over the two-step estimation procedure since the parameters are consistent and asymptotically efficient assuming proper model specification. Also, Monte Carlo experiment studies show that FIML estimation is superior to two-step estimation; in particular, the two-step estimator performs poorly when there is a high degree of multicollinearity between $Z\gamma$ and explanatory variables. FIML parameter estimates can be obtained from the follow;

$$L_i = \left(\beta_{A,}\beta_{N,}\sigma_{iA}\sigma_{iN}\rho_{iA\varepsilon}\rho_{iN\varepsilon}\right) \tag{10}$$
$$= \prod_{j=1}^{j}\left[\int_{-\infty}^{\gamma_I Z_I} f_A\left(Y_{ijA}-\beta_{iA}X_j,\varepsilon_{ij}\right)d\varepsilon_{ij}\right]^{A_{ij}} * \left[\int_{\gamma_I Z_I}^{\infty} f_N(Y_{ijN}-\beta_{IN}X_j, d\varepsilon_{il}\right]^{1-A_{ij}}$$

Where $f_A$ and $f_N$ are the jointly normal density functions for $(\mu_{ja}$ , $\varepsilon_j$ and$\mu_{jN}$ , $\varepsilon_j$, respectively. The logarithmic likelihood function is;

$$lnL_i = \left(\beta_{A,}\beta_{N,}\sigma_A\sigma_N\rho_{A\varepsilon}\rho_{N\varepsilon}\right) \tag{11}$$
$$= \sum_{j=1}^{j} A_{ij}\left[ln\varphi\left(\frac{Y_{ijA}-\beta_{iA}X_j}{\sigma_{iA}}\right) - ln\sigma_{iA} + ln\Phi(\theta_{ijA})\right] +$$
$$(1-A_{ij})\left[ln\varphi\left(\frac{Y_{ijN}-\beta_{in}X_j}{\sigma_{iN}}\right) - ln\sigma_{iN} + \ln\left(1-\Phi\left(\theta_{ijN}\right)\right)\right]$$

$$\theta_{ijA} = \frac{\left[\gamma_I Z_I - \frac{\rho_{iA\varepsilon}}{\sigma_{iA}}\left(Y_{ijA}-\beta_{iA}X_j\right)\right]}{\sqrt{1-\rho_{iA\varepsilon}^2}} \tag{12}$$

$$\theta_{ijN} = \frac{\left[\gamma_I Z_I - \frac{\rho_{iN\varepsilon}}{\sigma_{iN}}\left(Y_{ijN}-\beta_{iN}X_j\right)\right]}{\sqrt{1-\rho_{iN\varepsilon}^2}} \tag{13}$$

The marginal effects with respect to each regime follow as:

$$\frac{\partial E\left(Y_{ijA} \mid A_{ij}=1\right)}{\partial X_{jk}} = \beta_{iAk} + \gamma_k\sigma_{iA\varepsilon}\frac{\varphi\left(\gamma_i Z_j\right)}{\Phi(\gamma_i Z_j)}\left[\gamma_i Z_j + \frac{\varphi\left(\gamma_i Z_j\right)}{\Phi(\gamma_i Z_j)}\right] \tag{14}$$

$$\frac{\partial E\left(Y_{ijN} \mid A_{ij}=0\right)}{\partial X_{jk}} = \beta_{iAk} + \gamma_k\sigma_{iN\varepsilon}\frac{\varphi\left(\gamma_i Z_j\right)}{1-\Phi(\gamma_i Z_j)}\left[\gamma_i Z_j + \frac{\varphi\left(\gamma_i Z_j\right)}{1-\Phi(\gamma_i Z_j)}\right] \tag{15}$$

### 3.4.4 Partial budgeting framework

A partial budget helps agricultural owners/managers evaluate the financial effect of incremental changes. A partial budget only includes those resources that would be changed; it does not consider the resources in the businesses that are left unchanged. It is important to remember that only the change under consideration is evaluated for its ability to increase or decrease income in the agricultural business. Including costs or income outside the scope of the proposed change is not part of partial budget analysis and should be disregarded (Olson and Westra, 2022). In order to determine the net-benefits of adopting combine harvesting with traditional harvesting methods, partial budget analysis was used by (Tolentino, 2017).

**Partial Budgeting Principles:** A partial budget consists of two columns, a subtotal for each column and a total gain or loss calculation. The left hand column contains those items that increase income while the right hand column contains those items that reduce income in the business.

**Additional income**: hiring of combine harvester may bring additional income by improving crop productivity because of it reduce huge amount of on farm post-harvest loss.

**Reduced cost:** the given technology may eliminate the harvesting cost by its efficiency of operations as compared to the traditional method of harvesting.

**Reduced income:** may the technology has some drawbacks, it exacerbate loss of yield and the byproduct than the conventional method of production.

**Additional cost:** if the farmer hire combine harvester the hiring cost may be over the traditional method of harvesting.

Table 3. 2. Partial budgeting framework

| **Benefits** | **Cost** |
|---|---|
| Increased income | Increased costs |
| Elimination of costs | Elimination of income |
| Total benefit | Total cost |

### 3.5 Definitions of Variables and Development of Hypothesis

**A. Dependent variable**

**Combine harvester hiring decision:** A household is considered a combine harvester adopter on condition that the household harvests at least one wheat plot using a combine harvester in 2021/2022 G.C year and the household has used combine harvesters for more than three years (the farmer has been a combine harvester user for three harvest seasons).

**Intensity of Combine harvester adoption**: It is defined as the number of plot that had harvested by combine harvester mechanization technology in the household**.**

**B. Outcome variable**

**Crop productivity (yield per hectare of land**): it measured as total amount of wheat yield in quintal divided by the total area coverage of wheat field in hectare.

**Gross farm income**: it is a total annul earning of a farmer from livestock and only annual crop production farming activity in birr.

**C. Independent variable**

**Sex of the household head:** It is a dummy variable with the values of either 1 if the household head is male and 0 for female. Agriculture in Ethiopia has traditionally been labor-intensive and requires more family labor. Mechanized agricultural practices such as combine harvesters substitute human labor for mechanical operation. Female farmers were more willing to use tractor services when compared to male farmers (Astewel Takele and Yihenew G.Selassie, 2018).It was hypothesized that the male of the household head negatively affects the custom hiring of combine harvester technology.

**Age of household head:** is measured as the number of years since birth. As farmer age increases, the probability of adoption is expected to decrease. This is because as the farmer's age increases, it is expected that the farmer becomes conservative and negatively affects the hiring of a combine harvester. The youth group is a potential client for THS service (Tamrat Gebiso, 2016). Therefore, it was hypothesized that the age of the household head has a negative effect on the hiring of combine harvesters.

**Education:** the education of the household head is a categorical variable: illiterate farmers with no educational attainment valued as 1, religion and adult education valued as 2, primary education (1-4) valued as 3, secondary education (4-5) valued as 4, above secondary valued as 5. Education was assumed to increase a farmer's capability to obtain, process, and use information relevant to the decision to hire a mechanization service. It limits a person's level of understanding, thinking, and ability to adopt innovative technologies (Ayandiji and Olofinsao, 2015). It was expected that farmers with higher educational attainment would be more likely to hire combine harvesters.

**Years of farming experience**: It is a continuous variable measured by the number of years since a respondent started farming independently. Experienced farmers are often more knowledgeable and possess more comprehensive information. Longer farming experiences have a more significant relationship among factors that explain the behavior of agricultural innovation adoption. A substantial level of farming experience has a positive impact on the hiring decision. It could be hypothesized that farmers with more experience allocate resources more efficiently, which may lead to better crop yields and therefore more income from output sales.

**Number of economic active family labor**: The number of people living in the household who are between the ages of 15 and 60 years. Larger families can provide the labor needed for farming operations. There is no need to hire tractor for farmers with large households since they can use and grown-up crop through farm labor (Julius, 2014). So, it was hypothesized that negatively related to hiring mechanization services.

**Number of oxen:** This is the number of animals used to produce farm output by the household during the survey period. A substantial number of oxen decrease the proportion of combine hiring in a wheat field and farmers tend to use animal thrashing. It was hypothesized to be negatively related to the probability of custom hiring a combine harvester.

**Ownership of mobile phone:** The variable takes a value 1 if the household owns a mobile phone; otherwise it takes a value 0. It is a proxy to measure agricultural information access. With the development of information communication technology and farmer needs, mobile phones have become widely used as instruments or mediums of information communication.

Farmers with cell phones can support extension communication channels and access information more easily (Negussie Siyum *et al*., 2022). Therefore, the owner of a mobile phone was expected to have a positive impact on the hiring of a combine harvester.

**Participation in off farm activities:** It is a dummy variable that takes a value 1 if the household participates in off farm activity and 0, otherwise. Participating in off-farm activities facilitates the adoption of agricultural technologies. Additionally, it enhances agricultural production by increasing liquidity and credit constraints, making it easier to purchase productivity enhancing agricultural technologies, such as improved seed, fertilizer, machinery, and labor (Anríquez and Daidone, 2010; Diiro *et al*., 2015). We hypothesized that the participation of off farm activity would positive effect on the custom hiring decision of combine harvester technology.

**Frequency of contacts with extension agent:** This is a categorical variable that measures the number of farmers meeting with extension agents. The frequency of contact is measured as every year valued 1, every harvesting/sowing season valued as 2, every month valued as 3 and every weak valued as 4. The frequency of contact between the extension agent and the farmer is thought to be one factor promoting the useful dissemination of agricultural information to farmers. As a result, they are more likely to adopt new agricultural technologies. Consequently, it is hypothesized that the hiring decision and intensity of hiring combine harvesters were positively affected.

**Unseasonal rain suspicion**: It is a dummy variable that takes a value 1 if the household are too much concerned on unseasonal rain and less concerned valued as 0. Risks of yield loss caused by unexpected weather changes and erratic rain in the harvest season prompt farmers to hire combine harvesters. Agricultural mechanization services are useful for farmers who are in a state of uncertainty. Because of the unpredictable weather, there is a high risk of delaying the harvesting of wheat as rain may damage yields. Combine harvesters are gaining popularity in Pakistan today and are replacing conventional wheat harvesting and threshing methods for the timely harvesting of wheat crops (Latif *et al*., 2018).

**Fee opinion:** It is a dummy variable that takes a value 1 if the household who are perceived the hiring charge of custom hiring is too much expensive and 0 for fair. High hiring costs negatively affect the farmer's hiring decision. Having high costs is considered to be a hindrance to the adoption of some technologies (Mwangi and Kariuki, 2015). Hence, we hypothesized that a high cost perception negatively affected farmers' hiring decisions.

**Average plot distance to main road:** It is calculated by adding up the distance between each plot from the main road and dividing it by the number of wheat plots in the household. Distance to the main road is correlated with the accessibility of machinery service providers. The further away the farms are from towns and from a road, the more expensive it becomes to more fuel of combine harvesters (Berhane *et al*., 2017). The lower access to infrastructure increases production costs by raising transport costs (Semreab, 2018). Since households near main roads are easily accessible to service providers, it was hypothesized that it would be negatively related to the likelihood of custom hiring decisions.

**Immediate access to combiner:** In the study area, some households did not receive combiner hiring service whenever they needed it. It is a dummy variable that takes a value 1 if the household who able access service in time of need frequently valued as 1 and 0, otherwise. It was hypothesized that the availability of hiring services in times of need influences the hiring decision of farmers positively.

**Straw wastage suspicion:** It is a dummy variable that takes a value 1 if the household are too much concerned on straw wastage and less concerned 0. When they hire combine harvesters, they have a big problem with wheat straw. Combine harvesters collect only grain and leave stubbles and loose straw behind (Gill *et al*., 2013). It was hypothesized as negative on the intensity of combine harvester custom hiring service.

**Sources of custom hiring service:** In the study area, there were two types of combine harvester custom hiring service providers (private and cooperative), the farmer who hired from private providers valued as 0 and cooperatives as 1. There may be some difference in quality between private and cooperative machines. Due to feedback on one plot, the quality of the machine may reduce the intensity of hiring because the decision of the farmer would be affected. It was hypothesized that private leaser would has negative effect on the intensity of custom hiring services.

**Slop of wheat field:** This variable represents the average position of wheat plots in a household. The slope of a plot was valued as 1 if the slope is flat and 0 otherwise. In steeply sloped fields, heavy agricultural machinery could not be used, while in flat fields, the hiring of combine harvesters was expected to be successful.

### D. Control variable

**Pesticide**: Wheat diseases pose a significant threat to wheat production. It is a dummy variable indicating whether or not households use pesticides to produce output. Diseases can be controlled so that output can be enhanced. As a result of the use of pesticide input, household productivity varies between those who use pesticides and those who don't use pesticides (Aktar *et al*., 2009). It would be expected that pesticides are positively related to crop productivity.

**Improved seed**: The dummy variable took the value 1 if the farmer used improved seed, 0 otherwise. An improved variety of wheat seeds is essential for enhancing production and productivity. The production of wheat through the use of more improved wheat seeds was more efficient than using local seeds (Moges Dessale, 2019). Adopting improved seed can increase the farm yield per hectare. Therefore, an improved seed was hypothesized to affect wheat productivity positively.

**Number wheat plot**: This continuous variable served as a proxy for land fragmentation. Consequently, land fragmentation leads to an increase in unplanted boundary areas and a decrease in operated lands. Due to the increased number of plots, land fragmentation is also expected to increase farm management costs. There is a negative correlation between land fragmentation and technical efficiency (Assefa Ayele *et al*., 2019). Hence, the number of plots was hypothesized to be detrimental to productivity.

**Season of crop sale:** A categorical variable measures farmers' experience of selling seasons of crops frequently. Farmers who sell their crops within winter and fall are valued at 1, those who sell in summer are valued at 2, and those who sell in spring are valued at 3. Prices of staple grains are typically low right after harvest and rise gradually throughout the lean season. The unpredictable seasonal price fluctuations do not seem to offer farmers any opportunities for inter-temporal arbitrage. Instead, they often sell their output at low prices postharvest and buy back identical commodities several months later for prices far higher than they received postharvest (Stephens and Barrett, 2011). Therefore, it was hypothesized that it would a positive effect on smallholder farm income.

**Cultivation land**: Amount of farmland that the farm household cultivated in the 2021/2022 production year, measured in hectares. The larger the farm, the more opportunities to invest in agricultural production, and the reverse is true for owners of smaller farms. Bigger firms might benefit from economies of scale (Abraham and Pingali, 2020). Farm size has a negative and significant effect on technical inefficiency. This indicates that large farms are more technically efficient than small farms (Anbes Tenaye, 2020).

**Number of Livestock**: It is treated as a continuous variable and measured in tropical livestock unit conversion factors (TLU). It is considered an asset that can be exchanged for cash or used in the production process. Those who have more livestock may have more capital to invest. Owning more livestock also increases the level of adoption of improved agricultural technology (Leake and Adam, 2015).

**Market distance**: it is the distance from the farmer's home to the nearest market in kilometers. In the case of markets located far from farmers' homes, they would not have access to the most current market information (price, demand, and supply). The closer to the market, the lower the transportation cost and time spent. Access to the market and availability of the market would reduce marketing costs on matters such as transport and other transaction costs and would offer a more favorable price for agricultural products (Anyiro and Oriaku, 2011). Therefore, it was hypothesized to have a positive impact on smallholder farm incomes.

**Average home distance:** The average walking time from the homestead to the wheat field is converted to the standard unit of kilometers. By adding the distance between each field to their homestead area and dividing by the number of plots under a household, the average distance of plots was calculated. The closer the farm is to the residential location the closer supervision and monitoring of the entire production process. Also, less time and energy are needed to manage and maintain nearby plots than too far away plots; as a result, households may be discouraged from applying appropriate manure to their production.

**Number of crop produced:** It is a proxy variable for crop specialization. Farmers who grow more crops are considered to be more diversified. Most literature on smallholder cropping decisions focuses on the debate about specializing or diversifying. This suggests that crop specialization increases productivity and opens market opportunities for farmers (Sekyi *et al*., 2021). Therefore, specializing crops, which are assumed to have a higher value than diversified crops, may directly increase a household's income.

Table 3. 3. Variable description and hypothesis for custom hiring decision

| Variable | Type | Measurement | hypothesis | |
|---|---|---|---|---|
| | | | Adoption | Intensity |
| Sex | Dummy | 1 for male , 0 for female | Negative | Negative |
| Education | Categorical | 1 for illiterate, 2 for informal, 3 for primary , 4 for secondary, 5 for above | Positive | Positive |
| Age | Continuous | Year | Negative | Negative |
| Experience | Continuous | Year | Positive | Positive |
| Family labor | Continuous | Number | Negative | Negative |
| Oxen | Continuous | Number | Negative | Negative |
| Mobile phone | Dummy | 1 holder , 0 non holder | Positive | Positive |
| Off farm activity | Dummy | 1 for participant , 0 non participant | Positive | Positive |
| DA contact | Dummy | 1 yearly , 2 seasonal, 3 monthly & 4 weakly | Positive | Positive |
| Unexpected Rain fear | Dummy, | 1 for high, 0 moderate | Positive | Positive |
| Straw wastage Suspicion | Dummy | 1 very concerned 0 moderate | | Negative |
| Fee opinion | Dummy | 1 expensive 0 moderate | | Negative |
| Average Road distance | Continuous | Km | Negative | Negative |

| | | | | |
|---|---|---|---|---|
| Immediate access of | Dummy | 1 Yes , 0 no | Positive | Positive |
| Slope | Dummy | 1 for flat, 2 for steep | Positive | |
| Type of leaser | Dummy | 1 for union, 0 for private | | Positive |

Table 3. 4. Variable description and hypothesis for productivity and income

| Variable | Type | Measurement | Hypothesis | |
|---|---|---|---|---|
| | | | Productivity | Income |
| TLU | Continuous | Standard scale | Positive | Positive |
| Cultivation land | Continuous | Hectare | Positive | Positive |
| Crop diversification | Continuous | Number | | Negative |
| Land fragmentation | Continuous | Number | Positive | |
| Season of Crop sale | Categorical | 1 for winter-spring, 2 for summer, 3 for fall | | Positive |
| Improved Seed | Dummy | 1 for user , 0 non user | Positive | |
| Insecticide | Dummy | 1 user , 0 non user | Positive | |
| Average home distance | Continuous | Km | Negative | |
| Average market distance | Continuous | Km | | Negative |

# Chapter Four: RESULT AND DISCUSSION

This chapter presents the results and discussion of the study. The chapter has three main subsections. The first subsection gives the descriptive and inferential statistics result; the second subsection deals with the econometrics result. The third subsection examines the financial profitability analysis of combine harvester custom hiring by smallholder farmers, respectively.

## 4.1 Descriptive and Inferential Statistics Result

### 4.1.1 Combine harvester custom hiring decision by sample household

A household that harvests wheat field with combine harvester technology is an adopter only if there is at least one wheat plot harvested with combine harvester technology, and the farmer has used a combine harvester to harvest the crop at least in three harvest seasons. As shown in figure 4.1, the sample adopter of combine harvesters was 51.11%, and the non-adopter was 48.89%.

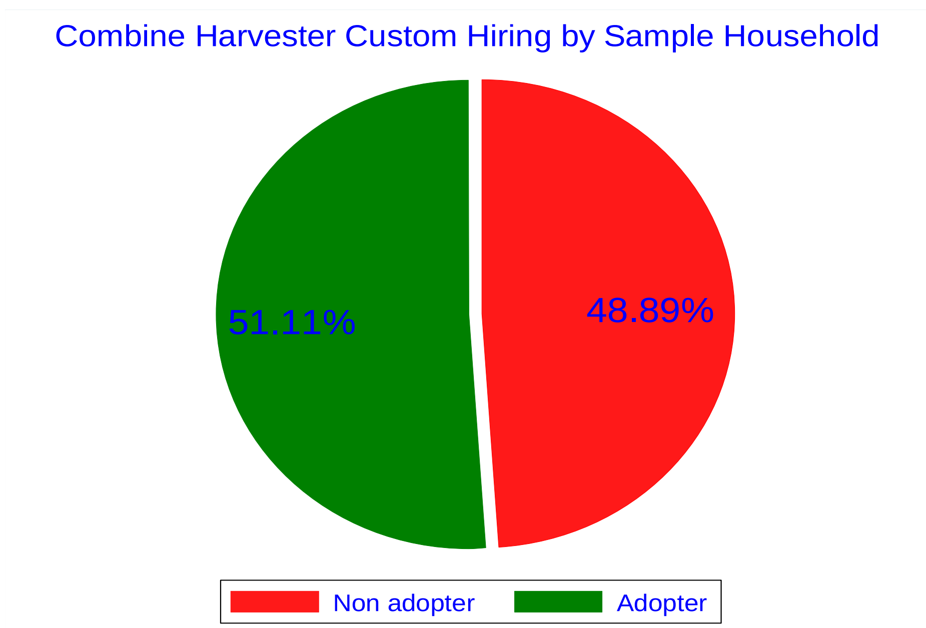


Figure 4. 1. Combine harvester custom hiring decision sample household

Source: Own survey, 2023

### 4.1.2 Intensity of combine harvester custom hiring by sample household

According to the summary statistics among 450 households 220 ( 48.89%) farmers didn't harvest wheat plots by combine harvester, 61 (13.56%), 26 (5.78%), 67 (14.89%), 54 (12.00%), 19 (4.22%) and 3(0.67%) of farmers hired combine harvester in one, two, three, four, five and six wheat plot, respectively. The distribution of hiring intensity is illustrated as follows;

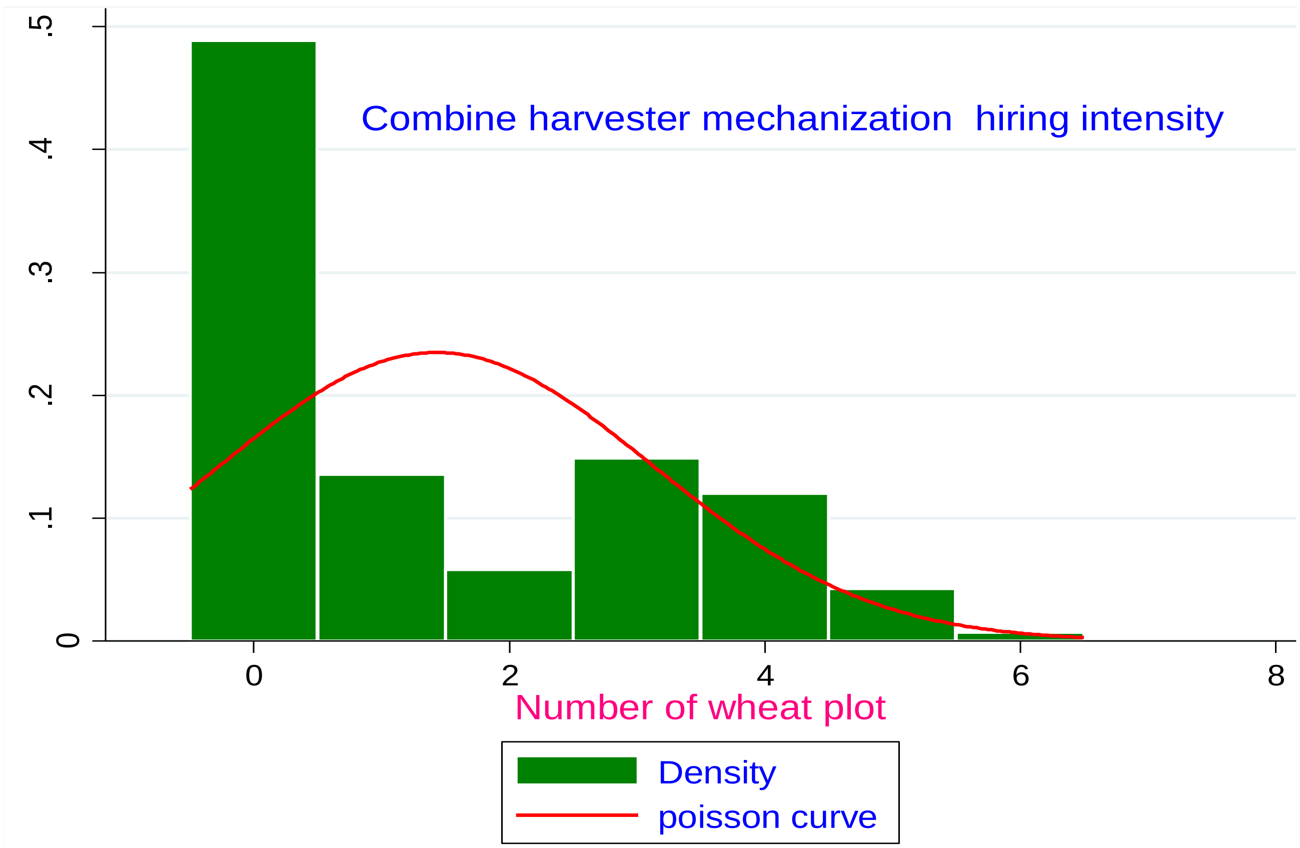


Figure 4. 2. Intensity of combine harvester custom hiring by sample household

Source: own survey, 2023

### 4.1.3 Descriptive statistics of custom hiring decision determinants

The average age of the sample household was 43.22 years old, with a standard deviation of 12.73 years old. The mean of age by category was 42.5 years & 43.90 years, and the standard deviation was 12.90 years & 12.53 years for adopters and non-adopters, respectively. The independent t-tests result was insignificant, which means there wasn't enough statistical evidence to conclude the age difference between the two groups.

The number of years the framers have been practicing crop production, the descriptive result shows the mean of farmers' experience was 22.64 years and standard deviation of 4.34 years for the total 450 sample household; the average year of agricultural practice by category was 21.89 with standard deviation 15.07 and 23.46 with standard deviation of 13.52 for adopter and non-adopter respectively. The independent t-test result shows there was no statistical significance difference between the categories in terms of farming experience.

The active family labor force is the number of people in the family that were able to work in agricultural activity above the age of 16. The mean number of people in the total sample was 3.98 with a standard deviation of 1.40. The average mean of non-adopters and adopters were 4.45 and 3.52 with 1.36 and 1.29 standard deviation, respectively. In the independent t-test, there was a mean difference between active family labors in the two regimes of the population with a significance level of 1%. Contrary to this the mean value for family labor of respondents were found to be not significantly different between the agricultural technology adopter and non-adopter groups (Muluken Gezahegn *et al*., 2021).

There is a strong relationship between the number of oxen owned by smallholder farmers and the hiring decision of combine harvester; the farmer who has a large number of oxen intends to use animal drafting power to thresh crops as opposed to the farmer with a small number of oxen. There were an average of 4.19 oxen in the sample household, 3.40 in the adopter category, and 5.01 in the non-adopter category. The independent t test for the variable was statistically significant at a 1% significance level. In line with this within the oxen ownership category of more than 5, a large (52.2 percent) number of respondents hadn’t hired tractor mechanization services, implying that farmers with no or fewer oxen are likely to hire tractor plugging services (Yohannes Mekonnen, 2021). The average number of oxen owned is one and two for adopters and non-adopters, respectively (Tigist Mekonnen, 2017).

The average wheat yield per hectare of land is 32.73 quintals with a standard deviation of 5.55 quintals and 27.15 quintals with a standard deviation of 4.94 quintals for adopters and non-adopters, respectively. The gross farm income was about 61243.6 birrs of mean 17048 birrs of standard deviation and 46158.9 birrs of mean 13683.8 birrs of standard deviation for both adopter and non-adopter groups. At a 99 percent confidence interval, the t-test was highly significant for wheat productivity and gross farm income by 15.57 and 9.45, respectively.

According to Yohannes Mekonnen (2021), in the study area the average farm income of the sampled households was 53,538 Birr per year. The mean farm incomes of households who hired mechanization services for tractors and combine harvesters are 72,154 Birr and 63,485 birr per year respectively.

Table 4. 1. Descriptive and test statistics of custom hiring decision continuous factor

| Variable | Adopter | | Non Adopter | | Total | | T –Test |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | |
| Age | 42.5 | 12.90 | 43.9 | 12.53 | 43.22 | 12.73 | 1.19 |
| Experience | 21.89 | 15.07 | 23.46 | 13.52 | 22.64 | 14.34 | 1.16 |
| Family Labor | 3.52 | 1.29 | 4.45 | 1.36 | 3.98 | 1.40 | 7.48 *** |
| No of oxen | 3.40 | 1.74 | 5.01 | 1.92 | 4.19 | 2.00 | 9.30 *** |
| Yield ha-1 | 32.73 | 5.55 | 27.15 | 4.945 | 30.01 | 5.55 | -11.2*** |
| Farm income | 61243.6 | 17048 | 46158.9 | 13683.8 | 53868.2 | 17220 | -10.3*** |

Among 450 observations, 350 (77.77%) households were headed by men, while the other 100 (33.33%) were headed by women. From the male-headed households, 160(45.51%) households were found to be adopters of combine harvesters and the remaining households 190(54.28) were non-adopters of combine harvesters. Out of the female-headed households, 70% were adopters and the rest were 30% non-adopters of combine harvesters. A Chi-square test was employed to check the association between the sex of the household head and the adoption category. An association between the sex of the household head and the adoption of a combine harvester was found to be 18.35, which is statistically significant. In line with this 108 (81.2 percent) were males and only 25(18.8 percent) were females household head respondents. But from the respondents who hired mechanization services (combine harvesters) 83.3 percent were male (Yohannes Mekonnen, 2021).

A better understanding of agriculture-related information and the proper use of agricultural technologies is possible through education. The educational backgrounds of the household heads in the total sample household were 222 of 450 about 49.33% illiterate, 108 out of 450 (24%) informal education qualified, 68 of 450 (15.11%) primary education qualified, 37 of 450 (8.22%) secondary education qualified, and 15 of 450 (3.33%) above secondary education qualified.

In the adopter regime out of 230 respondents, 86 (37.39 %) were illiterate, 65 (28.26%) had informal education attainment, 46 (20%) had attained elementary education, 21 (9.13%) had attained secondary education and 12 (5.21%) had attained more than secondary education. Whereas in the non-adopter regime out of 220 respondents, 136 (61.81%) were illiterate, 43 (19.54%) had attained informal education, 22 (10%) had completed elementary education, 6 (7.27%) had completed secondary education and 3 (1.36%) had achieved more than secondary education.

The Chi2-test confirmed that the association between technology adoption and education attainment by the adopter and no adopter categories was significant at 1% level. Better education attainment of farmers can increase the adoption of a technology. Literate households are expected to have better skills, more access and process information. In accordance with this, it was found only 2 to 3 % farmers were above high secondary 76 to77% were up to secondary and 18 to 20% of the farmer were up to higher secondary. It is a key factor for the implementation of new technology for agricultural practices such as harvesting by combine harvester(Kumar, 2020). Those farmers who have better education status have a higher probability to adopt agricultural new technology than those who do not (Alemayehu Keba, 2019; Bekele Shiferaw *et al*., 2014).

In addition, most of the respondents did not advance beyond primary school education and this makes up 41.94% of the sample followed by those that didn’t attend school at all accounting for 26.88%, those that didn’t go beyond secondary and tertiary are 15.05% and 16.13% respectively. Illiteracy is a big barrier to adoption as it limits the level of thinking, understanding, and is dormant to adopting new technologies capable of improving their current state of living (Ayandiji and Olofinsao, 2015).

The mass media (radio, TV, and mobile phones) play an influential role in disseminating awareness regarding a variety of activities, including the adoption process of new agricultural technologies. Vaughan (2015) indicated that mass media exposure such as radio, television, and mobile phones are significant sources of information for upcoming farm technology. The number of households that had mobile phones in the sample was 228 out of 450 (50.66%). Also 158 out of 230 (68.69%) and 76 out of 220 (34.54%) of adopter and non-adopter households owned a cell phone. A chi square test indicates a statistical difference in holding a mobile phone at a 1 % significance level. In alignment with this Solomon Asfaw et al. (2011), Radio and mobile ownership had a positive and significant effect on technology adoption; But it opposed the finding of (Simtowe *et al*., 2011).

Participation in the off-farm activity can affect the decision to adopt new technologies. This is particularly true if the adoption of the updated technology would require a minimum investment to purchase, hire or implement and supported by cash. As per the summary statistics from the sample household, 221 out of 450 (49.11%) participate in the off-farm activity, while the remainder is non-participants. As well, 157 of 230 (68.26%) and 64 of 220 (29.09%) adopter and non-adopter households engage in off-farm activities. On the other hand, 73 out of 230 (31.73%) and 156 out of 220 (70.90%) of the adopter and non-adopter households did not participate in off-farm activities.

The chi-square test was significant at a 1% significance level, indicates a statistical difference between the two regimes. As a result of off-farm income, farmers are expected to have liquid capital to spend on inputs that enhance productivity (Diiro, 2013). This is in line with the finding, access to off-farm income also showed a positive relationship with the household decision to adopt agricultural technologies from the chi-square test, the mean difference is statistically significant (Dawit Milkias and Gadisa Muleta, 2021; Gadisa Muleta and Addisu Getahun, 2022).

The frequency of extension contact refers to the closeness and relationship of the respondent made with extension agents. We hypothesized that the frequency of contact between extension agents and farmers would encourage the effective dissemination of agricultural information to the farmers. This would influence their decision to hire combine harvester technologies.

From the sample household, 130 out of 450 (28.88%) farmers had contact once a week, 72 out of 450 (16%) farmers had contact once a month, 101 out of 450 (22.44%) farmers had contact only in peak season and 147 out of 450 (32.66%) farmers had yearly contact with the district agriculture office. In the adopter regime 119 out of 230 (51.73%), 50 out of 230 (21.74%), 36 out of 230 (15.65%), and 25 out of 230 (10.86%) households had weekly, monthly, seasonally and yearly contact with the District Agriculture office. Also in the non-adopter regime 11 out of 220 (5.00%), 22 out of 220 (10%), 65 out of 220 (29.54%) and 122 out of 220 (55.45%) households had weekly, monthly, seasonally and yearly contact with the district agriculture office.

Access to participate in training, demonstration, field day and other extension services therefore creates the platform for the acquisition of the relevant information that promotes technology adoption. A Chi-square test of the frequency of extension contact between adopters and non-adopters is significant at the 1% level of significance, indicating that there are statistically significant differences between adopters and non-adopters. This result is similar to the one reported by (Gadisa Muleta and Addisu Getahun, 2022; Tesfamicheal Wossen *et al*., 2019).

Results from the survey showed that 247 out of 450 (54.88%) were very concerned about the occurrence of rain during harvesting season, whereas 203 out of 450 (45.11%) sample households were not much concerned. As well, 196 out of 230 (85.21%) and 51 out of 220 (23.18%) of the adopter and non-adopter households had a serious suspicion about unseasonal rain, while the rest 34 out of 230 (14.78%) and 169 of 220 (76.82%) respondents didn't have a high suspicion. At the 1% significance level, there were significant attitude variations toward unseasonal rain in harvesting season between two regimes, adopter and non-adopter.

Furthermore, straw wastage fear was another perception factor during combine harvester operation. In the sample household farmers' concerns, 257 out of 450 (57.11%) sample households had a strong anxiety about the combiner harvester operation in the straw issue; however, 193 out of 450 (42.89%) respondents weren't much concern. While 117 of 230 (50.86%) and 140 of 220 (36.37%) adopter and non-adopter respondents were seriously concerned, the rest 113 of 230 (42.89%) and 80 of 220 (36%) respondents weren't too concerned. A chi square statistic also confirms that there is a perception of straw wastage difference between adopter and non-adopter categories at a 1% significance level.

The descriptive statistics indicate that 251 of 450 (55.77%) total household sample, 111 of 230 (48.26%) adopter households, and 140 of 220 (66.63%) non-adopter households perceived the combiner hiring charge as expensive when compared with the benefits they gained. There are 199 of 450 (44.23%) sample households, 119 of 230 (51.73%) adopters and

80 of 220 (36.37%) non-adopter households who consider the combiner charge to be cheap as compared with the benefits of service. The associated test statistic indicates that there was a significant difference in the opinion of combiner charge in the study area at the 1% significance level. However, it contradicts the finding of Yohannes Mekonnen (2021), shows that 91.7 percent thought that the hiring rate for combine harvesting was too expensive and only 8.3 percent believed that it is a fair rate.

A market change in farm machinery renting price affects the rental demand for agricultural tractors. Farmers decide whether to rent tractors by comparing the costs of using animal power and other associated returns. Therefore, the negative and significant results of the rental price coefficient confirm the inverse relationship between the demand to use the tractor and the rental price (Wubamlak Ayichew *et al*., 2021).

The availability of the custom leasing service whenever needed influenced farms' decisions to hire it. In the survey period 181 out of 230 (78.69%) adopters, 35 out of 220 (15.90%) non-adopters, and 216 out of 450 (48%) sample households had possible to access a custom hiring service of combine harvester whenever it was required. However, 49 of 230 (21.30%) adopters, 185 of 220 (84.09%) non adopters, and 234 of 450 (52%) of total sample households did not access a service whenever it was needed. The chi square test was significant at a level of 1 %. Similarly to this, access to machines for hire is another factor limiting the adoption of mechanization. From the total sample 34.42% respondents were very accessible to agricultural machines, while 51.61% and 13.98% have moderate accessibility and were not accessible, respectively (Ayandiji and Olofinsao, 2015).

In the study area, there were two types of combine harvester leasing service providers, private and union. The source from which the farmer frequently hired the machine was also a factor that affects hiring decisions. But this variable was only observed in 230 combiner adopter households. This is because the farmer who didn’t hire a combine harvester even in one season had no experience to obtain from cooperative or private leasing service providers. However, it needs to take into account the intensity of the use of combiners. Out of 230 adopter households, 95 (41.30 %) use private providers, and 135 (58.69%), use cooperative providers.

Although agricultural mechanization is aimed at reducing grain loss, smallholder farmers have a different attitude towards combine harvester mechanization. Among 450 households, 228 (51%) consider that combine harvesters lose more grain than traditional harvesters, but 222 (49%) believe traditional harvesters lose more grain than combine harvesters. Furthermore, adopter and non-adopter respondents of combine harvesters have different attitudes related to grain harvesting loss; 92 out of 230 (40%) and 136 out of 220 (61.81%) perceived combine harvesters to worsen harvesting loss. In contrast, 138 out of 230 (60%) adopters and 84 out of 220 (38.19%) non-adopters perceived traditional harvesters caused significantly more losses than combine harvesters. The chi-square test revealed that there is a statistically significant difference between the two regimes in the perception of grain harvesting loss.

Table 4. 2. Descriptive and test statistics of custom hiring decision categorical factors

| Variable | | Adopter | | Non adopter | | Total | | chi-square |
|---|---|---|---|---|---|---|---|---|
| | | Count | % | Count | % | Count | % | |
| Sex | Male | 160 | 69.56 | 190 | 86.36 | 350 | 77.77 | 18.35*** |
| | Female | 70 | 30.43 | 30 | 13.63 | 100 | 22.23 | |
| Education | Illiterate | 86 | 37.39 | 136 | 61.81 | 222 | 49.33 | |
| | Informal | 65 | 28.26 | 43 | 19.54 | 108 | 24 | |
| | Primary | 46 | 20 | 22 | 10 | 68 | 15.11 | 30.08*** |
| | Secondary | 21 | 9.13 | 16 | 7.27 | 37 | 8.22 | |
| | Above | 12 | 5.21 | 3 | 1.36 | 15 | 3.33 | |
| Mobile | Yes | 158 | 68.69 | 76 | 34.54 | 228 | 50.66 | 44.75*** |
| | No | 72 | 31.30 | 144 | 65.45 | 222 | 49.33 | |
| Off farm | yes | 157 | 68.26 | 64 | 29.09 | 221 | 49.11 | 69.03*** |
| | No | 73 | 31.74 | 156 | 70.90 | 229 | 50.88 | |
| DA contact | Weakly | 119 | 51.73 | 11 | 5.00 | 130 | 28.88 | 172.8*** |
| | Monthly | 50 | 21.74 | 22 | 10.00 | 72 | 16 | |
| | Seasonally | 36 | 15.65 | 65 | 29.54 | 101 | 22.44 | |
| | Yearly | 25 | 10.86 | 122 | 55.45 | 147 | 32.66 | |
| Uncertainty | High | 196 | 85.21 | 51 | 23.18 | 247 | 54.88 | 174.76*** |
| | Moderate | 34 | 14.78 | 169 | 76.81 | 203 | 45.11 | |
| Straw Fear | High | 117 | 50.86 | 140 | 63.63 | 257 | 57.11 | 4.31*** |
| | low | 113 | 49.14 | 80 | 36.37 | 193 | 42.89 | |
| Fee opinion | Expensive | 111 | 48.26 | 140 | 63.63 | 251 | 55.77 | 10.77*** |
| | Cheap | 119 | 51.73 | 80 | 36.37 | 199 | 44.23 | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Access | Yes | 181 | 78.69 | 35 | 15.90 | 216 | 48 | 177.59*** |
| | No | 49 | 21.30 | 185 | 84.09 | 234 | 52 | |
| Slope | Flat | 190 | 82.60 | 99 | 45 | 289 | 64.22 | 69.21*** |
| | Steppe | 40 | 17.39 | 121 | 55 | 161 | 35.77 | |
| Source | Private | 95 | 41.30 | 0 | 0 | 95 | 21.11 | |
| | Union | 135 | 58.69 | 0 | 0 | 135 | 30 | |
| | Non user | 0 | 0 | 220 | 100 | 220 | 48.89 | |
| Grain loss perception | Mechanized | 92 | 40 | 136 | 61.81 | 228 | 0.51 | 21.41*** |
| | Traditional | 138 | 60 | 84 | 38.19 | 222 | 0.49 | |

4.1.4 Descriptive statistics of productivity and farm income determinants

Farm animals play a crucial role in the rural economy; they are sources of draught power, food, such as milk and meat, cash, animal dung for organic fertilizer and fuel and means of transport. Livestock production was the major occupation in the districts. Also they are important assets kept by rural households for both traction power and generating income. The study areas contain cow, oxen, heifers, calves, sheep, goats, donkeys, mules and poultry. To help the standardization of the analysis, the livestock number was converted to tropical livestock unit (TLU). The conversion factors were used based on Storck and Doppler (1991). The higher number of total TLU owned implies the household capacity to procure inputs (seed, fertilizer and all other inputs) at the right time, so that it contributed the improvement of agricultural productivity.

According to the descriptive result the mean value of TLU was 6.65 with the standard deviation of 2. The minimum and maximum livestock unit in the sample household was 1.9 and 13.75, respectively. The linear association between the total livestock unit and productivity was 0.13, whereas farm income was 0.2 with a higher statistical significance.

Total cultivation land size is one of the variables that characterize farm households. In this study, the total own, rent, and share of land were taken into consideration. The average land holding was higher than the national average, which was about 0.9 hectare per household (Leta *et al*., 2021). Our inconsistency is due to the randomization of both kebele selection as well as household selection; by chance of selection, we found that rent in and share in are much higher than share out and rent out of agricultural land in the sample household. The minimum, maximum, mean and standard deviation of total cultivation land in the household was 0.125, 3.9, 1.46 and 0.54 hectare, respectively. The Pearson correlation coefficient value indicates 0.33, it is higher significance.

Tenaye (2020) found that the size of the farm improves technical efficiency by decreasing management costs and increasing flexibility in the use of other inputs. On the other hand, this contradicts that a household operating in a large area is less efficient than a household with a smaller area. It might be that an increase in the cultivated area might entail that the farmer is no longer able to perform crop husbandry practices on time (Bhatt and Bhat, 2014; Moges Dessale, 2019).

The average distance from a farmer's homestead to their plots is first measured in minutes, and then converted to the unit of distance kilometer; conversion factor was that a normal person on average walks l kilometers in 15 minutes ( https://conditionandnutrition.com). The minimum, maximum, mean and standard deviation of average distance from a farmer's homestead to their plots in the household was 0.5, 18, 4.63, and 3.12 kilometer, respectively. The Pearson correlation coefficient value was -0.21, it is significance at 1 percent significance level. Farm distance from home showed a negative relationship with technical efficiency implying that nearer farms can be efficiently managed as compared to farther farms (Francis *et al*., 2020).

Market distance of the respondents is important for the producers to get attractive market price through reduction of transportation cost. The increase in market distance make farmers to get out-dates market information and becoming out of adopting agricultural new technologies (Gedefa Weyessa, 2014). Hence, decreasing the distance from the market decreased the transportation cost of agricultural inputs; market distance and use of agricultural technology had a negative relationship (Ogada *et al*., 2014)**.** The minimum, maximum, mean and standard deviation of Market distance in the household was 2.00, 19.5, 4.82 and 2.22 kilometer, respectively. The linear association of market distance and farm income was statistical significance -0.11, it indicates the small holder farmer residence far from the market center the lower the annual farm income.

Number of crop produced in the household was the proxy variable of crop specialization. It was hypothesized that the smallholder farmers more specialize on their farm earn the more annual farm income. The minimum, maximum, mean and standard deviation of a number of crops grown in the household was 1, 6, 3.12 and 1.09, respectively. The Pearson's Correlation coefficient is – 0.31. There is a statistical significance negative association between farm income and number of crop grown in the household. The result is in alignment with the study Sekyi *et al*. (2021) . Crop diversification is complex and requires appropriate skills and inputs as compared to specialized production (Mekonnen Sime and Edilegnaw Wale, 2018).

Table 4. 3 Descriptive and test statistics of productivity and farm income continuous factors

| Variable | Mean | SD | Min | Max | Pearson's Correlation coefficient | |
|---|---|---|---|---|---|---|
| | | | | | Productivity | Income |
| Livestock holding | 6.65 | 2.32 | 1.9 | 13.75 | 0.13*** | 0.2*** |
| Home distance | 4.63 | 3.12 | 0.5 | 18 | -0.21*** | |
| Number of plot | 2.94 | 1.14 | 1 | 8 | 0.0690 | |
| Market distance | 4.82 | 2.22 | 2.00 | 19.5 | | -0.11* |
| Number of crop | 3.12 | 1.09 | 1 | 6 | | -0.31*** |
| Cultivation land | 1.46 | 0.54 | 0.125 | 3.9 | | 0.33*** |

Based on the seasonal price fluctuations of cereal and pulse crops, the time of crop sale has a profound impact on the annual farm income of smallholder farmers; the farmer who sold a crop during the high price season receives higher gross income than a farmer who sold during the low price season. In Ethiopia, agricultural markets are characterized by seasonal price fluctuations as price seasonality is a fact of life in any agrarian production system. Prices of agricultural crops typically fall immediately after harvest and rise gradually thereafter until the next harvest (Bedaso Taye, 2015). It appears that due to over dependence on rainfall, agricultural production in Ethiopia is seasonal which involves a huge supply in times of harvest and little in off seasons. Farmers have to sell a portion of their crops immediately after harvest to pay loans, wages, school fees, or to meet other social obligations.

According to the descriptive statistics below, Among 450 sample household 179 (39.77%) frequently sold crops in winter up to spring season, 129(28.66%) sold in summer and 142 (31.55%) sold their crop in autumn season. The mean and standard deviation of farm income in winter up to spring, summer and autumn was 40345.04 with 13918.17, 43451.90 with 11084.38 and 56408.13 with 16430.81 birr, respectively. To evaluate the difference across the three seasons over annual farm income was tested using Kruskal Wallis test. It revealed that there is a strong significant mean difference between the three seasons (winter up to spring, summer, and autumn) with respect to the annual farm income. It similar the finding of Stephens and Barrett (2011) and Christian and Dillon (2018).

Crop price seasonality discourages smallholder farmers from investing to improve their farm income (Baffes *et al*., 2019). Price seasonality explains 10-14% of monthly food price volatility, availability of warehouse service has a statistically significant association with price seasonality (Solomon Bizuayehu *et al*., 2019). Based on Ethiopian grain trade enterprise (EGTE) main grain price data in 2022 at the zonal market of east gojjam (deber Markos) , teff seasonal average prices were 4366.66, 4483.33, 4625, 4750; wheat seasonal average prices were 2983.33, 3133.33, 3800, 3900; and maize seasonal average prices were 2050, 2183.33, 2500, 2,766.66 birr in summer, spring, winter, and autumn, respectively (https://www.egte-ethiopia.com). In general, the study indicates that major crops have strong seasonality of price, which has a substantial impact on smallholder farmer's income.

Table 4. 4 Descriptive and test statistics of farm income categorical factors

| Season of crop sale | | | Farm income | | Kruskal Wallis test | |
|---|---|---|---|---|---|---|
| | Count | % | Mean | SD | Mean Rank | Chi2 |
| Winter – spring | 179 | 39.77 | 40345.04 | 13918.17 | 30188.50 | 93.41*** |
| Summer | 129 | 28.66 | 43451.90 | 11084.38 | 27464.00 | |
| Autumn | 142 | 31.55 | 56408.13 | 16430.81 | 43822.50 | |

Using improved seeds or high-quality wheat seeds can improve wheat productivity significantly. From the total household 195 (43.33%) of farmer sown improved wheat seed in 2021/2022 G.C production year. The user mean and standard deviation of yield per hectare is 32.37 and 6.52 quintal respectively. While 255 (56.67%) farmers sown traditional wheat seed, the mean yield per hectare is 28.20 quintal with standard deviation of 4.75 quintal. The independent t test result reviled that a strong statistical significance mean yield difference between improved seed user and non-user. The tendency for any wheat farmers to increase their productivity depends on the type and quality of improved seed available at the right time of sowing; improved seeds are more productive and disease resistant (Kassaw *et al*., 2021).

Agricultural chemicals (pesticide) have a key role in yield improvement. It control and prevent crop pests and diseases. Wheat crop productivity was affected by the use of fungicides and insecticides. From the total 450 sample household 179 (39.77%) was used and 271 (62.23%) not used pesticide. The mean and standard deviation of wheat yield per hectare of user is 31.33 and 5.95 quintals, respectively. While the mean and standard deviation of wheat yield per hectare of non-user is 28.99 and 5.76 quintals, respectively. The independent test statistics showed significance at 1% significance level. Since the most detriment factor of wheat crop loss is disease, the use of pesticide improves smallholder farmer's crop productivity.

Table 4. 5 Descriptive and test statistics of crop productivity categorical factors

| Variable | | Yield per hectare | | | | |
|---|---|---|---|---|---|---|
| | | Count | % | Mean | SD | t-test |
| Improve seed | Yes | 195 | 43.33 | 32.37 | 6.52 | -3.12*** |
| | No | 255 | 56.67 | 28.20 | 4.75 | |
| Fungicide | Yes | 179 | 39.77 | 31.33 | 5.95 | -4.22*** |
| | No | 271 | 62.23 | 28.99 | 5.76 | |

## 4.2 Econometrics Model Result

### 4.2.1 Factor affecting combine harvester custom hiring decision

In logistic models, the joint significance test for goodness of fit and model specification is the likelihood ratio test, where the likelihood ratio is two times the difference in log likelihood between the restricted and unrestricted models, and the value follows a chi-square distribution. LR test were significant at a 1 percent significance level. The Hosmer-Lemeshow test statistic has a p-value greater than 10% significance level, the significance level is 0.38, and there is not enough evidence to conclude it is not a poor fit. The classification table is another method to evaluate the predictive accuracy of the logistic regression model; the model correctly predicted 88.89 % of the cases.

Also logistic regression assumes that the outcome variable's logit is a linear combination of its independent variables. There is a possibility that the logit function as the link function is not the right choice, or that the relationship between the logit of an outcome variable and an independent variable is not linear. There is an error in specification, whether our model has all the relevant predictors, and whether the linear combination of them is sufficient. This link test shows that the linear predicted value (y_hat) is statistically significant, whereas (y_hatsquare) is insignificant. Therefore, the link function is correctly specified.

The results in the table below found that out of the fourteen selected variables, eight variables were statistically significant with respect to hiring combine harvester mechanization services. A 1 %  level of significance indicated that , economically active family labor, having a mobile phone, extension contact, unseasonal rain suspicion, immediate accesses to custom hiring service, and the average distance of plot from the main road were significant factors. Similarly, at a significance level of 5% sex of the household head, number of oxen, immediate access of custom hiring service and at 10% education level were found to be significant in determining combine harvester hiring decisions.

**Sex:** According to the logistic model result male household odds of hiring a combine harvester are smaller by factors of 0.34 than the female household odds of hiring a machine. This variable was statistically significant at 5% significance level. The Ethiopian agricultural system traditionally required more labor, especially family labor. When we compare female and male household heads, the female household head usually rents and shares out their land. Even though farming on one's own land was more profitable than renting or sharing with others. Due to agricultural mechanization like combine harvesters, human labor can be replaced by mechanical operation, it able female farmers to produce their own farm.

This result is in line with the Mottaleb *et al*. (2016) and Astewel Takele and Yihenew G.Selassie (2018) studies. In contrast, male headed households are more likely to use a combine harvester than female headed households. Female-headed households typically have trouble arranging to hire combine harvesters from combine harvester owners due to sociocultural reasons (Mohammed Hassena *et al*., 2000).

Hiring service provision requires frequent movement within and between villages, and negotiation with client farmers. In addition, social convention in Bangladesh to some extent limits women's movement outside the household, especially without male supervision (Mottaleb *et al*., 2016). Males and females usually have different access to inputs and, as a result, make distinct decisions about technology adoption.

**Family labor:** One of the factors that negatively influenced combine harvester hiring decisions was the number of active workers in the household. It was a significant factor at the 1 percent level. The finding indicated that households with a higher number of economically active labor force are less likely to hire combine harvester mechanization services. This is because excess labor is used for carrying out harvesting operations. This can be interpreted as when other independent variables remain constant, for every unit increase in the number of economically active labor in the household, the odds of hiring combine harvester service decrease by a factor of 0.68.

Previous studies also claimed that households with high labor endowments of both farm and nonfarm workers are less likely to adopt and own agricultural machinery. Households with an excess labor endowment do not have a strong need to adopt mechanized agriculture unless there are considerable opportunity costs from engaging labor in other farm activities (Ahmed and Takeshima, 2020). Households with a larger number of members active in farming may be able to relax the labor constraints, which may augment the adoption of new technologies (Rahman *et al*., 2021).

Nevertheless, Yohannes Mekonnen (2021) found that for every additional household member, the likelihood of hiring a combine harvester increases. Farmers with large families are those with higher income levels that can afford to hire combine harvesters. Furthermore, a study by Quan and Doluschitz (2021) found that more family participation in agricultural production labor increases the likelihood of machinery adoption in plowing, seeding, and harvesting. It could be that these farms specialize in agricultural production.

**Education:** Education status was significant at a 10 percent significance level, and the odds of hiring a combine harvester who completed primary education are 2.49 times higher than compared to illiterate farmers. This indicates educated farmers are more motivated to adopt new farming methods, while illiterate farmers are conservative about traditional methods. It affects the attitudes and thoughts of respondents, making them more open and rational. Funding for this study is the same as that provided by Tolentino (2017). Nevertheless, (Rahman *et al.*, 2021) found that years of schooling reduced the likelihood of adoption. Because more education improves the likelihood of paid jobs and lowers the likelihood of agricultural technology adoption. The studies conducted by Ahmed and Goodwin (2016) show that education levels of households play a limited role in the adoption of agricultural machinery and it is not an influential driver of technology adoption in rural farm households.

**Number of oxen:** Ownership of oxen was found to be significant at 10%, negatively related to hiring decisions. This means that the odds of hiring combiners decrease by a factor of 0.83 for every unit increase in the number of oxen owned. The farmers who owned more oxen tended to employ the available draft animals instead of hiring combiners for threshing activity. However, it contradicts the finding of Astewel Takele and Yihenew G.Selassie (2018), the wealth class of the farmer as measured by oxen ownership and other characteristics used by farmers.

**Immediate access of custom hiring service:** This variable indicates the possibility of getting a combine harvester to hire when there is a need for both adopters and non-adopters. Logistic regression found that farmers with better access to technology were more likely to hire a combine by a factor of 2.66, its significance factor at 5% significance level. This finding is consistent with that of Mohammed Hassena *et al*. (2000).

**Average field distance to the main road:** So as to access the combine harvester to the wheat field, there needs to be a road and it must allow the machine to reach the field. Due to this, the distance of a wheat field from a main road was an important factor in smallholder farmer hiring decisions. When the wheat field was too far from the surrounding road, the combiner fee increased and the operator was unwilling to harvest the crop. The results show that as distance increases by 1 kilometer, the odds of hiring a combine decrease by factor of 0.72 at a significance level of one percent. A distance of farm fields to the main road were inversely affected by technology adoption decision(Adam Bekele, 2015; Menale Kassie *et al*., 2010).

**Uncertainty:** At the 1% significance level, weather factor suspicion (uncertainty about unseasonal rain) had a significant impact on hiring decisions for combine harvesters. A hypothesis was developed that unseasonal rain caused farmers to hire combine harvesters. The results of the model confirmed that farmers in general would make hiring decisions in order to avoid crop loss due to unexpected rain. For a farmer who is much concerned about unpredictable weather, the odds of success in hiring a combine harvester increase by factor of 11.72 when compared with a farmer who is less worried about the issue. The result is in line with Yohannes Mekonnen (2021), farmers' decision to hire combine harvesters in order to prevent crop loss due to unexpected rain.

**Extension contact:** Contact between extension agents and farmer was a major institutional factor influencing combiner hiring decisions. It was measured as a categorical variable every year, every picking season, every month, and every week. Communication could take place in the office or on the field. According to the results, farmers who had contact with extension agents in every weak were statistically significant at the 1 percent level. Since the benchmark of this category was only yearly contact with the agent, may for purchasing fertilizer or seed, the odds of farmers having contact in every weak increased by a factor of 6.26 as compared to the base group of yearly contact with extension agents. It plays a crucial role in the arrangement of combine harvesters. Extension personnel are constantly used as intermediaries in the dissemination of farmers input. Also provide inputs and technical advice to farmers (Mlenga and Maseko, 2015). The study is in line with the study of Ayandiji and Olofinsao (2015) and Sims and Kienzle (2016).

**Mobile phone:** Nodaway's mobile phone is very helpful for the daily tasks we have been accomplishing. However, the role of mobile phone possession in agricultural activity has been neglected except for a few findings. It was hypothesized that an individual with a phone would be more likely to make arrangements with a service provider whenever necessary. It is also possible to get information about agricultural technology like combine harvesters and access mass media like radio through mobile phones. It was statistically significant at a 1 percent level of significance, which confirmed the hypothesis. In the logistic result, the odds of a household having a mobile phone are 2.95 times higher than those who do not possess a mobile phone.

Mittal and Tripathi (2009) suggest that telecommunications, including mobile phones, can help to solve existing information asymmetry in lagging sectors such as agriculture. Mobile phone ownership is associated with improved network coverage infrastructure, increased purchasing power, and enhanced awareness of farmers to the importance of the market, technology-related and other information (Agajie Tesfaye *et al*., 2021).

Table 4. 6. Factor affecting the hiring decision of combine harvester

| VARIABLES | Coefficient & standard error | Odds ratio |
|---|---|---|
| Age | -0.02 | 0.98 |
| | (0.02) | (0.02) |
| Sex | -1.08** | 0.34** |
| | (0.46) | (0.16) |
| Experience | 0.01 | 1.01 |
| | (0.02) | (0.02) |
| Family labor | -0.39*** | 0.68*** |
| | (0.15) | (0.10) |
| Education | | |
| Illiterate | 0 | |
| Informal | -0.06 | 0.95 |
| | (0.43) | (0.40) |
| Primary | 0.91* | 2.49* |
| | (0.53) | (1.32) |
| Secondary | 0.29 | 1.33 |
| | (0.79) | (1.05) |
| Above | 0.30 | 1.36 |
| | (0.60) | (0.81) |
| Off farm activity | 0.22 | 1.25 |
| | (0.37) | (0.46) |
| Number of oxen | -0.19** | 0.83** |
| | (0.09) | (0.07) |
| Slop | 0.06 | 1.06 |
| | (0.42) | (0.44) |
| Immediate access | 0.98** | 2.66** |
| | (0.43) | (1.16) |
| Road distance | -0.33*** | 0.72*** |
| | (0.12) | (0.08) |
| Mobile phone | 1.08*** | 2.95*** |
| | (0.38) | (1.12) |
| Extension contact | | |
| Yearly | 0 | |
| Pick season | 0.43 | 1.54 |
| | (0.43) | (0.66) |

| | | |
|---|---|---|
| Monthly | 0.61 | 1.85 |
| | (0.56) | (1.03) |
| Weakly | 1.83*** | 6.26*** |
| | (0.52) | (3.28) |
| Fee opinion | -0.33 | 0.72 |
| | (0.36) | (0.26) |
| Rain uncertainty | 2.46*** | 11.72*** |
| | (0.40) | (4.66) |
| Constant | 2.09 | 8.12 |
| | (1.36) | (11.04) |
| Observations | 450 | |
| Pseudo R-squared | 0.63 | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2.2 Factors affecting the intensity of combine harvester custom hiring decision

In this section, the factors that affect the intensity of hiring a combine harvester on the number of wheat plots are discussed. The truncated poison results indicate that out of ten variables, active family labor force, immediate access to custom hiring service, source of hiring service, and straw wastage suspicion were significant barriers of the existing combine harvester hiring intensity.

**Family labor:** Similarly to the logistic estimation, the truncated result reveals an inverse relationship between the number of family laborers and the number of wheat crops harvested by combine harvesters. Because the farmer has an excess labor force, they harvest some of the plots by traditional method to utilize the excess labor force. There was statistical significance at a 5 percent significance level. As shown by the estimation results, the number of family workers increased by one, and the log count of wheat plots harvested using combine harvesters decreased by 0.09.

The availability of family labor plays a vital role in determining the adoption and intensity of using agricultural technologies. The existence of an active workforce in rural households usually discourages using of some labor saving agricultural technologies. Off course, the influence of labor availability on adoption depends on the characteristics of the technology to be adopted. A farmer with more labor would be more likely to adopt new technologies if the new ones are more labor intensive than the older ones. However, when technology is labor saving like tractors, harvesters, pesticides, and the like, its adoption would be negative. In alignment with this, Alemayehu Keba (2019) founds that due to the excess of family labor, most of the Ethiopian farmers have not used labor saving technologies like tractors and harvesters in their production system.

**Number of oxen:** The more oxen an adopter has, the lower the intensity of combine harvester hiring on the wheat field. In the same circumstances as the above argument to utilize excess labor the farmer would tend to use animal threshing. However, the opportunity cost of animal threshing would be higher than the utilization of oxen; animal drafting may adversely affect livestock productivity. With the remaining factor unchanged, the number of oxen increases by one, while the log count intensity of combiner mechanization hiring decreases by 0.07. Also, it was statistically significant at the 1 percent significance level.

**Immediate access:** Many farmers in the study area do not receive combiner hiring service whenever they require it, while others usually receive half of the harvesting operation. It was statistically significant at 1 percent. The farmer who gets immediate access to combiner hiring service was 0.98 times the log count more likely to hire the combiner than the farmer who doesn't get immediate access. The majority of rental service providers are large-scale farmers who own their own farmland and mostly reside in the southern part of the country. Moreover, mechanization dealers are located in Addis Ababa and Adama city, which are more than 300 km from the study area. Therefore, even though the demand for hiring mechanization was higher, the supply is very limited (Wubamlak Ayichew *et al*., 2021).

**Source of combiner:** In the study area, there were two types of combiner leasing service providers (private and cooperative). There might be some differences between private mechanization leasers and cooperative mechanization leasers in terms of their quality. A farmer's experience with the quality of service can affect his/her decision. As a result, the quality of a combiner may reduce the amount of hiring because of the quality of its operation. The empirical finding confirmed the above hypothesis; it was statistically significant at a 1 percent level. As compared to a private combiner, farmers that hire a combiner from the cooperative provider were 0.29 log count of the wheat plot more likely to hire a combiner.

**Straw wastage:** Farmers in the study area complain that wheat straw is a huge problem when they hire combine harvesters. The combiners don't flow down straws in one place and there is a significant amount of straw left on the field. Since the technology was designed from a foreign farming perspective, the winnowing of chaff is one limitation of the technology. Wheat straw and chaff are common sources of livestock feed, especially during periods of green fodder shortage. This variable shows the farmer's sensitivity to byproduct waste. The farmers who were more concerned about these issues decreased the intensity of adoption even though they were adopted in some wheat fields. According to the results, the intensity of hiring combine harvesters decreases by 0.27 log count of the wheat plot to the farmer most concerned about byproduct waste.

Similarly to this finding, Tolentino (2017) found that most farmer respondents in the study perceived combine harvested waste as more chaff than manual harvesting. This was also one of the reasons why they gave combine harvester a lower price. The cause of this was the inadequate winnowing implements in the combine harvester models used in the municipality. Combined harvesters result in huge losses of straw, the decomposition of straw and its burning, leading to serious environmental pollution.

Table 4. 7. Factor affecting the intensity of combine harvester hiring decision

| | Truncated Poisson regression model | |
|---|---|---|
| Variables | Robust | Non Robust |
| Family labor | -0.09** | -0.09* |
| | (0.04) | (0.05) |
| Education | | |
| Illiterate | 0 | 0 |
| Informal | -0.06 | -0.06 |
| | (0.06) | (0.11) |
| Primary | 0.05 | 0.05 |
| | (0.08) | (0.13) |
| Secondary | -0.05 | -0.05 |
| | (0.12) | (0.18) |
| Above | -0.11 | -0.11 |
| | (0.10) | (0.21) |
| Off farm activity | 0.07 | 0.07 |
| | (0.08) | (0.12) |
| Number of oxen | -0.07*** | -0.07** |
| | (0.02) | (0.03) |
| Immediate access | 0.98*** | 0.98*** |
| | (0.26) | (0.23) |
| Road distance | 0.00 | 0.00 |

| | | |
|---|---|---|
| | (0.03) | (0.04) |
| Extension contact | | |
| Yearly | 0 | 0 |
| Pick Season | -0.08 | -0.08 |
| | (0.17) | (0.25) |
| Monthly | -0.07 | -0.07 |
| | (0.16) | (0.23) |
| Weakly | -0.03 | -0.03 |
| | (0.15) | (0.22) |
| Rain uncertainty | 0.08 | 0.08 |
| | (0.12) | (0.17) |
| Source of combiner | 0.29*** | 0.29** |
| | (0.07) | (0.13) |
| Charge opinion | -0.01 | -0.01 |
| | (0.06) | (0.10) |
| Straw wastage fear | -0.27*** | -0.27** |
| | (0.08) | (0.12) |
| Constant | 0.17 | 0.17 |
| | (0.41) | (0.48) |
| Pseudo R-squared | 0.201 | 0.201 |
| Observations | 230 | 230 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 4.2.3 Impact of combine harvester hiring on crop productivity and farm income

The point estimation of the impact of combine harvester custom hiring on farm income and crop productivity is presented in the appendices. The full information maximum likelihood approach estimation employed both the selection and the outcome equations jointly. In this study, twelve variables sex, education, age, experience, family labor, off farm activity, livestock holding, average home distance, fungicide, improved seed, extension contact, and land fragmentation are controlled for the outcome equation of crop productivity. Five of them off farm activity, extension contact, improved seed, fungicide, average home distance to wheat filed were statistically important factors for crop productivity.

Also for gross farm income eleven determinants sex, education, age, experience, off farm activity, season of crop sale, market distance, extension contact, cultivation land, crop diversification and livestock holding were controlled; in the adopter regime education, season of crop sale, cultivation land, livestock holding, market distance were significance factor. Also in the non-adopter regime age, off farm participation, extension contacts, season of crop sale, crop diversification were significance factor. The identification variables used in the selection equation were immediate access of hiring service, average distance to the main road, straw wastage suspicion, mobile phone and combiner fee opinion that affect the adoption of combine harvester but have no direct effect on crop productivity and farm income.

The empirical result of ESRM confirms that there was the statistical systematic relationship between the outcomes equation error term and the selection equation error term. The covariance term of the selection error and the outcome error $\rho_{N\varepsilon}$ for productivity was 0.62 (0.21) which is statistical significance at 1% significance level and 0.27 (0.14) for farm income statistical significance at 10%. It suggests that the two regimes are a statistically difference on the average characteristics because of unobserved factors.

Treatment effects for both the adopters and non-adopters are executed after estimating the effect of different explanatory variables on the outcome variables of farm income and crop productivity. The expected yield per hectare of wheat under actual and counterfactual conditions is reported in the table below. The ATT is the difference in the average outcome variable between the observed and counterfactual adopters. The treatment or intervention's effect on the group of treated. The ATU is the difference in the average outcome variable between the observed and counterfactual of non-adopters (if they had adopted) of combine harvester; it is simply the effect of treatment or intervention on the untreated group. The transitional heterogeneity effect helps us to determine whether the impact of combine harvester adoption is smaller or larger for the adopter and non-adopter households relative to the counterfactual scenario, given by the difference between the ATT and the ATU for each outcome variable.

The results of ATT and ATU reveal that adoption significantly increases crop productivity for the treatment and control groups. The treatment group increase wheat crop productivity by 5.6

quintals because of adopting the technology and also the non-adopter group increased by 6.1 quintals if they had adopted the technology.

Also, the estimates for the average treatments effects on the treated population (ATT) and average treatment effects on the untreated population (ATU) results reveal 12764.34 & 8051.82 birr respectively. This indicates that the adoption of combine harvester increase small holder farmer's annual income of 12764.34 birr from the treatment group and if the non-adopter had adopted combiner they could be increased gross farm income by 8051.82 amounts of birr. In addition to reducing post-harvest losses, combine harvester mechanization increases the annual gain in livestock income, on-time collection of non-wheat crops, and wheat crop high market value. The finding is in line with Mohammed Hassena *et al*. (2000) and Januarti *et al*. (2018).

Table 4. 8. The impact of combine harvester hiring on small holder crop productivity

| Variable | Type | Decision stage | | Treatment effect |
|---|---|---|---|---|
| | | To adopt | Not to adopt | |
| Yield ha-1 | ATT | $E(Y_{iA} \mid A = 1) = 32.73$ | $E(Y_{iN} \mid A = 1) = 27.13$ | Diff = 5.60 |
| | ATU | $E(Y_{iA} \mid A = 0) = 36.01$ | $E(Y_{iN} \mid A = 0) = 29.90$ | Diff = 6.10 |
| | HE | Diff = -3.27 | Diff = -2.76 | Tdiff = -1.50 |

Table 4. 9. The impact of combine harvester hiring on smallholder farmers farm income

| Variable | Type | Decision stage | | Treatment effect |
|---|---|---|---|---|
| | | To adopt | Not to adopt | |
| Income (birr) | ATT | $E(I_{iA} \mid A = 1) = 52541.94$ | $E(I_{iN} \mid A = 1) = 39777.61$ | Diff =12764.34 |
| | ATU | $E(I_{iA} \mid A = 0) = 47312.44$ | $E(I_{iN} \mid A = 0) = 39260.62$ | Diff = 8051.82 |
| | HE | Diff = 5229.50 | Diff= 516.99 | Tdiff =2,517.32 |

### 4.3 Financial Analysis of Mechanized Vis –a -Vis Manual Harvesting Methods

Partial budgeting was used to compare the profitability of manual and combine harvesting of wheat in the study area. One of the tools in economics used to compare the economic benefit of technology is partial budgeting analysis. It assists the aim of quantifying and comparing the effect of the proposed technology on crop production to those of other alternative technology (Alimi, 2000).

The benefits were calculated by multiplying the average yield of wheat per hectare from the two regimes and price. The crop residue yield (straw yield) was derived by multiplying wheat yield with the conversion factors 1 quintal of grain to 1.53 straw developed by (Kossila, 1984; Tesfaye Feyisa *et al*., 2022). Market prices of yield and straw were observed by focus group decisions in the study area; it ranged between 26 to 30 birr per kg of grain and 200 to 300 birr on average 250 birr per quintal of straw in the production season. However, the price data of Ethiopian Grain Trade Enterprise (EGTE) shows the monthly price of harvesting season of December 2021 wheat in zonal market (Deber Markos Town) was 28 birr per kg (https://www.egte-ethiopia.com). In the study area, the oxen labor wage is the same as the human daily labor wage of 200 birr per oxen. The average operation cost of the traditional harvesting method is estimated to be 8078 birr, while the combine harvester was about 9252.5 birr.

Because of the excess supply of labor force and cheap wages in the study area, the operational cost of the traditional harvesting method is minimum by 1174.5 birr, but it consumes time and reduced the yield final bring on farm post-harvest loss as mentioned above. It contradicts the funding of (Islam *et al*., 2019) farmers that would be able to save 40% on harvesting costs by hiring combine harvesters. However, the net income of the traditional harvesting method is reduced by 4,057 birrs as compared to mechanized harvesting.

According to Hasan *et al*. (2019) it was worthwhile in Bangladesh, where the BCR of a combine harvester is approximately 1.55. However, in Ethiopian agriculture, despite the hiring of combine harvesters improving the incomes and productivity of smallholders, there is a waste of plentiful crop byproduct (straw), which is essential for animal feed. Traditional harvesting saves straw, which is valued at 10,392.5 birrs per hectare of land in the study district.

The average labor per day requirement in the traditional harvesting method was 11.12, 4.4, 2.6, 8.89, and 13.34 for reaping, hauling, heaping, threshing and animal labor, respectively. The combine harvester consumes 3.05, and 2.03 labors per day for cleaning and transporting grains. In line with this combine harvesting only requires 3 people to operate the combine harvester and can harvest a hectare of palay in 1-2 hours. Reapers and manual harvesting, on the other hand, requires the use of 10-20 harvester laborers per hectare and take about 1-2 days per hectare to harvest (Tolentino, 2017).

Table 4. 10. Financial profitability analysis of combine harvester custom hiring

| | | **Traditional** | **Mechanized** |
|---|---|---|---|
| **Benefit** | | | |
| Yield (qt/ha) | | 27.15 | 32.73 |
| Return of grain yield(birr) | | 76020 | 91644 |
| By product (qt) | | 41.57 | - |
| Return of straw(birr) | | 10,392.5 | - |
| Total benefit | | 86,412.5 | 91644 |
| **Cost** | | | |
| Activity | Labor per day | Wage(birr) | |
| Reaping | 11.12 | 2,224 | - |
| Hauling | 4.4 | 888 | - |
| Heaping | 2.6 | 520 | - |
| Threshing | 8.89 | 1,778 | - |
| Oxen labor | 13.34 | 2,668 | - |
| Cleaning | 3.05 | - | 610 |
| Transporting | 2.03 | - | 460 |
| Combiner charge | | | 8, 182.5 |
| Total cost | | 8078 | 9252.5 |
| **Net income** | | 78,334.5 | 82391.5 |

# Chapter Five: CONCLUSION & RECOMMENDATION

## 5.1 Summary and Conclusion

To feed the rapidly growing population, meet the high wheat demand, and substituting from importing wheat to exporting wheat; the smallholders need to improve wheat productivity through the adoption of mechanized farming practices of combine harvester technology. Baso-Liben, Gozamin, and Deber Elias districts in east Gojjam, Ethiopia are one of the largest wheat producer districts. However, the traditional harvesting methods are used by most of smallholder farmers.

Since combine harvester custom hiring services were introduced ten years ago in the districts, the study was intended to determine the barriers to smallholder farmers' custom hiring decisions for combine harvesters and assess its impact on smallholder farmers' crop productivity and farm income. Cross-sectional data were collected from a sample of 450 selected farmers by using multistage random sampling techniques.

The collected data were analyzed using descriptive statistical tools such as mean, standard deviation, frequency and percentage to describe the sample respondent's characteristics in relation to the custom hiring decision, crop productivity and income. An inferential statistics like chi-square, independence t test, Kruskal Wallis test and Pearson's Correlation coefficient were also used to infer mean, variance and correlations of population characteristics based on the sample data. Furthermore binary logistic, truncated Poisson and an endogenous switching regression model were used by STATA 15 version software to analysis the custom hiring decision, intensity and impact of combine harvester mechanization.

Descriptive results revealed that out of surveyed sample households, 51.11% of households were adopters and 48.89% were non-adopters. t- test results show that there is a statistically significant difference in yield and income between the two regimes. The logistic model results indicated that household head education, immediate access to combine harvester hiring service, mobile phones, frequency of extension contacts, and unexpected rain fears positively influence the hiring decision of agricultural mechanization in the study area. On the other hand, variables like sex (being male), family labor force, number of oxen and distance to the main road affect the hiring decision negatively.

According to the truncated Poisson regression analysis, the number of oxen, family size, and concerns about straw waste deter smallholder farmers from the intensity of hiring combine harvesters. In contrast, union mechanization leaser and immediate access to combiners had a positive effect on the custom hiring intensity of combiner harvester mechanization.

The result of ESRM indicates that due to the custom hiring of combine harvesters, wheat yield increased by 5.60 quintals per hectare and 12764.34 birrs per year. Non-adopter households could have increased yield by 6.10 per quintal and 8051.82 birr if they had hired combine harvester technology. Finally so as to evaluate the cost effective and profitable method of harvesting from our farming perspective the partial budgeting analysis was launched. The result indicates that the operational cost of the traditional harvesting method is lower. This may lead farmers to judge traditional harvesting method is profitable methods. However, the net farm income of mechanized harvesting is higher than the traditional harvesting method because of the presence of a huge amount of on-farm post-harvest loss in traditional harvesting methods.

As the hiring of combine harvesters reduces family labor burden, allows farmers more time in peak harvest season to collect another non-wheat crop at the right time, and reduces oxen drafting, which improves the market value of oxen and improves the market value of wheat grain, we can conclude that hiring combine harvesters improves smallholder households' income, besides the reduction of harvesting loss and financially viable. However, the current model of combine harvester wastes 10,392.5 birr value of crop byproduct (straw per hectare which is the most sources of smallholder framers livestock feed.

## 5.2 Recommendation

The findings of this study are indisputably vital for developing strategies and policies that aim to improve farm household welfare through agricultural mechanization. Farmers' participation in hiring this technology should be further advanced and barriers to access and utilize should be mitigated. Therefore, this study draws the following recommendations.

**Immediate access of custom hiring service:** Being unable to hire on time or failing to have the technology when in time of need is the biggest barrier. It is critical to make the leasing of machines available and affordable at the right time. The concerned body should facilitate the accessibility and distribution of farm machine hiring service to farmers. Moreover, it is recommended that to establish farm machinery custom hiring service facilitation center in the whole country that enable farmers access to appropriate farm machinery renting service.

**Having of mobile phone:** nowadays, a mobile phone is necessary for every day to day activity. The concerned body trains farmers to have mobile phones in their houses. Because hiring a particular technology requires communication between the farmer and the third party or service provider.

**The frequency of extension contacts:** influence farmers' decisions on hiring combine harvesters. Hence, the researcher suggests that farmers engage in more regular extension contacts and that the development agent identify farmers' problems that prevent them from employing mechanization. The district's agricultural and rural development office and other stakeholders have a crucial role to play in facilitating smallholder farmers' access to technology. Training and demonstrations on farm mechanization technologies could increase farmers' awareness of the economic and social benefits and motivate them to hire mechanization services.

**Family size**: As we all know, agriculture is a labor-intensive activity, carried out by many family members. Those households that have many family members intend to use traditional harvesting methods instead of agricultural mechanization. However, it is unprofitable, takes a lot of time and drudgery, and ultimately ends in a huge loss. It was recommended that household members participate in different farm and off farm activities rather than focusing on harvesting crops. Policymakers should design strategies to absorb the labor that is expected to be displaced from the agricultural sector into agricultural product processing industries or the non-agricultural sector to maintain their economical welfare. Therefore, the government and other stockholders should change labor intensive agriculture to capital intensive agriculture.

**Oxen:** In the study, the number of oxen owned is negatively correlated with the adoption of combine harvesters. The farmer that has many oxen threshes the crop by animal threshing instead of using a combine harvester. A large number of oxen can make it difficult to keep and decrease livestock productivity. The use of combiners can reduce crop loss and increase livestock productivity, as well as allow for oxen fattening activity. The small holder farmer should separate from oxen and they harvest their crop by mechanized harvesting methods. Also, inclusive farmers' training is needed for small holder farmer to start oxen fattening activity by shifting oxen based farming practices.

**Distance to the main road:** has become a critical factor in farmers' decision to hire combine harvester mechanization. It is recommended to upgrade rural roads and build new roads to connect farming villages. Improving rural infrastructure across the villages would assist in the delivery of agricultural mechanization. The development of road infrastructure in rural areas is necessary to increase farmer access to transportation facilities and to reduce transaction costs. This can enable them to gain access to agricultural mechanization. General attention should be given to the development of infrastructure, especially road facilities around production centers to enable farmers to produce in better quality, with lower losses and lower costs.

**Source of custom hiring service:** Within the study area, there are two types of combiner leasing service providers: private and union. The variable (union) positively affects the intensity of hiring decisions for combine harvesters. A majority of private combiner leasers provide inappropriate and overused agricultural machinery. It causes a complete loss of crops for small-holder farmers. Trust must be built between service providers and farmers, and offering quality services to satisfy farmers is essential. In this regard, the establishment of a regulatory body to supervise the quality of the technology is recommended.

**Byproduct (straw) wastage:** Since our agriculture system is mixed with livestock and crop production, the two complement each other. The fear of straw waste, which is necessary to feed livestock, is a decisive factor in hiring decisions. The cause of this was because of the inadequate winnowing implements in the current combine harvester models used in the study area. As a result, all combiners are imported from abroad and designed for large scales and commercial farming systems. The present models used in the country must be upgraded or replaced with models which have better winnowing implements to reduce straw loss. A manufacturer can also need to resolve problems encountered by farmers when operating combine harvesters, as well as make further improvements to the machine that would consider the residual of grains.

The hiring of combine harvesters has a significant impact on the economic welfare of smallholder farmers. Both ATT and ATU were implying that those households who adopted combine harvesters were better off in terms of crop productivity and farm income as compared to their counterfactual. The households who didn't adopt combine harvesters would be better off if they did adopt combine harvesters. In addition, the custom hiring of combine harvester is a financially profitable method. Since the only way to frontier shiftier is through technology, the entire agricultural activities in the nation should move from traditional to modern agriculture.

This study demonstrates the technology's suitability for domestic agriculture production practices and overcomes the barrier to custom hiring decision of combine harvester mechanization. It is generally recommended that the government should support and facilitate the smallholder custom hiring of agricultural mechanization in favor of wheat importing oriented policy to exporting oriented policy. Otherwise, the domestic public and private factories/suppliers import and produce agricultural mechanization technology that is suitable for Ethiopian smallholder farming perspective.

This study focused on only three districts in one zone in the Amhara region, with a relatively small sample, for more information on agricultural mechanization adoption barriers and its impacts on the welfare of small holder farmers at regional and national levels, it is imperative to conduct similar studies using more representative locations, larger sample size and panel data.

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# APPENDICES

Appendix table 1. Full logistic regression model estimation (*under logistic command*)

| Adoption | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| Age | -.022 | .022 | -1.00 | .317 | -.064 | .021 | |
| Sex | -1.079 | .464 | -2.33 | .02 | -1.987 | -.17 | ** |
| Experience | .015 | .019 | 0.76 | .446 | -.023 | .053 | |
| Family labor | -.392 | .148 | -2.64 | .008 | -.683 | -.101 | *** |
| Education | | . | . | . | . | . | |
| Illiterate | 0 | | | | | | |
| Informal | -.055 | .428 | -0.13 | .898 | -.894 | .784 | |
| Primary | .911 | .53 | 1.72 | .086 | -.129 | 1.951 | * |
| Secondary | .287 | .791 | 0.36 | .717 | -1.263 | 1.838 | |
| Above | .304 | .597 | 0.51 | .61 | -.865 | 1.474 | |
| Off farm income | .223 | .368 | 0.60 | .546 | -.499 | .945 | |
| Oxen | -.19 | .087 | -2.18 | .029 | -.361 | -.02 | ** |
| Slope | .059 | .419 | 0.14 | .889 | -.763 | .88 | |
| Immediate access | .977 | .435 | 2.25 | .025 | .125 | 1.83 | ** |
| Road distance | -.332 | .118 | -2.82 | .005 | -.564 | -.101 | *** |
| Mobile phone | 1.082 | .38 | 2.84 | .004 | .336 | 1.827 | *** |
| DA contact | | | | | | | |
| Yearly | 0 | . | . | . | . | . | |
| Pick season | .431 | .426 | 1.01 | .311 | -.403 | 1.266 | |
| Monthly | .613 | .558 | 1.10 | .272 | -.481 | 1.706 | |
| Weakly | 1.834 | .524 | 3.50 | 0 | .808 | 2.86 | *** |
| Fee opinion | -.334 | .359 | -0.93 | .352 | -1.039 | .37 | |
| Uncertainty | 2.461 | .398 | 6.19 | 0 | 1.682 | 3.241 | *** |
| Constant | 2.094 | 1.36 | 1.54 | .124 | -.571 | 4.759 | |
| Mean dependent var | | 0.511 | SD dependent var | | | 0.500 | |
| Pseudo r-squared | | 0.630 | Number of obs | | | 450 | |
| Chi-square | | 169.771 | Prob > chi2 | | | 0.000 | |
| Akaike crit. (AIC) | | 271.033 | Bayesian crit. (BIC) | | | 353.218 | |

**** p<.01, ** p<.05, * p<.1*

Appendix table 2. Full truncated Poisson regression model estimation (*under tpisson command)*

| Intensity | Coef. | St.Err. | t-value | p-value | 95% [Conf | Interval ] | Sig |
|---|---|---|---|---|---|---|---|
| Family labor | -.09 | .037 | -2.45 | .014 | -.162 | -.018 | ** |
| Education | | | | | | | |
| Illiterate | 0 | . | . | . | . | . | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Informal | -.062 | .062 | -1.01 | .315 | -.183 | .059 | |
| Primary | .049 | .076 | 0.65 | .515 | -.1 | .198 | |
| Secondary | -.048 | .124 | -0.38 | .702 | -.291 | .196 | |
| Above | -.11 | .098 | -1.13 | .26 | -.303 | .082 | |
| Off farm activity | .074 | .085 | 0.87 | .383 | -.092 | .24 | |
| Oxen | -.075 | .025 | -3.05 | .002 | -.123 | -.027 | *** |
| Immediate access | .979 | .258 | 3.79 | 0 | .473 | 1.484 | *** |
| Road distance | .003 | .026 | 0.13 | .9 | -.049 | .055 | |
| Extension contact | | | | | | | |
| Yearly | 0 | . | . | . | . | . | |
| Pick season | -.079 | .17 | -0.47 | .642 | -.413 | .254 | |
| Monthly | -.07 | .164 | -0.43 | .67 | -.392 | .252 | |
| Weakly | -.032 | .151 | -0.21 | .831 | -.328 | .264 | |
| uncertainty | .081 | .116 | 0.70 | .485 | -.147 | .309 | |
| Source of combiner | .293 | .073 | 4.03 | 0 | .151 | .436 | *** |
| Fee opinion | -.011 | .058 | -0.20 | .842 | -.124 | .102 | |
| Straw wastage fear | -.268 | .079 | -3.39 | .001 | -.423 | -.113 | *** |
| Constant | .168 | .405 | 0.41 | .678 | -.627 | .963 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 2.796 | SD dependent var | 1.350 |
| Pseudo r-squared | 0.201 | Number of obs | 230 |
| Chi-square | 170.505 | Prob > chi2 | 0.000 |
| Akaike crit. (AIC) | 654.034 | Bayesian crit. (BIC) | 712.481 |

*** *p<.01, ** p<.05, * p<.1*

Appendix table 3. Full maximum likelihood estimation of endogenous switching regression model for crop productivity (*under movestay command* )

| | Coefficient | Robust Std. Err. | Z | P>z | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Adopter productivity** | | | | | | |
| Sex | .1439821 | .8035066 | 0.18 | 0.858 | -1.430862 | 1.718826 |
| Education | | | | | | |
| Informal | .8973261 | .922154 | 0.97 | 0.331 | -.9100625 | 2.704715 |
| Primary | 1.556775 | .9790096 | 1.59 | 0.112 | -.3620481 | 3.475599 |
| Secondary | .7079702 | .9662202 | 0.73 | 0.464 | -1.185787 | 2.601727 |
| Above | .78215 | 1.577223 | 0.50 | 0.620 | -2.309151 | 3.873451 |
| Age | .0195873 | .0362065 | 0.54 | 0.589 | -.051376 | .0905507 |
| Experience | -.0184096 | .0363216 | -0.51 | 0.612 | -.0895985 | .0527794 |
| Home distance | -.1699884 | .1542991 | -1.10 | 0.271 | -.4724092 | .1324324 |
| Family labor | .2370207 | .3169781 | 0.75 | 0.455 | -.384245 | .8582864 |
| Fungicide | .6080388 | .7409303 | 0.82 | 0.412 | -.8441579 | 2.060236 |
| Improved seed | 3.739707 | .7184224 | 5.21 | 0.000 | 2.331625 | 5.147789 |
| Extension contact | | | | | | |
| Seasonally | -1.79192 | 1.579681 | -1.13 | 0.257 | -4.888038 | 1.304198 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Monthly | .1287647 | 1.721559 | 0.07 | 0.940 | -3.245429 | 3.502958 |
| Weakly | 1.2636 | 1.960235 | 0.64 | 0.519 | -2.57839 | 5.10559 |
| Land fermentation | -.4004581 | .2660546 | -1.51 | 0.132 | -.9219155 | .1209993 |
| Off farm activity | 1.439758 | .766523 | 1.88 | 0.060 | -.062599 | 2.942116 |
| TLU | .0066841 | .183746 | 0.04 | 0.971 | -.3534514 | .3668196 |
| Constant | 29.27531 | 3.183245 | 9.20 | 0.000 | 23.03626 | 35.51436 |
| **Non adopter productivity** | | | | | | |
| Sex | -.0711265 | .8777318 | -0.08 | 0.935 | -1.791449 | 1.649196 |
| Education | | | | | | |
| Informal | -.5813757 | .6507133 | -0.89 | 0.372 | -1.85675 | .693999 |
| Primary | .3742017 | .9319949 | 0.40 | 0.688 | -1.452475 | 2.200878 |
| Secondary | -1.054869 | 1.233196 | -0.86 | 0.392 | -3.471889 | 1.36215 |
| Above | .6744006 | 1.067394 | 0.63 | 0.528 | -1.417653 | 2.766454 |
| Age | -.034283 | .028438 | -1.21 | 0.228 | -.0900205 | .0214545 |
| Experience | .0214033 | .0253287 | 0.85 | 0.398 | -.02824 | .0710467 |
| Home distance | -.2121115 | .0888078 | -2.39 | 0.017 | -.3861716 | -.038051 |
| Family labor | .3925947 | .2431133 | 1.61 | 0.106 | -.0838987 | .869088 |
| Fungicide | 1.461528 | .5866148 | 2.49 | 0.013 | .3117841 | 2.611272 |
| Improved seed | 1.802566 | .6283316 | 2.87 | 0.004 | .5710584 | 3.034073 |
| Extension contact | | | | | | |
| Seasonally | 1.915562 | .633198 | 3.03 | 0.002 | .6745168 | 3.156607 |
| Monthly | 2.292762 | 1.477819 | 1.55 | 0.121 | -.6037103 | 5.189234 |
| Weakly | 3.287312 | 1.399533 | 2.35 | 0.019 | .5442772 | 6.030346 |
| Land fermentation | -.0347204 | .2501688 | -0.14 | 0.890 | -.5250422 | .4556013 |
| Off farm activity | 2.957415 | .7159305 | 4.13 | 0.000 | 1.554217 | 4.360613 |
| TLU | .1640593 | .1154282 | 1.42 | 0.155 | -.0621758 | .3902945 |
| Constant | 24.14449 | 1.81799 | 13.28 | 0.000 | 20.58129 | 27.70768 |
| **Selection equation** | | | | | | |
| Sex | -.5385035 | .2548933 | -2.11 | 0.035 | -1.038085 | -.038921 |
| Education | | | | | | |
| Informal | .1472876 | .2166164 | 0.68 | 0.497 | -.2772727 | .5718479 |
| Primary | .5412856 | .2435923 | 2.22 | 0.026 | .0638534 | 1.018718 |
| Secondary | .478893 | .4003008 | 1.20 | 0.232 | -.3056822 | 1.263468 |
| Above | .6633103 | .3550789 | 1.87 | 0.062 | -.0326316 | 1.359252 |
| Age | -.023328 | .0094092 | -2.48 | 0.013 | -.0417696 | -.004886 |
| Experience | .008517 | .0088849 | 0.96 | 0.338 | -.0088972 | .0259311 |
| Home distance | -.0072628 | .0285129 | -0.25 | 0.799 | -.0631469 | .0486214 |
| Family labor | -.0098283 | .0679308 | -0.14 | 0.885 | -.1429702 | .1233136 |
| Fungicide | -.3552506 | .1992952 | -1.78 | 0.075 | -.7458621 | .0353609 |
| Improved seed | .470974 | .2062439 | 2.28 | 0.022 | .0667435 | .8752046 |
| Extension contact | | | | | | |
| Seasonally | .4173527 | .2290856 | 1.82 | 0.068 | -.0316468 | .8663521 |
| Monthly | .7249875 | .2882312 | 2.52 | 0.012 | .1600647 | 1.28991 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Weakly | 1.642204 | .3003394 | 5.47 | 0.000 | 1.053549 | 2.230858 |
| Land fermentation | .4250218 | .0701772 | 6.06 | 0.000 | .2874771 | .5625666 |
| Off farm activity | .3775267 | .1991282 | 1.90 | 0.058 | -.0127574 | .7678107 |
| TLU | -.1175604 | .0433746 | -2.71 | 0.007 | -.202573 | -.032547 |
| Immediate access | .5089824 | .2178996 | 2.34 | 0.019 | .0819069 | .9360578 |
| Road distance | -.270343 | .064741 | -4.18 | 0.000 | -.397233 | -.143453 |
| Straw fear | .5871641 | .1953741 | 3.01 | 0.003 | .204238 | .9700902 |
| Mobile phone | .6833008 | .1849029 | 3.70 | 0.000 | .3208978 | 1.045704 |
| Fee opinion | -.3523897 | .1760173 | -2.00 | 0.045 | -.6973773 | -.007402 |
| Constant | .1465227 | .7406633 | 0.20 | 0.843 | -1.305151 | 1.598196 |
| /lns1 | 1.574713 | .0128186 | 122.85 | 0.000 | 1.549589 | 1.599837 |
| /lns2 | 1.440928 | .0337803 | 42.66 | 0.000 | 1.374719 | 1.507136 |
| /r1 | .1151609 | .2722923 | 0.42 | 0.672 | -.4185223 | .6488441 |
| /r2 | .6747689 | .3142718 | 2.15 | 0.032 | .0588074 | 1.29073 |
| sigma_1 | 4.829356 | .0619057 | | | 4.709534 | 4.952226 |
| sigma_2 | 4.224613 | .1427088 | | | 3.953967 | 4.513784 |
| rho_1 | .1146545 | .2687129 | | | -.3956848 | .5708913 |
| rho_2 | .5881081 | .2055743 | | | .0587397 | .8593177 |
| Wald test of indep. eqns. : | | | | chi2(1) = | 4.95 | Prob > chi2 = 0.0262 |

Appendix table 4. Full maximum likelihood estimation of endogenous switching regression model for farm income (*under movestay command*)

| | Coefficient | Std. Err. | Robust Z | P>z | [95% conf. | Interval] |
|---|---|---|---|---|---|---|
| **Adopter income** | | | | | | |
| Age | 37.22726 | 128.868 | 0.29 | 0.773 | -215.3494 | 289.8039 |
| Sex | 1922.243 | 2326.66 | 0.83 | 0.409 | -2637.926 | 6482.413 |
| Experience | 19.31882 | 111.2645 | 0.17 | 0.862 | -198.7555 | 237.3931 |
| Education | | | | | | |
| Informal | 3028.044 | 2509.491 | 1.21 | 0.228 | -1890.469 | 7946.556 |
| Primary | 5500.817 | 3062.616 | 1.80 | 0.072 | -501.7995 | 11503.43 |
| Secondary | 910.3758 | 3619.373 | 0.25 | 0.801 | -6183.465 | 8004.216 |
| Above | 5632.479 | 3749.947 | 1.50 | 0.133 | -1717.282 | 12982.24 |
| Off farm activity | 1743.618 | 2191.937 | 0.80 | 0.426 | -2552.5 | 6039.736 |
| Extension contact | | | | | | |
| Pick season | -5465.088 | 5051.88 | -1.08 | 0.279 | -15366.59 | 4436.415 |
| Monthly | -2941.618 | 6270.467 | -0.47 | 0.639 | -15231.51 | 9348.271 |
| Weakly | -682.7501 | 7897.093 | -0.09 | 0.931 | -16160.77 | 14795.27 |
| Season of crop sale | | | | | | |
| Winter | 2169.34 | 2372.936 | 0.91 | 0.361 | -2481.53 | 6820.21 |
| Fall | 14352.44 | 2671.587 | 5.37 | 0.000 | 9116.224 | 19588.65 |
| Cultivation land | 9744.53 | 2579.548 | 3.78 | 0.000 | 4688.709 | 14800.35 |
| TLU | 1065.412 | 605.4774 | 1.76 | 0.078 | -121.3019 | 2252.126 |
| Market distance | -933.679 | 453.0697 | -2.06 | 0.039 | -1821.679 | -45.67871 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Crop diversification | -1974.529 | 1468.457 | -1.34 | 0.179 | -4852.651 | 903.5938 |
| Constant | 29577.28 | 10847.02 | 2.73 | 0.006 | 8317.512 | 50837.05 |
| **Non adopter income** | | | | | | |
| Age | 113.7246 | 65.05417 | 1.75 | 0.080 | -13.77922 | 241.2285 |
| Sex | 872.9253 | 2135.489 | 0.41 | 0.683 | -3312.557 | 5058.407 |
| Experience | -17.38261 | 57.58527 | -0.30 | 0.763 | -130.2477 | 95.48245 |
| Education | | | | | | |
| Informal | 2513.219 | 2203.262 | 1.14 | 0.254 | -1805.095 | 6831.533 |
| Primary | 3695.004 | 2689.496 | 1.37 | 0.169 | -1576.311 | 8966.32 |
| Secondary | -1673.093 | 2578.98 | -0.65 | 0.517 | -6727.8 | 3381.614 |
| Above | 5163.645 | 6838.088 | 0.76 | 0.450 | -8238.762 | 18566.05 |
| Off farm activity | 3428.708 | 1707.538 | 2.01 | 0.045 | 81.99482 | 6775.42 |
| Extension contact | | | | | | |
| Pick season | -723.6206 | 1717.411 | -0.42 | 0.674 | -4089.684 | 2642.443 |
| Monthly | 3130.713 | 2936.042 | 1.07 | 0.286 | -2623.824 | 8885.25 |
| Weakly | 8010.491 | 4421.961 | 1.81 | 0.070 | -656.3927 | 16677.37 |
| Season of crop sale | | | | | | |
| Winter | 86.06527 | 1865.735 | 0.05 | 0.963 | -3570.709 | 3742.839 |
| Fall | 3762.255 | 2258.763 | 1.67 | 0.096 | -664.8383 | 8189.349 |
| Cultivation land | 2666.378 | 2015.593 | 1.32 | 0.186 | -1284.111 | 6616.868 |
| TLU | -450.3332 | 294.1207 | -1.53 | 0.126 | -1026.799 | 126.1328 |
| Market distance | 239.0166 | 323.1181 | 0.74 | 0.459 | -394.2832 | 872.3164 |
| Crop diversification | -2196.63 | 719.9205 | -3.05 | 0.002 | -3607.649 | -785.6119 |
| Constant | 38276.05 | 5985.019 | 6.40 | 0.000 | 26545.63 | 50006.47 |
| **Selection equation** | | | | | | |
| Age | .0026877 | .0088078 | 0.31 | 0.760 | -.0145753 | .0199507 |
| Sex | -.5382926 | .223909 | -2.40 | 0.016 | -.9771461 | -.0994391 |
| Experience | -.0011231 | .0080105 | -0.14 | 0.888 | -.0168235 | .0145772 |
| Education | | | | | | |
| Informal | .3831516 | .2125286 | 1.80 | 0.071 | -.0333968 | .7997 |
| Primary | .6044743 | .2731699 | 2.21 | 0.027 | .069071 | 1.139878 |
| Secondary | .6151872 | .3451009 | 1.78 | 0.075 | -.0611983 | 1.291573 |
| Above | .0663223 | .4656009 | 0.14 | 0.887 | -.8462386 | .9788832 |
| Off farm activity | .4123022 | .1834469 | 2.25 | 0.025 | .0527528 | .7718515 |
| Extension contact | | | | | | |
| Pick season | .6216112 | .2193868 | 2.83 | 0.005 | .1916209 | 1.051601 |
| Monthly | 1.169093 | .2645458 | 4.42 | 0.000 | .6505928 | 1.687593 |
| Weakly | 2.038223 | .267133 | 7.63 | 0.000 | 1.514652 | 2.561794 |
| Season of crop sale | | | | | | |
| Winter | .0933073 | .2111061 | 0.44 | 0.658 | -.320453 | .5070676 |
| Fall | .0459285 | .2554575 | 0.18 | 0.857 | -.4547591 | .5466161 |
| Cultivation land | -.2275208 | .2266838 | -1.00 | 0.316 | -.6718129 | .2167714 |
| TLU | -.1879862 | .0474465 | -3.96 | 0.000 | -.2809797 | -.0949928 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Market distance | .0379843 | .0424184 | 0.90 | 0.371 | -.0451543 | .1211229 |
| Crop diversification | -.442319 | .0938612 | -4.71 | 0.000 | -.6262835 | -.2583544 |
| Immediate access | .477892 | .2094158 | 2.28 | 0.022 | .0674445 | .8883394 |
| Straw waste fear | .5839488 | .2011819 | 2.90 | 0.004 | .1896396 | .978258 |
| Mobile phone | .623604 | .1649508 | 3.78 | 0.000 | .3003064 | .9469016 |
| Fee opinion | -.0928038 | .185725 | -0.50 | 0.617 | -.4568181 | .2712105 |
| Constant | .9826287 | .7949384 | 1.24 | 0.216 | -.5754219 | 2.540679 |
| /lns1 | 9.459798 | .023225 | 407.31 | 0.000 | 9.414278 | 9.505318 |
| /lns2 | 9.260044 | .012252 | 755.80 | 0.000 | 9.23603 | 9.284057 |
| /r1 | .1230104 | .6277921 | 0.20 | 0.845 | -1.10744 | 1.35346 |
| /r2 | .2711831 | .1425081 | 1.90 | 0.057 | -.0081275 | .5504938 |
| sigma_1 | 12833.29 | 298.0533 | | | 12262.21 | 13430.97 |
| sigma_2 | 10509.59 | 128.7637 | | | 10260.22 | 10765.02 |
| rho_1 | .1223936 | .6183876 | | | -.8031554 | .8748675 |
| rho_2 | .2647254 | .1325212 | | | -.0081274 | .5008902 |
| Wald test of indep. eqns. : | | | chi2(1) = | 3.63 | Prob > chi2 = 0.0568 | |

**Test of econometric problems after logistic model**

```
. lstat

Logistic model for adoption

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |       205            25  |        230
     -     |        25           195  |        220
-----------+--------------------------+-----------
   Total   |       230           220  |        450

Classified + if predicted Pr(D) >= .5
True D defined as adoption != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   89.13%
Specificity                     Pr( -|~D)   88.64%
Positive predictive value       Pr( D| +)   89.13%
Negative predictive value       Pr(~D| -)   88.64%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   11.36%
False - rate for true D         Pr( -| D)   10.87%
False + rate for classified +   Pr(~D| +)   10.87%
False - rate for classified -   Pr( D| -)   11.36%
--------------------------------------------------
Correctly classified                        88.89%
--------------------------------------------------
```

```
. . estat gof, group(10)

Logistic model for adoption, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       450
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         8.54
                  Prob > chi2 =         0.3828

. linktest

Iteration 0:   log likelihood = -311.80511
Iteration 1:   log likelihood = -120.14962
Iteration 2:   log likelihood = -119.81738
Iteration 3:   log likelihood = -119.81639
Iteration 4:   log likelihood = -119.81639

Logistic regression                               Number of obs     =        450
                                                  LR chi2(2)        =     383.98
                                                  Prob > chi2       =     0.0000
Log likelihood = -119.81639                       Pseudo R2         =     0.6157

------------------------------------------------------------------------------
    adoption |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   1.008559   .0882655    11.43   0.000     .8355614    1.181556
      _hatsq |  -.0337839   .0345269    -0.98   0.328    -.1014555    .0338876
       _cons |    .126644   .2128471     0.59   0.552    -.2905286    .5438166
------------------------------------------------------------------------------
```

Appendix table 5. Conversion factors used to calculate Tropical Livestock Units (TLU).

| Animal | TLU equivalent |
|---|---|
| Cow and oxen | 1 |
| Mule | 1 |
| Donkey adult | 0.75 |
| Heifer and bull | 0.75 |
| Donkey young | 0.35 |
| Calf | 0.25 |
| Sheep and goat | 0.13 |

**STRUCTURAL SURVEY QUESTIONNAIRE**

Hello, how are you? I am Mr.…………… This interview is used for the research of Mr. Tewodros Gete who is currently studying his MSc at Bahir Dar University. This research is a partial fulfillment for the awarded of MSc in Agricultural Economics. Dear respondent, now you are randomly selected and asked to give information about your demographic, socio economic and other relevant profiles. Your response to this questionnaire will serve as source of information to the research paper to be done for thesis entitled 'Impact of combine harvester custom hiring on farmers' crop productivity and farm income; in case of East Gojjam, Amhara region, Ethiopia'. Whatever information you provide here is strictly confidential and will use only for the research purpose. Your honest response and correct (genuine) answer is very important for the reliable research outcome.

*Thank you in advance for your kind cooperation and dedicating your time!*

PART 1: General Information

Date of Interview --------------- Name of Woreda …………Name of Kebele………….

1. Name ………………………..
2. Age of the household head __________(years)
3. Sex of the household head
   a. Male
   b. Female
4. Educational level of household head
   a. No education
   b. Informal education
   c. Primary (1-4)
   d. Secondary school (5-8)
   e. Above secondary
5. Marital status of household head:
   a. Never married
   b. Married
   c. Widowed
   d. Divorced

6. Total number of household members ________male__________female…………………..
    a. Below 15 years of age_________
    b. 16 -60 years of age_______
    c. Over 60 years _________

PART 2: Resource profile and farming activity of the respondent

7. How many years have you engaged in agriculture? ___________________
8. Total cultivation land size __________(timad)
    a. Amount of own land ……………(timad)
    b. Amount of share in and rent in land …………..(timad)
    c. Amount of rent out or share out wheat land __________(timad)
9. Did you use combiner harvester to harvest your wheat crop?
    a. Yes
    b. No
10. How many years did you hire combine harvester…………….?
11. Did you sown improve wheat seed?
    a. Yes
    b. No
12. How many times do you plow your farmland?
13. how much quantity wheat seed do you apply during sowing(kuntale)
    a. Traditional …………………………..
    b. Improved……………………………….
14. Did you use pesticide on your wheat crop?
    a. Yes
    b. No
15. Did you use pesticide on your wheat crop?
    a. Yes
    b. No
16. How may time did you contact extension agent (DA)?
    a. Weakly
    b. Monthly
    c. In pick production season

d. Annually

17. Did you take credit during the last 12 months?

a. Yes

b. No

18. Do have mobile phone?

a. Yes

b. no

19. Number of livestock own, and annual income earned.

| No | Type of | Number of owned | Number of sold over the last 12 month | Income earned (Birr) |
|---|---|---|---|---|
| 1 | Oxen | | | |
| 2 | Cow | | | |
| 3 | Bulls | | | |
| 4 | Calves | | | |
| 5 | Heifer | | | |
| 6 | Horse | | | |
| 7 | Mule | | | |
| 8 | Donkey | | | |
| 9 | Goat | | | |
| 10 | Sheep | | | |
| 11 | Chicken | | | |
| Total | | | | |

20. In what season frequently did you sale crops?

a. Winter

b. Spring

c. Summer

d. fall

21. Type of crop grown, area coverage, yield and amount of birr earned.

| No | Type | Area (*timad)* | Yield (*quintal)* | Amount *(birr)* |
|---|---|---|---|---|
| 1 | Wheat | | | |

| | | | | |
|---|---|---|---|---|
| 2 | Teff | | | |
| 3 | Maize | | | |
| . | | | | |
| . | | | | |
| . | | | | |
| 4 | Other | | | |
| 5 | Total | | | |

22. Does your family member participate in the labor market outside the farm yes?

    a. Yes
    b. No

23. How many birr you get from off farm income (labor market)?

24. How many day you used to finish all wheat harvesting operation in traditional?

    a. Harvesting ……………………………………..
    b. Transportation ……………………………………..
    c. Heaping ……………………………………..
    d. Threshing ……………………………………..

25. How many labor you used to finish all wheat harvesting operation in traditional?

    a. Harvesting ……………………………………..
    b. Transportation ……………………………………..
    c. Heaping ……………………………………..
    d. Threshing ……………………………………..

26. How many oxen you used to finish all threshing operation in traditional method?

PART 3: Perception toward combine harvester custom hiring practice

27. How did you see the combiner technology on your crop harvesting operations?

    a. Yes
    b. No

28. What methods do you perceive more bring wheat harvesting loss?

    a. Combine harvester
    b. Manual

29. Do you have anxiety on erratic rainfall in pack harvested time?

    a. Yes

b. No

30. What is your opinion on the cost of hiring a combine harvester?

a. expensive

b. fair

31. Do you have suspicion of straw wastage by combine harvester?

a. Strong

b. Weak

PART 4: Supply and Time factors

32. Are combiner is available whenever you need?

a. Yes

b. No

33. From where do you get the hiring services frequently?

a. cooperatives/union

b. private service providers

PART 5: Description of farm plots and plot-level questionnaires

34. Slope of wheat field?

a. Flat

b. Steep

35. How many plots did you hire a combine harvesting services?

a. all

b. Partially

36. Average distance from wheat plot to home in minute……………….

37. Average distance from wheat plot to main road in minute……………….

38. How far is your home from the market where output is sold in minutes of walking?

39. Number, area, distance from home, distance from road, position and combine harvester adopter wheat plot in the household.

| No of wheat plot | Area (timad) | Home distance (minute) | Road distance (minute) | Slope | | Combine harvester | |
|---|---|---|---|---|---|---|---|
| | | | | Flat | Steep | yes | No |
| 1 | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2 | | | | | | | |
| 3 | | | | | | | |
| 4 | | | | | | | |
| . | | | | | | | |
| . | | | | | | | |
| Total | | | | | | | |

PART 6: Key informant interview

- What crops are most commonly grown in the area?
- When did you begin using combine harvester technology in this kebele?
- What problem did farmers face when they hired a combine harvester?
- How much wheat straw is sold on the local market?
- What was the price of wheat on the surrounding market at harvest time (December)?
- How much were the combine harvester fees per quintal?
- How much is the wage for daily labor in your kebele?
- How much is the oxen labor wage per day in your kebele?
- What is the maximum amount of wheat that can be harvested per hectare in the kebele?
- Does the kebele experience unseasonal rain often in the harvesting season?
- How did you view the oxen fitting activity?
- Do a large number of farmers engage in oxen fitting activities alongside their agricultural activities in the kebele?
- Have you ever thought that a large number of wheat grains are lost during harvesting?
- What do you think of the reduction of post-harvest losses as a result of the combine harvester?