UNIVERSITÀ CATTOLICA DEL SACRO CUORE

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Dottorato di ricerca per il Sistema Agro-alimentare

Ph.D. in Agro-Food System

Cycle XXXVIII

S.S.D: Agricultural and Food Economics

Farm Transformation Status and Sustainability in High-Value Crops and Livestock Farms: Effects on Market Participation, Food Security, and the Role of Knowledge Networks. Evidence from Central Oromia Region, Ethiopia.

Coordinator:

Prof. Paolo Ajmone Marsan

Candidate:

Chala Hailu Hussen

Matriculation ID: 5215075

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DEDICATION

I dedicated this dissertation paper to my father Hailu Hussen Gobu and mother Jitu Hundesa Gana whose unwavering encouragement, and pray God for me throughout my journey.

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LISTS OF ACRONYMOUS AND ABBREVIATIONS

ADLI	Agricultural Development Led Industrialization
AfDB	African Development Bank Group
AIC	Akaike Information Criterion
AIS	Agricultural Innovation System
BIC	Bayesian Information Criterion
CA	Capability Approach
CFA	Confirmatory Factor Analysis
DHM	Double Hurdle Model
EFA	Exploratory Factor Analysis
ESE	Ethiopian Seed Enterprise
FAO	Food and Agricultural Organization
FCA	Factor Component Analysis
FCM	Formal Contract Market
FCS	Food Consumption Score
FE	Farmers' cooperative and Extension services
FS	Farmers' cooperative and social capital
FTC	Farmers Training Center
FYGTP	The Five-Year Growth and Transformation Plan
GDP	Gross National Product
GTP	Growth Transformation Plan
GoE	Government of Ethiopia
GHI	Global Hunger Index
GSEM	General Structural Equation Model
HDDS	Household Dietary Diversity Score
HH	Household Head
ICM	Informal Contract Market
ICT	Information Communication Technology
IRR	Incedence Rate Ratio
LPM	Linear Probability Model
MoFED	Ministry of Finance and Economic Development
NAEIP	National Agricultural Extension Intervention Program
NW	Net Working
OLS	Ordinary Least Square
OM	Open Market
PCA	Principal Component Analysis
PSNP	Productive Saftey Net Programme
PNC	Planning National Commission
SDG	Sustainable Development Goals
SE	Social capital and Extension services
VIF	Variance Inflation Factors
WFP	World Food Programme

GENERAL ABSTRACT

Agricultural transformation is a key driver to end hunger and achieve food self-sufficiency in developing regions. Hence, the study aimed to examine the factors influencing the transformational status of high-value farms, assess sustainability, investigate the effect on market participation, and evaluate household food security. Moreover, it explored the role of knowledge utilization networks on transformational farm practices. This study significantly contributes to Ethiopian agricultural development policy and is crucial as it highlights smallholder farmers' transformation status, sustainability implications, and institutional roles. Accordingly, multi-stage sampling techniques were employed to collect primary data from 422 randomly selected heads of farm households in the central Oromia region of Ethiopia. Data was gathered using a semi-structured questionnaire through personal interviews and analyzed using descriptive statistics, multiple factor analysis, and econometric models.

The results of the first objective indicated that approximately 48.81%, 28.91%, and 22.28% of respondents were classified as having partial, medium, and full transformation status, respectively. The size of farmland, the number of livestock in TLU, and the adoption of agricultural technologies positively influenced the likelihood of progress in farm transformation status. Furthermore, the existing transformational farming practices positively increased environmental and economic sustainability while decreasing social sustainability. The findings suggested that farmers' access to productive resources and agricultural technologies creates opportunities to enhance transformation progress, and that the current practices are economically and environmentally sustainable, although efforts towards improving social sustainability are needed.

Secondly, farmers' participation in contract marketing was examined, revealing that the age of farmers and the volume limitations imposed by buyers negatively impacted participation in informal contracts. Conversely, farm size, the number of adopted agricultural technology packages, and market trust positively influenced farmers' decisions to participate in the informal contract market. The truncated regression analysis indicated that the number of cropping systems, participation in irrigation, dummy districts, transformation status, adoption of cross-breed cows, distance to market, poultry feed availability, and access to extension services all positively affected the volume of crops, milk, and eggs sold. Hence,

improvements in the status of transformational practices enhance the level of high-value farm products sold in the study areas.

Thirdly, the relationship between transformational status and household food security was examined. The results indicate that 52.61% of the farmers in the study area have an acceptable food security profile, 39.34% are classified as borderline, and 8.06% have poor food consumption profiles. The food consumption score varies significantly by household age and district, with higher scores associated with a more diversified diet. The results of the Two-Stage Least Squares analysis revealed that the status of farm transformation, frequency of extension contacts, and access to information on healthy and nutritional food production significantly and positively affect food security. Conversely, income and distance from the nearest market negatively and significantly impact food security. In conclusion, the findings indicate that adopting transformational agricultural practices at the farmer level holds promise for improving access to and the availability of food.

Fourthly, the impact of the knowledge utilization network on farm transformational practices was examined. The results of the first stage probit regression showed that the distance from farmers' training centres and cooperative offices negatively influenced farmers' access to extension services and farmers' cooperatives, respectively. Whereas, attending community-level meetings positively influenced farmers' linkages to build social capital. The second stage of negative binomial regression revealed that knowledge utilization through extension services, farmers' cooperatives, and social capital channels directly and positively influences the number of transformational practices adopted. Conversely, the mediator variables, such as field day demonstrations and training, were positively influenced by extension services and a mix of knowledge generated through farmers' cooperatives and extension services. Additionally, extension services indirectly influence the number of transformational farming practices adopted through field day demonstrations, which had a positive sign. Overall, the study concludes that high-value farm transformations significantly improve marketability and food security, although most farmers remain in the lower transformation category. Moreover, extension services are instrumental in promoting the adoption of transformative farming practices.

Keywords: Contract Marketing, Food Security, High-Value Farm Products, Knowledge Use Networking, Smallholder Farmers, Sustainability, Transformational Farming Practices, Transformational Status .

CHAPTER ONE

1. General Introduction

1.1. Background of the study

Agricultural transformation is a key driver to end hunger and achieve food self-sufficiency in developing regions. It is evident that global agricultural production and food systems have been halted by dynamic changes in the world population and complex environmental calamities (DeBenedetti, 2021). Likewise, rural-to-urban migration is occurring at a rapid pace, and the sedentary nature of aging farmers limits the supply of the agricultural labour force, which reduces their role in food production (FAO, 2017). These factors have a tremendous effect on sustainable agriculture in developing regions where urbanization is increasing and food production is dominated by smallholder farmers.

The post-World War II agricultural growth highlights the rapid pace of industrial agriculture, where production was boosted using agricultural technologies. Nevertheless, this boom in agricultural production overlooked the stewardship of resource bases, leading to topsoil degradation and loss of biodiversity (Gliessman, 2014). Consequently, episodes of agricultural growth proved to be unsustainable. Therefore, the 1990 Sustainable Agriculture Bill in the USA defined "an integrated system of plant and animal production practices having a site-specific application" that, in the long run, would achieve social, economic, and environmental goals (Velten et al., 2015). This aligns with the 1987 Brundtland definition of sustainable development, which emphasizes justice in the alleviation of poverty (UN, 1987). Specifically rural poverty reduction requires stability of food systems, through balancing production with consumption.

For example, Ethiopia adopted a transformational agricultural policy to address the goal of sustainable agriculture. Agriculture is rain-fed, and climate change threatens food production. The transformation agenda allows farmers to use intensively purchased inputs to increase production. It refers to the "process that leads to higher productivity on farms, commercially oriented farming, and strengthens the link between farming and other sectors of the economy" (AfDB, 2016). It focuses on addressing production volume, value, and change agent’s interconnectedness, as well as structural changes in the industrial landscape. It also aimed to decline the relative share of GDP from agriculture, demographic transitions, and

high-value chain developments (Pritchett, 2013). Explicitly, transformation is the pathway for sustainable agricultural development, which requires innovations that complement production techniques suitable for environmental management (Adnan et al., 2018). It is believed to raise labor productivity and paves mobility to non-agricultural activities, and obtain higher prices for agricultural outputs (Bosc et al., 2012; de Vries et al., 2015; Lewis, 1954; Timmer & Akkus, 2008).

On the other hand, farmers' knowledge plays a key role in creating a stable food system. It involves the practical and social-change aspects of agroecology (Douglass, 1984). This knowledge stems from individual (tacit) or generic connections, including social networks, groups, and formal institutions, and influences decision-making (Kogut & Zender, 1992). In particular, it provides open insights to identify solutions for farm input constraints and transforms the food system through enterprise combinations. Thus, knowledge transfer facilitates decision-making by converting intention into action, allowing farmers to adopt and adapt to changes in economic, social, and environmental conditions (Adnan et al., 2018; Oliver-Smith, 1996).

Hence, the literature shows there is a success story of sustainable agricultural production through integrated crop-livestock farming systems, which play a significant role in improving material and social needs in both rural and urban areas (Sekaran et al., 2021). Notably, these systems enhance food security and support biodiversity conservation (Danso-Abbeam et al., 2021; Gliessman, 2014). Therefore, this study is important for examining the transformational status of high-value farm enterprises to understand the situation at the farmer level. It provides insights into contributions to food security, enhances market opportunities, and improves farmers' interactions with stakeholders in the acquisition of agricultural knowledge. Furthermore, the findings provide policy inputs that supplement the Ethiopian government's ambition to transform smallholder agriculture at the national level, particularly in the study areas.

1.2. Concepts and Theories in Agricultural Development

Agricultural development is a crucial component of rural development, addressing both material and social needs. This process requires the abandonment of traditional practices and the adoption of new production techniques. However, a significant challenge in agricultural

development is the stagnation of output growth and factor productivity, which fails to keep pace with the growth of other sectors (Ruttan, 1977). Hence, Ruttan (1977), outlines several theories related to agricultural development models.

Frontier Model: This model refers to the expansion of cultivated and grazing land that characterized the history of Western countries during the 18th and 19th centuries. It resulted in the establishment of settlements and the conversion of forestland into agricultural land.

Conservative Model: This model gained attention during the English Agricultural Revolution as a response to soil deterioration. It emphasized the maintenance of soil health through plant-nutrient recycling and the intensification of crop and livestock production. Supported by the law of diminishing returns on land, capital, and the model influenced agricultural practices well into the 20th century, addressing locational differences due to ecological factors.

Urban-Industry Impact Model: This model highlights the connection between the agricultural sector and non-agricultural sectors, and it is primarily recommended for the least developed countries.

Diffusion Model: This model proposes the dissemination of agricultural technologies through an extension system. While it gained popularity, it failed to achieve rapid growth in agricultural production and did not facilitate the transition from traditional to modernized agriculture.

High-Payoff Input Model: In 1960, a new approach to agricultural development emerged through the High-Payoff Input Model. This model focuses on the fundamental elements of knowledge generation, input-output market development, and farmers' capacity building. It was articulated by Theodore Schultz, and recommends investing in new technologies, such as improved seeds, fertilizers, and irrigation, to achieve significant growth in agricultural productivity.

The Green Revolution Model: Implemented in the mid-20th century, this model focused on scaling up high-yield crops, particularly wheat and rice. It emerged as a new approach to agricultural development in Latin America (notably Mexico) and Asia (including the Philippines and India) during the 1930s. The primary aim was to increase production by developing disease-resistant and high-yielding crop varieties. While it achieved significant

success in enhancing incomes in the 1950s, many poor farmers did not benefit. However, the Green Revolution contributed to food security by increasing caloric food production and promoting monoculture in densely populated regions like India (Flachs, 2016). Nevertheless, the sustainability of agricultural production is in question, as reliance on inorganic inputs has reduced soil quality and led to a loss of biodiversity due to the excessive application of chemicals (Gliessman, 2014)).

Agricultural Transformation: Agricultural transformation is defined as a process that shifts the agri-food system from a subsistence orientation to a commercial orientation. It encompasses both on-farm transformation, which includes changes in farming practices, and off-farm transformation, such as marketing, distribution, and the development of an agricultural industrial base (Laborde et al., 2019). The theory of agricultural transformation began with (Lewis, 1954), who illustrated the concept through the reallocation of factors of production from a low-productive agricultural sector to a more modern industrial sector. This theory assumes that the marginal productivity of labour in agriculture approaches zero. In contrast, Schultz (1964) criticized Lewis's perspective, arguing that resource inefficiencies in agriculture stem from farmers' adherence to traditional practices. Schultz contended that farmers act rationally by demanding the introduction of new technologies and inputs as drivers of agricultural transformation. Moreover, Johnston & Mellor (1961) advocate the importance of stimulating agriculture and maximizing its contributions to overall economic development, particularly in terms of income and employment opportunities. Despite, it remains an underdeveloped industry in many developing regions.

Similarly, Darity (1980) attempted to explore counter-Malthusian population growth. He argued that, regardless of population pressure, it is possible to achieve agricultural growth through the intensification of land-use practices. However, this approach lacks the consistency necessary to meet agricultural food demand in the face of high birth rates in developing countries. Moreover, Köberle et al.(2023) and Ruttan (1977) also examine cases of agricultural transformation in which input and output prices induce technological change in agriculture. This emphasizes the importance of developing forward and backward market linkages between the agriculture and industry sectors. However, the heterogeneity of farmers' wealth remains a significant factor in achieving broader market transformation and, ultimately, structural transformation in the economy. Above all, (Timmer, 1988) synthesizes various perspectives on the phases of agricultural development, highlighting how surplus

production can lead to industrialization. Accordingly, he outlined four phases of agricultural development (See Figure 1.1 below).

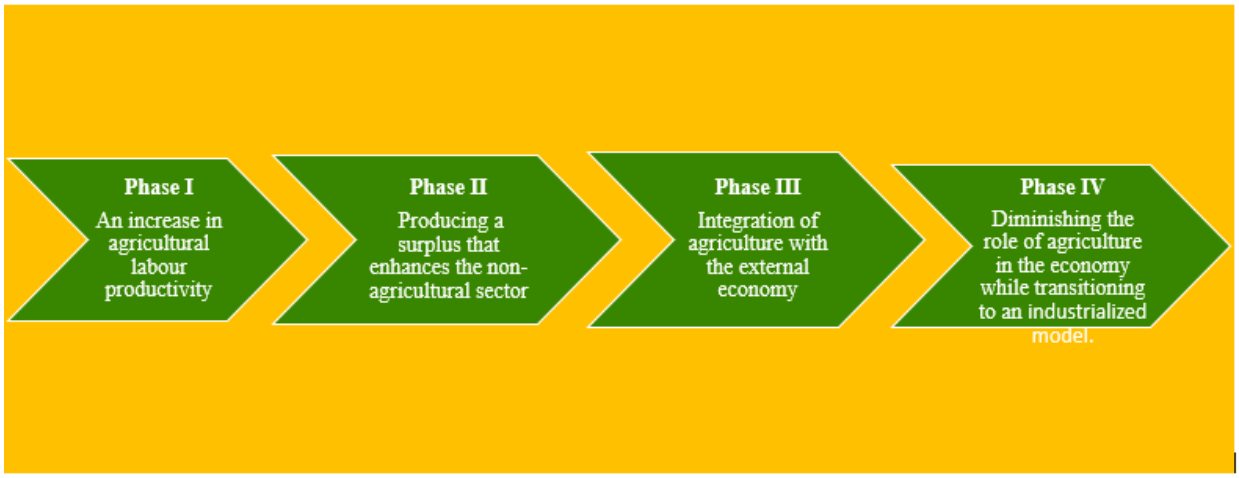

Figure 1.1. Phase of agricultural transformation
Source: Author's sketch by reviewing literature of Timmer (1988).

On the other hand, recent empirical research has expanded the understanding of agricultural transformation by comparing large farms with small farms, high-value crops with staple food production, and the adoption of new technologies and farming practices (Otsuka et al., 2016). The studies are grounded in a fundamental developmental pattern that highlights agriculture's effectiveness over the non-agricultural sector in alleviating poverty, ensuring nutrition, and promoting overall economic growth (Ligon & Sadoulet, 2018; Rankin et al., 2019). In addition, urbanization, dietary changes, and the modernization of food distribution underscore the importance of transformation. Climate change, environmental degradation, and advancements in technology present challenges to poverty reduction and emphasize the need to transform farming practices (Laborde et al., 2019). Therefore, the dynamic changes in economic performance and environment consistently demand empirical studies to accumulate knowledge that enables the provision of sustainable solutions.

1.3. Overview of Ethiopian Agricultural Economy, Reforms, and Interventions

The Ethiopian agricultural economy is dominated by smallholder agriculture, contributing 24% of GDP, which is higher than the average in sub-Saharan Africa (Gordon, 2019). At the national level, agricultural GDP has declined from 36.3% in 2016/17 to 32.40% in 2021/22 (NBE, 2022). The sector accounts for 66% of total employment and 76% of total export items (ATI, 2022). This reflects the relatively growing performance of structural changes within the

agricultural sector. The total cultivated land increased from 0.4% in 2018/19 to 1.4% in 2021/22, with cereal, pulses, and oilseed production constituting 82%,13.7%, and 3.4%, respectively, of all crop production (ESS, 2021). The shares of crop production, animal farming, forestry, and fishery in the agricultural sector are 65.6%, 25.6%, 8.3%, and 0.3%, respectively (ESS, 2021). However, challenges such as climate change (including drought and delayed rainfall during the onset season) and low input usage persist in hindering the sector's development path.

Since 1991, the Ethiopian government has implemented several interventions to transform the agricultural sector. The Agricultural Development Led Industrialization policy (ADLI) was adopted to achieve food security by enhancing production. Under this policy, several reforms were made in the input supply scheme. For instance, there was a partial liberalization of fertilizer from 1991 to 1995, the National Agricultural Extension Intervention Program (NAEIP) from 1995 to the present, fertilizer price liberalization from 1997 to 1998, and a shift in industry structure from 2000 to the present, where private companies withdrew from the fertilizer supply market and substituted by farmers' cooperative unions (Abate et al., 2014; Demeke et al.,1998; Spielman et al., 2013; Stepanek, 1999). However, the seed system was not fully liberalized like the fertilizer market, where formal seed supply is dominated by Ethiopian Seed Enterprises (ESE) and regional seed enterprises. This indicates that there are few private seed producers and a local (informal) seed system operated by farmers (Spielman et al., 2013). This suggests that Ethiopian agricultural development is primarily driven by public service interventions, which still exhibit significant transformational gaps.

On the other hand, the livestock sector is another potential economic resource. Despite Ethiopia's high cattle populations in Africa, there is low performance in this sector. The livestock composition is characterized by 97.8% indigenous, 1.9% cross-breed, and 0.3% exotic breeds (CSA, 2020). The production system is mainly mixed with crop production, followed by a pastoral system (Zeleke, 2021). Cattle play a vital role in mixed farming areas, providing power traction, threshing crops, and manure. They also serve as sources of income from the sale of milk, eggs, and live animals (Duressa et al., 2014). The low productivity of animal products is related to technical skills and animal feed shortages. For example, the price of commercial feed increased from ETB 500 per quintal in 2010 to ETB 3000 per quintal by 2021, making it expensive for smallholder farmers. Likewise, on-farm farm forage development is limited by land shortages, competition from crop production, and land tenure

(Zeleke, 2021). These factors indirectly contribute to the rising prices of animal-sourced food (Abegaz et al., 2018; FAO, 2020).

Simultaneously, Ethiopian public budget investment in the agricultural sector has shown an increase from year to year. It exceeds the 2003 'Maputo Declaration' target of allocating 10% of public budget expenditures to agriculture (African Union, 2003). Consequently, fiscal budget expenditure on agriculture rose from 12.2% in 2017/18 to 18.5% in 2021/22 (UNICEF, 2021). This increase in budget is focused on transforming the technical production of smallholder farmers through the intensive use of agricultural inputs, hiring agricultural extension workers, investing in research, and promoting sustainable land management (natural resource management). Accordingly, new knowledge is communicated to farmers through extension workers, who play a key role in disseminating agricultural technologies, commercialization, training, and conserving natural resources, though the process lacks uniformity (Gatdet, 2022).

Moreover, the government has designed a ten-year plan (2021-2030) focusing on three dimensions of development framework: economic growth, environmental protection, and social inclusion (PDC, 2022). The framework of the new development plan was based on lessons drawn from previous interventions, such as the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (2005/06-2009/10), the Five-Year Growth and Transformation Plan (FYGTP) (2010/11-2014/15) – aimed at achieving the Millennium Development Goals, and the Growth and Transformation Plan II (GTP II) (2015/16-2019/20) (MoFED, 2010).

Hence, the introduction of Agricultural Transformation strategies in the plan is focused on promoting the production of high-value cereal crops such as maize, teff, wheat, barley, haricot beans, and horticultural crops (market-driven approach). It is implemented by consolidating farming (cluster commodity) in which farmers are adjacent and produce the prioritized crops (ATA, 2013). According to, (FAO, 2020) report, notable achievements were regestered including increased adoption of improved seeds, greater use of agricultural inputs, expanded irrigation practices, and progress in selected crop value chains. However, livestock transformation has received comparatively limited attention, despite the predominance of mixed crop–livestock farming systems in the country. To ensure sustainable agricultural development, transformation efforts must be integrated to address both crop and livestock

sub-sectors transformation simultaneously. Therefore, the Ethiopian government has arranged the structure of agricultural offices from the top Ministry of Agriculture to the village level which enabling to implement agricultural development policy as it presented below Figure 1.2.

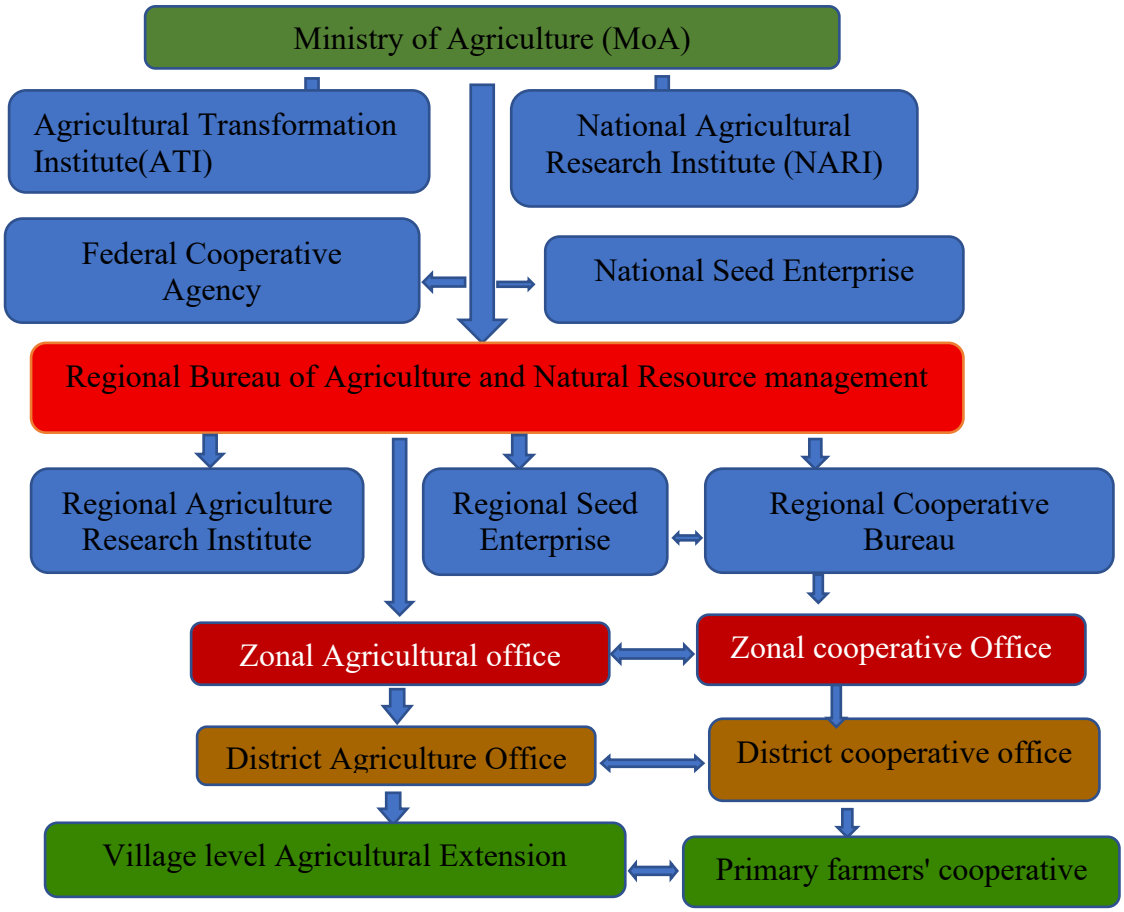

Figure 1.2. Organ hierarchy of the Ethiopian Agriculture Development Unit
Source: Own sketch extracted from Ethiopian Agricultural Report flow system.
Hint: ⟷ input supply & demand coordination at regional, zonal, district, and village level.

1.4. Statement of the Problem

For the next 30 years, the African labour force is projected to grow to 800 million, and the total population is expected to reach 2.5 billion by 2050, with the majority remaining in rural areas. This situation necessitates attention to sustainable rural economies (Tom et al., 2019). Nowadays, sustainable agriculture and food systems have garnered the attention of academics and policymakers worldwide. Frustrations arising from global climate change and the exponential growth of populations in developing countries have raised concerns about future healthy food provision. Several interventions and approaches exist to address the challenges of agricultural sustainability. A summarized review by Benton & Harwatt (2022) indicates that the supply-side approach aims to increase productivity with minimal environmental

impact, while the demand-side approach focuses on creating agricultural landscapes that are more conducive to agroecology. The former prioritizes higher production volumes, whereas the latter emphasizes diversified and nutritionally healthy food production, albeit at a smaller scale. However, regardless of the approach adopted, there are still disproportionate food price increases in low, middle, and high-income countries. Acute food insecurity affects approximately 258 million people in 58 countries, representing the worst level of food insecurity (World Bank, 2023). For example, in sub-Saharan Africa, food inflation is in double digits, exceeding 30% in Ethiopia and Malawi (AfDB, 2023). This is possibly due to climate shocks and the deterioration of natural resources, such as soil and irrigation water. However, in areas and regions where transformational adaptations have been implemented, there are positive developments in farming systems (Vermeulen et al., 2018). This has led to a commitment to climate-smart agriculture, capacity building, and farm transformations over the next ten years (2021-2030) for the sustainability of the agri-food system (FAO, 2021).

Accordingly, paradigm shifts through agricultural transformation play a significant role in poverty reduction by improving commercialization and diversification of products; however, this process is neither smooth nor uniform (Imai, 2017). For example, in Ethiopia, the size of agricultural land poses a major challenge for transformation, as land is under competition from crop production and grazing pressure from livestock. This affects the flexibility and stability of food systems (Tom et al., 2019). Additionally, there is limited mechanization and technology adoption, alongside high rural-to-urban migration and food self-insufficiency, with Ethiopia annually importing 1.5 million tons of wheat (ATI, 2022). According to a report by the (FAO, 2021) on the 'Political Economy of the Ethiopian Food System', the choice of farm enterprise value chains is constrained by growth and dietary diversity. For instance, while the vegetable value chain offers greater dietary diversity, it is associated with limited growth.

On the other hand, cereals exhibit high growth but offer narrow dietary diversity, while the dairy value chain provides dietary diversity and enhances growth, albeit with lower returns for poor households. This situation may be attributed to the fact that smallholder agriculture is characterized by limited enterprise diversity, low productivity, and weak market coordination (Dorward et al., 2005). It requires transformative activities coupled with knowledge utilization networks to bring about significant changes in dietary diversity and production volume by integrating high-value enterprises. This integration improves economic

structures and reduces poverty to achieve sustainable outcomes (Shapiro et al., 2017), ensures stable and resilience food systems (ESCAP, 2020), and offers more dietary diversity than mono enterprises (Jabbar & Cobbina, 1990).

Above all, the Ethiopian government has initiated the intensification of high-value cereal crops such as teff, wheat, malt barley, and maize (ATI, 2013). However, advocacy for intensification requires access to affordable purchased inputs and the endorsement of specialization (European Commission, 2017). For example, a report by the World Food Programme showed that the Government of Ethiopia (GoE) planned to import 15.1 million quintals of fertilizer but actually imported only 12.8 million quintals. This created excess demand over supply, leading to high fertilizer prices. The price of fertilizer at the farmer level is fixed at Birr 4900 per quintal, reflecting a price increase of 200 percent prior to the year 2021(WFP, 2022). This poses a significant challenge to the transformation process, following low production of high-value crops. Simultaneously, it affects biomass production for animal feed, where mixed farming systems dominate in the central highlands of Ethiopia.

Despite government ambitions to raise productivity, there is also a lack of transformational practices that farmers can develop (Haileslassie et al., 2005). This is attributed to a lack of skills and know-how, as well as inadequate access to extension services that provide technical skills and transfer knowledge (Pornpratansombat, 2010). Thus, knowledge utilization networking is fundamental to improving farmers' interactions with change agents (formal and informal institutions for change). Moreover, several barriers remain, including small landholdings, high input costs, limited mechanization, and inadequate access to credit and markets. Despite numerous studies on agricultural transformation, limited attention has been given to how mixed high-value crop and livestock enterprises are evolving at the household level. Hence, understanding the current transformation status and its determinants is essential for shaping effective policies that promote sustainable and inclusive agricultural development.

1.5. Conceptual Framework

The conceptual framework of the study is presented as follows: Factors influencing farm transformation are categorized into internal and external factors within the context of farm household decision-making. Internal factors relate to farmer-specific characteristics,

perceptions, behaviours, and resources. In contrast, external factors are beyond farmers' control and are influenced by their connections with stakeholders. These pull and push factors motivate farmers to engage in transformative activities that enhance the production of high-value crops and livestock enterprises. The extent of engagement in such transformational agricultural production varies among farmers, depending on these factors, resulting in different statuses ranked according to the types of high-value farms they produce. Each status has implications for sustainability, food security, and commercialization. Hence, the transformational status examined exogenously affects sustainability, food security, and market participation. Finally, knowledge utilization networking is essential factor that influences farmers' adoption of best practices on their farms. The mediating variables used for knowledge transfer in this study are field day demonstrations and participation in training. These variables are crucial for measuring the direct and indirect impact of knowledge sources on transformational farming practices. As the result, this leads to an improvement in the status of high-value farm product transformation in the study areas (see Figure 1.3).

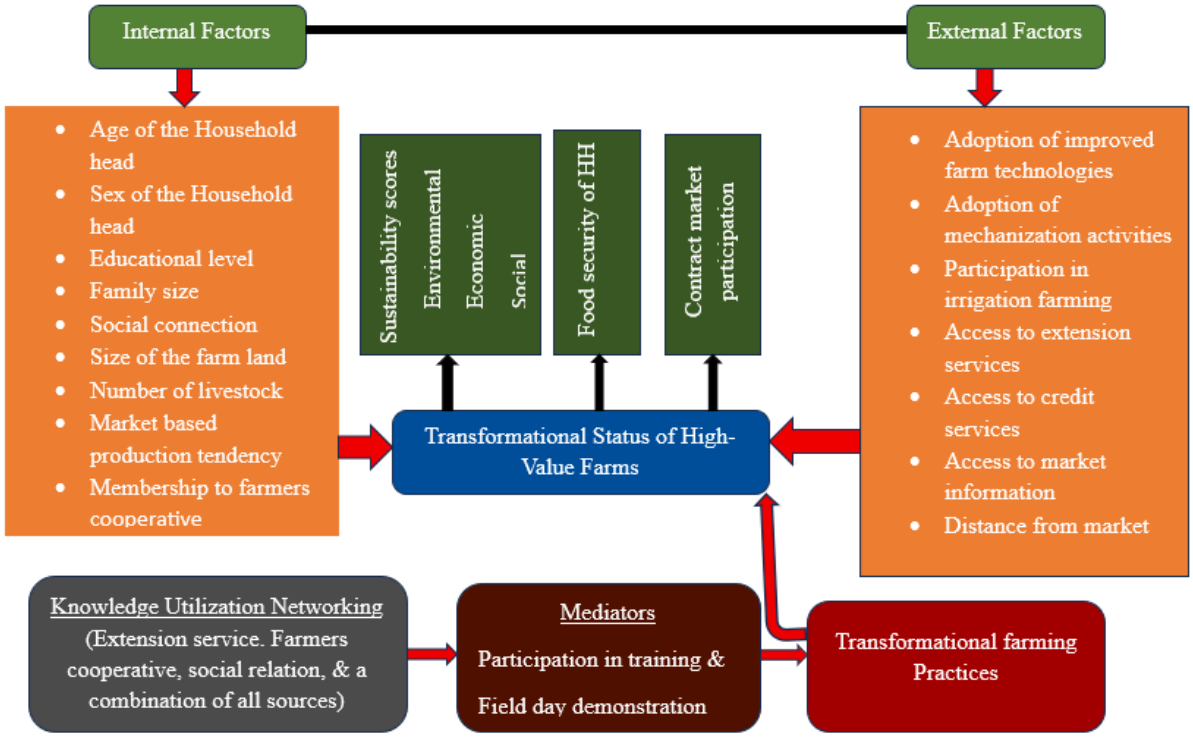

Figure 1.3. Conceptual framework of the study
Source: Author's Sketch.

Accordingly, there are two contextual meanings of the term 'transformation'. The first context focuses on the outcome of a process called 'transformational', while the other refers to the attribute of a process that leads to an outcome called 'transformative' (Mapfumo et al., 2017; Vermeulen et al., 2018). The transformational change resulted through transformative

learning (or practices of agriculture) and farmers' behavioural changes towards transformation (Vermeulen et al., 2018). A comprehensive reviewed from twenty-three articles by (Vermeulen et al., 2018) showed that agricultural practice (transformative adaptations) in response to climate change brings resilient farming system.

Likewise, several approaches have been used in agricultural transformation studies. Some are linked to the production of high-value crops (Anuja et al., 2020; Johnston & Mellor, 1961; Matthys et al., 2024) and intensification of farm technologies (Reardon & Timmer, 2014). Others approached transformations studies by farm size heterogeneity (small, medium, and large) (FAO, 2022; Jayne et al., 2019). Specifically, study in Poland indicates transformational changes as indications of land ownership in to different aggregations (Bąk et al., 2021). Further, farm size in dairy transformation in Ethiopia (Minten et al., 2020), by farm typology (small, medium, and commercial) in Tanzania (Wineman et al., 2020), mechanization adoption as indicator of transformation (Dendup, 2018 ; FAO, 2022), innovations in agricultural mechanization (Daum, 2023). Some studies confirmed that urbanization as driver of transformation in sub-Sharan Africa (De Bruin et al., 2021), proximity to urban in Ethiopia induces staple crops transformation such as teff (Vandercasteelen et al., 2016) ; and similarly in Bhutan urbanization driven transformation leads to entrepreneurial farmers (Dendup, 2018).

Furthermore, micro-income growth at farmer level is also the signal of transformation according to comparative study by (Amare et al., 2023) in South East Asia and Sub-Sharan Africa. The transformational changes also involve the reorientation of significant farming activities for decision-making (Huet et al., 2018). However, their study did not identify factors affecting those decisions based on farmers' preferences. There is also an exceptional trend analysis study on crop-livestock transformation in the semi-arid regions of North Africa, which enables farmers to diversify activities into milking and fattening (Alary & Frija, 2022). In general, previous studies were based on time series data (trend analysis) from records of agricultural growth in each respective country and did not address the transformation of both high-value crops and animal enterprises.

On the other hand, knowledge enhances the range of farm portfolios through innovations that transform farmers into entrepreneurs (Graskemper et al., 2021; Hansson et al., 2013; Morris et al., 2017; Seuneke et al., 2013). Knowledge is also crucial in decision-making regarding

technology adoption and practices, which are accessed through social interactions (Oriana et al., 2021; Šūmane et al., 2018; Tamako, Thamaga, et al., 2022; Villarroel-Molina et al., 2021). Generally, existing studies have not identified the factors influencing these decisions based on farmers' preferences and have overlooked high-value livestock sectors. Moreover, they have not addressed the relationship between food security and the level of transformation. Additionally, the direct and indirect effects of knowledge utilization on transformational farming practices have not been emphasized through mediation analysis. Hence, this study addresses the empirical and methodological gaps in the study of agricultural transformations in the existing literature.

1.6. Objectives of the Study

1.6.1. General objective

To examine the transformational status of high-value farms among smallholder farmers and its sustainability, as well as to analyze the role of farm transformation in food security and contract market participation. Finally, to examine the direct and indirect impact of knowledge utilization networks on farm transformational practices in the study areas.

1.6.2. Specific objectives

Based on discussion and synthesis of the above conceptual framework the specific objectives of this study were formulated as follows.

1. To estimate factors influencing the transformational status of high-value farms and its' sustainability;
2. To examine the relationship between high-value farms transformation and contract market participation;
3. To measure the relationship between farm transformational status and households' food security, and;
4. To Investigate the impact of knowledge utilization network on farm transformational practices in the study areas.

1.7. Research Questions

The motivation to investigate the status of farm transformation status stemmed from farmers' decisions to produce a mix of high-value crop-livestock farms.

Previous studies did not address the transformation levels of high-value crop and livestock enterprises. Instead, they focused solely on high-value crop production and overlooked the livestock sector, despite the fact that livestock are important sources of food and income for farmers. Furthermore, existing literature has not related how farmer-level agricultural transformations influence food security and market participation. This study evaluates the factors affecting food security and market participation. Additionally, several studies on agricultural transformation have used secondary data to illustrate transformation pathways in different countries. However, this study employs primary data collected from farmers to examine current practices that have the potential to enhance our understanding of the transformational process. Above all, the study aligns with the interests of Ethiopian agricultural development policy, which prioritises enhancing productivity and value chain development in the high-value crops and livestock sectors. It aims to shift subsistence production towards a more commercially oriented approach, ensuring food security and increasing farm income.

Furthermore, knowledge derived from individual farmers (tacit) and external sources through networking contributes to improving farming practices. Knowledge can be generated and utilized through farmers' organizations, extension workers, and social institutions. These are important for enabling farmers to become entrepreneurial and innovative. For example, it enhances on-farm field management by allocating scarce resources (Ndambi et al., 2019; Tarawali et al., 2011). However, there is heterogeneity among farmers in their use of knowledge due to location barriers and social capital. In addition, the conversion of knowledge into desired outcomes can measure the innovative practices farmers are adopting for sustainable farm production. It examines the direct and indirect impact of knowledge utilization networks on transformational farming practices, which is crucial for understanding stakeholder coordination that directs policy intervention. Accordingly, the following questions were addressed in this study.

Q#1. What transformative farming features exist in the study area? What is the distribution of the transformational level across the study districts? What factors influence high-value farm transformation? Are the current practices economically, environmentally, and socially sustainable?

Q#2. What types of market opportunities are there? What factors affect farmers' decisions to participate in contract markets and the level of high-value farm products sold?

Q#3. What is the food security profile of farm households? What is the relationship between farm transformational status and food security at the household level?
Q#4. Which knowledge utilization network is strongly benefiting farmers? How does it directly and indirectly effect farm transformational practices in the study areas?

1.8. Significance of the Study

Transformational changes in farming accelerate growth by introducing farm enterprises aimed at reducing rural poverty. Central Ethiopia is characterised by mixed farming and has the potential to produce high-value agricultural products. This suggests that the process of transformative practices creates sustainable farming systems through the integration of crop and livestock production. This approach fosters a stable environment and generates productive synergies to achieve sustainable food production. In other words, it enhances economic sustainability through market linkages and improves food security at the household level. However, these transformational changes do not apply uniformly across all farm households. It is influenced by variations in know-how, access to technology, socio-economic conditions, and institutional capabilities, which can hinder the transformation process. Furthermore, the integration of farm enterprises reflects farmers' behavioural tendencies towards managing risks and their market orientation, which are indicators of transformation and enhanced connections.

As a result, the study aimed to identify the current status of transformation and assess sustainability indicators. Furthermore, it examines the effect of transformational practices on food security and market participation. It also investigates how knowledge utilisation networks impact farm transformational practices. Therefore, the findings of the study significantly address the opportunities and challenges faced by smallholder farmers in transforming to high-value farms. This strengthens the role of extension workers, the private sector, agricultural cooperatives, and government and non-governmental organisations (NGOs) in the transformation process. It provides insights for the strategic implementation of the existing Ethiopian agricultural transformation policy and contributes empirical evidence to the existing agricultural transformation literature to support further studies.

1.9. Scope and Limitations of the Study

This study was conducted in the central Oromia regions of Ethiopia, specifically in the West Shewa and South West Shewa zones, which are close to the capital, Addis Ababa. Three

districts from West Shewa and two districts from South West Shewa were selected for study area. A total of 15 villages were randomly chosen to yield a sample of 422 farm household respondents. The study focuses on the socio-economic, institutional, and physical factors influencing to transform integrated high-value farms. These farms include: teff, wheat, malt barley, maize, chickpeas, vegetables, improved egg-laying poultry, cross-bred dairy cows, and animal fattening, which are central agenda to transform production and productivity. The dependent variable constructed for assessing transformational status is based solely on the aforementioned enterprises that farmers are integrating to produce.

In otherwards, it is qualitatively categorized to examine those factors influencing the level of transformation. Additionally, the research explored the relationship between high-value farm products and informal contract market participation. And it did not cover the formal contract and open market system. Furthermore, the study investigated how the status of transformation relates to food security outcomes at the household level. Finally, the direct and indirect role of knowledge utilization networks on transformational farming practices was assessed.

However, the study has limitations in providing information on the synergies between crop and livestock enterprises, as it focuses on the mix of enterprise types. It was intended to assess the magnitude of transformation at the farm household level. The linear methodological system and the use of econometric models did not capture the complexities of agricultural production and marketing. Therefore, methodologically, the findings have limitations in addressing dynamic changes. The cross-sectional nature of the data was affected by the time and conditions of the farmers, which means it will not provide long-term perspectives of transformational progress. The study also limited by its geographical scope, as the findings will represent the context of farmers in the central part of Ethiopia. Furthermore, the study was not comparing productivity between conventional farming systems and transformed farming systems, instead focusing on the status of integrating high-value crop-livestock enterprises. Finally, the economic, environmental, and social sustainability was only framed to current farming practices and does not predict the long-term implications of transformation in the study areas.

1.10. Organization of the Dissertation

The dissertation has seven chapters. The first chapter describes the general introduction, theoretical concepts of the study, statements of the problem, objectives of the study,

significance of the study, and limitation and scope of the study. The second chapter was emphasised on overall methodologies of the study mainly description of study area, sampling method and size determination, and method data collection. Chapter three addresses the status of high value crop and livestock farms focusing on categorization of level of transformation and its contributions in sustainability. Chapter four focuses on analysis of contract market participation and its level of sell. Chapter five emphasized the role of farm transformation in food security which measured through instrumental variables and food consumption score. Chapter six illustrates the impact of knowledge utilization network on transformational farming practices which addressed using mediation analysis. Finally, the last section of the paper illustrates overall conclusion, recommendation, references, and appendixes.

CHAPTER TWO

2. Methodologies

2.1. Description of the Study Areas

This study was conducted in the West Shewa and South West Shewa Zones of the Oromia National Regional State in Ethiopia. These two zones are centrally located, approximately 114 km from the capital, Addis Ababa. The West Shewa Zone spans latitudes from 8°17' north to 9°60' north and longitudes from 37°17' east to 38°45' east, with Ambo as its capital and comprising 20 districts (WSAO, 2024). Of 1.4 million ha of land, 880,211 ha used for crop cultivation, 249,645 ha for grazing, and 270,144 ha for other purposes. In contrast, the South West Shewa Zone is situated at 8°36'33.0"N and 38°14'07.2"E. This zone has 14 districts, and Weliso serves as the zonal capital (see Figure 2.1). In terms of land use, South West Shewa has approximately 304,484 hectares dedicated to agriculture, 51,541.40 hectares for grazing, and 10,191.40 hectares allocated for other purposes (SWSZAO, 2024). The annual mean temperature in the region ranges from 10°C to 35°C, while the average annual rainfall fluctuates between 900 and 1,900 mm. The major staple crops produced include teff, wheat, maize, and barley, alongside pulses such as faba beans, field peas, and chickpeas, as well as vegetables like tomatoes, potatoes, cabbage, and red onions.

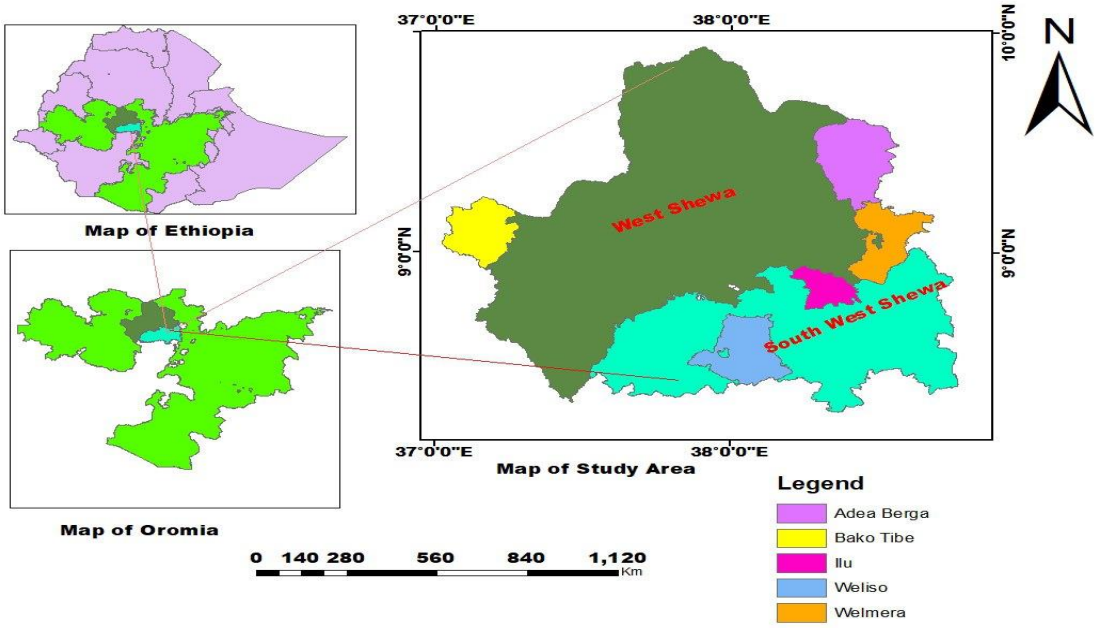

Figure 2.1. Map of the study area
Source: GIS laboratory, Ambo University.

2.2. Data Types, Sources, and Method of Collection

For this study, both qualitative and quantitative data were collected. The data collection method was handled using semi-structure questionnaire format which comprises both open ended and closed ended questions. Furthermore, a focus group discussion was held with farmers to validate the primary data and explore additional information on farming practices in the study area. The number of participants in the focus group discussion was 60, of which 42 were male and 18 were female. The semi-structured questions comprise specific household characteristics, agricultural practices (transformational practices), market factors, institutional factors, physical factors, food items consumed and its frequency, and knowledge use sources. Through consulting district agricultural offices, enumerators were recruited and trained prior to the survey for two days. A pre-test was conducted over two days to refine the questionnaire and assess time efficiency. After revisions of the questions, the actual data collection was conducted via personal interviews. For this data collection, 31 enumerators participated and per-village 2 enumerators were assigned to collect the data. The data were gathered between 15th March 2024 and 2nd May 2024.

2.3. Sampling Method and Size Determination

Multi-stage sampling procedure was employed:

1. ***Stratification by Agro-ecology***: districts were categorized into three agroecological zones—lowland, midland, and highland—based on the agricultural landscape, which facilitated the selection of sample districts. In the West Shewa zone, there are a total of 20 districts, with 7 in the highland, 8 in the midland, and 5 in the lowland areas. In the South West Shewa zone, there are 14 districts, comprising 8 in the highland, 4 in the midland, and 2 in *the lowland*.
2. **District Selection**: from each stratified district in the West Shewa and South West Shewa zones, *the districts of Welmera, Ada'a Barga, Bako*Tibe, *Ilu,* and *Weliso* were randomly selected.
3. **Village (Kebele) Selection**: Using a 10% sampling intensity, a rule of thumb developed by (Ary et al., 2006; Curry 1984), 15 villages (kebeles) were selected from a total of 147 villages. Accordingly, four villages from *Ada'a Barga*, and three villages each from the *Welmera, Bako Tibe*, and *Weliso* districts were randomly selected. Finally, two villages from *Ilu* were selected.

4. **Household Selection**: A total of 384 farm households were selected using probability proportional to size. The sample size was determined using Cochran formula, which allows for the proportional determination of sample size from a large population. Literature suggests that a sample size that is too large incurs higher costs and increases computational complexity, while a sample that is too small can lead to errors in representativeness and affect data quality (Ajay & Micah, 2014; Cochran, 1977). Hence, under assumption of normal distribution, the precision level calibrated at $\pm 5\%$ and the confidence level is 95% showing z-score of 1.96. The sample was slightly expanded to add 10% and obtained a total of 422 households in order to account for any non-response and guarantee sufficient representation across villages. The formula is given as:

$$n_0 = \frac{z^2 pq}{e^2} \tag{1}$$

Where, n_0= sample size, critical value of desired confidence level, *p*=estimated proportion of an attribute exists in the population, *q*=1-p, and *e*= desired level of precision. Therefore;

$$n_0 = \frac{(1.96)^2 (0.5)(0.5)}{(0.05)^2} = 384.16 \approx 384 \tag{2}$$

And the methodologies are summarized diagrammatically as follows (see Figure 2.2).

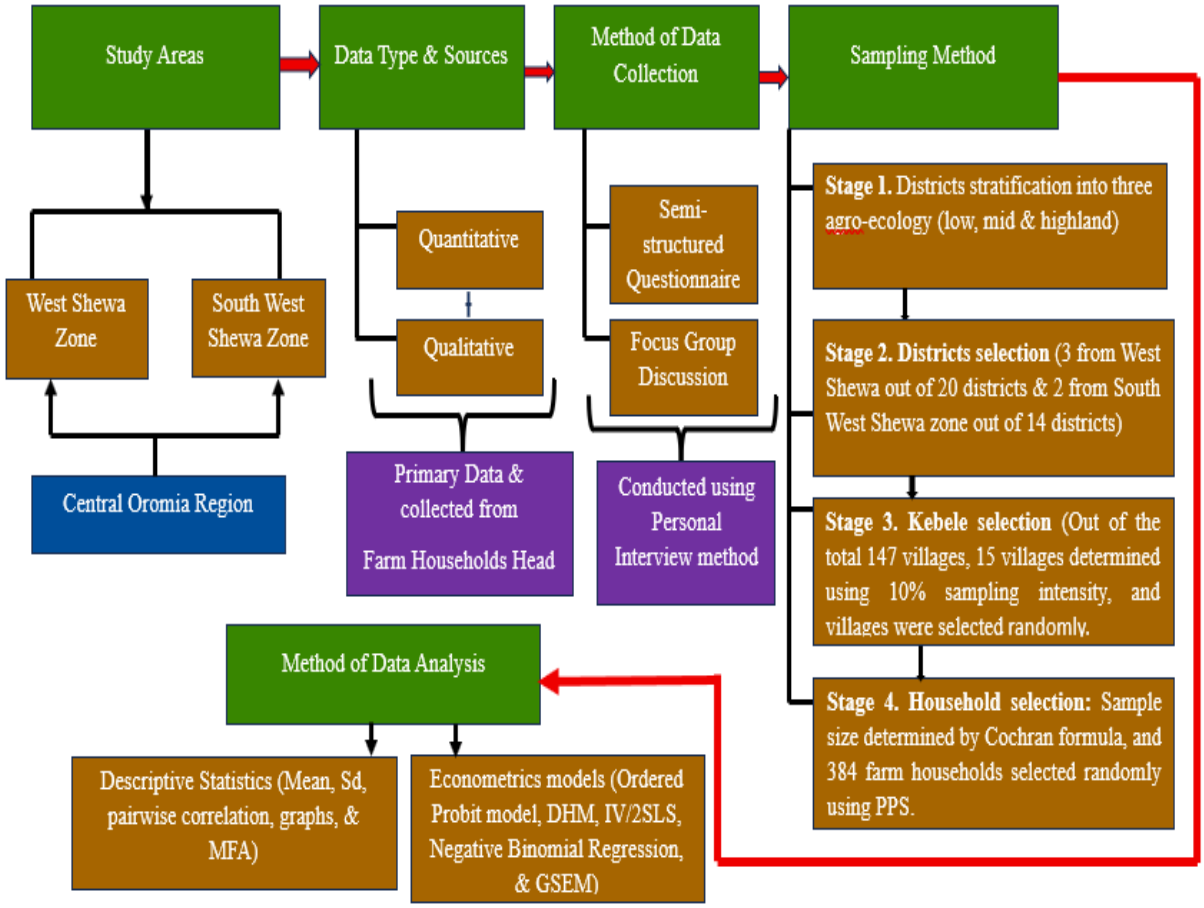

Figure 2.2. Summarized methodologies
Source: Author's sketch.

CHAPTER THREE

3. Status of High-Value Crop and Livestock Transformation and Its Sustainability

Abstract: *Transforming farm systems by integrating high-value crops and livestock is vital to achieving food security in Ethiopia. This study assessed the transformation status of such integration at the farm household level and identified key influencing factors. The study was conducted in five districts of West Shewa and South West Shewa zones in central Oromia. The study used a multi-stage sampling technique to collect primary data from 422 farm households. Data was gathered using a semi-structured questionnaire using personal interviews. For analysis, descriptive statistics, multiple factor analysis, and econometric models were utilized. The results indicated that 48.81% of households had partial transformation, 28.91% medium, and 22.28% full transformation status. Landholding size and livestock ownership were positively associated with medium and full transformation levels. Adoption of herbicide use increased the likelihood of medium and full transformation, while a negative association with partial transformation. On the other hand, seed saving behaviour and access to credit services positively increases the probability of farmers being in the category of medium and full transformation. While it decreases the probability of being in the partial status. The tendency to hire farm labor was positively increasing the probability of being in partial status while decreases in the category of medium and full status. Additionally, greater distance from veterinary services decreased the probability of partial and full transformation status. The result from multivariate linear regression showed that, farm transformation status had positive implications to environmental, and economic sustainability while reduces social sustainability. The findings highlight the role of socio-economic diversity in influencing transformation patterns which potentially influences overall farm sustainability. Hence, it requires strategical revision in the existing policy to address technology dissemination scope, farmer capacity building, and institutional support under the existing Ethiopian agricultural transformation.*

Keywords: Farm Households, High-Value Farm Products, Multiple Factors Analysis, Multivariate Regression Model, Ordered Probit Model, Sustainability, Transformation Status.

3.1. Introduction

Transforming farm systems by integrating high-value crops and livestock is vital to achieving food security in Ethiopia. To combat hunger, there are opportunities to transform food and agricultural systems. Global agricultural production and food systems are increasingly challenged by shifts in world population and complex environmental crises (DeBenedetti, 2021). Additionally, geopolitical tensions, policy gaps, and developmental patterns disrupt the balance of global food demand and supply (FAO, 2024). These factors significantly impact sustainable agriculture in developing regions, especially where urbanization is on the rise and food production relies heavily on smallholder farmers. Over the next 30 years, sustainable rural transformation will be crucial as Africa's labor force grows to 800 million and its population is projected to reach 2.5 billion by 2050 (Tom et al., 2019). This situation highlights the weak coordination between rural and urban development necessary to support the increasing population in developing countries (AfDB, 2016).

In response, an increasing number of African governments have implemented resilience-enhancing policies and strategies in recent years, many of which show promise, although further efforts are needed (Prasad et al., 2023). Agricultural transformation in Africa may not mirror the paths taken by other regions (FAO, 2017). For example, Ethiopia has adopted transformative agricultural policies aimed at achieving sustainable agriculture; however, competition for agricultural land between crops and livestock significantly limits progress. This competition affects the flexibility and stability of food production systems (Tom et al., 2019). Furthermore, Ethiopian agricultural development faces challenges such as limited mechanization, low technology adoption, high rural-urban migration, and food insecurity (ATI, 2022).

However, high-value crops, including maize, teff, wheat, barley, haricot beans, and horticultural products, are prioritized for production through land consolidation efforts (ATI, 2024). These crops have potential value chain development and prospering economic conditions of rural farmers though livestock transformation has been largely neglected in broader farm practices. To enhance productivity in areas of mixed crop-livestock farming systems, livestock transformation should occur alongside crop improvements. Therefore, this study has provided paramount information to investigate the transformation status of

integrated mixed farm enterprises, which is valuable for addressing the sustainability of agricultural production by smallholder farmers in Ethiopia.

3.2. Literature Review

Various approaches have been employed in agricultural transformation studies. Some research has concentrated on the production of high-value crops (Anuja et al., 2020; Matthys et al., 2024) and the intensification of farming technologies (Reardon & Timmer, 2014). Other studies have examined farm size heterogeneity (small, medium, and large) (FAO, 2022; Jayne et al., 2019). For instance, in Poland, land ownership serves as an indicator of transformational changes within agrarian communities (Bąk et al., 2021). In Ethiopia, dairy farm characterization is based on farm size (Minten et al., 2020), while in Tanzania, farm typologies include small, medium, and commercial categories (Wineman et al., 2020), Additionally, mechanization adoption is seen as a transformation indicator (Dendup, 2018; FAO, 2022), and innovations in agricultural mechanization are being explored (Daum, 2023). Moreover, some studies argue that urbanization drives transformation in sub-Saharan Africa (De Bruin et al., 2021), with proximity to urban areas in Ethiopia facilitating the transformation of staple crops like teff (Vandercasteelen et al., 2016). In Bhutan, urbanization has spurred the emergence of entrepreneurial farmers (Dendup, 2018).

A comparative study in Southeast Asia and Sub-Saharan Africa indicates that micro-income growth at the farmer level signals transformation (Amare et al., 2023). In contrast, transformational changes involve the reorientation of significant farming activities for decision-making (Huet et al., 2018). Additionally, exceptional trend analysis on crop-livestock transformation in semi-arid North Africa shows that farmers can diversify their activities into milking and fattening (Alary & Frija, 2022). However, existing studies have not identified the factors influencing these decisions based on farmers' preferences. Furthermore, previous research on agricultural transformation trend analysis has overlooked high-value livestock sectors.

There is an empirical and knowledge gap in the literature regarding farm transformation that categorizes high-value crop and livestock enterprises to assess the status of transformation and sustainability. While Ethiopia has adopted transformational policies focused on high-value crop intensification, several barriers remain, including small landholdings, high input

costs, limited mechanization, and inadequate access to credit and markets. Despite numerous studies on agricultural transformation, limited attention has been given to how mixed high-value crop and livestock enterprises are evolving at the household level. Therefore, understanding the current transformation status and its determinants is essential for shaping effective policies that promote sustainable and inclusive agricultural development

3.2.1. Theoretical Framework

The decision-making process for high-value crop and livestock production is grounded in the Agricultural Household Model (AHM). The model was developed by Becker (1965). This theory focuses on household production decisions, particularly in scenarios where the decision-maker allocates constrained resources altruistically. The head of the farm household serves as the primary decision-maker, responsible for distributing resources such as labor, land, and capital to adopt improved agricultural technologies. The goal is to maximize utility (or welfare) while adhering to resource constraints. There are two perspectives on household decision-making: the unitary model and the collective decision model. The unitary model is more relevant to this study, as it emphasizes that farm household heads are the sole decision-makers in Ethiopia. In this context, the household maximizes a single set of goals for all members and makes decisions collectively (Ellis, 1988).

Accordingly, farm households prefer specific agricultural technologies, such as cultivating high-value crops or improving livestock breeding. This preference aligns with the rational choice approach, a comprehensive methodology applicable to household-level agricultural production in developing countries. The household production function is a simplified model that incorporates elements of firm theory, including human capital, specialization, and comparative advantage (Chiappori & Lewbel, 2015). Farmers then decide which enterprises they want to produce for family consumption and generating income through sales in the market.

Therefore, to examine the transformation status of high-value farms, the study adopted a random utility model. Each farm household derives latent utility from various levels of high-value farm enterprises integration and selects the enterprises that maximize its utility. The transformation status is categorized in a natural order: partial, medium, and full. Latent utility is modelled using an ordered probit model, where the observed outcome is determined by the

unobserved utility crossing specific threshold points. This latent utility influences the level of farm transformation for households.

$$U_i^* = X_i\beta + \varepsilon_i \quad (3)$$

The ordered outcomes only observed based on the threshold levels:

$$T_i = \begin{cases} 1 \; if U_i^* < \mu_i \\ 2 \; if \; \mu_1 < U_i^* \leq \mu_2 \\ 3 \; if U_i^* > \mu_2 \end{cases} \quad (4)$$

- X_i: Socio economic, demographic, institutional, and infrastructure characteristics
- β vectors of the parameters
- εi random error, assumed to be standard normal (ordered probit)

3.3. Method of Data Analysis

3.3.1. Descriptive and inferential statistics

To describe the features of farm transformational status, and sustainability measures we utilized descriptive statistics, including mean, standard deviation (SD), minimum and maximum values, frequency tables, coefficient of variation, and percentages. We synthesized the analysis based on socio-economic, demographic, institutional, and transformation practice variables. The results were presented in tables, pie charts, stacked bar graphs, violin plot, and box plots. Additionally, inferential statistics, such as F-tests and chi-square tests, were used to compare independent variables across various categories of farm transformation.

Both Principal Correspondence Analysis (PCA) and Multiple Factor Analysis (MFA) can be utilized to calculate sustainability indices. PCA, implemented in STATA software, computes continuous and binary variables separately. In contrast, MFA, used in R software, simultaneously handles both types of variables. Given that our dataset contains a greater number of binary variables. Then, we chose MFA with R software for its comprehensive capabilities. The R packages *factoMineR* and *factoextra* are essential for rearranging data and generating scores for each sustainability indicator. We included 14 variables for environmental sustainability, 14 for economic sustainability, and 13 for social sustainability as detailed below Table 3.1

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Table 3.1. Indicators used to compute sustainability scores

Environmental indicators	Type	Economic indicators	Type	Social indicators	Type
Land used under cereal crops in hectare	Continuous	Average high-value products produced in quintals	Continuous	Perception to possess improved bull in group	Dummy
Land used under vegetables crops in hectare	Continuous	annual farm income in logarithm	Continuous	Do you have seed saving tradition	Dummy
Land used under grazing in hectare	Continuous	Food consumption score	Continuous	Your perception on existing seed quality	Dummy
Frequency of irrigation farming in a year	Continuous	Agricultural labor division availability	Dummy	Participate in dairy production training	Dummy
Number of cross breed dairy cow	Continuous	Average milk harvested per day	Continuous	Access to market information	Dummy
Total number of livestock	Continuous	Informal contract market participation	Dummy	Do you think your agriculture is in sustainable way	Dummy
Irrigation farming participation	Dummy	Formal contract market participation	Dummy	Do you have skill gap in seed multiplication	Dummy
Practices of row planting	Dummy	Buyers' limitation on volume of products	Dummy	Training on compost preparation	Dummy
Apply herbicides on farm land	Continuous	Participation in seed multiplication	Dummy	Knowledge about industry demand of farm products	Dummy
Number of cropping system in a year	Dummy	Renting improved bull as source of income	Dummy	linkage with agro-industry	Dummy
Practices of intercropping	Dummy	Renting bull decision for mating	Dummy	Obtain spatial farm output price	Dummy
Practices of crop rotation	Dummy	Market-oriented production	Dummy	Perception on social networking	Dummy
Availability of ecologically suitable seed	Dummy	Product grading for sale	Dummy	Confidence to use organic fertilizer	Dummy
Production of forage feed	Dummy	Credit arrangement for farm business	Dummy		

Source: Own conceptualizing from litratures of sustainable agriculture production.

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Finally, the R software summarizes the MFA results such as eigen values and overall sustainability score, economic, environment, and social sustainability scores were computed. Moreover, it was visualized using scree plot which have an elbow shape enables to determine number of dimensions to select highest variations which labelled in step (Jolliffe, 2002).

3.3.2. Econometric model specification

To identify factors affecting the transformation status of farm households, both ordered logit and ordered probit models were employed. These models are appropriate for analyzing ordinal response variables — in this case, levels of transformation:

- Partial transformation (y = 1)
- Medium transformation (y = 2)
- Full transformation (y = 3)

Marginal effects were computed to interpret how changes in explanatory variables affect the probability of each transformation status. The Categorization of Transformation is as follows:

- **Partial Transformation:** High-value crops combined with conventional livestock (e.g., teff + local cattle).
- **Medium Transformation:** High-value crops combined with at least one improved livestock practice (e.g., crossbred dairy, poultry, or fattening).
- **Full Transformation:** Integration of high-value crops with three or more improved livestock enterprises.

This modeling framework captures the heterogeneity of transformation outcomes and helps identify the critical drivers of change across farm households. Both ordered logit and probit models used to estimate factors affecting transformational changes by integrating high value crop-livestock enterprises. The logit model follows logistic functions while the probit model is cumulative density functions (CDF). The logit model assumes error term follows logistic distribution, and very simple in computation and revelation of odd ratio values (Greene, 2012). In contrast, the probit model assumes a normally distributed error term, adhering to standard normal distribution with a mean of zero and a variance of one. Furthermore, the ordered probit model is appropriately fitted to heterogeneous data (Greene, 2012) generated

by respondent backgrounds and the agroecological variation of the study areas. For estimating ordered categorical dependent variables, (McKelvey & Zavoina, 1975) the ordered probit model is introduced in its modern form. In this context, the transformational status can be categorized as partial (y=1), medium (y=2), and full (y=3). The ordered outcomes emerge sequentially as a latent variable, y*, which crosses progressively higher thresholds. In this study, y* is unobserved and is used to measure the status of transformational changes for farm households, as specified below.

$$y_i^* = x'_i \beta + u_i \tag{5}$$

The latent variable (y*) farm transformational status will exhibit ordinal categorical which is coded as 1,2,3…j. The response category j is observed when the underlying continuous outcome falls in the jth alternative as:

$$\begin{aligned} Y^* &= 0 \; if \; Y^* \le \delta_0 \\ Y^* &= 1 if \; \delta_0 < Y^* \le \delta_1 \\ Y^* &= 2 if \; \delta_1 < Y^* \le \delta_2 \end{aligned} \tag{6}$$

Normalization occurs when the regressors x do not include an intercept. In the context of high-value crops combined with a conventional livestock production system (y*), the status of transformational change is classified as partial. For $y^* > \mu 1$, the transformational change status is medium, and for $y^* > \mu 2$, the status indicates a full transformation in the combination of high-value crops and livestock. For k alternatives in the ordered status of farm transformation, the ordered probit model is defined as:

y_i=j if μ_j-1 <y_i*≤μ_j, for j= 1,…K (7)

Where $\mu_0 = -\infty$ and $\mu_k = \infty$, Then

$$\Pr(y_i=j) \begin{cases} = \Pr(\mu_j\text{-}1 < y_i^* \le \mu_j) & (8) \\ = \Pr(\mu_j\text{-}1 < x_i'\beta + u_i \le \mu_j) & (9) \\ = \Pr(\mu_j\text{-}1 < x_i'\beta < u_i \le \mu_j - x_i'\beta) & (10) \\ = F(\mu_j - x_i'\beta) - F(\mu_{j-1} - x_i'\beta) & (11) \end{cases}$$

Where F is the cumulative density functions (c.d.f) of U_i. The regression parameters βi, and the k-1 threshold parameters $\mu_1, \ldots \mu_{k-1}$, are obtained by maximizing the likelihood with $p_{ij} = \Pr(y_i = j)$ as explained above. The marginal effect provides the direction of the

probability for each categorical outcome. It is a positive or negative sign that the variable has on y and illustrated as follows (Greene, 2012).

$$\frac{P(y=j)}{\partial x_i} = \left[F'(\mu_k - x_i'\beta\right] - F'(\mu_{k-1} - x_i'\beta)\beta_i \quad (12)$$

Accordingly, there are seven enterprise combinations that grouped into three categories of transformational status. Enterprise combination is subject to farmers preferences and motives to produce a given product. On the survey questioner format each enterprise was listed and marked to be produced by the respective farmer. After that for the sake of investigating the transformational status, the model was fitted as ordinal outcomes. The first category considers those farmers who still practicing farming of high value crops (teff, maize, wheat, malt barely, chickpea, vegetables) along with the conventional system in livestock production. In this study the status level of transformational is considered as partial transformation. The second category includes those farmers who participated in high-value-crop with alternative livestock production (cross breed dairy cow, improved egg layer poultry or sheep or/animal fattening). This category will be labeled as medium transformational status. The third and the upper groups are those farmers who fully engaged in both high-value crop and livestock production system. The engagement is designated as farmers participated at least in three livestock production strategies.

3.4. Definitions of Variables and Working Hypothesis

3.4.1. Dependent variables

Partial Status: It is ordinal variable that takes nominal value of '1'; otherwise '0'. It represents farmers who combine high-value crop production with a conventional livestock system.

Medium Status: It is the ordinal variable that takes nominal value of '2'; otherwise '0'. It refers farmers who produce high-value crops alongside improved crossbred dairy cows/poulry.

Full Status: It is ordinal variable that takes nominal value of '3'; otherwise '0'. It refers farmers who integrate high-value crops, improved dairy cows, improved egg laying poultry, and animal fattening.

3.4.2. Independent variables

The independent variables used in this analysis is summarized in the following Table 3.2 below.

Table 3.2. Summary of independent variables used in the ordered probit model

Variables	Type	Expected sign on Transformational Status
Age of the household head in years	Continuous	+
Family size of the household	Continuous	+
Educational level in years of schooling	Continuous	+
Size of farm land in hectare	Continuous	+/-
Family labour division availability	Dummy (1=Yes;0=N0)	+
Fertilizer use adequacy	Dummy (1=Yes;0=No)	+
Number of livestock in TLU	Continuous	+/-
Participate in Irrigation production	Dummy (1=Yes;0=No)	+
Use herbicides for weed elimination	Dummy (1=Yes;0=No)	+
Own seed saving behaviour	Dummy (1=Yes;0=No)	+
Hiring labour for farming	Dummy (1=Yes;0=No)	+
Contract market participation	Dummy (1=Yes;0=No)	+
Market-oriented production	Dummy (1=Yes;0=No)	+
Experience sharing	Dummy (1=Yes;0=No)	+
Frequency of extension service contact	Continuous	+
Distance from nearest market in hour	Continuous	-
Distance from veterinary services	Continuous	-

Source: Author's compilation from related literature and study area context.

3.5. Relationship between Sustainability Score and Transformational Status

To investigate the effect of farm transformation status on economic, environmental, and social sustainability scores, a multivariate linear regression model (Mreg) is fitted in simultaneous equation form. Additionally, a structural equation model (SEM) is also a potential model for analysis; however, the data fails to meet the normality, RMSE, and chi-squared tests required as conditions (Kline, 2016). In this analysis, exploratory factor analysis (EFA) was computed for factors loading of environmental, economic, and social scores, contributions of group, individuals, and variables. This step provides dimensions (components) variance, and variance explained. Next, analysis of confirmatory factor analysis (CFA) was conducted to detect the efficiency of the first method and checking eigen values for factor loading. Then, accept if the MFA is greater than 70% (Brunner, 2023).

Finally, multivariate linear equation was set to estimate the relationship between endogenous dependent variables (environmental, economic, and social sustainability scores) and exogenous variables (dummy medium and full transformation status, and control variables). Here the partial transformation is used as reference category depending on size of farmers and plausibility to see how sustainability improves with the process of transformation. To develop the robust standard deviation, we use a bootstrap standard error that accounts for the effects of heteroscedasticity. Additionally, the variance inflation factor was employed after regression to test correlations between explanatory variables, and it was found to be less than 10%. The multivariate linear regression model is specified as following.

$$enviro.Score\ (Y_1) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon_1 \quad (13)$$

$$eco.score\ (Y_2) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon_2 \quad (14)$$

$$social\ score\ (Y_3) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon_3 \quad (15)$$

Where: β's are coefficients

X_1 = dummy medium transformation status

X_2 = dummy full transformation status

X_3 = age of the farm households

X_4 = sex of the households

X_5 = family size of the household head

X_6 = educational level in years of schooling

X_7 = total agricultural land size

$\varepsilon_1, \varepsilon_2, \varepsilon_3$ are error terms of each equation.

3.6. Result and Discussion

3.6.1. Result of descriptive statistics

Table 3.3 presents the findings from interviews with exactly 351 male and 71 female heads of farm households. Among the 422 sampled households, 206 (48.81%) were categorized as having partial transformation, while 122 (28.91%) and 94 (22.28%) were classified as medium and full transformation, respectively. The number of households with partial transformation status was significantly higher, consisting of about 171 male-headed and 35 female-headed households. In contrast, the number of households in the full transformation category was relatively small for both genders. Overall, the sample showed a greater proportion of male-headed households, with notable variations in gender distribution across the different transformation statuses in the studied districts.

Table 3.3. Sex of farm households by category of transformation status

Sex of Farm Households	Farm Transformation Status						Overall Total
	Partial		Medium		Full		
	Freq.	Percent	Freq.	Percent	Freq.	Percent	
Male	171	83.01	100	81.97	80	85.11	351
Female	35	16.99	22	18.03	14	14.89	71
Overall	206	48.81	122	28.91	94	22.28	422

Source: Own survey data (2024).

As indicated in Fig. 2 below, the proportions of farm households within and between districts varied by category of transformation status. The output of the '*ggplot'* showed that 39.42% and 7.4% of smallholder farmers from *Ada'a Barga* and *Bako Tibe* districts were in the category of full transformation status, respectively. Conversely, 75.8% and 22.12% of farmers from *Bako Tibe* and *Ada'a Barga* districts fell into the category of partial transformation status. On the other hand, 45.5% of smallholder farmers from *Ilu* district were in the category of medium status. The process of transformational practice in the Welmera and Bako Tibe districts is slow in integrating high-value farm enterprises. While farmers in Ada'a Barga and Ilu districts showed more advanced transformation practices compared to others.

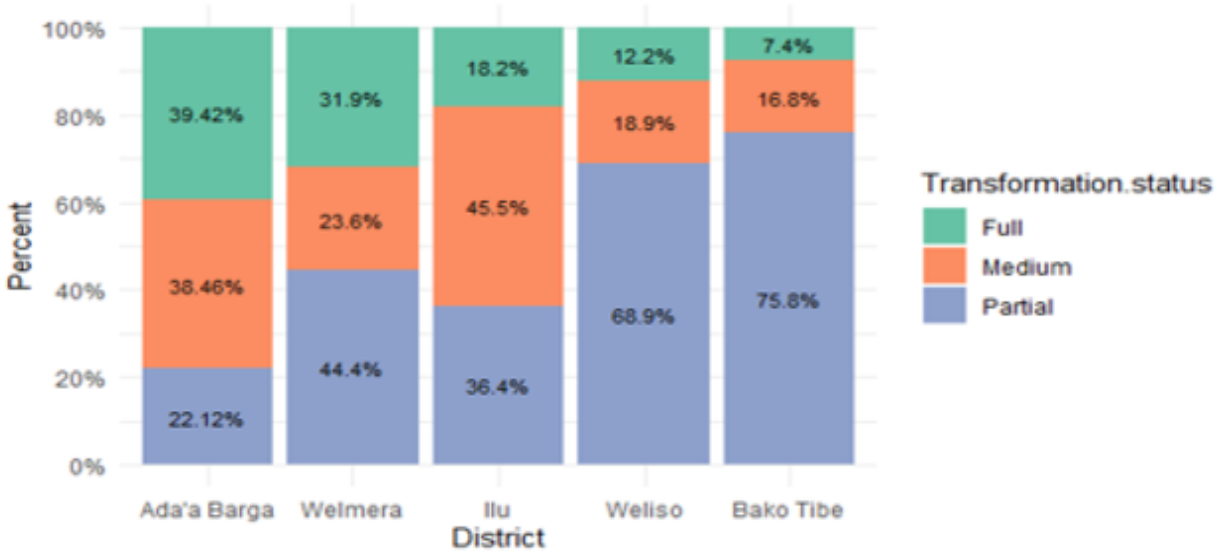

Figure 3.1. Distributions of transformational status by districts
Source: Own survey data (2024).

Following this, the stacked bar graph below illustrates the distribution of high-value farm enterprises categorized by transformation status across each district. The base of the stacked bars typically represents wheat enterprises across the transformation categories, except for the

Bako Tibe, Ilu, and Weliso districts, which fall under the category of full transformation. Conversely, the upper section of the stacked bar graph is occupied by animal fattening enterprises. The *Ilu* district has a higher number of animal fatteners under the category of medium status, while more crossbreed cows are found in the *Ada'aa Barga* district. Improved poultry egg layers, chickpeas, and exotic improved cows are more prevalent in the *Ilu* district. Additionally, maize is the dominant crop in the *Bako Tibe* district across the three transformation status categories. The graph also indicates that potatoes are more preferred in the *Welmera* district, while onions are a potential crop in the *Weliso* district. Improvement in transformational practices through the integration of high-value farm enterprises is observed in all study districts, except in the *Bako Tibe* district. Generally, medium and full transformation statuses are characterised by a diversification of crop and livestock enterprises, whereas the partial status is primarily dominated by crop enterprises and shows less integration with other enterprises (see Figure 3.2 below).

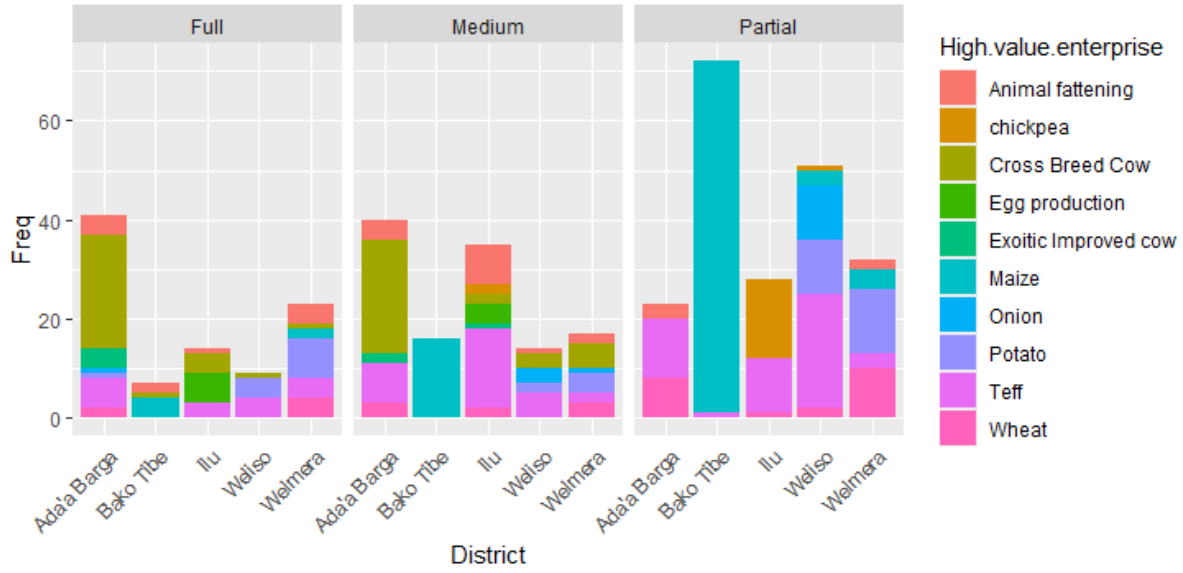

Figure 3.2. High-value enterprises distributions by category of transformational status
Source: Own survey data (2024).

3.6.2. Distributions of high value farm enterprises by number of farm households

During data collection, farmers were asked to identify the highest value enterprises they perceived as essential for their livelihood sustenance. Accordingly, the majority of farmers produced maize, followed by teff. The adoption of crossbred dairy cows ranked third, reflecting farmers' growing interest in diversifying their farm portfolios. However, few respondents reported adopting exotic improved dairy cows, which may be attributed to

farmers' limited exposure to animal technology and the intensity of their knowledge (see Fig. 3.3 below).

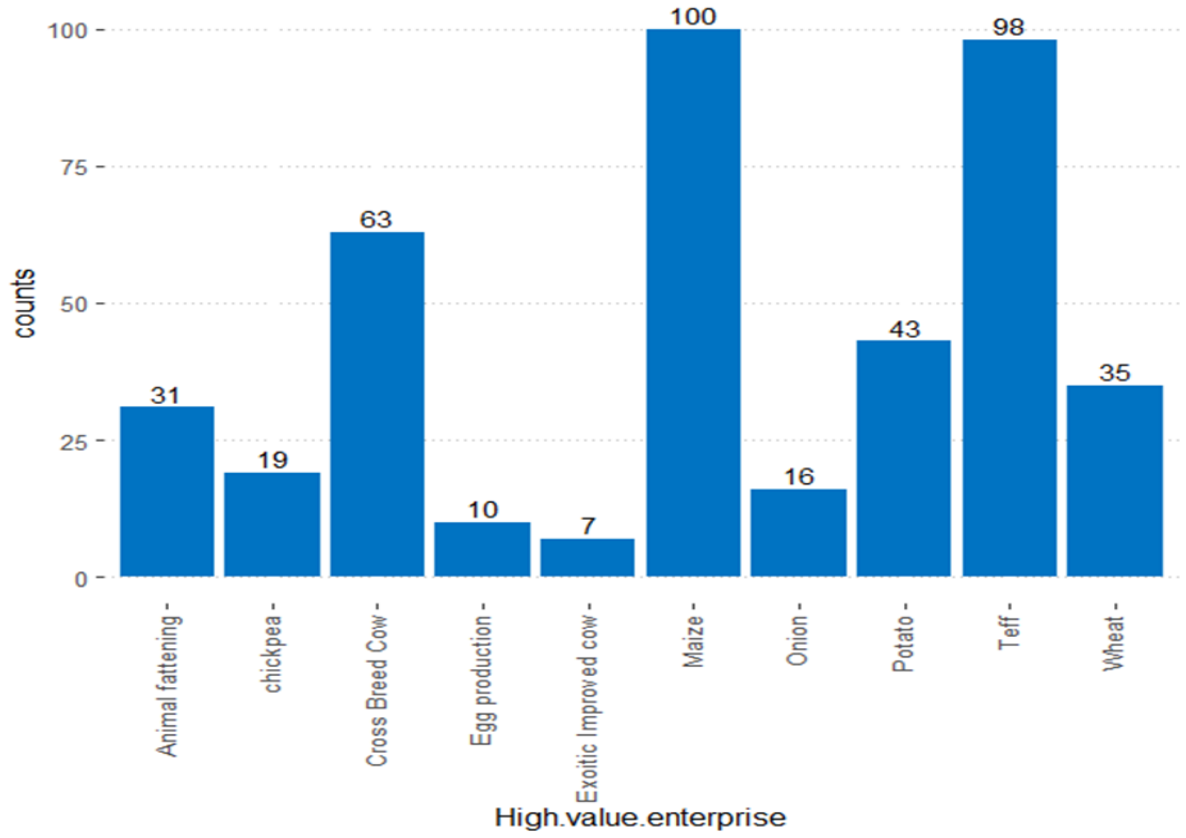

Figure 3.3. Bar chart of high-value enterprises by number of farm households
Source: Own survey data (2024).

3.6.3. Farm households transformational strategies

The following pie chart (see Figure 3.4) demonstrates how farmers classify their plowing methods based on the stage of transformation. About 48.61%, 38.36%, and 30.24% of farmers in the categories of full, medium, and partial status, respectively tilled their land through social cooperation and known locally as "*daboo*." Farmers can coordinate labor and ox power with the aid of an informal institution called the "*daboo*." For large-scale farmers, it's the best way to prepare land quickly and efficiently. Hence, developing connections is one of the transformation's key elements. Tractor use is also categorized under this strategy, although only 1.77% of farmers reported using them. The exchange of resources among farm households is improved by the tie of productive farm resources. For instance, farmers who do not have oxen might either rent or engage in cooperative social activities. Therefore, about 7.24%, 6.85%, and 3.04% of farmers in the categories of partial, medium, and full status are rented oxen, respectively.

Similarly, the percentage of farmers in the corresponding categories of partial, medium, and full status who plough land with their own oxen is 60.79%, 52.05%, and 46.58%. This reflects an increase in farmers' awareness, via extension services advocate farmers' transformational motives. Another possible reason is that the average land holdings of farmers influence the importance of renting tractors and oxen, as well as participating in "*daboo*," or social cooperation. This implies, how social capital plays a critical role in mechanization and land preparation, particularly among more transformed farmers. Overall, the findings demonstrated that the degree of social collaboration and external input purchases, such as renting tractors, increases with the transformative capacity of farmers, highlighting their progress (see Figure 3.4 below).

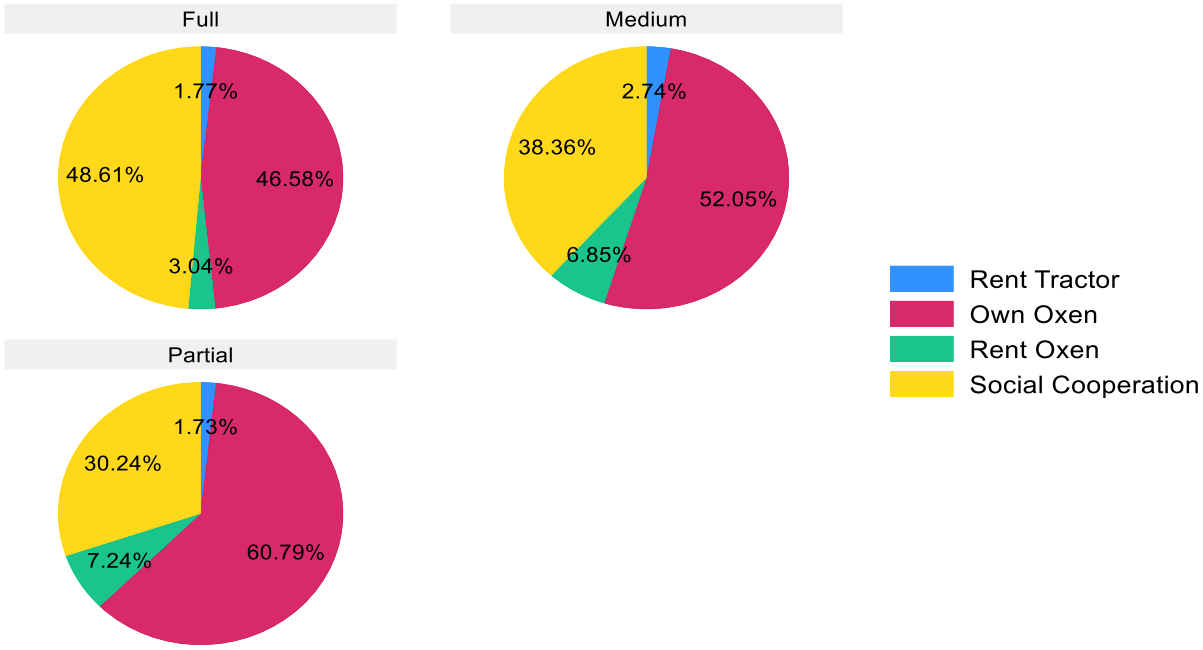

Figure 3.4. Pie chart of land plowing techniques by category of transformational status
Source: Own survey data (2024).

3.6.4. Mean and mean proportion comparison for continuous and dummy variables

The mean age of farm households varied across the transformation status, as shown in (see Table 3.4 below). This difference was statistically significant at P< 0.001, and the F test value was 1.51. Farmers in the category of partial status had an average age of 49 years, but those in the medium and full status categories had an average age of 47 and 44 years, respectively. The minimum respondents' age was 22, while the maximum was 75 years old. This shows the

average younger farmers were more driven than older farmers to change their farming operations.

Farmer assets like farmland and livestock were significantly differ among the category of status. Hence, farm land size in hectare was statistically significant at $P< 0.001$. For farmers in the category of partial status, the average land size was roughly 2 hectares. While for farmers in the categories of medium and full status, was 2.5 and 2.7 hectares, respectively. The minimum land size in hectares was 0.25 and the maximum was 5.5 hectares. It demonstrated that, the relatively large farm land size gives advantage to diversify farm enterprises. There were also variations in the number of livestock in TLU among the three categories and was significant at $P< 0.05$ and F test statistic = 1.48. The mean TLU for farmers in partial, medium, and full status was 6.78, 8.59 and 11.56, respectively. The minimum TLU was 0.026 and the maximum was 27.45. This shows that greater TLU has the opportunity to substitute other better breeds and adoption of forage development.

On the other hand, the number of agricultural packages adopted by farmers was a crucial strategy for implementing farm transformation. Farmers were asked about the number of packages they had running on their land during the survey period. Farmers have at least one package and at most six packages. The mean differences had a significant at $P< 0.001$ and the F test statistic was 7.24. Farmers with medium and full status had a mean of 2.2 and 3, respectively, while those in partial status had a mean of 2. Engaging in many packages offers benefits for enhancing farm businesses and providing access to better agricultural technologies (see Table 3.4).

The physical factor like distance from the local market center proved crucial in determining the operation of high-value farm enterprises. The variable distance from the near market was significant at $P< 0.05$, and the F test value was 1.56. The mean hour for farmers in partial status was 1.4, but for those in medium and full status, it was 1.15 and 1.20 hours. The minimum hour was 0.10 minutes, while the maximum was 4 hours. The result showed that the closer farmers to the market center might have the greatest advantages in diversifying high-value farm enterprises.

On the other hand, the tendency of farmers to hire labour inputs and adopting herbicides application contributing heterogeneity among farmers. As indicated in Table 3.4 below, there

is difference in the mean proportion of herbicides used by farmers. It was statistically significant at P< 0.001, and the chi2 test value was 33.52. The mean proportions of a dummy decision to use herbicides was 0.801, 0.967, and 0.989 for categories of partial, medium, and full status, respectively. Enhancements in farm productivity are likely to create chances for the usage of herbicides to eliminate weed.

Similarly, farmer seed saving behaviour was significant at P< 0.001, and the chi2 test statistic = 24.633. The mean proportion for a dummy decision to save seed for the categories of partial, medium, and full status was 0.616, 0.811, and 0.840, respectively. Farmers are more likely to use own seed sources when they become more transformative decision-makers and switch to seed shortage. Such transformative decision also induces market participation. Hence, decision to participate in contract market differ across the status and statistically significant at P< 0.001, and the chi2 test statistic equals 50.125. Accordingly, for categories of partial, medium, and full status, the corresponding mean proportion was 0.505, 0.780, and 0. 872.

Finally, the mean proportions of a dummy decision to hire labor for categories of partial, medium, and full status was 0.859, 0.811, and 0.702, respectively (see Table 3.4). The F test statistic equals 10.369, and it was statistically significant at P< 0.001. Due to the seasonal labor requirements for crop cultivation, more farmers in the category of partial status employ labor. Additionally, the acquisition of labor serves as a reliable predictor of transformational goals in agricultural lifestyles. There is also a substantial variance in the farmers' labor division and the mean proportion was 0.64, 0.73, and 0.79. for categories of partial, medium, and full status, respectively. It shows farm diversification favours family labor responsibility share among farm family.

Table 3.4. Summary of descriptive and inferential statistics

	Transformation Status									
	Partial (n=206)		Medium (n=122)		Full (n=94)		Total			
Continuous Variables	Mean	SD	Mean	SD	Mean	SD	Mean	F-Value	Min.	Max.
Age of the household head in years	49.362	10.127	47.409	10.211	44.961	9.368	46.649	1.51***	22	75
Family size of the household in number	5.650	2.169	5.983	2.053	5.883	2.089	5.798	0.62	2	14
Educational level in years of schooling	5.272	4.098	4.934	4.145	4.659	3.853	5.037	0.78	0	12
Land size in hectares	1.851	1.052	2.519	1.193	2.739	1.031	2.242	2.64***	0.25	5.5
Number of livestock in TLU	6.788	4.313	8.591	4.439	11.588	5.085	8.372	1.48**	0.026	27.45
Number of agricultural packages	1.922	0.989	2.180	1.028	2.713	1.365	2.173	7.24***	1	6
Frequency of extension service in a month	2.228	0.938	2.254	0.958	2.245	0.911	2.284	1.91	1	5
Distance from the market in hours	1.417	0.782	1.156	0.697	1.212	0.718	1.296	1.56**	0.1	4
Dummy Variables								**χ2-value**	**Min.**	**Max.**
Participate in irrigation farming (1=yes, 0=No)	0.553	0.498	0.615	0.488	0.627	0.486	0.587	3.787	0	1
Use herbicides (1=yes, 0=No)	0.801	0.401	0.967	0.179	0.989	0.103	0.891	33.852***	0	1
Seed saving behaviour (1=yes, 0=No)	0.616	0.487	0.811	0.393	0.84	0.368	0.723	24.633***	0	1
Participate in contract market (1=yes, 0=No)	0.505	0.501	0.787	0.411	0.872	0.355	0.668	50.215***	0	1
Produce market-based product(1=yes,0=No)	0.403	0.492	0.361	0.482	0.521	0.502	0.417	7.644	0	1
Share experience from others(1=yes,0=No)	0.184	0.388	0.270	0.446	0.308	0.464	0.237	6.559**	0	1
Hiring farm labor (1=yes,0=No)	0.859	0.349	0.811	0.393	0.702	0.459	0.810	10.369***	0	1
Existence of farm labor division (1=yes,0=No)	0.645	0.479	0.737	0.442	0.798	0.404	0.706	8.032**	0	1
Adequate quantity of fertilizer (1=yes,0=No)	0.228	0.421	0.180	0.386	0.255	0.438	0.220	1.879	0	1

Source: Own Survey Data (2024). (**, &*** indicates 5%, and1% probability level respectively)

3.7. Results of Econometric Model

Before the variables were fitted into the model, assumptions were considered to test. Accordingly, the assumption of proportional odds tested to check the parallel regression assumption which is the main premise of the ordinal probit model. The Brant test checks the parallel lines and $p<0.05$ (see Appendix 2A4). It indicates that every predictor variable has the same impact on the result at every level of the ordinal dependent variable (partial, medium, and full). Furthermore, the model makes the critical assumption that the error components are regularly distributed, which is essential for estimating maximum likelihood. Additionally, the assumption of constant variance was evaluated using one-way ANOVA, and Bartlett's test for equal variances yielded significant results, indicating the presence of heteroscedasticity. This issue is common in cross-sectional data and addressed by adjusting the regression analysis using the robust standard errors.

The multicollinearity test was conducted using the VIF (Variance Inflation Factor), resulting in an average of 1.28, which indicates no serious correlation between the independent variables (see Appendix 2A3). To further examine the relationships among the independent variables, Pearson's correlation coefficient and Spearman's correlation were applied. The model specification test was conducted using the 'linktest' command and found that the p-value for the predicted values is significant, while the p-value for the squared predicted values is insignificant (see Appendix 2A5). This is evidenced that the ordered probit model is correctly specified. The model's goodness of fit was demonstrated by $p = 0.000$, Wald chi2 = 251.89, and pseudo R2 = 0.34. For robustness in estimation, the results of the ordered probit and logit models are consistent in terms of sign and significant variables (see Appendix 2A6). And order probit model was selected due to lower AIC and BIC (see Appendix 2A7). Subsequently, of the seventeen explanatory variables, seven were found to be statistically significant. And results were interpreted using the marginal effect, which indicates how a unit change in the explanatory variables affects the probability of each outcome category.

3.7.1. Factors affecting the transformation status of high-value farms

The likelihood that farmers being in a category of transformation status was influenced by household wealth characteristics, such as land size and livestock in Tropical Livestock Units (TLU). A one-hectare increase in farm land size was associated with a 6.3% decrease in the probability of a farmer being in partial status, while the probabilities of being in medium and

full status increase by 3.7% and 2.7%, respectively. The variable was statistically significant at $p<0.01$ (see Table 3.5 below). The findings suggest that access to more land enables farmers to adopt improved agricultural technologies and anchor decision to diversify farm enterprises, thereby supporting the transformation progress. This result is consistent with (Malapit et al., 2020), found that socioeconomic factors, such as access to land, have a greater influence on agricultural enterprise diversification. Conversely, it contradicts the result of (Ricciardi et al., 2021), which stated that small landowners in developing countries have more agricultural landscapes than large landowners.

On the other hand, the number of Livestock in TLU is important economic assets for smallholder farmers. Hence, a unit increase livestock number in TLU was associated with a 2.2% decrease in the probability that farmer is being in category of partial status, while increasing the probability of being in medium, and full status by 1.3% and 0.9%, respectively. The variable was statistically significant at $p<0.01$ (see Table 3.5 below). This finding shows that having a diversified herd size is used as substitution assets either to generate income or exchange to buy improved breeds. It might be associated with size of the farm land which have potential to limit availability of animal feed or grazing. During focus group discussions, farmers confirmed that having a large herd size is advantageous for replacing some of local breeds with crossbred dairy cows through sale and purchase. This results to enhance dairy productivity which aspires to transformation the livestock sector and reduces large herd size pressure on grazing land ecology. This finding aligns with (Byerlee et al., 2009; Erdaw, 2023; Sharma et al., 2018), which highlights the increasing demand for animal products due to economic growth leads to change consumption patterns that offering opportunities for livestock development. On the hand, land-poor farmers often maintain smaller herds due to restricted access to grazing fields (Mugumaarhahama et al., 2021).

On the other hand, the use of farm mechanization, such as the adoption of herbicides, is more widespread among smallholder farmers. The adoption of herbicides decreases the probability of a farmer being in partial status by 10.2%, while it increased the probability of being in the medium and full categories by 29.8% and 11.3%, respectively. This implies that farmers are making high-value crop production decisions, as their focus is on enhancing per hectare productivity, leading to the adoption of herbicides to eliminate weeds. An increase in productivity signifies a transformation due to improvements in factor productivity. Similar results from a study conducted in Ethiopia (Tamru et al., 2017) demonstrated that the

application of herbicides has led to significant improvements in crop productivity. Likewise, Nigerian farming practices could change as a result of increased awareness on the use of herbicides (Adewuyi & Offar, 2022).

Moreover, the availability of seed affects crop production, and farmers often save seed from their harvests. However, there is heterogeneity among farmers in developing seed-saving behaviours, which are influenced by farming experience. Thus, a decision to save own seed is decreases the probability of farmer being in partial status category by 17.4%. However, it increases the probability of being in the medium and full categories by 11.1% and 6.3%, respectively. The variable seed save was statistically significant at $p<0.01$ (see Table 3.6). Farmers' understanding of agro-ecological suitability, as well as seed scarcity, drives them to be innovative in adjusting their seed demand. This is particularly important because the commercial seed distribution system has a shortcoming in terms of quantity and quality. This implies that farmers using their experience, adjusting innovative strategies to mitigate seed demand. This finding is confirmed by a study conducted in Kenya, which indicates that strengthening smallholder farmers' capacities through organizational frameworks improves farmers' innovative skills (Eli Wortmann, 2019).

On the other hand, farm family is a key feature of Ethiopian farmers, as agriculture employs both family labour and hired labour. Hence, the decision to hire agricultural labour increases the probability farmer being in partial status by16.4%. While it decreases the probability of being in medium and full status by 8.3% and 80.4%, respectively (see Table 3.6). This implies that as the level of transformation improves, farmers adopt mechanization, which tends to reduce labour dependency in farm production. This finding, supported by studies in Haiti (Paul & Régis, 2024) and China (Zou et al., 2024), revealed that the demand for hired labour declined following increasing productivity, in which mechanization played a role in labour dynamics.

Access to credit is essential for adopting advanced agricultural technologies; however, it remains a significant barrier for smallholder farmers. A dummy change in access to credit services decreases the probability of a farmer being in partial status by 15.7%. Conversely, it increases the probability of a farmer being in the medium and full status categories by 9.8% and 5.9%, respectively. The variable, credit, was statistically significant at the $p<0.05$ level (see Table 3.6). This implies that access to credit provides the opportunity to acquire improved agricultural technologies, thereby enhancing the progress of farm transformation.

This finding is similar to studies in Indonesia, China, and Bangladesh by (Haryanto et al., 2023; Jimi et al., 2016; Lu et al., 2023), which indicate that access to sufficient credit supports enhanced productivity and technological efficiency.

The distance from veterinary clinic services influences farmers' adoption of improved dairy and poultry practices. Access to veterinary service is very important because poultry disease is very common in rural areas, which reduces farmers' adoption rate. Accordingly, an increase distance in hour from local veterinary services increases the probability of a farmer being in partial status by 6%, while it decreases the probability of being in full status by 3.9%. The result was statistically significant at the $p<0.05$ level (see Table 3.6). This suggests that farmers who are far from veterinary services are less likely to adopt improved livestock breeds due to risk of livestock deaths, which has negative implications for the progress of livestock transformation. During field surveys, farmers expressed their reluctance to adopt improved egg-laying poultry primarily due to concerns about poultry diseases. This aligns with the findings of (Korir et al., 2023; Minten et al., 2020), which indicate that herd size and location significantly influence the adoption of improved livestock breeds while controlling for other factors.

Therefore, the overall findings revealed that the adoption of improved agricultural technologies, farmers' endowment resources (such as land and livestock), and institutional factors significantly influence the advancement of agricultural transformation in the study area. Additionally, the status of transformation showed a progressive move to medium, though further investments are required to bring the status to a higher level.

Table 3.5. Result of ordered probit regression model estimation at marginal effect.

	Dependent variables = Transformational status of high-value farms								
	(1) =Partial (n=206)			(2) =Medium (n=122)			(3) =Full (n=94)		
Explanatory variables	dy/dx	Std. Err	P>|Z|	dy/dx	Std. Err	P>|Z|	dy/dx	Std. Err	P>|Z|
Age of the household	-0.001	0.003	0.889	0.001	0.002	0.899	0.003	0.001	0.805
Family size of the household	0.008	0.012	0.506	-0.005	0.007	0.506	-0.003	0.005	0.589
Educational level in years of school	0.002	0.007	0.808	0.001	0.004	0.808	0.001	0.003	0.906
Size of the farm land in hectare	-0.063***	0.024	0.008	0.037***	0.014	0.011	0.027***	0.010	0.007
Labor division availability*	-0.107	0.062	0.084	0.066	0.041	0.103	0.039	0.022	0.074
Fertilizer use adequacy *	0.121	0.068	0.075	-0.076	0.047	0.101	-0.044	0.023	0.052
Number of livestock in TLU	-0.022***	0.006	0.000	0.013***	0.037	0.000	-0.009***	0.003	0.000
Participate in irrigation production*	0.082	0.054	0.127	-0.051	0.031	0.100	-0.036	0.024	0.129
Use herbicides for weed*	-0.402***	0.074	0.000	0.298***	0.066	0.000	0.103***	0.018	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1
p<0.01 (***), and P<0.05(**)

Source: Own survey data (2024).

Table 3.6. Result of ordered probit regression model estimation at marginal effect (Cont'd…)

Explanatory variables	Dependent variable = Transformational status of high-value farms								
	(1) =Partial (n=206)			(2) =Medium (n=122)			(3) =Full (n=94)		
	dy/dx	Std. Err	P>|Z|	dy/dx	Std. Err	P>|Z|	dy/dx	Std. Err	P>|Z|
Save own seed*	-0.174***	0.061	0.004	0.111***	0.042	0.009	0.063***	0.021	0.003
Hire labor for farming*	0.164***	0.061	0.008	-0.083***	0.028	0.003	-0.804**	0.036	0.027
Access to credit services*	-0.157**	0.064	0.014	0.098**	0.043	0.023	0.059***	0.023	0.009
Market-oriented production*	0.016	0.055	0.758	-0.010	0.033	0.759	0.007	0.022	0.757
Shared experience*	-0.050	0.066	0.448	0.029	0.037	0.437	0.021	0.029	0.466
Frequency of extension service	-0.012	0.027	0.647	0.007	0.016	0.645	0.005	0.011	0.650
Distance from nearest market in hour	-0.044	0.041	0.284	0.026	0.025	0.289	0.017	0.016	0.285
Distance from veterinary services	0.096**	0.049	0.049	-0.057	0.030	0.059	-0.039**	0.019	0.046
Log pseudo likelihood =-290.38									
No. of Obs. =422									
Wald chi2 (19) =251.43									
Prob.>chi2=0.000									
Pseudo R2=0.3381									

(*) dy/dx is for discrete change of dummy variable from 0 to 1; p<0.01 (***), & P<0.05(**).

Source: Own survey data (2024).

3.7.2. Results of sustainability indicators

Farm transformation is significantly encouraging the achievement of sustainable agricultural development in line with sustainability indicators. As depicted in Table 3.7, sustainability scores were computed for environmental, economic, and social sustainability. The overall coefficient of variation in the partial category was negative, indicating that current agricultural practices are not leading to sustainability in this category. In contrast, the coefficient was positive in the medium and full status categories. Additionally, the economic and environmental sustainability scores showed less variation as the transformation improved from medium to full status. This implies that improvements in farm transformation stabilize the variation in environmental and economic benefits.

However, the coefficient of variation in full status was higher at 54.61 in terms of the social sustainability score. This suggests that agricultural practices conducted under full status were contributing more variations in social sustainability. Possibly, farmers have different levels of food security, knowledge, and perception under the current agricultural practices. The result also showed the mean scores for environmental and economic sustainability were -0.59 and -0.49 in the category of partial status. This suggests that the less integration of farm enterprises may degrade environmental services and bring poor resilience to the economy. While the mean score for social sustainability was positive at 0.05, it was relatively socially sustainable, and farmers embedded with traditional farm operation.

In general, the findings showed that the mean scores for environmental, economic, and social sustainability were positive as the transformation progressed from partial to full status. Nevertheless, the existing agricultural practices across the categories exhibited greater social variations. Therefore, integrating high-value farms to enhance economic, environmental, and social sustainability requires farm operations aimed at balancing sustainability indicators (see Table 3.7).

Table 3.7. Summary statistics of sustainability indices by status of transformation

	Status of High-value crop and livestock Transformation								
	Partial			Medium			Full		
Sustainability score	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Environmental	-0.59	1.31	-2.24	0.26	1.13	4.31	0.96	1.31	1.39
Economic	-0.49	0.91	-1.86	0.28	0.93	3.32	0.70	0.98	1.40
Social	0.05	0.87	18.26	0.10	0.91	9.60	0.02	1.07	54.61
Overall sustainability	-0.25	1.55	-6.31	0.19	1.21	6.26	0.29	1.20	4.19

Source: Own survey data (2024).

On the other hand, the results below (Table 3.8) shows that the total variance explained by each principal dimension (factor) as it reduces the dimensionality of the variables. The dimensions were computed using forty-one variables, which are indicators of environmental, economic, and social sustainability (see Appendix 2A12). The eigenvalue was computed, with a higher value indicating that a greater amount of sustainability information captured by the respective dimension. If the eigenvalues of the multiple component factors exceed 70%, it indicates that the dimensions explain significant variations. Accordingly, the first five dimensions represent the data set for farm transformation sustainability indicators. The first dimension (Dim. 1) accounts for the largest source of variation, characterized by an eigenvalue of 1.971 and a variance percentage of 10.799. While the fifth dimension (Dim.5) accounts the lowest variation which indicated by eigen value of 0.776 and variance of 4.254 (see Table 3.8).

Table 0.1. Eigen value of multiple factor analysis results

	eigen value	percentage of variance	Cumm. Percentage of variance
Dim.1	1.971	10.799	10.799
Dim.2	1.104	6.05	16.849
Dim.3	0.856	4.692	21.542
Dim.4	0.791	4.337	25.879
Dim.5	0.776	4.254	30.132
Dim.6	0.682	3.737	33.865
Dim.7	0.671	3.675	37.544
Dim.8	0.647	3.546	41.090
Dim.9	0.623	3.416	44.506
Dim.10	0.583	3.192	47.698

Source: Own survey data (2024).

We also examined how environmental, economic, and social sustainability contribute to overall farm sustainability. As shown in Table 3.9 below, under dimension 1, environmental indicators account for 34.23% of the variation. This is likely due to the high inertia in variables such as the number of livestock, participation in irrigation farming, the number of cross-breed dairy cows, and the frequency of irrigation (see Appendix 2A12). In contrast, economic indicators contribute to 73.34% of the variation in dimension 4 (see Table 3.9), with factors such as yield per hectare, availability of labour division, renting bulls, and market-oriented production (see Appendix 2A12).

Regarding the contributions of social indicators, 32.16% and 31.87% in dimensions 1 and 3 were attributed to these indicators. Social indicators include farmers' perceptions of the existing production system, ownership of improved bulls by the group, linkages with industries, knowledge about the demand for their farm products, participation in compost preparation training, access to spatial price information, and confidence in using organic fertilizer (see Appendix 2A12). Therefore, the findings conclude that the adoption of dairy technology, irrigation farming, land productivity, farmer business orientation, and access to information and knowledge contribute to the sustainability of existing farm transformations at the farmer level.

Table 0.1. The contributions of indicators to the overall sustainability

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
Environmental	34.323	35.866	14.370	15.139	9.068
Economic	33.520	57.226	53.756	73.329	72.665
Social	32.157	6.970	31.874	11.531	18.266

Source: Own survey data (2024).

3.7.3. Visualization the relationship between transformation status and sustainability

The violin plot in Figure 3.5 illustrates the relationship between the sustainability score (shown on the y-axis) and farm transformation status (shown on the x-axis). This type of plot is particularly effective for continuous data, such as farm sustainability scores, and facilitates comparisons across groups defined by farm transformation status. It provides a visual summary of statistics and densities for each variable, combining elements of both box plots and kernel density plots.

Environmental and economic scores have a lower median for farms with partial transformation status, while higher scores are observed for the category of full status. In contrast, the median score for economic sustainability is highest for farms with medium transformation status. Additionally, social sustainability score is high median value for the partial status. The findings suggest that integrating high-value crop and livestock enterprises enhances environmental and economic sustainability. However, social sustainability is hindering the progress of transformation, might be strong social embedded traditional farming system (see Figure 3.5).

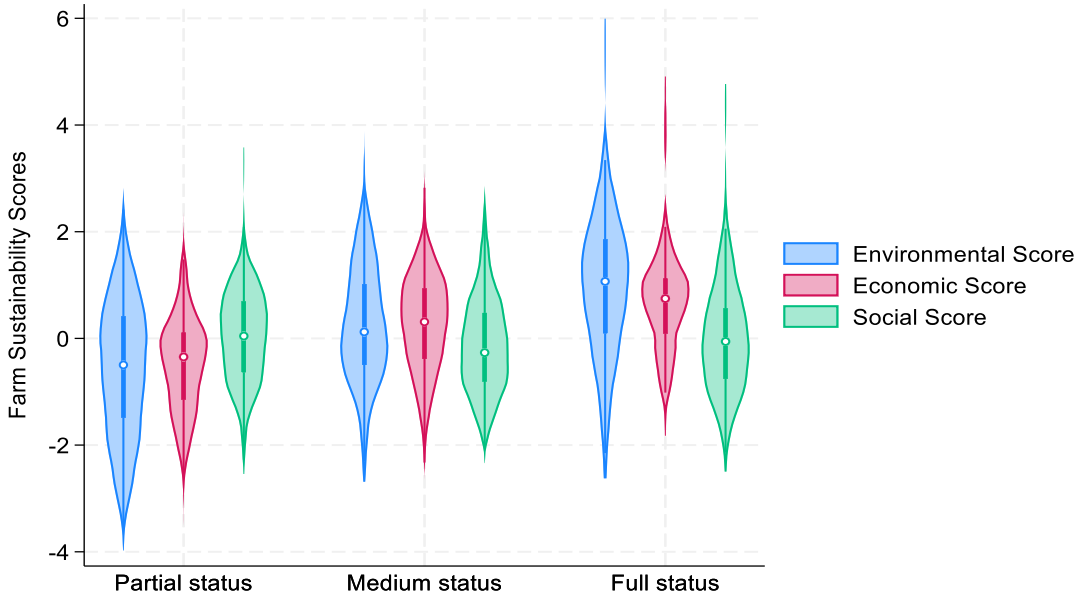

Figure 0.1. Sustainability score comparison by transformational status
Source: Own survey data (2024).

3.7.4. Effect of high-value farm product transformation on farm sustainability

The relationship between farm transformation status and its sustainability was analysed using a multivariate regression model. The partial status was set as the reference category to estimate the effects of medium and full status on sustainability scores. The dependent variables, eco_score, env_score, and soc_score were significantly influenced by the explanatory variables at $p < 0.05$ (see Table 3.10). Hence, the improvements of high-value farms being of medium status improve environmental and economic sustainability scores by 0.63 and 0.66 points, respectively, compared to partial status, holding other factors constant. It was statistically significant at $P < 0.001$ (see Table 3.10). Conversely, being in the medium status, social sustainability score was decreased by 0.22 points higher than partial status and

was statistically significant at $p < 0.05$. This indicates that the environmental and economic aspects are bolstered by the introduction of environmental management through sustainable farm practices and market-oriented production. However, the reduction in social sustainability might be attributed to farmer's inseprability of the traditional farming statusquo which altered by knowledge gap to improve agricultural practices.

On the other hand, as the transformation status of high-value farm products is in the category of full, the environmental and economic sustainability scores were increased by 1.25 and 1.05 points higher than partial status respectively. This indicates that improvements to the farm portfolio mix enhance sustainability in both environmental management and reduce economic risks. Therefore, significant extension efforts are needed to engage a broader farmer population to achieve overall sustainability. Likewise, high-value farm product sustainability is influenced by control variables such as family size, educational level, and total agricultural land size. A unit increase in family size positively increases the score of social sustainability by 0.09 points higher than, holding other factors constant, and is statistically significant at $p<0.05$ (see Table 3.10). This suggests that family size contributes labour for environmental management, provides diversified income sources, and fosters social cooperation in agricultural livelihoods. This result is consistent with Alelign et al. (2023); a large family size has the advantage of labour availability, enabling improved food security diversity and land degradation management.

The educational level of the farmer improves the environmental score. Hence, a unit increase education level, increases environmental score by 0.082 point higher than partial status, while decreases economic sustainability score by 0.039 point lower than partial status, holding other factors constant. Educational attainment is recognized for broadening perspectives on resource utilization, particularly in fam businesses, which promotes wise environmental management. Though education can enhance the adoption of new farm technologies, sometimes might not be guarantee to manage external factors (labour shift and change in technology). This result is confirmed with (Ali et al., 2025: Channaveerayya and Bondita, 2025), higher educational level of farm household heads enabling to adopt sustainable agricultural practices and climate smart agriculture. The negative sign to coefficient of economic sustainability consistent with findings of (Eric, 2015: padhy 2015), higher educational level will shift labor from agricultural sector to other sectors. Additionally, the

dynamic change in agricultural technology not meet the existing traditional knowledge so that leads to less farm productivity.

Finally, a unit increase in land size in hectares increases the environmental, economic, and social sustainability scores by 0.322, 0.137, and 0.102 points, respectively higher than partial status. This implies that improvements in the agricultural landscape through sustainable practices reduce land degradation and enhance farm productivity which indicates good environmental and economic performance. These findings are consistent with (Getnet, 2025; Aberahm et al., 2023) showed that improvements in agricultural land through climate-smart crop intensification and climate adaptation strategies, such as home gardens, improve households' food security. Generally, the transformation of high-value farm products boosts environmental and economic sustainability, though it necessitates improvements in social sustainability in the study areas (see Table 10).

Table 0.1. The results of the multivariate linear regression model

	Equation	Obs	Parms	RMSE	"R-sq"	F	P > F
	env_score	422	8	0.901	0.228	22.87	0.000
	eco_score	422	8	0.161	0.329	29.01	0.000
	soc_score	422	8	0.906	0.060	3.779	0.005

Explanatory variables	Continuous Dependent variables											
	Environmental sustainability score				Economic sustainability score				Social sustainability score			
	Coeff	Bootstrap std.err	Z	p>|z|	Coeff	Bootstrap std.err	Z	p>|z|	coeff	Bootstrap std.err	z	p>|z|
Medium transformation status	0.632***	0.131	4.84	0.000	0.666***	0.103	6.17	0.000	-0.221**	0.101	-2.18	0.029
Full transformation status	1.246***	0.157	7.96	0.000	1.049***	0.125	8.35	0.000	-0.101	0.128	-0.79	0.430
Age of the households	0.009	0.006	1.49	0.137	0.005	0.005	0.12	0.908	-0.008	0.005	-1.79	0.080
Sex of the households	-0.178	0.166	-1.07	0.283	0.195	0.115	1.70	0.089	0.065	0.120	0.54	0.591
Family size of the household	0.023	0.027	0.87	0.384	-0.031	0.022	-1.37	0.171	0.091***	0.021	4.42	0.000
Educational level	0.082***	0.015	5.33	0.000	-0.039***	0.012	-3.36	0.001	0.003	0.012	0.29	0.771
agricultural land size in hectare	0.322***	0.056	5.71	0.000	0.137***	0.046	3.00	0.003	0.102**	0.042	2.43	0.015
_cons	-1.967	0.419	-4.69	0.000	-0.615	0.294	-2.09	0.036	-0.387	0.305	-1.27	0.205

Source: Own Survey data (2024).

(***, and ** indicates 1% and 5% probability level).

Partial transformation status is reference category.

3.8. Conclusion

Decision-making at the farm household level is crucial for adopting high-value farm enterprises to transform farm portfolios. Agricultural land management, improved agronomic practices, the adoption of advanced farm technologies, and institutional services significantly influence the progress of high-value farm transformations. This entails farmers commitment to improve socio-economic factors affecting rural communities which enables to achieve food security. Consequently, the ongoing transformation efforts also indicate commitments to environmental, economic, and social sustainability. Therefore, the Ethiopian government should broaden the scope of capacity building for farmers through strengthening extension service to improve integrated farm enterprise production system.

3.9. Recommendations

The following recommendations are forwarded.

- The findings of this study underscore the significance of farmland size and the number of livestock in enhancing the status of high-value farm transformation. Therefore, farmers should adopt land intensification system to improve productivity and pursue farm diversification.
- Farmers' innovations about seed saving, hire labour, access to credit, and utilise veterinary services are important factors influencing the progress of transformation. Therefore, agricultural stakeholders should improve the quality of service provided to support farm businesses, focusing on capacity building, financial services, and veterinary infrastructure.
- Farm transformation to medium and full category improves the environmental and economic sustainability while it reduces social sustainability. Therefore, awareness should be enhanced to address agricultural production using improved technologies to create sustainable agricultural production.

CHAPTER FOUR

4. Role of High-Value Farm Product Transformation in Contract Marketing

Abstract: *Smallholder farmers are the leading agricultural food producers in the developing world, yet they face significant challenges in securing market access. This study is significant to understand how transforming high-value products enhances marketing decisions and sales volume. It investigates the factors influencing participation in informal contracts and estimates the volume of high-value farm products sold in the central Oromia region of Ethiopia. We collected data from 422 randomly selected farm households using a semi-structured questionnaire and analyzed it using descriptive statistics and a double-hurdle model. The descriptive statistics revealed that approximately 264 farmers (62.56%) had access to informal contracts, 20 farmers (4.74%) engaged in formal contracts, and 138 farmers (32.7%) utilized open markets. The histogram results showed that 34.04%, 38.4%, and 47.87% of high-value crops, milk, and eggs, respectively, were sold in the fourth quartile of the full* status category. *The age of farmers and buyer volume limits negatively impacted participation in informal contracts. Conversely, farm size, the number of adopted agricultural technology packages, and market trust positively influenced farmers' decisions to engage in the informal contract market. The truncation regression analysis indicated that the number of cropping systems, participation in irrigation, dummy districts, transformation status, adoption of cross-breed cows, distance to market, poultry feed availability, and access to extension services all positively affected the volume of crops, milk, and eggs sold. The findings suggested that transforming high-value products improves sales volume. Therefore, the government should strengthen agricultural institutional services by aligning stakeholder transformational goals with national development.*

Keywords: Double Hurdle Model; High-Value Farm Products; Informal Contract Market; Smallholder Farmers.

4.1. Introduction

Smallholder farmers are the major producers of agricultural foods in the developing world. About 475 million smallholders are employing land plots on less than 2 hectares (Rapsomanikis, 2015). For example, the Ethiopian agricultural economy is dominated by smallholder agriculture and contributes 24% of GDP bigger than in sub-Saharan Africa (Gordon, 2019). At the national level, agricultural GDP showed a decline from 36.3% in the year 2016/17 to 32.40% in 2021/22 (NBE, 2022). Nevertheless, climate change and poor market linkage challenge agricultural livelihoods.

In Ethiopia, major high-value crops such as teff, wheat, barley, maize, pulses, and vegetables are widely adopted by smallholder farmers to commercialize. Teff, maize, and wheat dominate the staple food crop and share 23%, 20%, and 15% of cultivated land (CSA, 2020). However, production contracts and market contracts for staple crops are weak due to insignificant quality differences among smallholder farmers in the developing world (Otsuka et al., 2016). On the other hand, Ethiopia ranks higher in cattle populations in Africa, however; low production and market performance in the sector. The livestock composition is characterized by 97.8% indigenous, 1.9% cross-breed, and 0.3% exotic breeds (CSA, 2020). Annually, 4.37 billion litres of fresh milk are produced of which 57% is consumed by rural households and 43% processed for marketing (Farrell, 2021). In addition, indigenous chicken lays eggs annually 30-80 eggs per hen while exotic 135-250 eggs per hen annually (Mengesha et al., 2022). And 95.86% of national poultry output (eggs and meat) is contributed by village base poultry management while 1.35% and 2.79% are contributed by exotic breeds and hybrids respectively (Mengesha et al., 2022).

Likewise, the Ethiopian agricultural development plan for the coming ten years (2021-2030) targeted to increase crop production from 543-925 million quintals, improve the proportion of improved breed from 2.7%-17%, raise milk production from 4.37 billion liters to 11.8 billion liters, and egg production from 2.8 billion to 5.5 billion (PDC, 2022). This is coupled with improvements in the commercialization process by producing high-value farm products and increasing competitiveness. Reasonably, engaging in a contract market reduces transaction costs, improves agricultural technology adoption, and meets the needs of future consumers (Penone et al., 2024). Nevertheless, market development in developing countries like Ethiopia is characterized by high transaction costs, low farm performance, inadequate

infrastructure, and weak extension services owing to scanty contract farming (Regasa Megerssa et al., 2020). In other words, agricultural marketing is not well institutionalized to broader market systems and low incentives for farmers to produce in surplus (Mitiku, 2014). Therefore, inadequate market access circumstances lead farmers to sell farm outputs through an informal contract market system besides to the traditional open market system.

4.2. Literature Review

Contract market participation is a misleading term unless need to define what the 'contract' really refers to. A contract market can be "informal" if it fails to satisfy the third party's standard interest and is insurmountable to establish legal written agreements (Battigalli & Maggi, 2002; Schwartz & Scott, 2003). It revealed that relationships are built with customers like individuals, middlemen, consumers, or business organizations based on trust. While the "formal" contract has pushed the provision of incentives for agent participants in the market. It has governance mediations which legally accepted by all parties involved in the contract agreement (Gil & Zanarone, 2017). Thus, because of small quality variations, production inefficiencies, and inadequate availability of inputs contract farming is poor among smallholder farmers to develop formal contract production and marketing (Otsuka et al., 2016). That means spot market transaction prevails in which farmers sell farm products using informal contracts.

There are several reasons why smallholder market participation is vital in developing countries and in particular in Ethiopia. Because the cause and effect of economic development are catalysed through market participation. It is disinformation that a "reasonable price" is not a guarantee to access a stable market provided that reparation by investment in productive technologies improves access to public and private goods, and the development of institutions and infrastructure (Barrett, 2008). This means, market participation improves the process of moving from subsistence farming to more commercialization to reflect agricultural and rural transformation to dignify economic diversification (Timmer & Akkus, 2008). Research conducted in developed countries like Europe indicated the rise of interest in the implementation of farm product contracts owing to improving farm incomes (Ton et al., 2018; Vabi Vamuloh et al., 2019). Household-specific characteristics, farmers' economic resources such as farm size, and farmer's preferential to risk have significant impacts on participation in the contract market (Dubbert & Abdulai, 2022; Giagnocavo et al., 2022; Ma & Abdulai, 2016).

Thus, the success of smallholder farmers can be justified if they access profitable markets (Machete, 2004). And calls for systematic acquisition and access to market intelligence, market information, and efficient farmer organization (Jari & Fraser, 2012). Because market access is a pre-condition for market participation. However, it is challenging for smallholder farmers to engage in markets in the majority of emerging economies because of many limitations (Jari & Fraser, 2012). According to Paulson et al. (2008), determinants of contract marketing of corn and soybean are not the same. That means, each crop has specific market demand factors and choices. Likewise, a study in Vietnam showed that pig farmers participated in the informal contract market due to social capital and farmer's asset size (Costales et al., 2008). Currently, in Ethiopia, several studies have been conducted on the marketing of agricultural products. Some approaches by smallholder commercialization and found that an advantage to wealth accumulation, and poverty reduction in Ethiopia (Geffersa & Tabe-Ojong, 2024; Getahun, 2020; Yohannes & Adi, 2021). And other specifically studied crop commercialization (Gebiso et al., 2023), maize, and teff commercialization (Endalew et al., 2024; Haile et al., 2022; Wassihun et al., 2022) vegetables commercialization (Gosa et al., 2024), commercialization of cow milk (Lemma et al., 2023).

Others examined, that factors affecting market orientation are not the same as market participation, and found orientation translates into participation (Moti & Birhanu, 2010). However, market participation studies by itself are not adequate for understanding agents in the market, and important to know to whom the product is sold. Hence, some studies embark on smallholder market outlet choice but do not measure the level of sold (Ali & Kenee, 2023; Ketema & Lika, 2023; Ozkan et al., 2022; Worku et al., 2023). So, it is necessary to look at driving factors for informal contract markets that enable to transit future market development to formal contracts.

Hence, the vast majority of scholars emphasize contract farming participation which conveys both production and marketing, commercialization, and scanty articles on contract marketing in particular informal contract marketing. Hence, this study is important to identify knowledge and practical gaps about factors that determine informal contract marketing study. It also contributes to a rethink about market development strategies in study areas and in general in Ethiopia. Moreover, it fills limitations on market participation and market outlet choice studies by directing how customer-based selling is regarded as informal contract

marketing. And identifies factors affecting informal contract market participation and the extent of high-value farm products sold in the study areas.

4.2.1. Theoretical framework of the study

This study is based on the relational contract theory which ultimately transition to more discrete arrangements, where farmers become attached to specific buyers (Campbell, 2004; Macneil, 1980). This indicates that relational theory inherently promotes cooperation, even though there are situations in which sellers establish distinct contractual arrangements (Campbell, 2004). On the other hand, (Granovetter, 1985) argued that economic transactions (the marketing of high-value farm products) are embedded within the social relationships formed between farmers (seller) and their customers (buyer), which may include traders, individual consumers, hotel owners, or other private companies. This elucidates the non-randomness of market participation and explains why some individuals may be more or less inclined to sell given quantities of output.

Therefore, the relational, social embedment, and economic transaction theories aim to enhance the decision-making processes within households. Consequently, decisions regarding market participation and the level of sales primarily focus on achieving utility maximization. (Singh, 1986) provide insights into the fundamental questions of how and why it is crucial to analyze agricultural production decisions at the household level. This analysis is essential because agriculture serves as a vital source of income and employment for many in developing countries. (Barrett, 2008) further explores these concepts by illustrating household market participation decisions. Therefore, the utility maximization for farmers participating in a contract market can be expressed mathematically as follows. Let:

$U(C,T)$ utility functions based on consumption (C) and leisure time (T)

$Q = f(x)$ production function depending on input X.

$I = P_s.Q_s$: Income from market sales

($Where: P_s\ is\ price\ of\ high\ value\ farm\ products;\ Q_s\ is\ quantity\ sold$)

$C = C(Q_s, I)$ consumption depend on both the quantity of high value farm products sold and income from sale. Then the farmer maximizes;

$$MaxU_{Q_S} = (C(Q,I),T) \quad (16)$$

Subject to

$$Q = Q_c + Q_s; I = P_s.Q_s \quad (17)$$

Market participation involves a discrete choice to participate or not. Once the decision to participate is made, a continuous decision on the quantity follows. This leads to the double hurdle logic: the first hurdle is the decision to participate (a binary choice), and the second hurdle is the decision on how much to sell (a continuous choice). The conceptual framework for market participation decisions and sales levels is influenced by relational factors, institutional factors, farm resource use, and household-specific factors, as illustrated in Figure 4.1 below.

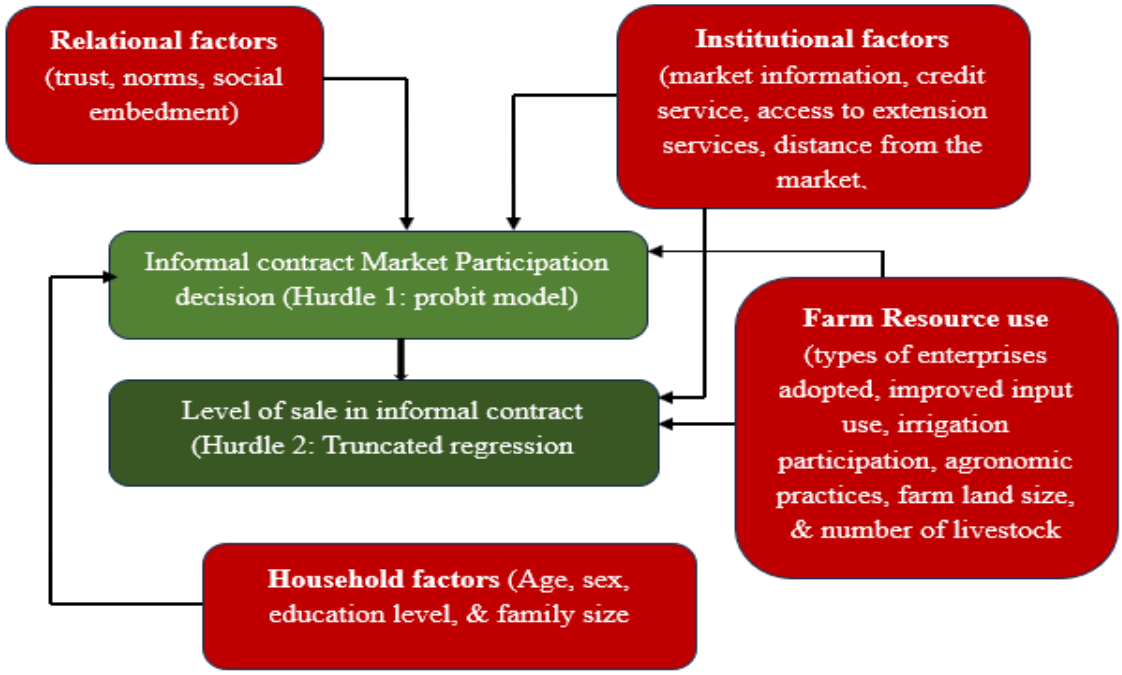

Figure 4.1. Theoretical framework of contract market participation
Source: Author sketch.

4.3. Method of Data Analysis

4.3.1. Descriptive and inferential statistics

Under descriptive analysis, respondent's characteristics by market type and participation in the informal contract market were presented by mean, SD, minimum and maximum, frequency table, and percentages. Moreover, distributional results were illustrated using stack bar graphs, and histograms. The inferential statistics were used to compare informal contract market participants and non-participants using t-tests and chi-2 tests.

4.3.2. Econometric model specifications

To determine factors affecting informal contract market participation and level of participation double hurdle model was used. The participation decision was estimated by the probit model because the error terms assume standard normal distribution while the logit is logistic distribution. The level of participation was estimated by the truncation regression model because it accounts for the positive outcomes of the first decision. Most studies in commercialization and market participation presented their result using the double hurdle model of two-step estimation. Because there are cases in which factors affecting participation decisions are quite different from the level of participation. In such cases, the estimation procedure went separately. Hence, the DHM (Double-Hurdle Model) is designed to explain the mechanism of an individual's decision process and is decomposed into separate components i.e. informal contract market participation decision (whether to participate or not); and level of sell decision (the volume of high-value farm products sold in kilogram).

Each hurdle is conditioned by socio-economic, demographic, institutional, and physical factors. The model considers the possibility of zero outcomes in the second hurdle arising from the individual's deliberate choices or random circumstances. The model assumes that zero values can be reported in both decision stages (Greene, 2012). The zeros reported in the first stage arise from zero participation in the informal contract market, and those in the second hurdle come from zero participation in the level of sale due to a farmer's deliberate decision or random circumstances. Smallholder farmers are categorized into two categories, participants in the informal contract market ($U_n > 0$) and non-participants ($U_n = 0$). Where Un is a decision to participate in the informal market. Let y_1 represent the category to which the smallholder farmers belong, since the participant, non-participant partitions give an ordered response. Let the ordered response y_1 be such that;

$$Ali = 0 \text{ if } Uni = 0 \quad (18)$$

$$Ali = 1 \text{ if } Uni > 0 \quad (19)$$

In such cases, the standard probit model is used to assess the household informal contract market participation, and its specification is given below (Wooldridge, 2012); and the empirical model used to estimate the Probit model or the first hurdle equations is given below.

Where the index equation is written as,

$$y_1^{*} = \beta_1 X_{1i} + \varepsilon_{1i} \quad (20)$$

Where, y^*_1 is a latent discrete participation choice variable that denotes binary censoring, which is the utility the farmer gets from participating in the informal contract market. X_1i is a vector of explanatory variables hypothesized to influence the probability of participation, β_1i is a vector of parameters and ε_1i is the standard error term.

$$yi = \begin{cases} 1 & \text{if smallholder farmers participate in the informal contract market; } y^*>0 \\ 0 & \text{if } y^* \leq 0 \text{ (otherwise} \end{cases} \quad (21)$$

In the second stage, a truncated regression model was employed to examine factors that influence the level of high-value farm products sold (crop, milk, and eggs). A truncated regression model fits on a sample drawn from a restricted part of the population. Under the normality assumption of the whole population, the error term in a truncated regression model has a normal distribution that will be scaled up so that the distribution integrates to one over the restricted range. Thus, the model is given as:

$$Z^*i = Xi\lambda + \mu i, \mu i N(0, \delta^2) \quad (22)$$

Zi = Z*i if Z*i>0 and *y*i =1; 0 otherwise

Where: *Zi* is the level of high-value farm products sold (crops, milk, and eggs) which depends on latent variable *Z*i* being greater than zero and conditional to the decision to participate in informal contract market *y*i; λ is a parameter to be estimated.

4.3. Variables Definitions and Working Hypothesis

4.3.1. Dependent variables

Contract Market Participation: This is a dummy dependent variable that takes a value of '1' if farmer participated in informal contract market; otherwise '0'. It is influenced by socio-economic, demographic, and institutional variables.

Level of high-value farm products sold: This represents continuous dependent variable refers to the amount of high-value crop, milk, and egg sold to market and measured in kilogram. It is influenced by the level of high-value farm transformation, socio-economic, demographic, adoption of technologies, and institutional variables.

4.3.2. Independent variables

Table 4.1. Summary of independent variables and expected sign

Variables	Type	Expected sign on market participation	Expected sign on level of sold
Age of the household head in years	Continuous	-	
Sex of the household head	Dummy (1=male; otherwise, 0)	+	
Family size of the household head	Continuous	+	
Educational level in years of schooling	Continuous	+	
Farm size in hectare	Continuous	+	
Buyers limit volume of buying	Dummy (1=Yes; 0=No)	-	
Access to market information	Dummy (1=Yes; 0=No)	+	
Access to credit service for farming	Dummy (1=Yes; 0=No)	+	
Distance from the market in hours	Continuous	-	-
Number of agricultural technologies package adopted	Discrete	+	
Social network connection	Dummy (1=Yes; 0=No)	+	
Trust market opportunity	Dummy (1=Yes; 0=No)	+	
Number of cropping system	Continuous		+
Availability of adequate quantity of fertilizer	Dummy (1=Yes; 0=No)		+
Irrigation participation	Dummy (1=Yes; 0=No)		+
District in West Shewa zone	Dummy (1= in West Shewa zone: otherwise '0')		+
District in South West Shewa zone	Dummy (1= in South West Shewa zone: otherwise '0')		+
Full transformation status	Dummy (1= full status; otherwise '0')		+
Medium transformation status	Dummy (1= medium status; otherwise '0')		+
Number of livestock in TLU	Continuous		+
Frequency of extension contact in month	Continuous		+
Market-driven production	Dummy (1=Yes; 0=No)		+
Availability of farm labour division	Dummy (1=Yes; 0=No)		+
Farmers experience on cross-breed cow	Dummy (1=Yes; 0=No)		+
Availability of animal feed	Dummy (1=Yes; 0=No)		+
Training on milk production	Dummy (1=Yes; 0=No)		+
Adoption of cross-breed cow	Dummy (1=Yes; 0=No)		+/-
Poultry disease problem	Dummy (1=Yes; 0=No)		-
Adoption of improved egg laying poultry	Dummy (1=Yes; 0=No)		+
Availability of poultry feed	Dummy (1=Yes; 0=No)		+

Source: Author's compilation from related literature and context of study areas.

4.4. Result and Discussion

4.4.1. Proportion of respondent by market access

Table 4.2 below presents the distribution of farmers by market access across the study districts. Farmers had access to open markets, formal contract markets, and informal contract markets for selling their agricultural products. Hence, 62.56% (n=264) of respondents sell high-value farm products through an informal contract market system. Whereas, 4.74%(n=20) participated in formal contract market which was very low participants. The remaining 32.7% (n=138) sell high-value farm products in open market places located in rural areas and nearby towns. On the other hand, the percentages of participants in the informal contract market higher in Ada'a Barga district and lower in Weliso district. This shows that market access across study districts varied by location.

Table 4.2. Percentage of farmers' access to various markets across district

	Districts											
	Ada'a Barga		Bako Tibe		Ilu		Weliso		Welmera		Total	
Market Access	N	%	N	%	N	%	N	%	N	%	N	%
ICM	67	64.4	60	63.16	52	67.53	39	52.7	46	63.89	264	62.56
FCM	11	10.6	2	2.11	5	6.49	0	0.0	2	2.78	20	4.74
OM	26	25.0	33	34.74	20	25.97	35	47.3	24	33.33	138	32.70
Total	104	100	95	100	77	100	74	100	72	100	422	100

Source: Own survey data (2024).
Hint: ICM (Informal contract market), FCM (Formal contract market), and OM (Open market).

4.4.2. Distribution of farmers' market access by farm transformation status

Farm transformation is an important process to diversify the market access system by transforming farm production oriented to the market. The stacked bar graph below indicated 10%, 6%, and 4% of farmers who were being in the category of medium, full, and partial status participated in the formal contract market. Further, the proportion of farmers who access informal contract market among the categories of partial, medium, and full status was 99%, 90%, and 75%, respectively. In other words, more proportions of farmers who belong to medium and full status access informal contract market than partial status. Finally, 103%, 22%, and13% of farmers who were being in the category of partial, medium, and full status

access open market system. Therefore, this finding suggest that the transformation progress less improves the formal contract marketing access while large percentage of farmers are still enggaged in informal contract and traditional open marketing system (see Figure 4.2).

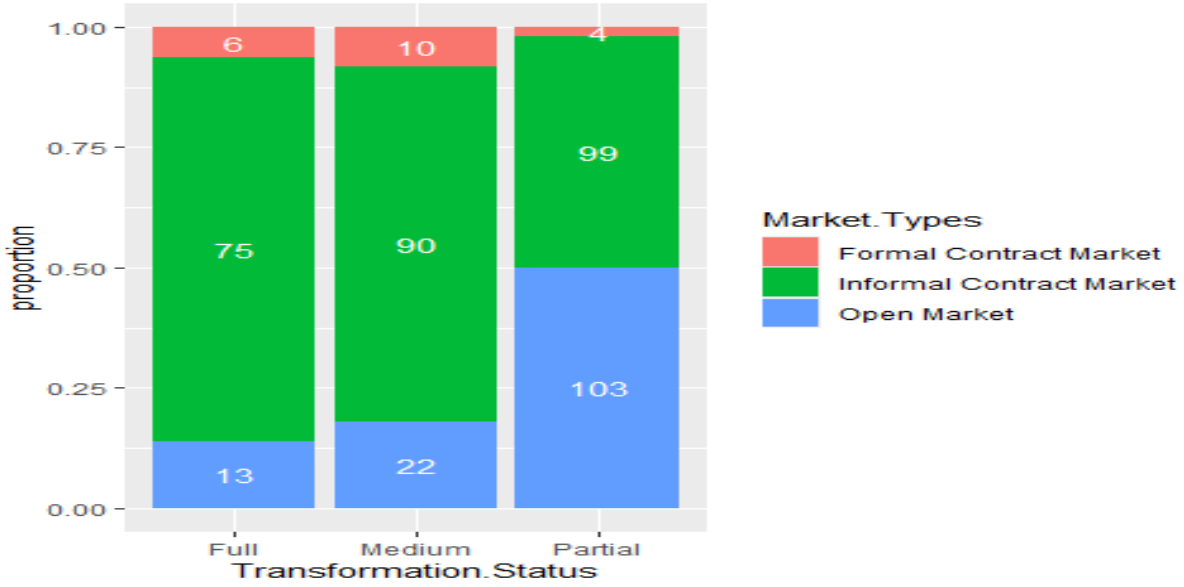

Figure 4.2. Distributions of market access by category of status
Source: Own survey data (2024).

4.4.3. Farmers' response to unsold farm products

Rural farm households often suffer from the unavailability of a stable market which affects market confidence. In such cases, farmers adopt resilient mechanisms to cope with unsold agricultural products. Farmers were asked about what to do with unsold farm products. And farmers either consume or process into another product form. This is common for perishable products like milk and vegetables. As indicated in Figure 4.3 below, most farmers processed unsold agricultural raw products among the participants of the informal contract market. They process milk into cheese and butter while the non-participants consumed the product directly and a significant number of farmers process it for home consumption. Especially, farmers reported conditions in which milk was unsold owing to buyers' limitations on volume and irregularity of milk supplied daily.

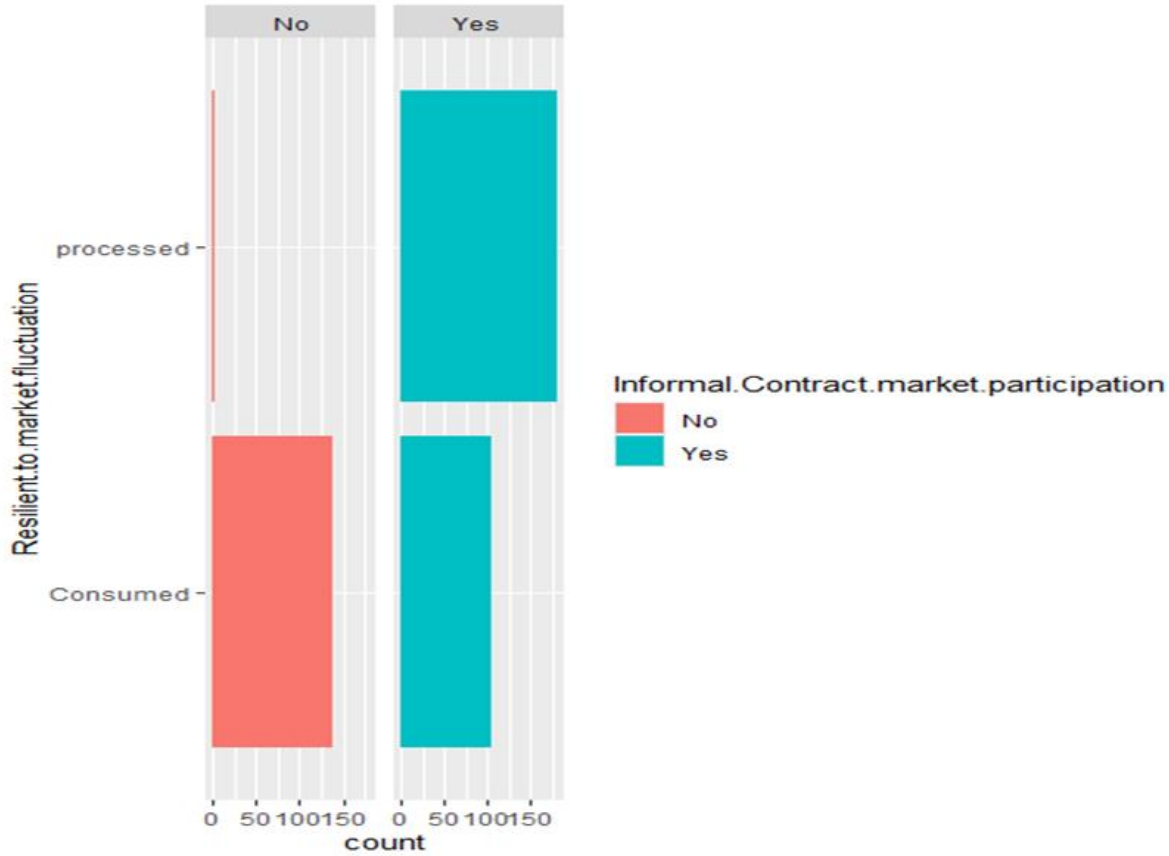

Figure 4.3. Distributions of farmer's response to unsold farm products
Source: Own survey data (2024).

4.4.4. High-value farm products sold by status of farm transformation

Figure 4.4 depicts a histogram of crops sold by quartile, across the category of transformation status. The vertical y-axis represents percentages, while the horizontal x-axis indicates the quartiles of crops sold (Q1, Q2, Q3, and Q4). The kernel density function illustrates the distribution of crops sold within each quartile. For farms in full status, the highest proportion of crop sales was in the 4th quartile at 34.04%, while the 1st and 3rd quartiles had similar, low sales figures. In contrast, the sales distribution for farms in medium status was more uniform, with the highest proportion in the 1st quartile, gradually declining through to the 4th quartile, showing no strong concentrations of sales in any quartile. For farms in partial status, there was a notable concentration of crop sales in the 1st quartile at 40.78%, while sales in the 2nd quartile were lower at 16.5%. Overall, the distribution suggests that farm transformation status significantly impacts commercialization volume, as evidenced by the high sales in Q4 in full status category and lower sales in Q1 in partial status.

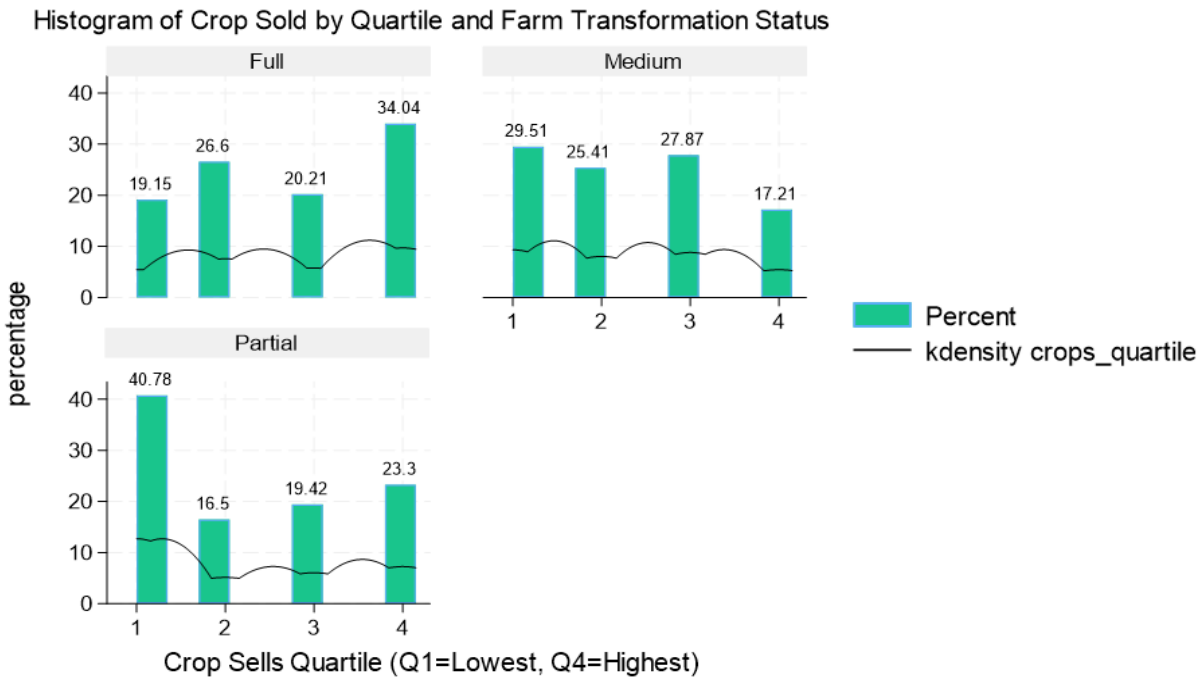

Figure 4.4. Distribution of crop sold by quartile and transformational status
Source: Own survey data (2024).

On the other hand, the sale of raw milk by smallholder farmers to their customers is common in milk marketing. Figure 4.5 shows that the highest concentration of sales occurred in the full status category in the 4th quartile (38.3%), while sales were relatively low in the 3rd quartile (18.09%). The proportions of sales in the 1st and 2nd quartiles were symmetric with no significant variations. Similar to the sales of high-value crops, the distribution of milk sold is uniform in medium status across the 2nd, 3rd, and 4th quartiles; however, there is a notable concentration of sales in the 1st quartile (31.15%). Farmers in the category of partial status exhibited the highest concentration of milk sales in the 3rd quartile (31.07%) and the lowest in the 4th quartile (17.48%). Additionally, the distribution of milk sold in the partial status category is not uniform. We also noted that the kernel density line rises for high sales proportions in the quartiles and declines for low sales proportions across each transformation status. These finding highlights that adopting improved dairy cows increases the volume of milk sold in the market. It was also argued that the fourth quartile represents the highest level of milk sold in full status compared to medium and partial status.

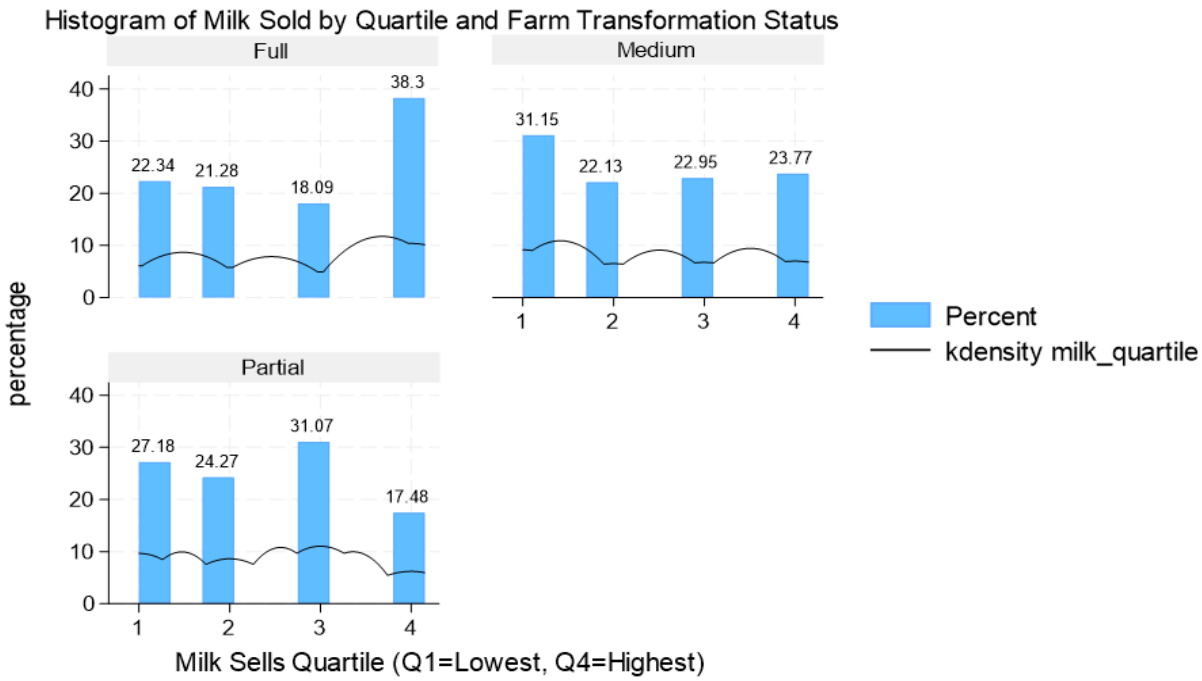

Figure 4.5. Distribution of milk sold by quartile and transformational status
Source: Own survey data (2024).

Furthermore, the dissemination of improved poultry technology is progressing strategically though not reaching the wider smallholder farmers at large. Farmers typically sell eggs directly to hotels and restaurants or to local collectors to generate income. Accordingly, the highest proportion of egg sales occurs in the 4th quartile (47.87%), while the lowest is in the 2nd quartile (11.7%) in the category of full status (see Figure 4.6). While in the medium status, we observed equal proportions of eggs sold in both the 2nd and 4th quartiles, with similar figures in the 1st and 3rd quartiles. In the partial status, sales in the 1st, 2nd, and 3rd quartiles are symmetric, while the 4th quartile shows a lower sales proportion (12.02%). The distribution of sales declines from the 3rd quartile to the 4th quartile (see Figure 4.6). Thus, milk transformation is correlated with improved commercialization. This highlights the need for adopting improved poultry technologies to increase sales concentrations in the highest quartiles as the status changes from partial to full transformation.

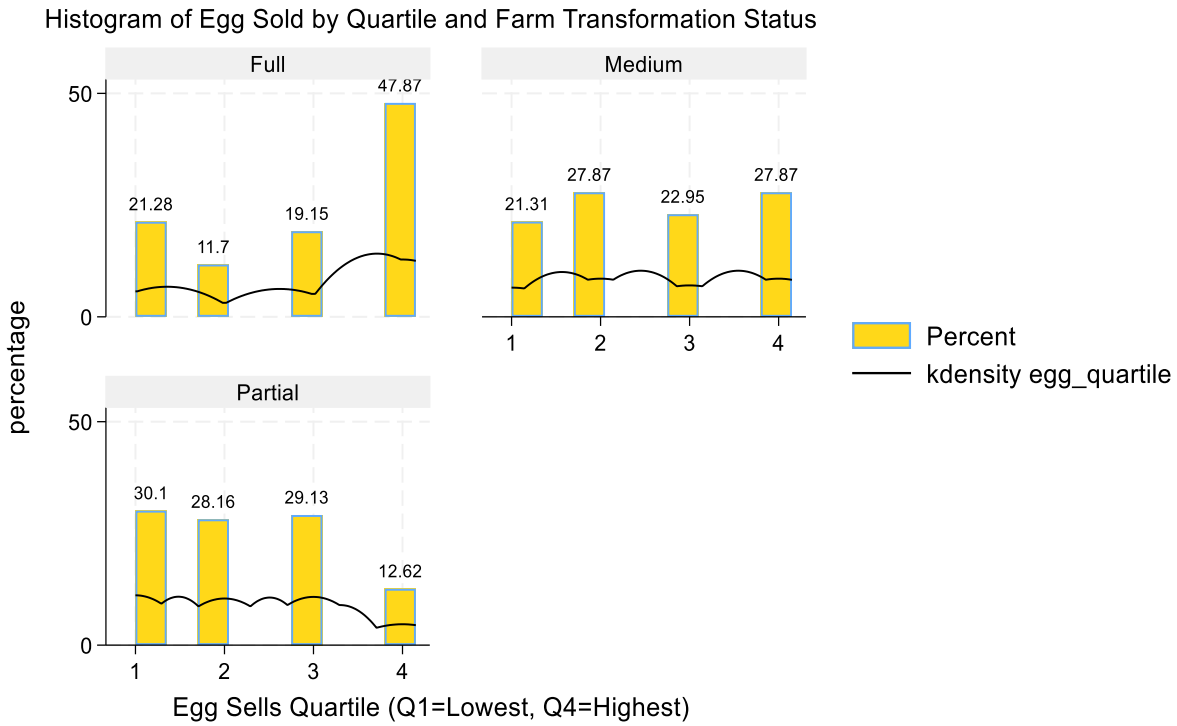

Figure 4.6. Distribution of eggs sold by quartile and transformational status
Source: Own survey data (2024).

4.4.5. Summary of descriptive statistics results

Table 4.3 below summarizes the socio-economic, demographic, and institutional variables for participants and non-participants in the informal contract market. A t-test was applied to continuous variables, while a chi-square test was used for categorical variables. Regarding, the farm land size in hectare, the minimum and maximum was 0.25 and 5.5 hectares, respectively. On average, informal contract market participants had 2.4 hectares, compared non-participants, who had 2 hectares. The average farm land size difference was statistically significant, at $P < 0.001$ and a t-value = -4.408. This suggests farm land size matters amount produced and enabling decision to engage in commercialization. On the other hand, the number of livestock measured in Tropical Livestock Units (TLU) for participants was 9, while 7.2 for non-participants, with minimum and maximum TLUs of 0.026 and 27.45, respectively. This difference is statistically significant at $P < 0.001$ and t-value = -3.434.

The introduction of various agricultural technology packages for smallholder farmers is a key government strategy aimed at transforming agriculture. During the survey period, farmers were asked about the number of agricultural packages they had adopted, with responses

ranging from 0 to 7 packages. On average, farmers engaged in informal contract marketing adopted 2 packages, while non-participants adopted 1. The difference was statistically significant at $p<0.001$ and t-value = -3.987. The government supporting technology dissemination system through agricultural extension workers. Accordingly, extension workers contacted farmers for a maximum of 7 days in a month or less. Farmers who participated in informal contract market on average contacted approximately 3 days in a month, while those who were not participated access extension services 2 days in a month. The difference was statistically significant at $p<0.05$ and t-value = -2.133 (see Table 4.3).

Likewise, the volume of high-value farm products produced influences farners' decision to participate in the informal contract market. Farmers who participated in the informal contract market supplied an average of 2,216.54 kilograms of high-value crops, 547.14 kilograms of milk, and 18,215.92 kilograms of eggs. In contrast, those who were not participate supplied an average of 610.87 kilograms of high-value crops, 244.16 kilograms of milk, and 2,818.76 kilograms of eggs. The differences in the mean volumes of high-value crops, milk, and eggs between the two groups were statistically significant at $P<0.001$, and the minimum and maximum kilograms of high-value crops, milk, and egg ranged from 0 to 10,000, 6015.20, and 789,345, respectively (see Table 4.3).

Finally, Institutional factors, such as access to market information services and social network connections, influence farmers' participation in the informal contract market. The average proportion of farmers who access market information and participate in the informal contract market was 52.5%, compared to 42% for those who do not participate. The difference was statistically significant at $p<0.05$ and a chi-2 value of 4.047. Additionally, social network connections serve as a source of power, energy, and resources. The average proportion of social networks for participants is 90.8%, while for non-participants it is 81.8%. This difference is also statistically significant, with $P<0.05$, and the chi-2 value was 7.019 (see Table 4.3)

Table 4.3. Mean and Mean Proportion Comparison of contract market participants and non-participants

	Informal Contract Market							
	Participants' (n=264)		Non-Participants' (n=158)					
Continous variables (N= 422)	Mean	SD	Mean	SD	t-value	Total	Minimum	Maximum
Age of the household head	46.482	10.204	46.993	9.985	0.485	46.649	22	75
Educational level in years of schooling	5.158	4.048	4.789	4.078	-0.875	5.038	0	12
Family size of the household	5.782	1.983	5.833	2.382	0.235	5.798	2	14
Farm size of the household	2.411	1.194	1.894	0.987	-4.408***	2.242	0.25	5.5
Number of livestock in Tropical livestock unit	9.002	5.182	7.205	4.75	-3.434***	8.414	0.026	40.65
Number of agricultural packages engaged	2.109	1.186	1.233	1.071	-3.987***	2.153	0	7
Frequency of xtension workers' contact in months	2.652	0.934	2.145	0.941	-2.133**	2.284	0	5
The volume of crop sold annually in kilogram	2216.59	2299.595	610.869	1447.043	-7.509***	1691.469	0	10000
The volume of milk sold annually in kilogram	547.145	867341	244.158	570.342	-3.729***	469.448	0	6015.2
The volume of eggs sold annually in kilogram	18215.2	56517.65	2818.761	8177.295	-3.182***	13180.83	0	789345
Distance from the nearest market center in hours	2.262	0.288	2.276	0.202	0.509	2.266	0.3	4
Dummy variables (N=422)					χ2-value			
Sex of the household head (1= male; 0= female)	0.845	0.362	0.804	0.398	1.101	0.832	0	1
Access to market information (1= Yes; 0= No)	0.525	0.500	0.420	0.495	4.047**	0.491	0	1
Access to credit services (1=Yes; 0=No)	0.059	0.237	0.073	0.260	0.246	0.064	0	1
social network connection (1= Yes; 0= N0)	0.908	0.288	0.818	0.386	7.019**	0.879	0	1

** and *** indicate 5% and 1% probability levels respectively.

Source: Own survey data (2024).

4.4.6. Results of the econometric model

The double hurdle model was employed to estimate factors affecting the decision to participate in the informal contract market and the level of participation. The participation decision was estimated using a probit model that bears the binary nature of the dependent variable. The level of participation was determined by the truncation model where it accounts only for the positive continuous outcome. Different variables were used for participation decisions and level of sales. In the participation model twelve variables were used, while fourteen variables were used to determine level of products sold. The result of the model was interpreted using marginal effects.

Before running the model, the assumption of normality was checked and the continuous dependent variables were not normally distributed and data transformed into a natural logarithm. Next, a multicollinearity test was conducted for explanatory variables using the variance inflation factors (VIF). The VIF was 1.34 and less than 10% showing fewer correlations (see Appendix 3B1). The heteroscedasticity problem was captured by running the model set to the robust standard error in the probit estimations. The coefficient of variables was jointly determined and different from zero so that the null hypothesis was rejected (see Appendix 3B2). The goodness to fit of the probit model is significant at ($p=0.000$) and the Wald chi2 test =114.29. On the other hand, the truncation model was significant at ($p=0.000$) and the Wald chi2 in the truncation model regression for crop, milk, and egg was 313.02, 538.07, and 142.73, respectively (see Table 4.6 below).

The metric of high-value farm products (crops, milk, and egg) measured in kilogram. Indeed milk in a liter is converted to an equivalent standard of the kilogram based on milk density and one liter of milk equals 1.03 kilogram (Rutz et al., 1955). For an egg, there are two sizes of eggs observed during data collection which ranged from small to large. The size of the egg depends on age and breed type. In the study areas, the small-sized egg weighs 40 grams, and the large-sized egg weighs 50 grams. Then, average grams of weight were computed to metrics of eggs sold in kilograms.

4.4.7. Determinants of informal contract market participation

Market participation is the key driver of rural transformation. However, in most developing countries it is subjected to institutional and capital constraints. The result in Table 4.4 showed the age of farm households had a negative sign and decreases the probability of participating in the informal contract market by 0.5% and statistically significant at P<0.05. It shows that older farmers are unable to produce multiple enterprises to look for market opportunities and build customers. Furthermore, the physical capabilities of older farmers to distribute farm products to market and negotiation intelligence might be low as compared to younger ones. This result conforms with (Barrett, 2017; Chikhawo et al., 2024; Cohen & Sherman, 2014; Hlatshwayo et al., 2021; Nigus et al., 2024; Regasa Megerssa et al., 2020) in which an increase in age is associated with less risk-taking, access to technologies, and utilization of market information.

An economic resource like farm size enhances production efficiency and fortune to farm expansion horizon. In this study, farm size had a positive sign and increases the probability of farmers' participation in the informal contract market by 21.6% while keeping other factors constant. The variable was statistically significant at p<0.05. As farmers become innovative in enterprise mixes there are chances to expand farm enterprises tailored to market linkages given adequate farm size to operate. The positive sign of land size is similar to the study conducted in Ethiopia by (Belete & Nigatu, 2023; Nigus et al., 2024) in the production of vegetables and teff crops. Furthermore, in South Africa (Kalauba et al., 2023) found that more land size had advantage in production of high-value vegetables products. Contrarily some studies showed that land size had a negative connotation with market participation and justified unexpected signs (Chikhawo et al., 2024; Zakari et al., 2023) in the Sahelian region and South Africa.

In addition, there were also circumstances in which buyers limited the volume of purchases from farmers. Particularly vegetable and milk producer farmers in Ada'a Barga, Welmera, and Weliso reported about buyers limiting their daily purchases. Most dairy producer farmers take home unsold milk and process it into cheese. Thus, a dummy change to limit the volume of purchases by buyers reduces the probability of participation in the informal contract market by 156% and it was statistically significant at p<0.001. Possibly, it reduces farmers' confidence to enhance the technical efficiency of farm products. This result is aligned with

(Bellemare & Barrett, 2006) farmers' decisions to commercialize are greatly influenced by limitations such as volume limits in Kenya and Ethiopia. Also monopolistic features limit volume and market participation in Madagascar (Stifel & Minten, 2008).

On the other hand, there are success strategies revealed to enhance farmers' market participation. For instance, the number of agricultural technologies being adopted by farmers had positive signs and increased the likelihood of participation in the informal contract market by 21.4%. Farmers as suppliers opt to maximize production utility by diversifying farm products and producing a surplus through adopting high-yield varieties of crops, improved dairy cows, improved poultry, and use of other farm input technologies. This finding consistent with a study conducted in Mali showed agricultural technology adoption is a key driver for farmers' market participation (Bird, 2024; Singbo et al., 2021).

Finally, farmers' trustability of selling through customers also affects the long-run linkage to the market. Market trust is cultural, and behavior is reflected during product distributions. Accordingly, a dummy change to build market trust increases the likelihood of participation in the informal contract market by 47.3% and it was statistically significant at $p<0.001$. Possibly, the trust that farmers have on customer-based selling enhances social bondage and improves the quality and quantity of products delivered. This finding is similar to a systematic review published by (Magakwe & Olorunfemi, 2024) and a study conducted in Uganda and Tanzania showed that trust through collective marketing and psychological attachments had a positive effect on market participation (Ismail, 2024; Mdoda et al., 2024).

Table 0.1. Results of the probit regression model for determining participation decision

	Decision to Participate in Informal Contract Market (1= Participate; otherwise=0)				
Explanatory Variables	Coeff.	dy/dx	Robust Std. err.	Z	P>|Z|
Age of the household head in years	-0.018	-0.005**	0.008	-2.21	0.027
Being a male head household head	0.122	0.030	0.198	0.61	0.539
Family size of the household in number	-0.005	-0.001	0.035	-0.15	0.882
Educational level in years of schooling	0.012	0.003	0.019	0.58	0.562
Farm size in hectares	0.216	0.054***	0.074	3.08	0.002
Buyers limit the volume of buying	-1.563	-0.389***	0.175	-13.05	0.000
Access to market Information	0.087	0.022	0.152	0.58	0.565
Access to credit services for farming	-0.108	-0.027	0.287	-0.38	0.704
Distance from the market in hours	0.148	0.037	0.193	0.77	0.442
Number of agricultural technology packages	0.214	0.053**	0.071	3.17	0.002
Having a social network connection	0.325	0.081	0.233	1.41	0.160
Having trust in the market opportunity	0.473	0.118***	0.11	4.65	0.000
Number of Observations = 422					
Wald chi2 (12) = 114.29					
Prob > chi2 = 0.0000					
Log pseudo likelihood = -186.917					

(** and ***) indicates 5% and 1% probability level

Source: Own survey data (2024).

4.4.8. Determinants of the level of high-value farm product sales

The truncation regression model presented in Table 4.5 illustrates the volume of high-value farm products sold through informal contract markets in the study areas. Farmers primarily employ crop rotation, intercropping, and multiple cropping systems to promote diversified production. As a result, increasing the variety of cropping systems increases the probability of producing diversified high-value crops for sale by 19.1%. This finding aligns with research conducted by (Emran et al., 2022; Kurdyś-Kujawska et al., 2021), which argued that diversified production enhances food production and profitability in Bangladesh and Poland, respectively. Additionally, farmers' involvement in irrigation agriculture creates opportunities to cultivate cereal crops, such as wheat, as well as vegetables. Consequently, participation in irrigation agriculture increases the probability of producing surplus high-value crops for sale by 19%, with statistical significance at P<0.05. The result is consistent with (Rosegrant et al.,

2009; Umer et al., 2024), irrigation has the advantage of crop diversification and fortune to sell the surplus.

Agroecological variations also influence the level of production intended for surplus sale. Being the district is in West Shewa zone, the probability of selling surplus high-value crops increases by 149%. In contrast, being the district is in South West Shewa zone, the probability of selling surplus high-value crops increases by 71.7%, holding other factors remain constant. High-value crops, such as teff, wheat, malt barley, maize, potatoes, and chickpeas, are predominantly produced in both zones. However, district-specific agroecological conditions leads to variations in productivity. In addition, districts in the West Shewa zone experience a significant decrease in the probability of milk and egg sales by 218% and 128%, respectively, and statistically significant at $p<0.001$ (see Table 4.5). This might be due to devoid of grazing land shortage which may limits the adoption of improved animal technologies. This might have potential reduction in animal productivity. This finding is supported by (Sariyev & Zeller, 2023), which agricultural land constraint is a bottleneck for the adoption of improved animals in Ethiopia.

Whereas, districts within the South West Shewa zone experienced a 44.10% increase in milk sales, which is statistically significant at the $p<0.05$ probability level. This increase may be attributed to the midland altitude, which offers a more favorable agricultural landscape that supports animal feed opportunities through open grazing and crop residue consumption. Literature indicates that agroecology-based production fosters farm specialization (Gliessman, 2014). Additionally, studies (Gebiso et al., 2023; Jayne, Muyanga, Wineman, Ghebru, Stevens, Stickler, Chapoto, Anseeuw, Westhuizen, et al., 2019; Moti & Birhanu, 2010) and demonstrate that district-level factors, including cultural aspects, infrastructure, and agricultural landscape, positively influence the level of marketable surplus.

Smallholder production oriented toward the market is a crucial aspect of farm transformation. As farmers undergo full transformation—characterized by the adoption of high-yield varieties (HYVs) and improved animal breeds—the probability of selling high-value crops and eggs increases by 27.1% and 32%, respectively, and statistically significant at $p<0.05$ (see Table 4.5). This shows advancements in farm transformation, driven by the adoption of improved agricultural technologies enhance farm business innovations. Furthermore, being the status of transformation was in medium category, the probability of selling milk increases by 32.9% keeping other things remain constant and statistically significant at $p<0.05$ level. This

suggests that adopting improved dairy cows complemented by effective feed management enhances milk productivity and increasing the opportunities for milk sales. This result is supported by (Schneider, 2010),who argued that market-oriented production enhances farmers' welfare. Additionally, dairy transformation through market-oriented production positively impacted milk marketing in Ethiopia (Ndambi et al., 2019).

The number of livestock owned by smallholder farmers plays a crucial role in providing food and income. Hence, a unit increase livestock number in Tropical Livestock Unit (TLU), increases the probability of selling high-value crops, milk, and eggs by 3.1%, 10%, and 7.5%, respectively, and statistically significant at $p<0.001$ (see Table 4.5). This shows that livestock are important sources of income to purchase improved seeds, fertilizer, agricultural equipment, and adoption of improved dairy cows and poultry to enhance farm productivity. This creates an advantage to acquire farm technologies to link farm production into market orientation. This finding is similar to other studies by (Gebiso et al., 2023; Jebessa et al., 2024) in which livestock in TLU positively enhances productivity and improves milk marketing in Ethiopia.

Institutional factors such as the frequency of extension contact affects the extent of market information disseminated to farmers. Accordingly, an increase in the frequency of extension contact raises the probability of high-value crop and milk sales by 10.5% and 13.3%, respectively, and statistical significance at $p<0.05$ (see Table 4.5). This indicates that extension workers provide essential services to farmers regarding farm technology and market information, which may contribute to surplus production for marketing. The result is similar to the study conducted in South Africa and Ethiopia by (Lemma et al., 2023; Mdoda et al., 2024) extension contact positively affects smallholder commercialization.

Likewise, market-driven production is complementary strategy for farm transformation. Since farm output is aligned with market demand. Therefore, being production is driven by market demand, the probability of milk sales increases by 35.5%, and statistically significant at $P<0.05$ (see Table 4.5). The higher demand for milk by urban consumers induces an opportunity to raise the level of dairy production through the adoption of improved dairy cows and improves their management as well. Similar findings argued that market-oriented production enhances market opportunities and welfare (Ndambi et al., 2019; Schneider, 2010).

However, distance from the market, affects possession and time utility for products like milk and vegetables. Accordingly, the nearest distance from the market, increases the probability of milk and eggs sales by 111.6% and 58.3%, respectively (see Table 4.6). Most peri-urban rural villages benefited from the sale of milk and eggs owing to the immediate delivery of the product to restaurants, urban consumers, and collectors. A short distance from the nearest market reduces losses of perishable farm products and damage to eggs during transportation. This finding is consistent with a study conducted in Kenya and Ethiopia by (Kena et al., 2022; Vandercasteelen et al., 2016) indicated that proximity to the market affects milk productivity and the level of dairy farming.

Apart from market driven, and near to market center, a farmer's experience in farming is significantly influence the volume of milk sold. Thus, a year increase in farmer's expertise associated with increasing the probability of milk sales by 5.9% and statistically significant at $p<0.05$ (see Table 4.6). This implies experience development enables production innovation and expands market information sources. This finding is consistent with a study conducted in Ethiopia where experience with cross-breed cows increases the intensity of milk production and increases farmers' participation in milk marketing (Roschinsky et al., 2015). However, it is important to note that in some cases, owning a cross-breed cow does not guarantee a surplus supply of milk to the market.

Despite of farmers accumulate experience and adopt cross-breed dairy cows, the expected milk yield was not enough for surplus sale. That means, the result in (Table 4.6) showed that being a farmer adopted cross-breed dairy cows, the probability of milk sales decreases by 67.4%, and statistically significance at $p<0.001$. This suggests that a farmer's managerial role plays a crucial part in enhancing milk productivity through effective dairy management, including housing, feeding, and health practices. The negative correlation is supported by (Duguma, 2022), who noted that feed shortages limit both the quantity and quality of milk in urban and peri-urban Ethiopia. However, this finding contrasts with (Jebessa et al., 2024), who reported that cross-breed cows positively influence market participation in the Jimma Zone of Ethiopia. These contradictory results may stem from the varying social and environmental contexts of the study areas, as well as the heterogeneity among dairy farmers.

Finally, the adoption of improved egg-laying poultry and the availability of poultry feed significantly impact the level of egg supply in the market. The result in Table 4.6. indicated

that adopting improved egg-laying poultry increases the probability of egg sales by 71.7%. Whereas, the unavailability of poultry feed decreases the probability of egg sales by 97.1% and statistically significant at $p<0.000$ (see Table 4.6). This highlights poultry production in rural areas remain to traditional feeding system which reduces egg yield and the commercial feed system is not affordable and access difficulties tiles to market information. This finding aligns with a study by (Sariyev & Zeller, 2023; and Yesuph et al., 2024) , which indicates that the adoption of improved poultry for egg production, constrained by feed and disease problem. Therefore, the level of high-value farm products sale was determined by socio-economic, institutional roles, and farmers intrinsic knowledge factors. This calls for socio-economic investment to reduce heterogeneity among farmers and focus to produce market-driven products that improve agricultural commercialization in the study areas.

Table 4.5. Results of truncation regression model

	Volume of High value farm products sold in kilogram											
	High value Crops				Cow Milk				Egg			
Variables	dy/dx	Delta-method std.err.	Z	P>|Z|	dy/dx	Delta-method std.err.	Z	P>|Z|	dy/dx	Delta-method std.err.	Z	P>|Z|
Number of cropping system	0.191**	0.082	2.32	0.020								
Availability of adequate quantity of fertilizer	0.094	0.107	0.86	0.387								
Irrigation participation	0.190**	0.078	2.41	0.016								
Dummy Districts in West Shewa zone	1.497***	0.108	13.82	0.000	-2.187***	0.192	-11.32	0.000	-1.286***	0.296	-4.34	0.000
Dummy Districts in South West Shewa	0.717***	0.119	6.02	0.000	0.441**	0.209	2.10	0.036	-0.181	0.305	-0.60	0.552
Dummy full transformation status	0.271**	0.112	2.41	0.016	-0.041	0.199	-0.21	0.836	0.801**	0.320	2.50	0.012
Dummy medium transformation status	0.070	0.091	0.77	0.439	0.329**	0.152	2.17	0.030	-0.072	0.237	-0.30	0.761
Number of livestock in TLU	0.031***	0.007	4.26	0.000	0.024**	0.100	2.33	0.020	0.075***	0.209	3.57	0.000
Frequency of extension contact	0.105**	0.039	2.68	0.007	0.133**	0.060	2.21	0.027	0.186	0.099	1.87	0.062
Market-driven production	0.111	0.067	1.65	0.100	0.355**	0.121	2.94	0.003	0.083	0.181	0.46	0.645
Availability of farm labour division	0.106	0.087	1.21	0.226	0.208	0.134	1.55	0.120	-0.176	0.215	-0.82	0.414

Hint: (** and ***) indicates statistically significant at 5% and 1% probability level.
Source: Own survey data (2024).

Table 4.6. Results of truncation regression model (Cont'd)

	The volume of High-value farm products sold in kilogram											
	High-value Crops				Cow Milk				Egg			
Variables	dy/dx	Delta-method std.err.	Z	P>|Z|	dy/dx	Delta-method std.err.	Z	P>|Z|	dy/dx	Delta-method std.err.	Z	P>|Z|
Distance from the market in hours	0.009	0.138	0.07	0.945	1.116***	0.123	9.05	0.000	0.583**	0.250	2.33	0.020
Experience on cross breed cow use					0.059**	0.028	2.09	0.036				
Availability of Animal feed					0.107	0.122	0.88	0.379				
Training on dairy production					0.071	0.096	0.78	0.438				
Adopt a cross-breed dairy cow.					-0.674***	0.185	-3.64	0.000				
Poultry disease problem									0.001	0.212	0.00	0.997
Adoption of improved egg poultry									0.717	0.257	2.79	0.005
Availability of poultry feed									-0.971***	0.273	3.55	0.000
/Sigma	0.630	0.023	26.91	0.000	0.978	0.041	24.06	0.000	1.821	0.063	28.79	0.000
	Number of observations =284				Number of observations =307				Number of observations =370			
	Wald chi2(13) =313.02				Wald chi2(13) =538.07				Wald chi2(13) = 142.73			
	P > chi2=0.000				P > chi2=0.000				P > chi2=0.000			
	Log pseudo-Likelihood=-271.939				Log pseudo-Likelihood= -428.801				Log pseudo-Likelihood=-746.512			

Hint: (** and ***) indicates statistically significant at 5% and 1% probability level.
Source: Own survey data (2024).

4.5. Conclusion

In the study areas, rural transformation is in its early stages and requires complementary farm production and market development improvements. Consequently, formal contract market development is still far from achieving the necessary market transformations. As a result, farm households are increasingly reliant on open markets and customer-based sales, particularly for perishable products like milk and vegetables. However, the initiative taken by farmers to transform high-value farm enterprises and seek market-oriented production is commendable. As a result, farmers are adopting improved agricultural technologies, and produce tradable farm products for sale. These advancements indicate a need for a marketing system to accommodate surplus production. Hence, the study addresses the driving factors influencing informal contract markets participation, which have often been overlooked in broader discussions of contract market participation. Consequently, the existing farmers' market linkages through individuals and urban businessmen lay the groundwork for future formal contract market developments, which market actors and institutions will support.

4.6. Recommendations

The following recommendations are given based on the findings.

- Age negatively impacts participation in the contract market. This requires to enhance road infrastructure to assist older farmers in transporting their products and accessing transport services. Older farmers bring valuable experience in product selection, production techniques, and the effective use of natural resources, like land and water.
- Buyers' limits on purchase volume reduce participation in the contract market. This suggests that the government should enhance market opportunities to foster competition among buyers through regulations, licensing, and product standardization.
- The adoption of agricultural technologies, such as improved dairy cows and poultry, significantly influences contract market participation. To support this, both private and public sectors collaborate to ensure a consistent supply of inputs to a broader range of farmers. This can be achieved through training programs, field demonstrations, and sharing experiences among farmers to encourage more widespread adoption of these technologies.
- Farmers' trust in the market influences their participation decisions. Therefore, investments from both the government and private sectors are crucial for enhancing product quality and fostering a competitive environment through value addition.

- Better agronomical practices, such as more cropping system, and irrigation participation increases level of high-value crops sold. Therefore, the existing soil fertility management and use of irrigation water production system should be utilized effectively.
- Behavioural changes resulting from farming experience, along with the transformation of the agricultural production system and market-oriented production, positively influence the levels of crops, milk, and eggs sold. Therefore, existing institutions should support capacity-building activities, disseminate knowledge within farmer networks, and promote a digital agricultural marketing system that brings significant transformation to smallholder agriculture.
- Locational variations also affect the opportunity of milk and eggs sell potential. Hence, improvements of feed availability, enhance forage development, and access to improved dairy breeds and poultry require further extension services to enhance market participation. Therefore, livestock development requires complementary input development to encourage farmers adoption of technologies to integrate with local market opportunities.
- Economic factors, such as the size of farmland and the number of livestock, positively influence both the decision to participate in contract markets and the level of sales. Therefore, it needs to encourage existing sustainable land management practices and to implement livestock breeding programs that focus on strategically enhancing sustainable animal feed security options.
- Agricultural extension services play a pivotal role in knowledge transfer among farmers in rural communities. The Ethiopian government's initiative to recruit extension workers at the village level is commendable. However, to achieve sustainable agricultural production and address dynamic changes in climate and the global economy, it is essential to adjust skills and enhance implementation capacity. Therefore, the government should monitor gaps among extension workers and address them through capacity building.
- Physical factors, such as distance from the market, positively affect the sales of high-value farm products. Therefore, the development of agricultural marketing near roadways and market infrastructure should be widely implemented through public expenditure, while also encouraging private sector participation.

CHAPTER FIVE

5. The Impact of Farm Transformation on Food Security Among Smallholder Farmers

Abstract: *The Ethiopian agricultural economy is fueled predominantly by smallholder agriculture, which accounts for 24% of the GDP, and significantly greater than the average in sub-Saharan Africa. This study investigated the effect of farm transformational status on household food security. It was conducted in the central Oromia region, where data were collected from 422 sampled farm households via multistage sampling techniques. Both descriptive and econometric models were employed for data analysis. The results indicate that 52.61% of the farmers in the study area have an acceptable food security profile, 39.34% are classified as borderline, and 8.06% have poor food consumption profiles. The food consumption score varies significantly by household age and district, with higher scores associated with a more diversified diet. The dummy index for farm transformation revealed that 56.6% of households had a low transformational status, whereas 43.4% had a high transformational status. The results of the instrumental variable regression model indicated that market-oriented production positively and significantly influences the status of farm transformation. The 2SLS analysis revealed that the status of farm transformation, frequency of extension contacts and access to information on healthy and nutritional food production significantly and positively affect food security. Conversely, income and distance from the nearest market negatively and significantly impact food security. In conclusion, the findings suggest that adopting transformational agricultural practices at the farmer level can improve access to and availability of food. However, scaling up these practices across larger smallholder farmers is essential for achieving sustainable food production.*

Keywords: Farm Households, Farm Transformation, Food Consumption Score, Food Security, Two-Stage Least Square Regression.

5.1. Introduction

The Ethiopian agricultural economy is fueled predominantly by smallholder agriculture, which accounts for 24% of the GDP and is significantly greater than the average GDP in sub-Saharan Africa (FAO, 2021). Nationally, the agricultural GDP declined from 36.3% in 2016/17 to 32.4% in 2021/22 (NBE, 2022). Agriculture accounts for 66% of total employment and 76% of total export items (ATI, 2022), reflecting significant structural

changes within the sector. The total area of cultivated land increased from 0.4% in 2018/19 to 1.4% in 2021/22, with cereal, pulse, and oilseed production accounting for 82%, 13.7%, and 3.4% of total crop production, respectively (FDRE, 2022). Crop production accounts for 60% of the national GDP, the livestock sector contributes 27%, and other sectors account for 13% (FDRE, 2022). However, the sector faces persistent challenges such as climate change, including drought and delayed rainfall during the onset season, as well as low input usage, which hinders its development to achieve food security.

Despite its abundant resources capable of feeding its population, Ethiopia is facing severe food crises. This means that two types of food insecurity are present: chronic food insecurity, linked to deep-rooted poverty, and a lack of productive resources. Acute food insecurity is associated with short-term shocks and production inefficiencies (FDRE, 2002). Therefore, Ethiopia is recognized as a hunger hotspot alongside countries such as the Central African Republic, Lebanon, Mozambique, Myanmar, Nigeria, Sierra Leone, Zambia, Burkina Faso, Malawi, Somalia, and Zimbabwe. Approximately 15 million people in Ethiopia, including approximately 4 million internally displaced persons (IDPs), urgently require humanitarian food aid (World Bank, 2024; WFP, 2024). Current and anticipated causes of food insecurity in Ethiopia include conflict, high food prices, overlapping agroclimatic shocks, insecurity, displacement, and widespread poverty (IPC, 2020).

For example, in the National Meher season of 2023, average crop yields declined by 20–30%, primarily due to flooding, pest and disease infestations, moisture stress, and a shortage of agricultural inputs such as fertilizers and seeds (USAID, 2024). Additionally, significant animal mortality during the 2020–2022 drought led to low livestock holdings for households in the southern and southeastern pastoral areas, which are their main sources of income (USAID, 2024). Beyond climate shocks, the annual inflation rate has increased to 28.2% (ESS, 2024), which has a potential impact on food access from the market.

The Ethiopian food security strategy, drafted in 1996, aimed to address chronic food insecurity in moisture-deficit areas by developing income-generating activities. Its goal was to achieve food security at the household level through agricultural development led industrialization (ADLI). This strategy was later revised into the ‘Productive Safety Nets Program’ (PSNP), which was implemented from 2010--2014. The program achieved significant success, benefiting over seven million people through PSNP payments that helped

them meet their consumption needs while reducing risks and providing alternatives to selling their productive assets. Additionally, the government's Federal Food Security Budget Line extended credit to approximately 3.5 million individuals (FAO, 2023). Furthermore, Growth and Transformation Plan II (GTP II) focused on enhancing agricultural production by continuously delivering improved technologies to farmers to achieve the Sustainable Development Goals (SDGs) (NPC, 2021). Notable successes under this program include effective natural resource management through community participation, the adoption of improved agricultural technologies to address climate change challenges, and intensive irrigation production.

The government's home-grown economy agenda emphasizes the need to improve smallholder agriculture. This highlights that current yield growth is insufficient to meet both industrial and domestic food security demands and that farmers struggle to profit from their investments due to underdeveloped markets (FDRE, 2022). According to the (FAO, 2022), Ethiopia produces enough food to meet the daily energy needs of its population; however, food security remains a significant issue. Nonetheless, this situation varies across different regions. This means that several factors contribute to food insecurity, including low crop diversity (cereal-dominated diets), limited distribution networks, underdeveloped markets, and purchasing power constraints caused by high poverty levels.

Additionally, significant postharvest losses and a production system primarily reliant on smallholder farmers exacerbate this problem (UNDP, 2022). For example, in the Oromia region, approximately 1.6 million people are engaged in the Productive Safety Net Program (PSNP), with 1.3 million directly benefiting from relief efforts. This number is expected to rise to 1.5 million people at risk of acute food shortages by the end of June, 2025 (ORAT, 2024). Thus, food security is often undermined by low technology adoption and inadequate institutional support for smallholder farmers. Various interventions have been introduced to transform agricultural practices through the expansion of mechanisation, the use of improved seeds, the introduction of animal breeds using artificial insemination, and improvements in agronomic practices. However, the presence of heterogeneity at the farmer level leads to the existence of both low and relatively high transformational practices, which affects the availability of diverse food at the household level. It contributes to an understanding of the status of transformational farming practices to achieve food security, providing valuable

inputs to strengthen agricultural development strategies. Therefore, this study aimed to investigate the food security status at household level and determine the relation between food security and status of transformational farming practices.

5.2. Literature Review

Food security refers to a situation in which everyone has both physical and financial access to sufficient, nutritious food that meets their dietary needs and preferences for an active and healthy life (FAO, 2000). This concept is based on four key pillars: availability, accessibility, utilization, and stability. The Food and Agriculture Organization (FAO) reported that hidden costs in global agrifood systems reached approximately $12 trillion each year. Additionally, the World Food Programme (WFP) reported that 343 million people are experiencing acute food insecurity in the 74 countries where it operates. This represents a 10 percent increase from 2023 and is nearly 200 million more than pre-pandemic levels (World Bank, 2024). In other words, compared with Asia (8.1 percent), Latin America and the Caribbean (6.2 percent), and Oceania (7.3 percent), Africa has the highest percentage of its population experiencing hunger (20.4 percent) (FAO, 2024).

This cautioned us in revisiting agricultural policy and strategies in African countries. Hence, Ethiopia, Rwanda, Kenya, Malawi, Uganda, Tanzania, Zambia, Nigeria, Burkina Faso, Senegal, Mali, Mozambique, Ghana, and South Africa are among the African nations actively pursuing agricultural transformation policies to achieve SDGs. Many of these countries are also participating in the Comprehensive Africa Agriculture Development Programme (CAADP), which promotes national agricultural investment plans to facilitate this transformation (AfDB, 2016; FAO, 2017; World Bank, 2024). Drivers such as urbanization, dietary changes, agri-food transformation, shifts in rural factor markets, and the intensification of agricultural technologies are key factors for change and provide solutions for eradicating hunger (Reardon & Timmer, 2014).

According to (Dillon & Barrett, 2017; Ecker, 2018), agricultural policy continues to have a significant effect on food and nutrition security beyond the conventional boundaries of farm revenue and productivity, due to inseparability of production and consumption decisions. In Ethiopia, agricultural transformation policies are designed to increase productivity by eliminating barriers to the adoption of modern techniques that are expected to enhance food

security (FAO, 2022). These measures will benefit farm households primarily by providing them with greater access to food for their own consumption or increased income to purchase food through the commercialization of agricultural products (ATI, 2024; Barrett et al., 2001); however, food insecurity is still prevalent among rural farmers and poor urban communities. This likely results from a combination of structural and contextual factors that hinder agricultural output, preventing it from meeting food demands (Ameye et al., 2025; Minten et al., 2020). This means that small and shrinking farms due to increasing population pressure, declining soil fertility linked to intensive farming practices, and recurrent agricultural shocks from events such as locust invasions (ATI, 2024; Minten et al., 2020). At the individual and community levels, wealth status heterogeneity is also a source of food insecurity in Ethiopia (Bogale et al., 2025). On the other hand, inefficiencies in institutional support, such as extension services, supplies of agricultural technologies, and a lack of crop diversification, increase farmers' vulnerability to food insecurity (Cheber et al., 2025; Haile Aboye et al., 2024). In southern Ethiopia, food insecurity arises mainly from a lack of food supply and increasing agricultural prices (Gujo & Modiba, 2025).

On the other hand, success stories related to the adoption of agricultural practices were examined. For example, the joint adoption of seeds and fertilizers has positively impacted food security in Zimbabwe (Amankwah & Gwatidzo, 2024). In Ghana, various home gardening techniques have been implemented (Asante et al., 2024). Additionally, the use of irrigation (Ebrahim & Toy, 2024; Guyalo et al., 2022; Y. Zhang et al., 2024), full mechanization (Liu et al., 2025), and conservation agriculture (Opoku-Acheampong et al., 2024) has significantly contributed to household food security.

Nutrition-sensitive training and improved management practices in aquaculture enhance food security (Dompreh et al., 2024). Research on climate change adaptation and climate-smart agriculture has also revealed positive effects on food security (Bergene et al., 2025; Debela & Lemma, 2024; Tilahun et al., 2025). The adoption of solar pumps and water harvesting technologies has been found to increase farmer incomes and food security in Ethiopia (Negera et al., 2025). Furthermore, smaller farm sizes and labour-intensive crops targeted at local markets contribute to improved food security at the community level (Muder et al., 2024).

However, the effects of climate change on agricultural productivity, particularly in sub-Saharan Africa, are significant and contribute to rising poverty levels (Jean Galbert, 2023).

Despite numerous studies conducted on food security at the household, local, and regional levels, previous research has focused on measuring the socioeconomic determinants of food security in specific areas and exploring the impact of agricultural policies on food security with regard to specific development interventions. However, much of the existing research indirectly highlights the transformative practices of farmers in addressing food security challenges. Given the diversity of agricultural production practices, it is essential to categorise these practices based on indicators of transformational practices—whether high or low—to analyse their impact on food security. And the market demand-oriented production systems as instrumental variable can foster transformative activities, and leading to increased food production at the household level.

5.2.1. Theoretical framework

The relationship between farm transformational status and food security can be theoretically framed within the context of *sustainable livelihoods, agricultural transformation*, and *food security dimensions*. Hence, (Nussbaum et al., 2009) introduced three key concepts: capability, equity, and sustainability, to measure human well-being and development. He argued that traditional utility-based approaches to economics were insufficient, limited, and unethical for understanding actual human well-being and development. Hence, by adopting the concept and we put definitions that meet the theoretical framework supporting this study. Accordingly, the Capability Approach (CA) is crucial for determining farmers' ability to access land, water, and improved agricultural technologies. Equity involves the fair distribution and access to agricultural technologies, such as improved seeds, livestock breeds, and adequate farmland, which enable effective decision-making. And sustainability refers to the economic, social, and environmental aspects of integrated crop and livestock transformation.

Thus, integrated livelihood principles—capability, equity, and sustainability—enhance the ability to choose and engage in valued activities that improve quality of life (Chambers & Conway, 1991). This approach aims to achieve sustainable livelihoods and is influenced by social, economic, and environmental factors. There is interdependence between these factors

and agricultural livelihoods (Chambers & Conway, 1991). The dynamism in social, economic, and environmental factors directly influences dynamic changes in agricultural livelihoods that create opportunities to shift farming practices. In such circumstances, the adoption of transformational farming practices (integration of high-value crop and livestock enterprises) contributes to poverty reduction, food security, and raises income (Christiaensen et al., 2011; Jayne, Muyanga, Wineman, Ghebru, Stevens, Stickler, Chapoto, Anseeuw, Van Der Westhuizen, et al., 2019; Rankin et al., 2019). Hence, the level of transformation affects the outcomes related to food security, such as food access, availability, utilization, and stability at the household level (FAO, 2006). Therefore, the summarized theoretical concept of the study design is illustrated in Figure 5.1. below.

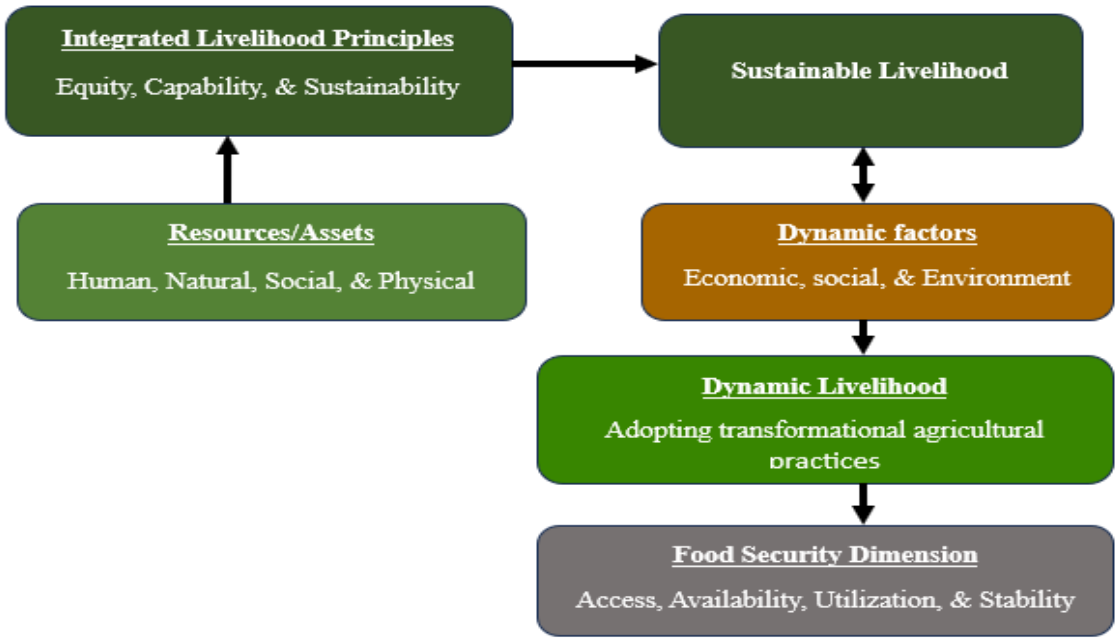

Figure 5.1. Theoretical framework of the study
Source: Author sketch.

5.3. Method of Data Analysis

5.3.1. Descriptive and Inferential Statistics

The descriptive statistics used in the analysis of the food consumption profile and index for transformational changes included the frequency table, percent, mean, standard deviation (SD), and minimum and maximum values. The results are presented in tables and graphs (stacked bar graphs, box plots, and margin plots). Additionally, inferential statistics, specifically F tests and chi-square tests, were employed to compare independent variables across different categories of food consumption profiles.

5.3.2. Measurement of food security indicators at the household level

According to Elliot (2014), there are three types of food security measurements: dietary diversity and food frequency (direct measurement), consumption behaviors (indirect measurement), and the Global Hunger Index (GHI). The indicators for these measurements are explained as follows: dietary diversity and food frequency, which are measured via the Food Consumption Score (FCS), Household Dietary Diversity Scale (HDDS), and food spending. Wheras, the consumption behaviour is assessed through the Coping Strategy Index, Reduced Coping Strategy Index, Household Food Insecurity Access Scale, and Household Hunger Scale. In this study, we used the Food Consumption Score (FCS), which was initially developed by the World Food Program (WFP) in 1996. It is a frequency-weighted diet diversity score calculated on the basis of the consumption frequency of different food groups over a seven-day period. It serves as a proxy indicator for caloric intake and diet quality at the household level (Kennedy et al., 2011).

In contrast, the Household Dietary Diversity Scale (HDDS) reflects the number of different foods consumed over a reference period, typically assessed through a 24-hour recall, and serves as a proxy measurement for food access (Marivoet et al., 2019). Both the HDDS and the FCS were created as potentially helpful indicators to measure both quality (nutrient adequacy) and quantity (energy). However, the Food Consumption Score has limitations; it does not capture seasonal changes in food availability, quantifies food gaps, or accounts for intrahousehold variations in food consumption. In accordance with the standards outlined by the World Food Programme (WFP), various food groups were assigned the following weights to calculate the FCS: cereals and tubers = 2, pulses = 3, vegetables = 1, fruits = 1, meat and fish = 4, milk = 4, oil = 0.5, and sugar = 0.5. The procedure for estimating the FCS is described as follows (WFP, 2018).

I. Standard 7-day food frequency data were used to categorize all the food items into their respective food groups.
II. The consumption frequencies of food items within the same group are summed, and any group whose total exceeds 7 as 7 is recorded.
III. The value obtained for each food group is multiplied by its corresponding weight (refer to the food group weights in the table above) to generate new weighted food group scores.

IV. The weighted food group scores are summed to create the food consumption score (FCS).

V. The appropriate thresholds (see below) are used to recode the food consumption score from a continuous variable to a categorical variable. The food consumption score (FCS) has the following thresholds: 0--21 (poor), 21.5--35 (borderline), and above 35 (acceptable).

5.3.3. Econometric model specification

To measure the relationship between the continuous dependent variable FCS and the dummy index for transformational status, we employed ordinary least squares (OLS). However, OLS regression relies on a number of assumptions that could make the results untrustworthy if they are violated, three most crucial presumptions: residual normality, homoscedasticity, and independence. Hence, OLS estimation is biased when endogeneity exists in the regressor. The concept of residual independence postulates that the residual of one observation is unrelated to the residual of another (Greene, 2012). The OLS model can be specified as:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \tag{23}$$

where y_i is the continuous dependent variable, β_0 is a constant, β_1 is the coefficient of the independent variables, and ε_i is the error term. Hence,

$$Cov(x, \varepsilon) \# 0 \tag{24}$$

Under such circumstances, the instrumental variables method is effective regardless of the correlation between x and u; if x and u are uncorrelated, OLS should be applied for the following reasons:

When x and u are associated, we can obtain reliable estimators of β0 and β1 by requiring more details. A new variable that meets specific requirements provides the information. Assume that the observable variable z meets both of the following two requirements: There is no correlation between z and u; therefore,

$$Cov(z, u) = 0; \tag{25}$$

z is correlated with y, that is,

$$Cov(z, y) \# 0 \tag{26}$$

Then, we call z an instrumental variable for y, or sometimes simply an instrument for y.

Hence, the empirical model revealed that there is a positive correlation between the status of farm transformation and the market-oriented production decisions of farmers. This position considers the endogeneity issue arising from the impact of farm transformational status as one of the factors influencing household food security. This study used a two-stage least squares (2SLS) technique to analyze the effect of farm transformation status on food security. And in the first stage we estimated using linear probability model (LPM) which specified as:

$$x = \beta_0 + \alpha_i z_i + \delta_i w_i + \varepsilon_i \quad (27)$$

where x is a dummy index of transformational status (1=high;0=low) and where z_i =instrumental variable- market-oriented production decision (1=yes;0=No), which is hypothesized to directly influence the status of farm transformation and indirectly influence food security through transformational status. The literature has shown that market-oriented production ensures the adoption of modern agricultural technologies, which fosters transformation (Zhang & Zhu, 2023).

w_i =other exogenous variables, which include age, sex, educational level, family size, land size, livestock in the TLU, irrigation participation, social network, log of farm income, nonfarm income participation, frequency of extension contact, access to market information, distance from the market, information on health food, and access to training, and the ε_i disturbance term, while α and δ are parameters to be estimated. In the second stage, the effect of farm transformation status on food security, measured as the food consumption score (FCS), was estimated as follows:

$$\log fcs(y_1) = \beta_i + \alpha_i \hat{x} + \delta_i w_i + \varepsilon_i \quad (28)$$

The model can be specified as

$$\begin{aligned} log\, f\, sc(y_1) &= \beta_0 + \alpha_1(IndexTstatus) + \delta_1(age) + \\ &\delta_2(sex) + \delta_3(fmsize) + \delta_4(landS) + \delta_5(educ) + \delta_6(Tlu) + \\ &\delta_7(log\, i\, ncome) + \delta_8(dumIrrig) + \delta_9(dumSnw) + \\ &\delta_{10}(Frqext) + \delta_{11}(dumAMI) + \delta_{12}(distMkt) + \\ &\delta_{13}(Nofincome) + \delta_{14}(Hfood\, inf) + \delta_{15}(AccTrain) \end{aligned} \quad (29)$$

Where: *log(fcs)* – Food consumption score in logarithm (dependent continuous variable), *Age* (Age of the household head), *IndexTstatus* (index for transformation status), *Sex* (sex of the household head), *fmsize* (family size of the household), *lands* (farm land size in

hectares), *educ* (educational level), *tlu* (livestock in tropical livestock unit), *logincome* (farm income in logarithmic), *dumIrrg* (dummy irrigation participation), *dumSNW* (dummy social network participation), *Frqext* (frequency of extension contact), *dumAMI* (dummy access to market information), *distMkt* (distance from the nearest market in hour), *Nonfincome* (participation in nonfarm income activities, *Hfood inf* (access to information on nutritious and healthy food), *AccTrain* (access to training on healthy food production).

5.4. Variables Definitions and Working Hypothesis

5.4.1. Dependent variable

Food Consumption Score: This is continuous dependent variable referring the score of food items consumed within seven days based on data collected during the survey period at household level. It is influenced by socio economic, demographic and institutional factors.

5.4.2. Independent variables

It refers variables which are influencing the food consumptions scores and described in below table (see Table 5.1).

Table 5.1. Summary of independent variables and expected sign

Variables	Type	Expected sign on Food consumption Score
Index of transformation status	Dummy (1=high;0=low)	+
Age of the household head in years	Continuous	+
Sex of the household head	Dummy (1=male; otherwise, 0)	+
Family size of the household head	Continuous	+/-
Educational level in years of schooling	Continuous	+
Farm size in hectare	Continuous	+
Total number of livestock in TLU	Continuous	+
Income of household in logarithm	Continuous	+
Irrigation participation	Dummy (1=Yes; 0=No)	+
Social network connection	Dummy (1=Yes; 0=No)	+
Frequency of extension contact in a month	Continuous	+
Access to market Information	Dummy (1=Yes; 0=No)	+
Distance from the nearest market in hour	Continuous	-
Participation in non-farm income activities	Dummy (1=Yes; 0=No)	+
Information on nutrition & healthy food	Dummy (1=Yes; 0=No)	+
Training on healthy food production	Dummy (1=Yes; 0=No)	+

Source: Author reviewed from related studies and study area context.

5.5. Results and Discussion

5.5.1. Percentages of respondents by food consumption score profile

As shown in Table 5.2 below, a significant number of farmers fall into the acceptable food consumption score category, whereas only a small portion belong to the poor consumption category. Specifically, 34 respondents (8.06%) had a poor food consumption score, 166 respondents (39.34%) were classified as borderline, and 222 respondents (52.61%) were deemed to have an acceptable food consumption profile. In other words, the food security status in the study districts appears promising for more than 50% of the farmers, despite existing variations between districts.

Table 5.2. The number of respondents by food consumption score

Food Consumption profile	Freq.	Percent	Cum.
Acceptable (>35)	222	52.61	52.61
Borderline (21.5-35)	166	39.34	91.94
Poor (0-21)	34	8.06	100
	422	100	

Source: Own survey data (2024).

Similarly, the box-whisker plot in Figure 5.2 illustrates the distribution of food security scores across different age groups of farmers. For the age group between 18–30 years, the food consumption score is negatively skewed, with the median close to the third quartile (75th percentile), indicating that most farmers in this group have higher food consumption scores and better food security. The whisker for this age group is relatively short, suggesting that the data on food scores are less dispersed. In contrast, the food consumption score for the age group between 30-50 years was positively skewed, with the median approaching the second quartile (50th percentile), indicating that the average food consumption score is more prevalent within this group. The scores in this age group also show greater dispersion. Similarly, the food consumption score for those aged over 50 years is positively skewed but is closer to the first quartile (25th percentile). Overall, the distribution of food consumption scores varies with age category of farmers.

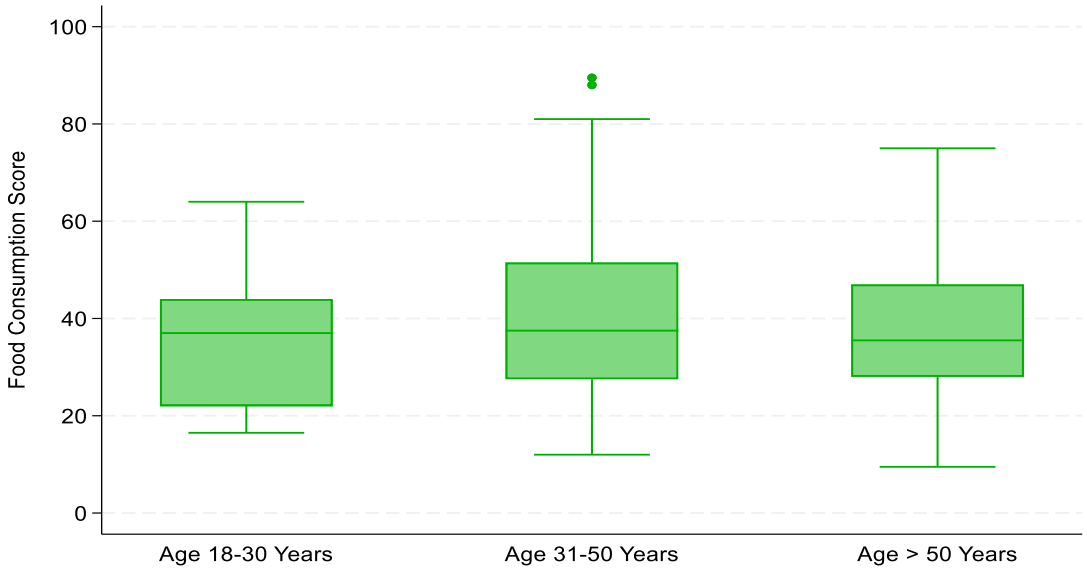

Figure 5.2. The distribution of food consumption scores by age group
Source: Own survey data (2024).

5.5.2. Distribution of percentage food consumption profiles by district

The food consumption scores varied across the study districts, as illustrated in Figure 5.3 below. The Welmera district exhibited the highest percentage of poor food consumption, with approximately 21% of farmers falling into this category, whereas the Bako Tibe district had the lowest percentage at only 3%. Conversely, 74% of the respondents from the Bako Tibe district had acceptable food consumption scores, followed closely by those from the Ada'a Barga district. Additionally, Weliso district presented a relatively high percentage of borderline food consumption profiles compared with the other districts. Overall, food security varied significantly across the study districts due to differences in socioeconomic factors, agroecological conditions, agricultural practices, and the level of agricultural technology adoption among farm households.

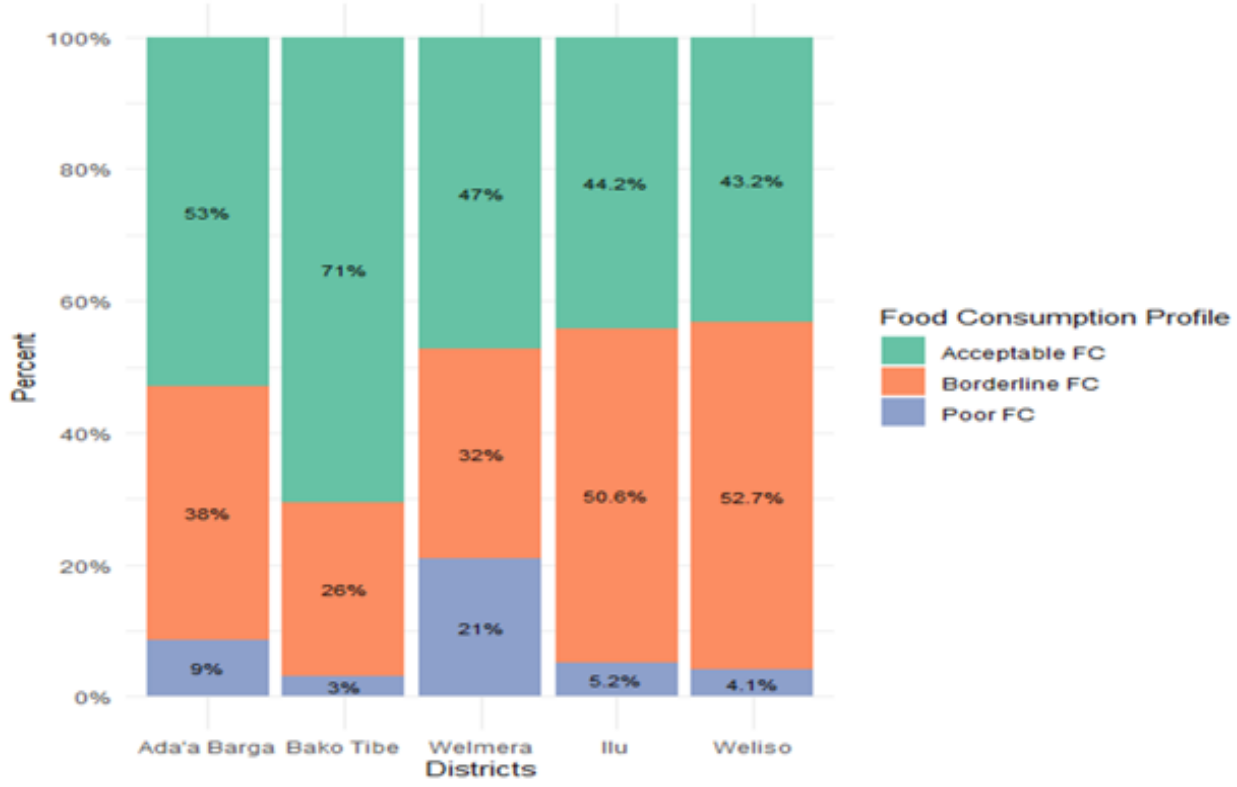

Figure 5.3. The distributions of food consumption profiles by district
Source: Own survey data (2024).

5.5.3. Distribution of food consumption scores by food item

As shown in Figure 5.4 below, the food consumption score of farmers increases with the frequency of consuming a diverse range of food items. The figure highlights the contributions of various food items at each level of the food consumption score. Access to a variety of food enhances household food security. However, the overall frequency of food item consumption was low, indicating that fewer diversified foods were consumed, which could lower the consumption score. Conversely, a higher frequency of consumption suggests an increase in both the level of food consumption and the variety of food items. The results indicate that food items such as cereals, meat, legumes, egg, fish, and milk were consumed frequently across all levels of the food consumption score. In contrast, vegetables,sugare, root and tubers, and oil relatively less than 50% cumulative freqeuncy and less diversified. There is strong evidence that improvements in agricultural practices through the adoption of new technologies enhance food availability at the household level. These advancements also encourage investments in agricultural transformation, which are essential for achieving food security goals at both the local and national levels.

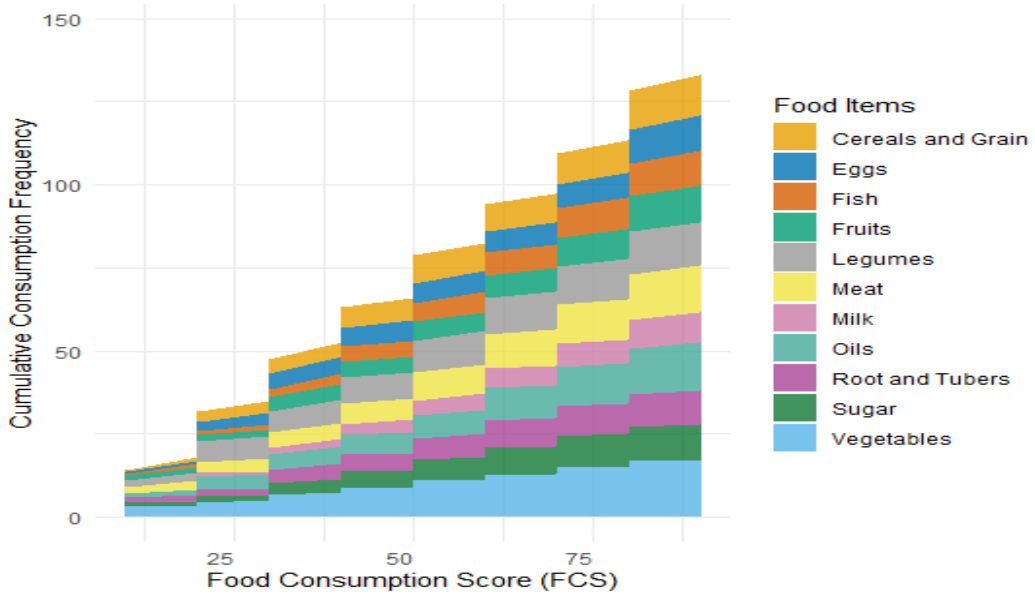

Figure 5.4. The distributions of food consumption scores by food item
Source: Own survey data (2024).

5.5.4. Village level agricultural transformation status

To investigate the practices of agricultural transformation at village level an index was constructed. We presented nine indicators to assess farmers' response. These indicators are based on agricultural practices at the village level and include the following: Q1. Production of high-value cereal crops, Q2. Production of high-value vegetables, Q3. Adoption of crossbred dairy cows, Q4. Adoption of improved egg-laying poultry, Q5. Mechanization practices, Q6. Increased irrigation production, Q7. Participation in commercialization, Q8. Connection with change agents, and Q9. Knowledge of climate information and adaptation practices.

The farmers' responses were recorded in a questionnaire format using a scale of 1--4, where 1 represents "very low" 2 represents "low," 3 represents "medium," and 4 represents "high" status for each indicator. We calculate the index ratio by multiplying the frequency of each response by its corresponding weight, summing the results, and dividing by the number of indicators (see Appendix 4C2). Using the "summarized" command in STATA 18, we selected the median (P50) as the cutoff point to create a dummy variable. The median transformation index ratio was found to be 2.44. Then if a respondent's index ratio was ≥ 2.44, it was classified as "high transformation status"; otherwise, it was classified as "low transformation status" if the index ratio was < 2.44 (Appendix 4C2). Accordingly, 184

(43.6%) respondents had perceived that village-level transformation was high, whereas 238 (56.6%) perceived low transformation status (Table 5.3).

Table 5.3. The frequency of respondents by index of transformational status

Transformation status index	Freq	Percent
Low transformation status	238	56.6
High transformation status	184	43.6
Total	422	100

Source: Own survey data (2024).

5.5.5. Distribution of food categories by source

As shown in Figure 5.5 below*,* 'own production' is the primary source of food items such as cereals, eggs, legumes, milk, and root vegetables. This indicates that farmers cultivate these foods on their farmland. In contrast, items such as sugar, oil, vegetables, meat, and fruits are obtained primarily through *'cash purchases.'* Additionally, some farm households acquire oil, sugar, meat, and legumes through 'credit purchases.' Other farmers receive food items such as fruits, sugar, vegetables, legumes, meat, and milk as 'gifts from family.' Moreover, a very small percentage of farmers obtain food by 'beg,' 'borrowing,' 'gathering,' or 'exchanging labor' to support their family's food security. Overall, farmers in the study areas have diverse sources of food for their family's consumption though 'own production' and 'cash purchases from nearby markets' being the most significant.

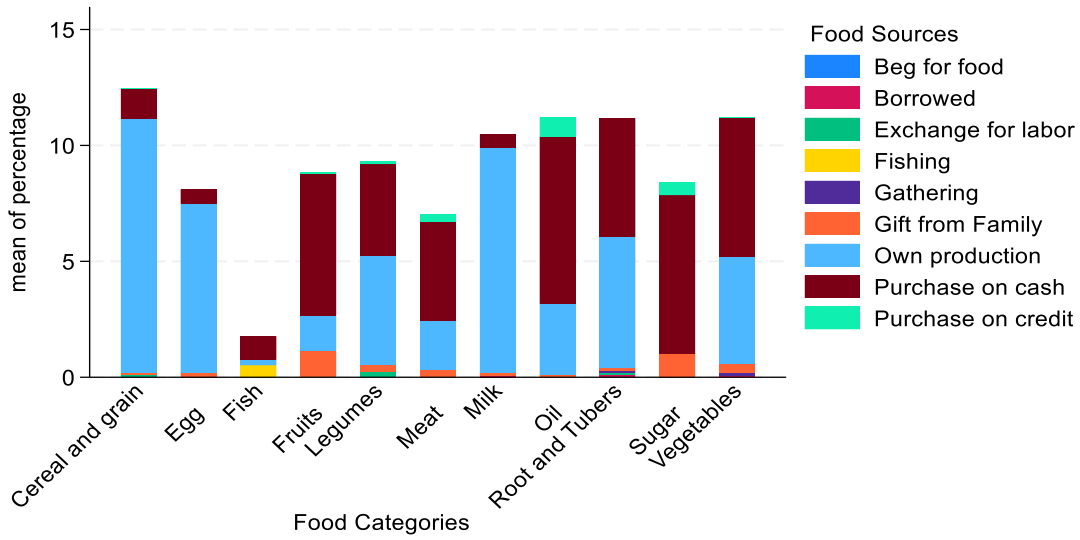

Figure 5.5. The distribution of food categories by food source
Source: Own survey data (2024).

5.5.6. Summary of descriptive statistics

To compare variations in food consumption profiles, one-way ANOVA is suggested to test the means and variances of independent variables, assuming they are normally distributed. Equal variance was checked using Bartlett's test, with a significance level of $p < 0.05$; however, the normality assumption was violated. Therefore, we employed the nonparametric Kruskal–Wallis test to assess the significance of the p-values. As the result, the food consumption score (FCS) was significant at $p < 0.01$ (F statistic = 396.32), indicating strong evidence that the distributions of FCS differ significantly among food consumption profiles (Appendix 4C5). Similarly, the distribution of educational levels varied significantly across food consumption profiles at $p < 0.01$ (F statistic = 7.64), suggesting that different levels of educational attainment may influence dietary patterns and food choices. Additionally, the frequency of visits by agricultural extension workers to farm households in a month also differed significantly among food consumption profiles at $p < 0.05$ (F statistic = 5.96) (See Table 5.4).

The dummy index for farm transformation status (1 = high; 0 = low) yielded significant results at $p<0.01$ and a chi-square statistic of 12.818. The mean proportions of dummy index for farm transformation showed 0.518, 0.343, and 0.353 for acceptable, borderline, and poor

consumption profile, respectively. This indicates a strong association between farm transformation status and household higher food consumption profiles. (Table 5.4).

The awareness of farmers regarding the consumption of nutritious and healthy food is a crucial factor influencing their food consumption profiles. This difference was found to be significant at $P<0.01$, and the Chi-square statistic was 14.716. The mean proportions of the dummy information on nutritious and healthy food consumption were 0.954, 0.849, and 0.823 for the acceptable, borderline, and poor food consumption profiles, respectively (see Table 5.4). The results indicated that access to information on the consumption of nutritious and healthy food improves the decision to produce and consume diverse food sources (items) and possibly improves the status of food security. Relatively small and large proportions of farmers obtain information on nutritious and healthy food consumption in the categories of poor and acceptable food consumption profiles, respectively.

Finally, farmers' access to training on healthy food production was significantly associated with their food consumption profiles. The mean proportion for an acceptable food consumption score was 0.738, whereas the borderline and poor food consumption profiles had mean proportions of 0.584 and 0.676, respectively. This finding indicates that improvements in food consumption profiles, supported by increased awareness and capacity building, promote the consumption of a more diverse diet.

Table 5.4. Summary of descriptive statistics

Explanatory Variables	Food Consumption Profiles						F value	Min.	Max.
	Acceptable		Borderline		Poor				
Continuous	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**			
Food consumption score	51.218	11.734	28.762	4.488	18.176	3.162	396.32***	9.5	89.5
Age of the respondent	45.648	10.385	47.982	9.724	46.676	9.840	2.540*	22	75
Family size of the respondent	5.927	2.025	5.644	2.251	5.705	2.053	0.880	2	14
Educational level	5.689	4.050	4.530	3.927	3.265	3.948	7.640***	0	12
Farm size in hectare	2.266	1.194	2.194	1.135	2.136	1.014	0.260	0.25	5.5
Number of livestock in TLU	8.768	5.165	8.15	4.776	6.965	3.876	2.280	0.03	27.45
Frequency of extension contact in a month	2.427	0.971	2.151	0.892	2.000	0.816	5.960**	0	5
Annual farm income in Ethiopian Birr currency	33682.35	48591.77	33097.77	36736.24	29927.06	26456.17	0.110	0	362000
Distance from the market in hour	1.263	0.731	1.311	0.781	1.436	0.741	0.840	0.05	4
Dummy							**χ2-value**	Min.	Max.
Sex of the respondent (1=male;0=female)	0.842	0.365	0.825	0.381	0.794	0.41	0.571	0	1
farm transformation status index (1= high; 0=low)	0.518	0.501	0.343	0.476	0.353	0.485	12.818***	0	1
Participation in irrigation (1=Yes; 0= No)	0.603	0.490	0.602	0.491	0.441	0.503	3.388	0	1
Connection to social network (1=yes;0=No)	0.914	0.280	0.843	0.364	0.823	0.386	5.588	0	1
Access to market information (1=Yes; 0=No)	0.509	0.501	0.481	0.501	0.412	0.499	1.196	0	1
Participation in nonfarm income (1=Yes;0=No)	0.423	0.495	0.397	0.491	0.235	0.430	4.355	0	1
Information on nutritious and health food consumption (1=Yes;0=N0)	0.954	0.207	0.849	0.358	0.823	0.386	14.716***	0	1
Access to training on healthy food production (1=Yes;0=No)	0.738	0.440	0.584	0.494	0.676	0.475	10.291***	0	1

Source: Own survey data (2024).
(** and *** indicate the 5% and 1% probability levels, respectively).

5.5.7. Interaction between food consumption scores and transformation status

To evaluate how transformation status varies with food security across districts, we first regressed the food consumption score (FCS) via an interaction term between the dummy variable for transformation status and the districts. The model resulted significant variation across districts. The Y-axis displays the anticipated food consumption score (FCS) for each transformation status in each district, whereas the X-axis represents the dummy variable for the transformation status (0 = low; 1 = high). The lines on the graph illustrate the predicted FCS for each district. As shown in Figure 5.6, the lines intersect, suggesting that transformation status has varying effects on food security across districts. Additionally, the slopes of the lines extend from left to right and are not equal. In the Welmera district, a negative slope, suggesting that lower levels of agricultural transformation correlate with relatively high food security scores. This may be attributed to farmers who insisted to purchase food from market rather than producing on their farm.

In contrast, higher levels of farm transformation practices lead to improved food consumption scores (FCSs) in the Bako-Tibe and Ada'a Barga districts than in the Ilu and Weliso districts. Additionally, the differences in the vertical gaps of the FCS lines indicate that the impact of transformation status on food consumption scores is significant in some districts but weak in others. Finally, the joint significance of the interaction term (transformation status and district) was tested via '*testparm*', yielding $P<0.05$ and an F statistic =10.56 (Appendix 4C3). It indicates that district variation influences the effect of transformation status on food security (see Figure 5.6).

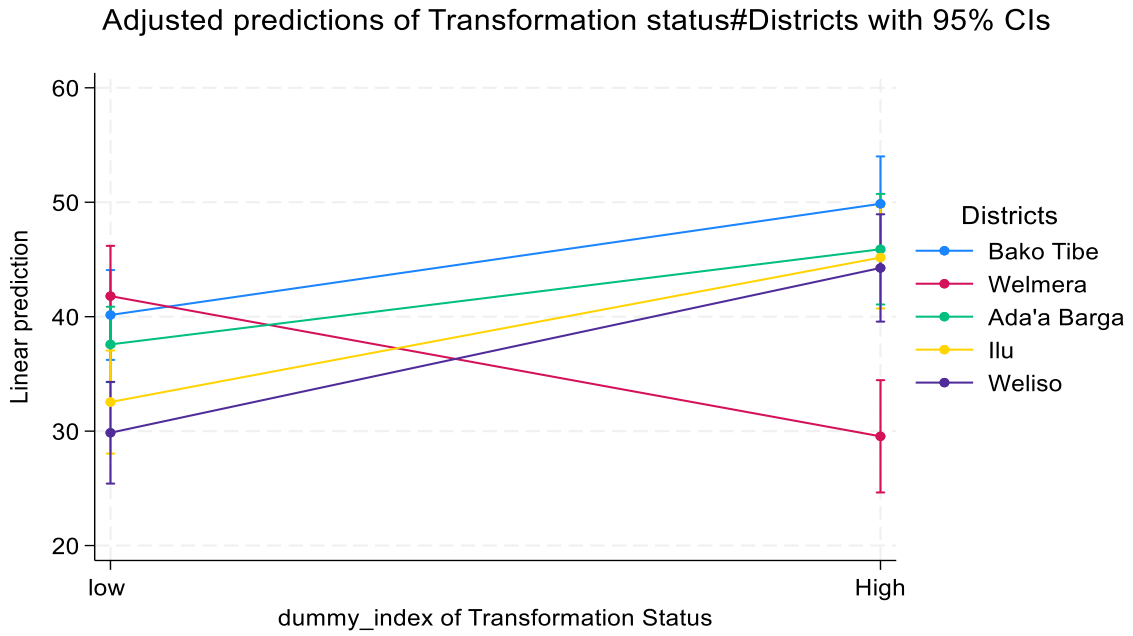

Figure 0.1. Interaction effect of transformational status and the FCS by district
Source: Own survey data (2024).

5.5.8. Results of Instrumental variable model regression

The results below present the regression analysis of the food consumption score using OLS and instrumental variable regression (2SLS). Before delving into the detailed analysis, several preliminary tests were conducted. First, the assumption of normality was assessed using a pnorm plot and a one-sample Kolmogorov–Smirnov test against a theoretical distribution. The results revealed a $p < 0.05$, indicating that the food consumption score was not normally distributed (Appendix 4C6). Besides to this, the residual plot for the food consumption score is also tested to check whether the variance is normally distributed and found the kernel density curve is slightly left skewed. This means, the data were not normally distributed and forced to transform into a logarithm function to capture the variation in distribution. Furthermore, the relationship between food security and the dummy index of transformation status was checked by regressing the continuous food consumption score against the dummy transformation index. The transformation index was significant at $P<0.01$ and had a positive impact on food security. To address the issue of heteroskedasticity, robust standard errors were employed in the regression analysis. In addition, a multicollinearity test on the independent variables revealed a variance inflation factor (VIF) of 1.19 (Appendix 4C4) which is below the threshold of 10, indicating no serious correlation among the independent variables. Nevertheless, estimating the relation between food consumption score

and the dummy farm transformation status using the OLS model's results biased estimates because endogeneity problems exist. Thus, an instrumental variable was introduced to run the 2SLS after the endogeneity problem was identified. Accordingly, the market-oriented production decision is an instrumental variable that directly influences the status of the farm transformation. Accordingly, the results of the linear probability model (LPM) indicated strong evidence of an endogeneity problem in the first stage model estimation, with F = 48.70. The endogeneity test between farm transformation status and market-oriented production was statistically significant at $P < 0.05$ (Appendix 4C7 & AC8). Hence, as a farm product is oriented towards market demand, the probability of farm transformation at higher indices increases by 0.324 percentage points for farms with a higher transformation status (see Table 5.5).

Table 5.5. Results of the first regression of the instrumental variable

	Unrestricted model		Restricted model	
Index of Transformation status (Dependent Endogenous Variable)	Coeff.	Robust std.err	Coeff.	Robust std.err
Dummy Market-oriented production decision (instrumental variable)	0.324***	0.046	0.239***	0.050
Age of the respondent in years			-0.001	0.002
Sex of the respondent (1=male;0=female)			-0.026	0.058
Family size of the respondent			-0.007	0.011
Educational level of the respondent			0.012	0.006
Total farm size in hectares			0.052**	0.023
Total number of livestock in TLU			0.014***	0.005
Income of household in logarithmic			-0.002	0.011
Dummy irrigation participation			0.147***	0.047
Dummy social network connection			0.112	0.059
Frequency of extension contacts in a month			0.032	0.025
Dummy access to market information			0.104**	0.047
Distance from the nearest market in hour			0.005	0.031
Participation in nonfarm income activities			-0.007	0.046
Information on nutritious and health food			0.063	0.072
Access to training on healthy food production			0.034	0.049
_cons	0.301	0.300	-0.098	0.166
Observation	422		422	
R^2	0.104		0.22	
F-Statistic (IV Strength Test)	48.7		11.2	

Source: Own survey data (2024) computation. ** (5%), *** (1%) probability level.

Therefore, market-oriented production significantly influences farmers' decisions to transform their farm enterprises, regardless of the control variables. The results also indicated that farm size, total number of livestock, and access to market information notably impacted the status of farm transformation, without endogeneity problem detected.

5.5.9. Determinants of food security at the household level

Table 5.6 below shows the factors affecting the food consumption score. The 2SLS result showed that a change in index of transformation status from low to high category, associated to increase the level of food consumption score by 0.41 keeping other factors held constant. While the OLS result had lowered the association to 0.117 and showed biased. The result was statistically significant at the 1% probability level. The positive coefficient and consistency in estimation indicates that improvements in agricultural practices through adoption of technologies enhances the potential for securing food consumption at the household level. Furthermore, diversifying farm operations creates opportunities to meet annual family food requirements. This finding aligns with that of (Day & Cramer, 2022), who reported that regenerative agriculture enhances food production. Similarly, the adoption of sustainable farming practices is influenced by decision-making throughout the farm transformation process (Huet et al., 2018).

Likewise, the educational level of farm households positively impacts food security at the 5% probability level in the OLS estimation, but this effect is insignificant in the 2SLS model. Each additional year of school attendance is associated with a 0.011 increase in the food consumption score, holding all other control variables remain constant. This positive effect indicates that higher school enrolment enhances individuals' ability to utilize information, leading to improved dietary choices and the production of high-value farm products. Education empowers individuals to make informed decisions to food consumption and helps for achieving a balanced diet. A study by (Gebrehiwot et al., 2024) in northern Ethiopia demonstrated that farmers' educational levels enhance the adoption of improved farming technologies, which favor food production. Similarly, (Gatobu et al., 2020) reported in Kenya that education enhances choices of agricultural practices and decision-making processes. In Mali, higher educational attainment is associated with improved perceptions of food security (Nurjihadi & Guindo, 2024). Additionally, in Nigeria, education improves nutrition-related knowledge and decision-making abilities (Otekunrin et al., 2021).

On the other hand, wealth factors, such as the annual income of farm households, negatively impact food consumption scores. This is a rare finding, given that farmers' behaviour might shift to allocate income to non-food items, which has the potential to result in lower food security scores. This suggests that, when controlling for other variables, an increase in annual income from farming is associated with a 0.033 decrease in the food consumption score, with statistical significance at $P<0.01$. One possible explanation for this trend is that farmers may prioritize their income for non-food expenditures, including fertilizer and seed purchases, taxes, children's education, credit payments, and other social obligations. Additionally, the seasonality of farm income can contribute to food insecurity, further lowering food consumption scores. This finding aligns with a study in China, which demonstrated that initial income growth enhances food security; however, higher income can suppress it due to increased non-food expenditures (Dong et al., 2024). Additionally, research by (Devereux & Tavener-Smith, 2019) indicates that seasonal fluctuations in agricultural employment and income negatively affect farmers' food security, particularly in winter, when job opportunities and income decline, leading to increased food insecurity.

Institutional variable like monthly contact with extension agents positively affects food security. An increase in extension worker visits correlates with an 0.084 increase in the food consumption score, holding that other factors remain constant. However, this estimate is biased in ordinary least squares (OLS) regression and decreases food consumption score by 0.075. The result was statistically significant at $P<0.01$. Extension agents play a crucial role by advising farmers on the adoption of new technologies, demonstrating effective agricultural practices, and recommending diverse product mixes. These efforts increase the availability of a variety of food items on farms, which in turn facilitates their consumption. Additionally, extension agents may provide guidance on balanced diet consumption, contributing to improved food consumption patterns. This finding aligns with the work of (Anang & Ayambila, 2020; Mugizi, 2025; Okwama et al., 2022; Ranjan et al., 2024), indicating that regular interactions between farmers and agricultural extension agents positively impact food security by increasing agricultural output, increasing access to knowledge, and promoting the adoption of innovative techniques. Physical factors, such as the distance from the nearest market, negatively influence the food consumption score, with statistical significance at $P<0.01$. The 2SLS regression presented in Table 5.6 indicates that for every additional hour's distance from the nearest market, associated to a 0.061 decrease in the food consumption score, keeping that all other factors remain constant. This coefficient of 2SLS was larger than

the OLS estimate which is about 0.058, suggesting that the OLS model underestimates the true impact due to endogeneity biases. This distance affects the sources of food purchased from the market, as farmers may not provide all food items from their own fields. Particularly, food items such as oil, vegetables, and meat are purchased from the market and constrained by locational distance. Consequently, peripheral farmers face disadvantages in accessing these essential items. Similar findings indicate that greater distances hinder market access, resulting in increased transportation costs and higher food prices (Achilana et al., 2020; Li & Cao, 2024). Distance significantly affects food access, as vendors are often located far from customers. This can negatively impact food security by limiting the availability and accessibility of essential food items (Pona et al., 2023).

Access to information about nutritious and healthy food significantly enhances farmers' food consumption scores. The 2SLS results presented in Table 5.6 indicate that access to information associated to increases the food consumption score by 0.137, holding other factors remain constant. The result was statistical significance at $P<0.01$. However, the results of OLS estimation overestimate the effect of access to information on food security by 0.158 points and was susceptible to endogeneity bias. However, the 2SLS result suggested that farmers' access to nutritious and healthy food might enhance their decision to consume diverse sources of food and improve consumption patterns. This result aligns with that of (Shafieisabet & Mirvahedi, 2021), who argued that rural–urban linkages empower farmers by providing information and altering their perceptions of food security plans. Furthermore, food security status is positively influenced by access to sufficient information on safe, and nutritious food that meets dietary requirements and preferences (Olarinde et al., 2020).

Finally, farmers' access to training affects the food security level of the household. Farmers who participated in training related to healthy food production increased their food consumption score by 0.074 and statistically significant at $P<0.05$. This suggests that demonstration-based training at farmer training centers (FTCs) positively affects farmers' decision-making toward adopting new farm technologies and enhancing production. Because training provides farmers with skills and knowledge, they need to increase agricultural output and decision-making. This finding aligned with (Amoak et al., 2022; Stewart et al., 2016; Thapa et al., 2025) reported that training in agricultural practices, climate services, and agro-processing improving farmers capability to acquire agricultural knowledge

Table 5.6. Results of Two-Stage Least Square Regression

	(1) OLS			(2) IV-2SLS		
Log Food Consumption Score (Dependent variable)	**Coeff.**	**Robust std.err**	**P>|t|**	**Coeff.**	**Robust std.err**	**P>|Z|**
index for transformation (Endogenous variable)	0.117***	0.037	0.002	0.410**	0.160	0.012
Age of the respondent in years	-0.001	0.002	0.836	-0.001	0.002	0.858
Sex of the respondent (1=male;0=female)	-0.007	0.049	0.894	0.002	0.052	0.972
Family size of the respondent	0.004	0.008	0.649	0.006	0.009	0.521
Educational level of the respondent	0.011**	0.004	0.015	0.007	0.005	0.172
Total farm size in hectares	0.001	0.017	0.955	-0.010	0.018	0.595
Total number of livestock in TLU	0.002	0.004	0.537	-0.002	0.005	0.647
Income of household in logarithmic	-0.033***	0.009	0.000	-0.033***	0.009	0.000
Dummy irrigation participation (1=Yes; 0= No)	0.045	0.038	0.233	-0.011	0.051	0.822
Dummy social network connection (1=Yes; 0= No)	0.067	0.058	0.247	0.027	0.064	0.662
Frequency of extension contacts in a month	0.075***	0.019	0.000	0.084***	0.021	0.000
Dummy access to market information (1=Yes; 0= No)	-0.043	0.036	0.228	-0.081	0.043	0.058
Distance from the nearest market in hour	-0.058**	0.023	0.014	-0.061**	0.023	0.010
Participation in nonfarm income activities (1=Yes' 0= No)	0.015	0.057	0.666	0.008	0.038	0.824
Information on nutritious and health food (1=Yes; 0=N0)	0.158***	0.055	0.004	0.137**	0.057	0.017
Access to training on healthy food production (1=Yes;0=No	0.074**	0.037	0.047	0.056	0.04	0.162
_cons	3.247	0.124	0.000	3.29	0.135	0.000
	Number of obs = 422			Number of obs = 422		
	F (16,405) = 7.10			F (16,405) = 11.20		
	Prob > F = 0.0000			Prob > F = 0.0000		
Endogeneity test (Hausman test)				P = 0.05		

Source: Own survey data (2024). **(5%), ***(1%) probability level

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5.6. Conclusions

Agricultural practices implemented by smallholder farmers significantly impact food security at the household level. The findings of this study indicate a positive association between food security and farm transformational status. Despite this, food security varies across districts due to agroecological and socioeconomic conditions. Most food sources in the studied districts come from own production and cash purchases from the market. The food consumption score tends to increase as farmers access a more diversified range of food. Furthermore, market-oriented production encourages farmers to adopt improved agricultural technologies, which potentially enhance food security at the household level. Therefore, the commercialisation orientation of smallholder farmers aspires substantial hope to achieve food security at household level.

5.7. Recommendations

- An improvement in adopting transformational farming practices, positively influencing the household food security score. Therefore, the existing agricultural transformation should be enhanced to boost agricultural productivity across a broader segment of the farming community in the study area.
- Simultaneously, farmer income is an important factor that influences the food security score. Hence, activities that enhance farmer income or engagement in diversified sources of income should be advised to enhance farmers' adaptive capacity to mitigate food insecurity.
- Institutional services, such as extension services, access to nutrition and healthy food information, and training on healthy food consumption, positively influence food security scores. Therefore, the Ethiopian agricultural development strategy should strengthen the effectiveness of these institutional services and enhance coordination with farmers to provide reliable information on healthy food consumption.
- Finally, the distance from the nearest market negatively influences the level of food security. The government should improve road accessibility and other infrastructure in rural areas so that ageing and remote villages can access locally available food for consumption

Chapter Six

6. The Impact of Knowledge Utilization Networking on Transformational Farming Practices

Abstract: *Knowledge utilization is essential for addressing the challenges faced by smallholder farmers in agricultural production. Hence, the study aimed to examine the direct and indirect effects of knowledge use on farm transformation using mediation analysis. Data were collected from 422 farm households selected using a multi-stage sampling method in the central Oromia region of Ethiopia. The data were analyzed using descriptive statistics and a control-function regression model (first-stage probit and second-stage negative binomial regression). The results of the descriptive analysis showed that 39.95%, 25.1%, 19.5%, 7.91%, 6.18%, and 1.35% of farmers utilized agricultural knowledge through extension services, a mix of social capital and extension, farmers' cooperatives, social capital, a mix of cooperative and extension, and a mix of cooperative and social capital, respectively. The results of the first-stage probit regression indicated that distance from farmers' training centers and cooperative offices negatively influenced farmers' access to extension services and farmers' cooperatives, while attending community-level meetings positively influenced farmers' linkages to build social capital. Accordingly, the second stage of negative binomial regression indicated that knowledge utilization through extension services, farmers' cooperatives, and social capital channels directly and positively influences the number of transformational practices. The log-linear model results revealed that the mediator variables, such as field day demonstration and training, were positively influenced by extension services and a mix of farmers' cooperatives and extension services. Likewise, field day demonstration mediated extension services to influence the number of transformational farming practices indirectly with a positive sign. The findings conclude that knowledge used through extension services plays a crucial role, both directly and indirectly, in enhancing transformational farming practices. It also suggests investment in capacity building for extension workers, promoting farmers' organizations, and enhancing field day demonstrations to accelerate transformational farming practices on a larger scale.*

Keywords: Knowledge Utilization network, Mediation Analysis, Negative Binomial regression model, Transformational Framing Practices.

6.1. Introduction

Knowledge utilization is essential for addressing the challenges faced by smallholder farmers in agricultural production. In Ethiopia, where subsistence farming has traditionally formed the backbone of economic growth (Mellor, 2014), effective dissemination and utilization of agricultural knowledge is critical. The agricultural economy contributes 24% of the GDP, which is higher than that of sub-Saharan Africa (Gordon, 2019). At the national level, agricultural GDP declined from 36.3% in the 2016/17 fiscal year to 32.4% in 2021/22 (NBE, 2022), signalling the need for structural transformation. This underscores the importance of government efforts to mobilize farmers' participation and connect them to diverse knowledge sources aimed at enhancing productivity and promoting agricultural modernization.

Accordingly, Ethiopia has developed an agricultural extension strategy aimed at transforming subsistence farming into a market-oriented approach (MOANR, 2017). This strategy emphasizes that access to knowledge and information can empower smallholder farmers and other practitioners, ultimately boosting agricultural productivity and alleviating food insecurity (MOANR, 2017). However, several challenges hinder the effective utilization of knowledge among farmers. These includes insufficient use of ICT, limited access to agricultural knowledge and information, inadequate infrastructure in urban and peri-urban areas, and a failure to adequately address farmers' interests (Maldayo et al., 2024; Shitaye et al., 2025; Van Asten et al., 2009).

As a result, farmers are compelled to establish multiple connections to access knowledge sources. And formal and informal linkages serve as means to acquire opportunities for learning agricultural practices (Simpson & De Loë, 2017). This enabling to make decisions by integrating various ideas, and information sent, received, and stored indefinitely (Kursat, 2014). However, linkage with knowledge sources depends on the type of information farmers need (Adetimehin et al., 2018; Fidelugwuowo, 2021; Melash et al., 2023). Likewise, farmers connected with local farmers, private sectors, non-governmental organizations (NGOs), and research institutions to gain knowledge aimed at improving food security (Tamako et al., 2022). Nevertheless, the level of social capital network heterogeneity influencing the effectiveness of information flow (Morrison et al., 2025). For example, structural positions enabled farmers to learn about agricultural innovations (Ncube & Pittock, 2025). This implies social capital has potentially influencing knowledge utilization to transform farm practices.

Since 2004, the Ethiopian government has built approximately 45,000 Farmer Training Centres (FTCs) in villages to promote agricultural development through a knowledge-based approach aimed at transferring technology, enhancing resource-use efficiency, and fostering social capital development (MOANR, 2017). However, misinformation among smallholder farmers is common, particularly where reliance on traditional knowledge predominates, which may reduce the adoption of improved agricultural technologies (Kuntosch & König, 2018). Consequently, achieving food security through sustainable farming presents a significant challenge that requires transforming agricultural practices. In such cases, formal interventions, such as farmers' cooperatives and extension services, helping to regulate the quality of knowledge dissemination.

On the other hand, the use of knowledge through social networks has garnered significant attention from researchers, particularly farmers' involvement in seed production, agroforestry practices, resource conservation, climate-smart agriculture, and decision-making (Abid et al., 2017; Albizua et al., 2021; Isaac et al., 2014; Isaac & Matous, 2017; Lin et al., 2021; Ofolsha et al., 2022). Also there is increasing evidence of improved adoption of agricultural technology in Ethiopia, following challenges persist due to global competition, climate change, and resource management (Tefera et al., 2012).

In general, farmers' knowledge plays a key role in creating a stable food system. It encompasses the practical and social change aspects of agroecology (Nimmo et al., 2023). This knowledge arises from individual (tacit) or generic connections, such as social networks, groups, and formal institutions, and influences decision-making (Adnan et al., 2020; Grimsdottir & Edvardsson, 2018; Kogut & Zander, 1992; Russ, 2021). Specifically, it provides insights to help farmers to identify solutions to knowledge networking and achieve stable food system by adopting transformational farming practices.

6.2. Literature Review

Timely, accurate, and relevant agricultural information is essential for enhancing production, alleviating poverty, and promoting economic development in both rural and urban areas (Roland, 2014). Particularly, the success of small-scale farmers depends on reliable and sustainable agricultural information, which benefits communities worldwide. This is critical in developing countries, where a significant portion of the population relies on agriculture as their primary source of income. For instance, case studies revealed that formal "agricultural

advisors" primarily disseminate codified managerial knowledge through centralized networks (Sutherland et al., 2017) in which farmers linearly connected to the source of information. On the other hand, a study conducted in the Republic of South Africa showed that agricultural knowledge networks positively impacted smallholder food security, especially for farmers connected to local farmers, private sectors, non-governmental organizations (NGOs), and research institutions (Tamako et al., 2022). Whereas in Kenya, the level of social capital contributed to network heterogeneity among dairy farmers influencing the effectiveness of information flow (Morrison et al., 2025). Additionally, structural positions in Tanzania enabled farmers to learn about agricultural innovations and the adoption of irrigation schemes (Ncube & Pittock, 2025).

In Ethiopia, farmers' access to agricultural information enhances their production skills (Alemu et al., 2020; Maldayo et al., 2024). It influenced the adoption of cassava production in Southern Ethiopia (Waje et al., 2024). The adoption scale and type of knowledge needed varies by agro-ecology and level of agricultural livelihood diversities. In addition, indigenous knowledge plays a vital role in organic farm production and the management of natural resources (Melash et al., 2023). This approach supports the socio-ecological sustainability of agrarian systems, contributing to agricultural transformation.

Another report on Ethiopian agricultural transformation and knowledge systems shows a significant gap between the government's ambition to transform agriculture and the institutional capabilities to provide technological knowledge (Tefera et al., 2012). This gap is related to infrastructural development and weak institutional coordination. The intensification of knowledge utilization and networking enables to achieve stable food production, and sustainable natural resource management (Maguire, 2000). Some studies indicate that knowledge use through modern agricultural extension services reduces the gap for sustainable agricultural practices (Prajapati et al., 2025). However, locational barriers due to underdeveloped infrastructure may limit access to extension services for peripheral farmers (Bor, 2024).This suggests that farmers seek alternative sources of agricultural knowledge within the context of local interactions.

Some studies focus on knowledge gap analysis using stakeholder participation, indicating that inadequacies in policy, institutions, skills, and adaptation to improved technologies are significant barriers (Antwi-Agyei et al., 2025). Conversely, linkage with knowledge sources

depends on the type of information farmers need (Adetimehin et al., 2018; Fidelugwuowo, 2021; Melash et al., 2023). Furthermore, friends/relatives, radio, and ICT serve as potential information sources. However, poor infrastructure limits access to modern communication (such as radio and mobile phones), which impacts the adequacy of information. Under such circumstances, farmers alternatively looking for cooperatives, extension workers, and social capital to acquire agricultural information by attending training and field day demonstrations. In general, the existing literature highlights the importance of agricultural knowledge in technology adoption and food security. However, previous studies did not address unobservable factors contributing to access to knowledge sources, nor did they examine how mediator instruments, such as farmers' participation in training and field day visits, influence farmers' engagement in transformational farming activities.

Accordingly, this study contributes by describing the effect of unobservable factors on knowledge use networks and estimating the expected direct and indirect impacts on smallholder agricultural transformation, which can inform Ethiopian agricultural development policy. It provides insights to improve strategic tools for knowledge dissemination to support smallholder agriculture. Therefore, this study aims to analyze the direct and indirect effects of knowledge sources on transformational farming practices using an instrumental variables approach and mediation variables.

6.2.1. Theoretical framework

Agricultural Innovation Systems (AIS) facilitate the development of a conceptual framework for analysing the impact of knowledge utilization networks and transformational agricultural practices. The concept of the innovation system was broadly introduced by (Lundvall, 2007). Innovations in agriculture are crucial for mitigating fluctuations in agricultural production due to dynamic changes in societal demand, economic patterns, and environmental quality. It is also needed for designing national development policies that require strong institutions to disseminate knowledge among stakeholders within the agricultural business sector (World Bank, 2012).

Therefore, multi-dimensional knowledge sources, including both private and public sectors, are essential for generating new ideas that regulate the changing farming practices (World Bank, 2012). For example, coordination, group efforts, knowledge sharing among various

actors, incentives, and accessible resources are linked to the capacity for innovation. These elements help to establish collaborations, grow enterprises, and create conditions that enable farmers to apply innovations.

On the other hand, social network theory suggests that farmers are connected to knowledge sources based on their levels of social capital, cohesion, and structural equivalence (Luu et al., 2019). In other explanation, the complex interactions among participants in knowledge sharing promote agricultural innovations. Hence, in this study, farmers leverage their social networks, including opinion leaders, extension services, and cooperatives, to build social relationships to adopt better agricultural practices.

6.3. Method of Data Analysis

6.3.1. Descriptive and inferential statistics

The result of summarized statistics on knowledge sources, transformational farming practices, and relation between explanatory variables were analysed by the descriptive statistics. Analysis was conducted using mean, standard deviation, minimum, and maximum. Further, a pairwise correlation coefficient was computed to observe the relationship between variables. The results were presented in tables, graphics and pie charts to visualize the distributions of the knowledge use network and number of transformational farming practices.

6.3.2. Econometric model specification

The econometric models were used to analyse the relationship between transformational farm practices and knowledge use networking. Knowledge utilization by farmers is derived by the distance proximity to knowledge sources and social cohesion. Hence, knowledge utilization network is endogenous to transformational practices. Then to estimate the endogeneity of dummy knowledge sources, a first-stage probit and second-stage negative binomial regression model was selected based on the a priori need to control the dependency of dummy regressors. Next, we used a log-linear model to regress knowledge sources, along with control variables, on mediator variables. Thirdly, we employed negative binomial regression to regress knowledge sources, mediator variables, and control variables on the outcome dependent variable (the count of transformational farming practices). Theoretically, the model specification was developed around behavioral variables. This means that farmers'

behaviour towards practicing the number of agricultural technological will varies with their level of experience. The practice of farm transformation is linked to self-efficacy, which is built on the confidence to respond to changes in agricultural livelihoods. In the process of estimation, we implement two-step control function estimator to capture possible endogeneity of farmers' cooperative, extension services, and social capital.

Hence, in the first stage we computed separately using probit model for each binary endogenous regressor on its instrument and exogenous control variables, and construct generalized residuals. In the second stage, we estimated the negative binomial regression of the count outcome number of transformational farming practices on endogenous dummy knowledge use network, control variables, and computed residuals. Finally, the coefficient on the residuals test for endogeneity and joint significant indicates the need for corrections (Wooldridge, 1997). Accordingly, the first stage probit model is specified as follows:

For j = 1,2,3:

$$d_{ji}^{*} = Z_{ji}'\pi_j + X_i'\delta_j + V_{ji}, V_{ji} \sim N(0,1) \quad (1)$$

$$d_{ji}^{*} = 1\{d_{ji} > 0\}, P_{ji} \equiv Pr(d_{ji} = 1 \mid Z_{ji}, X_i) = \boldsymbol{\phi}(\boldsymbol{Z_{ji}^{*}}\pi_j + X_i'\delta_j \quad (2)$$

$$fcoop* = distCoop_i\,\gamma + Control\ var_i\delta + U_i, fcoop_i = 1[fcoop* > 0] \quad (3)$$

$$ExtenServ* = distFTC_i\gamma + Control\ var_i\delta + U_i, ExtenServ_i = 1[ExtenServ* > 0] \quad (4)$$

$$SocialCap* = PartComm_i\gamma + Control\ var_i\delta + U_i, SocialCap_i = 1[SocialCap* > 0] \quad (5)$$

Where:

$fcoop*$ = endogenous farmers' cooprative

$ExtenServ*$ = endogenous Extension service

$SocialCap*$ = endogenous Social capital

$distcoop_i$ = instrumental variable (distance from farmers' cooperative office)

$distFTC_i$ = instrumental variable (distance from farmers' training center)

$PartComm_i$ = instrumental variable (participation in community level meeting)

γ, δ, parameters for instrumental variables and control variables

Compute fitted probability $\widehat{P_{ji}}$ from each probit and the generalized (control-function) residual for each j: $r_{ji}' = \frac{d_{ji} - \widehat{P_{ji}}}{\widehat{P_{ji}}(1-\widehat{P_{ji}})}$ (6)

The second stage negative binomial (NB2) with control functions specify mean:

$$E\left[y_i \mid d_{1i}, d_{2i}, d_{3i}, X_i, r_{1i}, r_{2i}, r_{3i}\right] = \mu \quad (7)$$

$$\mu_i = exp(\alpha + X_i\beta + \sum_{j=1}^{3} r_j d_{ji} + \sum_{j-1}^{3} \lambda_i r_{ji}) \quad (8)$$

Variance (NB2):

$$Var(y_i|.) = \mu_i + k\mu_i^2, k > 0 \quad (9)$$

Accordingly, the second stage, negative binomial regression model is fitted as:

$$E[y_i | fcoop_i, ExtenServ_i, SocialCap_i, Control\ variables, \widehat{Ui}] = exp(\alpha fcoop_i + \sigma ExtenServ_i + \sigma SocialCap_i + X_i\beta + \rho\widehat{U}_i) \quad 10)$$

Where: $y_i =$ *dependent variable (count of transformational farming practices*

$X_i = Control\ variables, \beta =$ *coefficent of control variables,*

Likewise, the Poisson distribution is appropriate for a dependent variable *y* that takes only non-negative integer values: 0, 1, 2, 3, and so on. It can be used to model the number of occurrences of an event, such as the number of agricultural technology practices adopted by farm households. In this study, the dependent variable was the number of transformational farming practices which is a pivotal element of Ethiopian development policy. These practices aimed to manage soil fertility (through biological conservation) and enhance crop and livestock productivity by adopting improved agricultural technologies. The adoption of these practices is influenced by farmers' connections to various knowledge utilization networks. The econometric model for this analysis assumes that the response variable *Y* follows a Poisson distribution, and the logarithm of its expected value can be modelled as a linear combination of unknown parameters. The model specifies a random variable *Yi* with rate parameter λ_i is:

$$Prob(Y = y_i|x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, y_i = 0,1,2,\ldots \quad (11)$$

with mean and variance, $E(Y_i) = Var(Y_i) = \lambda_i$

The Poisson regression model is derived from the Poisson distribution by parameterizing the relation between the mean parameter λ_i and covariates (regressors) $\boldsymbol{x}$. A regression model specifies the parameter to vary across individuals according to a specific function of regressor vector **x** and parameter vector λ_i (Greene, 2012). The usual Poisson specification is:

$$\lambda_i = \exp(x'_i, \beta), i = 1, \ldots, n \quad (12)$$

which has the advantage of ensuring that the mean λ_i regression model is given by:

$$P(y_i/x_i\beta) = \frac{e^{-\exp(X'_i\beta)}(\exp(X'_i\beta))^{y_i}}{y_i!}, y_i = 0,1,2,\ldots \quad (13)$$

The assumption of equality between the mean and variance often fails due to overdispersion, making the Poisson regression model inappropriate. Consequently, it becomes necessary to adopt the negative binomial regression model. Overdispersion occurs when the variance exceeds the mean. The negative binomial regression model is a direct extension of the Poisson model that accommodates overdispersion. It is characterized by two parameters λ and α, where α is typically termed the negative binomial dispersion parameter. The probability mass function for the negative binomial distribution with parameters (λ, α) for a random variable y_i is given by:

$$P(y_i) = \frac{\Gamma(y_i+1/\alpha)}{y_i!\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha e^{X'_i\beta}}\right)^{1/\alpha}\left(\frac{\alpha e^{X'_i\beta}}{1+\alpha e^{X'_i\beta}}\right)^{y_i}, i = 1,2,\ldots n \quad (14)$$

With mean $E(y_i/x'_i) = \lambda_i = e^{x'_i\beta}$ and variance $var(y_i/x_i) = \lambda_i(1+\alpha\lambda_i)$. Where α is the dispersion parameter and characterizes the degree of over-dispersion in count data Γ(.) is a gamma function. The likelihood function of negative binomial model is given by:

$$L(\alpha,\beta) = \prod_{i=1}^{n}\frac{\Gamma(y_i+1/\alpha)}{y_i!\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha e^{X'_i\beta}}\right)^{1/\alpha}\left(\frac{\alpha e^{X'_i\beta}}{1+\alpha e^{X'_i\beta}}\right)^{y_i} \quad (15)$$

and the log-likelihood function is

$$Ln\,L(\alpha,\beta) = \sum_{i=1}^{n}(y_i ln\alpha + y_i(X'_i\beta) - (y_i+\frac{1}{\alpha})\ln(1+\alpha e^{X'_i\beta}) + ln\Gamma(y_i+\frac{1}{\alpha}) - lny_i! - ln\Gamma(\frac{1}{\alpha})) \quad (16)$$

As for the Poisson model, the estimation of the model parameters can be done by differentiating the log likelihood function with respect to the parameters α and β. Under negative binomial regression model, if the estimated alpha coefficient is zero, then the conditional mean is equal to the conditional variance $(E(y_i) = var(y_i/x_i))$ and the Negative binomial model reduces to the Poisson model. If the estimated alpha coefficient is significantly greater than zero, then the conditional variance exceeds the conditional mean $var(y_i/x_i) > E(y_i/x_i))$ and over-dispersion is present in the data. Under such circumstance, the Poisson model is inappropriate and prefer to employ the Negative binomial regression model (Greene, 2012).

Finally, to evaluate the relationship between the knowledge utilization network, and the number of transformational farming practices, we adopt the mediation analysis model developed by (Iacobucci, 2008). In this mediational structure, the mechanism by which an independent variable influences a dependent variable is conceptualized differently. This influence occurs not directly, but through an intervening process captured by the mediator variable. Farmers networked to obtain knowledge from farmers' cooperatives, extension service, and social capital channels, and mix of the alternatives through field day demonstrations and training participation. Literature shows that active learning and agricultural training serve as mediation variables facilitates the adoption of drip fertigation systems among banana producers in Ghana (Yang et al., 2021). Thus, the mediation path diagram below indicates that the effect of the knowledge utilization network (X) on the outcome variable (count of transformational practices) is a direct effect, as indicated by path c'. Meanwhile, paths 'a' and 'b' represent the indirect effects of knowledge utilization on farm transformation practices. Literatures showed that there are different approaches to conduct mediation analysis (Baron & Kenny, 1986) which illustrated as a four-step method for mediation analysis.

Step 1: The initial variable, the knowledge utilization network, has been correlated and regressed on the outcome variable (the number of transformational farming practices). This relationship is illustrated below as path c'. In this study, it was estimated by negative binomial regression model.

Step 2. The initial variable, the knowledge utilization network, has been correlated with and regressed on the mediator variables (M). In this study, the mediator variables are "field day demonstration" and "participation in training." This step treats the mediator as an outcome variable. This can be estimated by using log-linear regression model.

Step 3: It refers to the mediator affecting the outcome variable. This means that field day demonstrations and participation in training influence the number of transformational farming practices which is indicated by path 'b'.

Step 4. This step shows the regression of X (knowledge utilization network) and M (field day demonstration and training) on Y (number of transformational farming practices). In this regression model, both predictors (X and M) are analyzed to determine their impact on the

outcome variable. To make the analysis we used both negative binomial regression and generalized structural equation model. The mediation analysis diagram is illustrated as follows (see Figure 6.1).

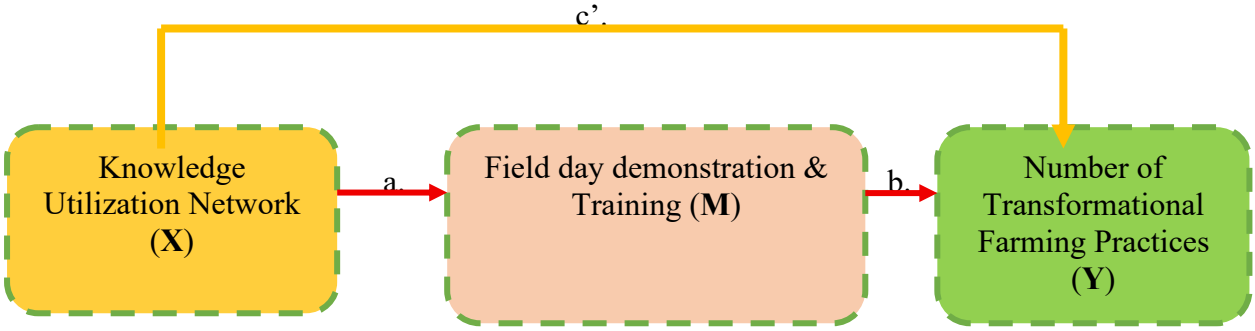

Figure 6.1. Mediation path effect of knowledge utilization network

Where:

X: Knowledge utilization network refers farmers connections to farmer's cooperative, extension workers, social relation, cooperative and extension, cooperative and social relation, and social and extension workers. Knowledge use network affects the number of transformational farming practices through mediation variables (field day demonstration, and training). It is casual relationship between X, M and Y (Morgan, 2013).

M: mediators variable for knowledge use networking is field day demonstration, and training participation which influences number of transformational farming practices.

Y: It is the outcome variable which directly influenced by the variable X and indirectly through the variable M.

To regress the independent variable (X) on the dependent mediation variables (M), we used the logit-linear model and is specified as:

$$logit\big(P(Field\ day\ demonstration = 1|X, C)\big) = \alpha_0 + \alpha_1 X_i + \alpha_2 C_i \quad (17)$$

$$logit\big(P(Training\ Participation = 1|X, C)\big) = \beta_0 + \beta_1 X_i + \beta_2 C_i \quad (18)$$

Where: X_i is knowledge utilization network (farmers' cooperative, extension worker, social relation, cooperative plus extension worker, cooperative plus social relation, and social relation plus extension worker). C_i refers control variables such as age of farmers, sex of the household, education, farm land size, being model farmer, farm income, and farmers perception on social networking. $\alpha_0, and\ \beta_0$ are coefficient of constant parameters for field day demonstration and training participation respectively. And $\alpha_i, and\ \beta_i$ are coefficient of the estimated knowledge utilization network and control variables. There are five methods

commonly used to compute the indirect effect of mediation variables. The product coefficient is the most widely recommended method, especially when used with bootstrapping (Sobel, 1982). The difference in coefficient method, introduced by (Baron & Kenny, 1986), involves subtracting the direct effect from the total effect. Bootstrapping, as detailed by (Preacher& Hayes, 2004) and (MacKinnon et al., 2004), is another effective approach. Structural equation modelling, which integrates indirect paths within a system of equations, is discussed by (Kline, 2011). Finally, the Monte Carlo method is useful for computing confidence intervals (Preacher & Selig, 2012). To test the indirect effect of mediation, we apply the product coefficient method when normality is assumed (Baron & Kenny, 1986; Sobel, 1982).

$$nlcom(_b[M_1] * _b[X_i]) \quad (19)$$

$$nlcom(-b[M_2] * -b[X_i]) \quad (20)$$

Alternatively, (MacKinnon et al., 2004; Preacher & Hayes, 2004) introduced the bootstrapping method if the dependent variable is not normally distributed. The estimation procedure is as follows:

$$Path\ a: logit\ MX; Scalar\ a = _b[X] \quad (21)$$

$$Path\ b: nbregY\ M\ X; Scalar\ b = _b[M] \quad (22)$$

Then compute the indirect effect as return scalar ab = a*b and now set bootstrapping methods as follows.

$$bootstrap\ ab = r(ab), reps(1000)\ seed\ (12345): mediate \quad (23)$$

Where: M_1 refers the first mediation variable "Field Day demonstration" M_2 refers the second mediation variable "Participation in Training", X_i refers knowledge utilization network (farmers' cooperative, extension worker, social relation, cooperative plus extension worker, cooperative plus social relation, and social relation plus extension worker).

To test overdispersion, the median of the dependent variable should higher than the mean. To counter balance the biasedness, robustness was employed by comparing results of the negative binomial regression model with those of the general structural equation model (GSEM). Using the command '*estat ic*,' we compared the model's AIC and BIC values. The AIC and BIC for the negative binomial regression model were 2106.412 and 2175.178, respectively, while for GSEM, they were 3078.129 and 3260.154, respectively (see Table 6.9). For the interpretation of the results, we selected the model with the lower AIC and BIC values, concluding that the negative binomial regression model is the relatively fit for the

estimations of the variables. A multicollinearity test was conducted and found with a mean VIF of 1.43 and revealed that variables were not seriously correlated (see Table 6.5). Additionally, to address heteroskedasticity, we used robust standard errors to ensure stable coefficients, reliable p-values, and standard errors.

6.4. Variable Definition and Working Hypothesis

6.4.1. Dependent variable

Number of Transformational Farming Practices: This is a discrete variable, based on count data, refers to typical farming practices employed by farmers. These practices include agronomic methods, technology adoption, and marketing participation, all of which help improve farmers' agricultural livelihoods. The effectiveness of these practices is influenced by farmers' access to knowledge and their participation in training and field day events.

6.4.2. Independent variables

Below table shows independent variables used to estimate the number of transformational farm practices (See Table 6.1 below)

Table 6.1. Independent variable description and expected sign

Variables	Type	Expected sign on Transformational farm practices
Knowledge source from farmers' cooperative	Dummy (1=yes; otherwise=0	+
Knowledge source from social capital	Dummy (1=yes; otherwise=0)	+
Knowledge source from extension service	Dummy (1=yes; otherwise=0	+
Knowledge source from cooperative & social capital	Dummy (1=yes; otherwise=0	+/-
Knowledge source from cooperative & Extension	Dummy (1=yes; otherwise=0	+/-
Participation in field day demonstration	Dummy (1=yes; otherwise=0	+
Participation in training	Dummy (1=yes; otherwise=0	+
Age of the household head	Continuous	-
Sex of the household head	Dummy (1=male 0=No)	+
Education level in years of schooling	Continuous	+
Total farm size in hectare	Continuous	+
Farmer is model farmer	Dummy (1=Yes; 0=No)	+
Farm income in logarithm	Continuous	+
Perception on networking	Dummy (1=Yes; 0=No)	+/-

Source: Authors.

6.5. Result and Discussion

6.5.1. Distributions of farmers by knowledge utilization network categories

Farmers in the study areas accessed knowledge from both single and hybrid sources. Figure 6.2 below shows that 39.96% (n=207) of farmers obtained knowledge through agricultural extension workers, while 19.5% (n=101) accessed it via farmers' cooperatives. In rural Ethiopia, extension workers and farmers' cooperatives primarily facilitate the dissemination of improved agricultural technologies to farmers. Additionally, 25.1% (n=130) of farmers utilized both cooperatives and extension workers for knowledge acquisition. Approximately 7.91% (n=41) relied on social networks, 6.18% (n=32) combined social networks with extension workers, and 1.35% (n=7) depended on cooperatives alongside social networks.

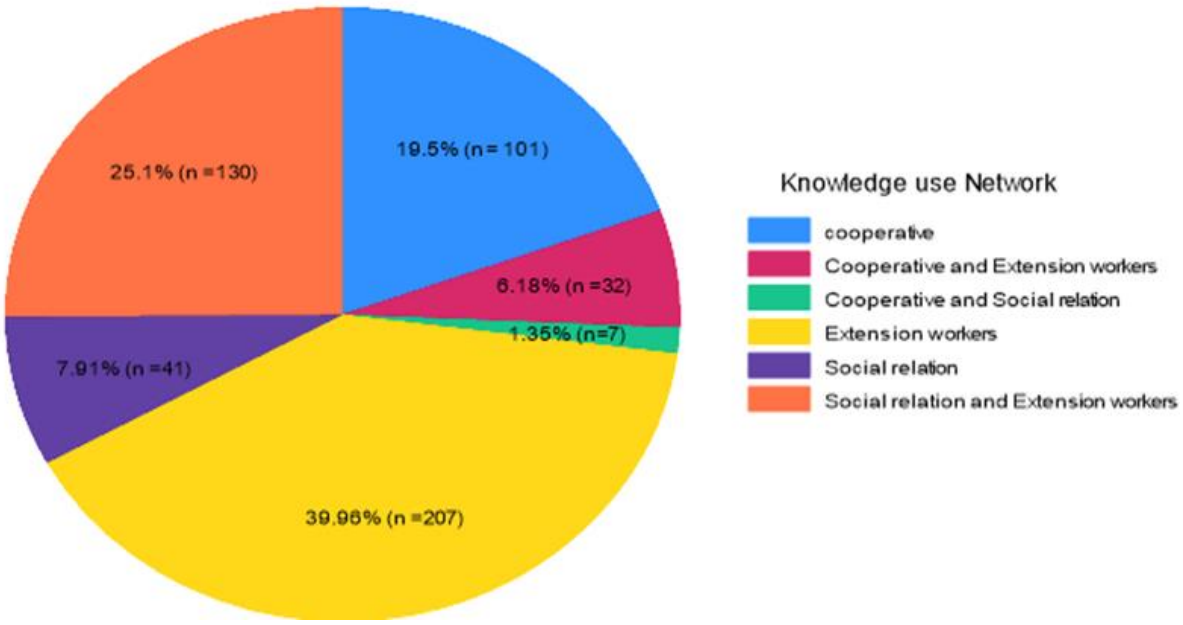

Figure 6.2. Pie chart of the distribution of knowledge utilization networks
Source: Own survey data (2024).

Furthermore, the relational frequency of knowledge sources and transformational farming practices was described in Figure 6.3 below. Hence, the connection between transformational farming practices and acquiring knowledge through extension services, a mix of extension services and social capital, and cooperatives was very strong. In otherwards, the node is relatively close to the transformational farming practices and higher frequency. Specifically, 207 farmers were connected to extension services to adopt transformational farming practices, while 130 and 101 farmers used a mix of extension services and social capital, and

farmers' cooperatives, respectively. In contrast, only a very small number of farmers, specifically 7, accessed knowledge through a mix of cooperatives and social capital.

Additionally, the number of farmers who accessed knowledge through a mix of cooperatives and extension services was 32 and 41, respectively. These findings suggest that farm transformational practices had less derived by knowledge dissemination through mixed sources of cooperatives and social capital as compared to extension services and farmers' cooperatives. Therefore, formal institutions such as agricultural extension services and farmers' cooperatives are more influential than hybridized sources of knowledge to enhance the number of transformational farming practices.

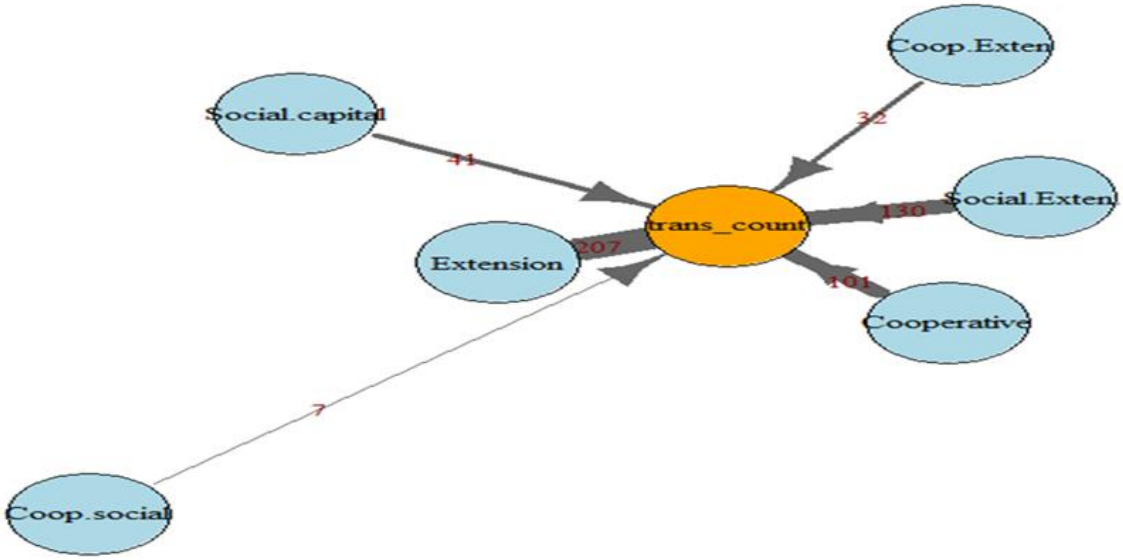

Figure 6.3. Relational frequency of knowledge sources to transformational farming practices
Source: Own survey data (2024).
Hint: '*trans_count'* is the dependent variable referring number of transformational farm practices.

6.5.2. The distribution of farmers by types of farm transformational practices

We observed heterogeneity in the number of farmers practicing different agricultural technologies. About 82.23% (n=347) sampled farm households engaged in mechanization, with farmers using herbicides to eliminate weeds. However, the use of tractors for plowing farmland is very low, with only 12.32% (n=52) farmers reported during the survey period (see Table 6.2) This implies that the majority of farmers are not using tractors to plow their land, which may be due to limited access to rental services, locational barriers, or a lack of interest in using tractors. On the other hand, participation in agricultural irrigation, and

production of cluster commodity is also increasing, with 56.87% (n=240) and 57.82% (n=244) farmers reported, respectively. Likewise, the use of high-yielding seed varieties is relatively large among farmers, who are practicing row planting. It shows that government initiatives have encouraged the adoption of row planting techniques though most Ethiopian farmers have traditionally used the broadcast sowing method.

Regarding the adoption of crossbred dairy cows and improved egg-laying poultry, 48.10% (n=203) and 70.85% (n=299) farmers reported implementing these technologies, respectively (Table 6.2). However, the improvements in productivity and benefits depend on the farmers' managerial skills, which require continuous institutional support. In general, changing agronomic practices, improving livestock productivity, and utilizing agricultural mechanization are key strategies in Ethiopia's agricultural transformation plan. However, the program has not yet been enhanced at a wider community level and needs attention to strengthen stakeholder cohesion to transform the subsistence-dependent farming system.

Table 6.2. The distribution of farmers by on-farm transformational practices

	Who Practiced		**Who don't**	
On-Transformational Practices (N=442)	**Freq.**	**Percent**	**Freq.**	**Percent**
Adopt a crossbreed dairy cow	203	48.1	219	51.9
Adopt improved egg-laying poultry	299	70.85	123	29.15
Participated in agricultural irrigation	240	56.87	182	43.13
Adopted row planting techniques	229	54.27	193	45.73
Applied herbicides to elimination weeds	347	82.23	75	17.77
Practiced intercropping techniques	131	31.04	291	68.96
Practiced crop rotation techniques	325	77.01	97	22.99
Use high-yield seed varieties	289	68.48	133	31.52
Participated in the production of cluster commodities	244	57.82	178	42.18
adopted methods for compost preparation and application	203	48.1	219	51..90
Adopted forage development on farmland	253	59.95	169	40.05
Planting according to weather report information	206	48.82	216	51.18
Cultivate the land using tractor	52	12.32	370	87.68
Adopt a market-oriented production approach	187	44.31	235	55.69

Source: Own survey data (2024).

6.5.3. Summary of the descriptive analysis

In the study areas, farmers adopted a minimum of 2 and a maximum of 14 farm practices. On average, farmers implemented approximately eight practices, indicating that on-farm transformation is influenced by their access to knowledge through various networking channels. About 49% of farmers connected with agricultural extension services to obtain information. Additionally, 31% of farmers combined social capital with extension services for knowledge acquisition. Farmers' cooperatives offer another avenue for accessing knowledge, with 24% of farmers engaging with them. However, only a small percentage (1.6%) of farmers utilize cooperatives alongside social capital for knowledge networking (see Table 6.3 below).

Table 6.3. Summary of the descriptive statistics

Variables	Obs	Mean	Std.Dev	Min	Max
On farm transformational practices	422	7.941	3.106	2	14
Farmers' cooperative	422	0.239	0.427	0	1
social capital	422	0.097	0.299	0	1
Extension workers	422	0.490	0.500	0	1
Cooperative and social capital	422	0.016	0.128	0	1
Social and extension workers	422	0.308	0.462	0	1
Cooperative and extension workers	422	0.076	0.265	0	1

Source: Own survey data (2024).

Furthermore, we found a very weak relationship between the practices, except for a moderate relationship between herbicide application and the use of improved seeds (r=0.544), herbicides and crop rotation (r=0.568), while weather information and crop rotation were r=0.503. This indicates they are correlated moderately and the remaining farm practices had weak correlation which was r<0.50. However, the complementarity between the practices were acknowledged, despite the study was interested in counting the number of transformational farming practices (see Table 6.4. below).

Table 0.1. The result of the correlation coefficient of transformational practices

	Transformational Practices	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Adopt a crossbreed dairy cow	1.000													
(2)	Adopt improved egg-laying poultry	0.262	1.000												
(3)	Participated in agricultural irrigation	0.189	0.257	1.000											
(4)	Adopted row planting techniques	-0.211	0.219	0.295	1.000										
(5)	Applied herbicides to elimination weeds	0.323	0.365	0.394	0.308	1.000									
(6)	Practiced intercropping techniques	0.017	0.266	0.333	0.449	0.314	1.000								
(7)	Practiced crop rotation techniques	0.189	0.232	0.275	0.283	0.568	0.357	1.000							
(8)	Use high-yield seed varieties	0.315	0.265	0.371	0.053	0.544	0.398	0.533	1.000						
(9)	Participated in cluster farming	-0.051	0.125	-0.089	0.322	0.345	0.056	0.255	0.066	1.000					
(10)	adopted compost preparation and application	0.256	0.107	-0.037	0.013	0.277	-0.034	0.248	0.315	0.235	1.000				
(11)	Adopted forage development on farmland	-0.118	0.102	0.141	0.134	0.377	0.008	0.295	0.313	0.287	0.248	1.000			
(12)	Planting based on weather information	0.162	0.293	0.353	0.226	0.357	0.503	0.415	0.471	0.028	0.028	-0.023	1.000		
(13)	Cultivate the land using tractor	0.116	0.402	0.53	0.488	0.214	0.461	0.209	0.224	0.244	0.319	0.347	0.398	1.000	
(14)	Adopt a market-oriented production	0.151	0.202	0.468	0.392	0.311	0.484	0.299	0.319	0.105	0.031	-0.017	0.459	0.401	1.000

Source: Own survey data (2024). r = 0.00-0.19 (very weak), 0.20-0.39 (weak), 0.40-0.59 (moderate), 0.60-0.79 (strong), 0.80-1.00 (very strong (source: Cohen, 2009).

6.5.4. Results of the correlation coefficient for explanatory variables

The pairwise correlation shown in Table 6.5 illustrates the relationships among the variables used to analyse the impact mechanism of the knowledge network on farm transformation practices. Knowledge network use, facilitated by interactions of farmers' cooperatives with social capital, was negatively associated with the transformational farming practices. Conversely, agricultural extension workers exhibited a strong positive correlation (0.910) with transformational farming practices. Knowledge networking involving cooperatives and extension services showed a weak positive correlation (0.110) with transformational framing practices, while the combination of social and cooperative factors demonstrated an even weaker correlation. Mediation variables, such as farmers' field day demonstrations and training, had strong positive correlations with values of 0.62 and 0.79, respectively. Control variables—including household sex, age, education, being a model farmer, income, perception of social networking, and farm size—were positively correlated with on-farm transformation practices.

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Table 0.2. Result of correlation coefficient and multicollinearity

Variables	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Transformational practices		1.000															
(2) Cooperative	2.17	0.130	1.000														
(3) Social capital	1.53	-0.087	-0.184	1.000													
(4) Extension	2.80	0.910	-0.106	-0.018	1.000												
(5) Cooperative and Social	1.09	-0.056	-0.073	-0.043	-0.016	1.000											
(6) Social and Extension	1.35	0.037	-0.073	0.058	-0.059	-0.046	1.000										
(7) Cooperative and Extension	1.51	0.110	-0.139	-0.094	0.041	-0.037	0.003	1.000									
(8) Field day Demonstration	1.16	0.621	-0.064	0.340	0.111	-0.028	0.014	0.051	1.000								
(9) Participation in Training	1.14	0.790	0.054	-0.118	0.154	0.093	-0.032	0.488	0.231	1.000							
(10) Age of the Household	1.41	0.043	-0.096	-0.041	0.018	0.122	0.008	-0.017	0.144	0.079	1.000						
(11) Sex of the Household	1.09	0.134	0.074	-0.045	-0.015	0.058	-0.043	0.009	0.012	0.003	0.014	1.000					
(12) Educational level of HH	1.34	0.115	0.016	0.001	0.099	-0.024	0.025	0.088	0.116	0.085	-0.351	0.201	1.000				
(13) Being a model farmer	1.27	0.302	-0.029	0.081	-0.091	-0.046	0.082	-0.158	-0.203	-0.158	-0.153	-0.180	-0.206	1.000			
(14) Size of farm Land	1.35	0.260	0.037	-0.038	0.072	-0.019	-0.009	0.017	0.168	0.073	0.342	0.109	-0.049	-0.307	1.000		
(15) Income in logarithm	1.11	0.129	0.034	0.011	0.085	-0.032	-0.023	0.028	0.041	-0.016	0.038	0.011	-0.047	-0.132	0.274	1.000	
(16) Perception on Social NW	1.12	0.226	0.037	-0.026	0.102	-0.066	0.074	0.024	0.172	0.148	0.045	0.008	0.096	-0.166	0.191	0.115	1.000
Overall VIF	1.43																

Source: Own survey data (2024). r = very strong (≥0.70), strong (0.50-0.70), weak (0.10-0.30), none (< 0.10).
Hint: VIF (Variance Inflation Factor), HH (Household), and NW (Network).

6.5.5. Result of focus group discussion

A focus group discussion was conducted with a total of 60 smallholder farmers (42 males and 18 females). The minimum and maximum age of the participant was 35 and 57 years, respectively. From each five districts, 12 smallholder farmers were held for group discussions between November 10, 2024, and November 15, 2024. The average duration of the discussions was 2 hours, emphasizing on knowledge networking access, opportunities and challenges of agricultural transformation practices. Accordingly, discussants consistently highlighted that extension workers are the main channel for accessing agricultural knowledge, even though limitations in acquiring the necessary agricultural inputs. This means, farmers noted that seeds and fertilizers are not adequately available, which can impact production decisions. Additionally, the lack of road infrastructure inhibits access to training centers and farmers' cooperatives, making it difficult to obtain information. This is because of the farmer training centers and offices of the cooperatives are not conveniently located in their village so that farmers often rely on friends or neighbors for information.

> *"We complain the extension services and farmers' cooperatives to provide adequate information on agricultural technologies. Consequently, district agricultural offices have admitted several times and promise to improve the quality of their services; however, their efforts to tackle the challenges is minimal and inadequate*."

> On the other hand, discussants raised opportunities and challenges related to farm transformation. They highlighted that the adoption of improved agricultural technology and agronomic practices enhances their farm productivity. Consequently, field day demonstrations and occasional training sessions were beneficial for acquiring agricultural knowledge. Despite this, issues such as land size, irregular awareness among farmers, and unfair selection for attending field days and training opportunities were dominant problems. *"It is pertinent that unfair selection for participation in field day demonstrations and access to training is common, with advantages given to model farmers while other fellow farmers are sometimes ignored and miss the opportunity to acquainted with newly released agricultural technologies."* Generally, participants in the focus group discussion understood the benefits of extension services and cooperatives that provide new agricultural knowledge, which enables the adoption of transformational farm practices to improve their agricultural livelihoods.

6.5.6. Results of econometrics model

The dependent variable in this model is the number of farm transformational practices implemented by farmers in the study areas. The negative binomial regression model was used to measure counting data representing total number of farming practices, not the complementary practices. The model assumes independence of explanatory variables. To check the independence of explanatory variables, we conducted pairwise correlation and found relatively weak relation though contain biasedness (Table 6.5 above). In addition, the control function was tested after running the second stage of negative binomial regression and found $p < 0.001$, which is statistically significant, confirming the presence of endogeneity. Furthermore, bootstrapping regression methods were used for the control function to ensure that the standard errors and p-values are valid even though the model has endogeneity in the first probit. Hence, we confirmed that instrumental variables were used along with control variables to estimate the direct effect of knowledge-use networking on farm transformation.

6.5.7. Direct effect of knowledge utilization on farm transformational practices

As described in Table 6.6 below, knowledge utilization through farmers' cooperatives, extension services, and social capital is endogenous with the number of transformational farm practices. Hence, we employed an instrumental variable to control for biased estimation of the direct effect on the outcome variable. Accordingly, distance to the closest cooperative center and farmer training center as an instrument to address any endogeneity of knowledge sources through cooperative and extension service access. Aside from their impact on participation (exogeneity), these factors are expected to influence the likelihood of joining cooperatives and extension program (relevance) but not directly affect the outcomes of farm transformation. Rather than directly altering the transformation process, it is assumed that physical proximity influences information exposure and ease of access. Likewise, attending community-level meetings provides farmers with the opportunity to engage, develop trust, and make decisions collectively. Social connections facilitate knowledge sharing to enhance social capital. However, aside from their influence on farmer collaboration and social networks, attending such events has no direct impact on farm transformation practices or production.

In the first stage, a probit model was used to regress instrumental variables on dummy knowledge sources. The endogeneity test was not applied when farmers combined sources from the aforementioned channels. Thus, for each dummy knowledge source, fitted probabilities and residuals were computed. The residual for a probit regression computes a generalized residual to adjust for the binary nature of the variables (Gourieroux et al., 1987). Finally, the corresponding variables were tested for endogeneity and found to be significant at $p < 0.01$, confirming that knowledge-use networking through farmers' cooperatives, extension services, and social capital is endogenous to transformational farming practices.

Accordingly, with controlled variables, the distance to the cooperative center decreases the probability of participation in farmers' cooperatives by 2%, whereas without controls, this decrease is 2.8% and is significant at $p<0.001$ (see Table 6.6). The distance to the cooperative center influences the frequency of attending training, resulting in a low frequency of participation and inadequate agricultural knowledge acquisition through farmers' cooperatives. This finding is consistent with (Ahmed & Mesfin, 2017; Miroro et al., 2023; Rwela, 2023), which indicate that geographical heterogeneity influences farmers' membership in cooperatives.

Likewise, the distance to farmers' training centers decreases the probability of access to agricultural extension services by 31.4% with control and by 4% without control, respectively. This effect is significant at $p<0.01$ (see Table 6.6). Agricultural extension workers demonstrate and arrange training on improved agricultural technologies at farmer training centers (FTCs). Consequently, farmers who are located further away from the training center have less access to the knowledge needed to adopt better agricultural practices through extension services. The result is similar to a study conducted in Ethiopia by (Alemu, 2021; Gebremariam et al., 2021), which found that distance from farmer training centers reduces farmers' interaction with extension services.

On the other hand, farmers' social interactions at the community meeting level are vital for enhancing social bondage. Accordingly, participation in community meetings increases the probability of establishing social capital by 7.1% with control and by 5.9% without control of other variables, respectively (see Table 6.6). This suggests that relationships built during interactions at meetings strengthen farmers' linkage, thereby opening opportunities to share agricultural knowledge. In other words, it establishes an agenda to discuss their agricultural

production challenges and opportunities. This result is similar to the study conducted by (Duguma, 2022; M. Lemma et al., 2025), which showed that community-level dialogue enables mutual learning, helps to solve communal problems, and creates self-awareness.

Subsequently, an increase in the age of farm household heads decreases the probability of membership in farmers' cooperatives by 0.7%, holding other factors constant. This suggests that getting older influences the frequency of visits and access to agricultural knowledge. The result is consistent with (Gebremariam et al., 2021), who found that as age increases, farmers' interaction levels through cooperatives decline. Additionally, (Miroro et al., 2023) reported mixed results, indicating that older farmers' perceptions either positively or negatively affected their participation in cooperatives.

On the other hand, an increase in the educational level and farm land size increases the probability of connecting to extension services by 0.6% and 3.9%, respectively (see Table 6.6). This implies that a higher educational level enhances the capability to access information and influences active participation in agricultural extension services. The same finding also reported that an increase in educational level enhances farmers' access to extension services (Gadissa, 2023; Midamba & Ouko, 2024). Similarly, farmers with relatively larger farm sizes are more likely to link with extension services to access improved agricultural knowledge. The finding is consistent with (Gashu & Beyene, 2024; Midamba & Ouko, 2024; Shitaye et al., 2025), which indicate that farmers with larger hectares of land have access to agricultural extension services to improve their farm businesses. Overall, the findings in the first stage showed that locational differences and community meeting participation influence access to agricultural knowledge channels. Moreover, control variables such as farm land size, education level, and the age of farmers significantly influence knowledge use through farmers' cooperatives, extension services, and social relations.

Table 6.6. First stage estimation of instrumental variables using probit model regression

	Knowledge use base source								
	Farmers' Cooperative			Extension service			Social capital		
Variables	dy/dx	Robust std.err.	p|z|	dy/dx	Robust std.err.	p|z|	dy/dx	Robust std.err.	p|z|
With out control variables									
Distance from farmers' cooperative center in hour	-0.020**	0.032	0.039						
Distance from farmers' training center in hour				-0.314***	0.105	0.003			
Participation in community meeting							0.071**	0.170	0.019
With control variables									
Distance from farmers' cooperative center in hour	-0.028***	0.035	0.007						
Distance from farmers' training center in hour				-0.040***	0.108	0.010			
Participation in community level meeting							0.059**	0.181	0.042
Age of farm household head in year	-0.007***	0.008	0.005	-0.002	0.009	0.679	-0.001	0.001	0.794
Education in years of schooling	0.004	0.018	0.469	0.006**	0.022	0.049	0.001	0.023	0.831
Model farmer	0.018	0.149	0.649	0.056	0.182	0.056	0.027	0.181	0.337
Farm land size in hectare	0.026	0.068	0.212	0.039**	0.094	0.015	0.002	0.087	0.675
Total number of livestock in TLU	-0.029	0.015	0.523	0.001	0.017	0.721	-0.005	0.022	0.123
Annual farm income in logarithm	0.005	0.053	0.524	0.003	0.038	0.660	0.007	0.039	0.301
No. of obs = 422									
Wald chi2 (7) = 12.88									
Prob chi12 = 0.0150									
Pseudo R^2 = 0.0312									

Source:. Own survey data. (** and ***, 5% and 1% probability level

In the second stage, we estimated the direct effect of knowledge use sources on transformational practices. The residuals computed for farmers' cooperatives, extension services, and social capital were included in the second stage as explanatory variables. The results were interpreted using the incidence rate ratio (IRR), which is technically more feasible than the coefficient. If the IRR is higher than 1, it indicates that the variable increases the expected count of the outcome. Conversely, if it is less than 1, the variable decreases the expected count of the outcome, while an IRR equal to 1 indicates no effect (Cameron & Trivedi, 1998). As described in Table 6.7 below, a farmer who utilizes knowledge through farmers' cooperatives reduces the expected count of transformational farm practices by 30.9% (IRR = 0.691, $p < 0.01$), holding other variables constant. This suggests that some farmers located a considerable distance from the farmers' cooperative center may not adopt improved agricultural practices due to inaccessibility to knowledge dissemination through the cooperative. It is argued by (Miroro et al., 2023; Rwela, 2023) that distance negatively influences the type and intensity of technology adoption among farmers who are members of cooperatives.

Comparatively, farmers who network with extension services increase the expected count of transformational farming practices by 34.9% (IRR = 1.349, $p < 0.01$), keeping other variables constant (see Table 6.7). This implies that extension services provide an opportunity to disseminate agricultural knowledge, thereby enhancing the number of transformational farming practices. It is apparent that the Ethiopian government has assigned agricultural extension workers in each village, with expertise in Animal Science, Plant Science, and Natural Resource Management. This result is similar to study conducted by (Prajapati et al., 2025) indicating agricultural extension services empowers farmers, enhance participatory effort and enable decision-making through knowledge dissemination. High demand for agricultural products also raises knowledge generation through extension service in Ethiopia (Gatdet, 2022).

On the other hand, using knowledge networking through social capital reduces the expected count of transformational farming practices by 90.4% (IRR = 0.096, $p < 0.05$) (see Table 6.7). This may be due to the social capital gained from community meetings, which can lead to inaccuracies in knowledge, as well as reliance on traditional, impractical information associated with conventional practices. Additionally, while farmers possess social capital, their willingness to take risks may decrease the number of innovative farming practices

implemented. This finding aligns with (Lai et al., 2025), which found that social capital negatively impacts conservation tillage, as farmers reinforce their existing practices rather than adopting new technologies.

Furthermore, an increase in age reduces the expected count of transformational practices by 0.5%, holding other variables constant. This suggests that some older farmers may reduce certain practices that are difficult to manage. In other words, getting older may not completely diminish the tendency towards transformational practices. Additionally, an increase in the size of farmland, measured in hectares, increases the expected count of transformational practices by 4.9%, holding other variables constant. The results indicate that a larger size of farmland is advantageous for implementing a greater number of transformational farming practices. It also enables farmers to diversify their portfolios and effectively utilize their land resources. The fining in this study consistent with study by (Hu et al., 2022). Moreover, (Girma Asefa & Ayalew Muluken, 2024; Hailu et al., 2024; Isgin et al., 2008) ;Hailu et al., 2024; Parré et al., 2024) found that farm land size affects farmers' willingness, technical preferences, perceptions to adopt improved agricultural practices, and the number of technologies adopted.

Nevertheless, the proactiveness of the farmer in becoming acquainted with better farming practices enables them to become a model (lead) farmer. This represents those farmers who are proactive in adopting better agricultural technologies and are motivated to improve their agricultural livelihood. The Ethiopian government annually provides an award by selecting farmers who improve their agricultural productivity through the use of agricultural technologies, designating them as ‘model farmers’. Hence, a change to being a model farmer increases the expected count of transformational farming practices by 87%, holding other variables constant (see Table 6.7). This suggests that the motivation created by the government and among farmers encourages the practice of better agricultural production techniques, thereby improving traditional farming methods.This finding is consistent with (Holden et al., 2018), which indicates that lead farmers in Malawi are more likely to adopt conservation agricultural practices.

Table 6.7. Results of the second stage using the Negative Binomial regression model

Number of transformational practices	Coeff.	IRR	Robust std.err.	p>|Z|
Knowledge use via farmers' cooperative	-0.370	0.691***	0.075	0.001
Knowledge use via extension services	0.299	1.349***	0.105	0.000
knowledge use via social capital	-0.301	0.740**	0.096	0.021
Age of farm household head in year	-0.005	0.995**	0.002	0.011
Education in years of schooling	0.004	1.001	0.004	0.402
Dummy being a model farmer	-0.139	1.870***	0.034	0.000
Farm land size in hectare	0.047	1.049***	0.018	0.007
Annual farm income in logarithm	0.007	1.006	0.008	0.422
Residual farmers' cooperative	0.058	1.061	0.016	0.000
Residual extension services	0.006	1.993	0.003	0.040
Residual social capital	0.018	1.019	0.009	0.049
_cons	2.053	7.792	0.144	0.000
/lnalpha	-16.609		0.617	
Alpha	4.40e-08		2.72e-08	
Number of obs = 422				
Wald chi2(12) = 158.86				
Prob > chi2 = 0.0000				
Pseudo R2 = 0.1506				

Source: Own survey data (2024). ** and *** indicates 5% and 1% probability level.

6.5.8. Result of the mediation analysis

The mediator variables used in this analysis are 'field day demonstration' and 'participation in training,' which indirectly impact the use of knowledge in farm transformations. Both the log-linear model and the General Structural Equation Model (GSEM) were employed for estimation. Based on model selection criteria, the model with the lowest AIC and BIC values was chosen to present the results, and the log-linear estimation was used to interpret these findings.

The results in Table 6.8 indicate that farmers' connections to extension services increase the log-odds of participating in field day demonstrations by 0.831, which is significant at $P < 0.05$. In the study areas, extension workers demonstrate improved agricultural technologies at Farmer Training Centres (FTCs) located in the villages. This approach enables them to share knowledge among farmers and empowers the farmers. Similar findings argued that extension workers arrange multi-stakeholders' demonstrations to trade-off knowledge based on user

driven (Adamsone-Fiskovica & Grivins, 2022). In addition, interventions of extension services through on-farm demonstration improves knowledge of agricultural technologies (Hussain & Maharjan, 2025).

Furthermore, a combined networking to cooperatives and agricultural extension services are more likely to adopt agricultural practices through training participation. Specifically, being connected to these networks increases the log-odds of participating in training by 1.24, a result that is statistically significant at $p < 0.01$ and has a positive sign (see Table 6.8). Extension service is more effective to transfer knowledge via conducting training (Abebe & Wolteji, 2024; Asante et al., 2024; Megersa et al., 2023; Mesfin et al., 2023). Though other knowledge utilization networks do not show significant effects on field day demonstrations, they exhibit a positive trend.

Additionally, control variables such as the farmer's age increase the log-odds of attending field day demonstrations by approximately 0.041, which is significant at $p < 0.01$. This is practical for farmers in the active age group; however, it declines for older farmers. In our dataset, the majority of farmers were aged below 50 years, suggesting they are able to participate in field days. This finding aligns with (Sutherland et al., 2021), who found that younger farmers attend field day demonstrations more than older farmers. farmer's educational level also increasing the log-odds of attending field day demonstrations by 0.087 and is statistically significant at $p < 0.05$ (see Table 6.8). Education gives farmers the advantage of connecting with agricultural extension workers, providing them with opportunities to attend field days and acquire complementary knowledge. This finding aligned with (Noor-E-Sabiha, 2017) showed that education enabling farmers to strongly connected to extension services.

A dummy change to designate as model farmer reduces the log-odds of attending field day demonstrations to share knowledge and experience by 0.609. This suggests that model farmers are less likely to participate in such demonstrations compared to non-model farmers. A possible explanation is that field day demonstrations often present technologies or practices that model farmers have already been exposed to, either through earlier training, extension contacts, or prior adoption. As a result, their marginal benefit from attending is lower, and their expectations regarding new knowledge or techniques are limited. Consequently, they may prioritize other activities over attending demonstrations. This finding is consistent with

(Hussain & Maharjan, 2025) found that model farmers less prefer field day visit to attending training. Additionally, farmers' perceptions of social networking positively influence their participation in field days and training. Farmer dummy changes to have good perception to social networking increases the log-odds of attending field days by 1.872, which is statistically significant at $p < 0.05$. Furthermore, it increases the log-odds of participating in training by 1.067, and statistically significant at $p < 0.01$ (see Table 6.8). This illustrates that farmers who understand the importance of social bonds gain valuable information and advantages that encourage their participation in both field days and training. This finding is similar with (Ofolsha et al., 2022; Zeleke et al., 2023) showed that social network linkage to relative and extension workers provides opportunity to participate in field days and training in Ethiopia.

Table 6.8. Results of the log-linear model for estimating mediation variables

	Mediators Dependent Variables							
	Field Day Demonstration				Participation in Training			
Explanatory variables	Coeff.	Robust std.err.	Z	P > |Z|	Coeff.	Robust std.err.	Z	P > |Z|
Dummy Farmers' cooperative	0.280	0.427	0.66	0.519	0.209	0.393	0.53	0.594
Dummy Social capitalization	0.808	0.492	1.64	0.101	-0.797	0.465	-1.72	0.086
Dummy Extension services	0.813**	0.382	2.13	0.033	-210	0.363	0.58	0.562
Dummy Cooperative and social capitalization	-0.210	0.457	-0.14	0.885	1.573	-1.147	1.37	0.172
Dummy social capitalization and extension	0.237	0.292	0.81	0.417	-0.199	0.255	-0.78	0.435
Dummy cooperative and extension	0.724	0.499	1.45	0.147	1.240**	0.494	2.51	0.012
Age of the household head	0.041***	0.015	2.78	0.005	0.018	0.012	1.51	0.130
Sex of the household head	-0.275	0.346	-0.79	0.428	-0.294	0.299	-0.98	0.326
Educational level in years of schooling	0.087**	0.036	2.47`	0.014	0.046	0.305	1.52	0.128
Total farm size in hectare	0.143	0.299	1.18	0.239	0.024	0.106	0.22	0.824
Being a farmer is model (1=Yes;0=No)	-0.609**	0.122	-2.04	0.041	0.338	0.231	-1.47	0.143
Farm income in logarithm	-0.004	0.064	-0.06	0.949	-0.051	0.548	-0.94	0.347
perception on social networking (1=important; 0= Not)	1.872**	0.766	2.44	0.015	1.067***	0.397	2.68	0.007
_cons	-5.275	1.381	-3.82	0.000	-1.700	0.982	-1.73	0.083
	Number of obs. = 422 Wald chi2(13) = 44.86 Prob > chi2 = 0.000 Pseudo R2 = 0.1133				Number of obs. = 422 Wald chi2(13) = 34.09 Prob > chi2 = 0.000 Pseudo R2 = 0.0819			

Source: Own survey data (2024). (** and *** indicating 5% and 1% probability level).

6.5.9. Indirect effect of knowledge use networking on farm transformation

The result presented in Table 6.9 indicates the combined direct and indirect effects of the knowledge use network on farm transformations. Additionally, to enhance the robustness of the analysis, we employ both negative binomial regression and a general structural equation model (GSEM). Both models yield similar results; however, the GSEM output is presented with default standard errors, and the estimation is simultaneous rather than step-by-step, as in the negative binomial regression. Consequently, knowledge networking with agricultural extension services positively and significantly influences the number of agricultural practices conducted on a farm.

Hence, when farmers are connected to extension workers, the expected count of agricultural practices increases by 0.101 in both models and is statistically significant at $p < 0.01$ (see Table 6.9). This illustrates the effectiveness of extension workers in disseminating agricultural technologies and providing support and advice to farmers. Such connections may encourage farmers to diversify their agricultural practices. On the other hand, knowledge use networking indirectly influences the improvement of farm practices adopted by farmers, possibly through participation in field days and training. Extension services improve farm productivity and enhance farmers knowledge use to adopt better agricultural practices (Cawley et al., 2015; Loki & Moda, 2023).

Both field day and training participation increase the log of the expected count of farm transformations by 0.095 and 0.077, respectively, and are statistically significant at $p < 0.05$ (see Table 6.9). This indicates that farmers who participate in the field day program and training have a greater opportunity to gain knowledge and share experiences with one another. As a result, this enhances their decision-making and improves the number of farming practices conducted on their farms. This result aligns with (Hailu et al., 2024), which indicates that effective field days and training enhance farmers' willingness to adopt agricultural practices. Additionally, the complementary use of knowledge generated from training and demonstration by extension workers significantly contributes to sustainable agricultural practices (Mungai et al., 2024; Tamako, Thamaga-Chitja, et al., 2022). Generally, farmers' knowledge used through extension services had both direct and indirect effects on the adoption of various transformational farming practices. This provides an opportunity to obtain formal knowledge to encourages farmers and change traditional farming practices.

Table 6.9. Indirect effect of knowledge use networking on transformational farm practices

	Transformational Farming Practices in count (Dependent variable)					
	Negative Binomial Regression			General Structural Equation Model (GSEM)		
Explanatory variables	Coeff	Robust std.err.	P > |Z|	Coeff	std.err.	P > |Z|
Knowledge use network variables						
Dummy Farmers' cooperative	0.012	0.043	0.332	0.042	0.044	0.346
Dummy Social capitalization	-0.057	0.059	0.109	-0.096	0.063	0.128
Dummy Extension services	0.101***	0.035	0.003	0.103***	0.035	0.004
Dummy Cooperative and social capitalization	0.204	0.152	0.281	0.164	0.129	0.206
Dummy social capitalization and extension	0.004	0.041	0.929	0.048	0.060	0.422
Dummy cooperative and extension	0.089	0.065	0.167	-0.089	0.068	0.190
Mediation variables						
Field day demonstration	0.095**	0.041	0.022	0.095**	0.042	0.023
Participation in training	0.081**	0.039	0.038	0.077**	0.037	0.040
Control variables						
Age of the household head	-0.003	0.002	0.110	-0.004	0.002	0.076
Sex of the household head	0.091	0.055	0.100	0.096	0.051	0.057
Educational level in years of schooling	-0.001	0.004	0.738	-0.002	0.005	0.974
Total farm size in hectare	0.054***	0.016	0.001	0.053***	0.017	0.002
Being a farmer is model (1=yes;0=No)	0.144***	0.038	0.000	0.146***	0.039	0.000
Farm income in logarithm	0.009	0.008	0.261	0.009	0.008	0.277
perception on networking (1=important; 0= Not)	0.194***	0.055	0.000	0.170***	0.063	0.007
_cons	1.939	0.157	0.000	1.976	0.151	0.000
/lnalpha	-16.257	1.458		-17.047	239.29	
Akaike's Information Criteria (AIC)	2106.412			3078.129		
Bayesian Information Criteria (BIC)	2175.178			3260.154		

Source: Own survey data (2024).

6.5.10. Roubsut estimation of the indirect effect in mediation analysis

It is crucial to validate the effect of the knowledge utilization network on farm transformational practices. Before selecting the test method, we examined the normality of the dependent variable by conducting skewness and kurtosis tests. The result indicated P<0.05 and leads us to reject the normality assumption. Consequently, we chose to use the bootstrapping method for our analysis. The result revealed that the knowledge utilization network related to extension services and the interactions of farmers' cooperatives with extension services were significant at P<0.05 (see Table 6.10). The confidence interval did not include zero so that the p-value is significant.

As shown in above Table 6.9, extension services, training, and field day demonstrations significantly affect farm transformational practices. Hencet, the test result showed that the extension services enhance transformational farming practices, partly through training and field day demonstrations. Additionally, interactions between farmers' cooperatives and extension services significantly influence the mediator variable (field day demonstrations). However, when both are regressed simultaneously on transformational framing practices, knowledge utilization networking with a combination of farmers' cooperatives and extension services becomes insignificant, while the mediator variable, field day demonstrations, remains significant. This suggests that the effect of farmers' knowledge networking with farmers' cooperatives and extension services on farm transformational practices is fully mediated by field day demonstrations (see Table 6.10 below).

Table 0.1. Results of the bootstrap analysis to estimate the indirect effect

	Mediator variables					
	M1: Training; M2: Field Day demonstration					Normal-based
Variables	Indirect effect	Observed coefficient	Bootstrap std.err.	Z	P|Z|	[95% conf. Interval]
Farmers' cooperative	Ab	-0.031	0.067	-0.47	0.642	-0.16238 – 0.10078
Social capital	Ab	-0.068	0.093	-0.73	0.466	-0.25006 – 0.11451
Extension services	Ab	0.099**	0.049	2.01	0.044	0.00259 – 0.19576
FS	Ab	0.047	0.133	0.35	0.723	-0.21384 – 0.30807
SE	Ab	-0.004	0.054	-0.08	0.936	-0.11135 – 0.10263
FE	Ab	0.213**	0.095	2.24	0.025	0.02702 – 0.39994

Source: Own survey data (2024). Hint: FS= Farmers' cooperative & Social capital, SE= Social capital & Extension services, FE= Farmers' cooperative & Extension services.

6.6. Conclusion

The study highlights the crucial role of farmers' knowledge networking through cooperatives, extension services, social capital, and a combination of these networks in impacting smallholder farmers' transformational farming practices. The results suggest that improving farmers' access to cooperatives, extension services, and social interactions enhances the implementation of agricultural practices provided that road infrastructure and knowledge disseminations mechanisms is concern for improvements. These findings contribute to a broader understanding of knowledge networking, mediated by field day demonstrations and training participation, which directly and indirectly affect the number of transformational practices adopted. In particular, the role of extension services through training indirectly influences the number of farming practices implemented. Therefore, the Ethiopian government should focus to improve rural road infrastructure, enhance formal knowledge dissemination channels, build extension workers capacity, and upgrade farmers' training centers infrastructure to achieve a sustainable agricultural transformation process.

6.7. Recommendations

The following recommendations are suggested for policy consideration.

- Location variations, such as the distance from cooperative offices and farmer training centers, are negatively influencing farmers' access to knowledge sources. Therefore, to enhance peripheral farmers' participation in extension services and membership in farmers' cooperatives, the government should improve road infrastructure and decentralize the knowledge dissemination system at the village level.
- The community meeting provides an opportunity for farmers to interact with one another. However, formal knowledge should be enhanced through lead farmers to complement the informal knowledge in agricultural practices. This approach highlights the role of social capital in farm transformation.
- Extension services directly and indirectly influence transformational farming practices. In particular, training and field day demonstrations provide opportunities for extension workers to disseminate better agricultural production knowledge to farmers. Therefore, the government should enhance the skills of extension workers and improve the infrastructure of farmer training centers to address knowledge dissemination throughout the farmer community.

7. OVERALL CONCLUSION AND RECOMMENDATIONS

7.1. Conclusion

This study was conducted in the central Oromia region of Ethiopia, where 422 smallholder farm households participated in survey interview questions. It investigates the status of transformational practices in integrating high-value farming, with an emphasis on major cereal and vegetable crops and improved livestock breeds. Furthermore, the study examines the role of high-value farm transformation in contract market participation and food security. Additionally, it addresses farmers' knowledge utilization networks that enable the adoption of a range of transformational farming practices. The study is significant for identifying farm-level transformational features and understanding how high-value farm transformation contributes to market participation, and food security to prosper smallholder farmers. The findings showed that the majority of farmers have engaged to transform high-value crop production, while a relatively low percentage of farmers were transforming their agricultural livelihoods by integrating high-value crops and livestock. While the improvements in farm transformation enhanced the level of high-value farm products sold and improve household food security. It was also observed that the existing transformational practices improves environmental and economic sustainability though social sustainability needs great attention for future. On the other hand, farmers' networking with knowledge sources was influenced by farmer proximety to training center and farmers' coopertaive endogeneity, which affected farming practices. Hence, extension services is indirectly impacted the number of transformational farming practices adopted through field day demonstrations.

However, the study is limited by its cross-sectional design, which does not allow for inferences about long-term farm transformation perspectives. Data were gathered based on farmers' recall and self-reporting, which may have introduced biases. The analysis primarily focuses on smallholder farmers in the central regions of Ethiopia who engage in mixed farming systems and may not represent other parts of the country. Notwithstanding these drawbacks, the study employed robustness tests to ensure the validity of the results and utilized econometric approaches, such as instrumental variable regression, to address any endogeneity. Therefore, it is anticipated that the insights offered will significantly advance our understanding of how transformational status in integrating high-value farms will impact commercialization, food security, and effective knowledge networking to benefit the economy of smallholder farmers in the context of the study areas.

7.2. Recommendations

- The findings of this study underscore the significance of farmland size and the number of livestock in enhancing the status of high-value farm transformation. Therefore, farmers should adopt land intensification system to improve factor productivity and pursue farm diversification.
- Farmers' behaviour to save seed, hire labour, access to credit, and utilise veterinary services are important factors influencing the progress of transformation. Therefore, agricultural stakeholders should improve the quality of service provided to support farm businesses, focusing on capacity building, financial services, and veterinary infrastructure.
- The existing transformational practices of high-value farms has low social sustainability so that government should provide adequate awareness for wider farming community to transform high-value farms that prospers their economic conditions.
- Government should enhance market infrastructure, to transform local food security and facilitate aging farmers market access. Additionally, expand training programs, field demonstrations, and sharing experiences among farmers to encourage widespread adoption of improved technologies.
- Enhance and encourage the role of extension service to support soil fertility management, efficient use of irrigation water, feed development and adoption of improved animal breeds
- Promote diversified food production through delivering information on healthy food consumption. There is also a need to diversify the income source strategy, which may facilitate income allocations to both food and non-food items.
- The community meeting provides an opportunity for farmers to interact with one another. However, formal knowledge should be enhanced through lead farmers to complement the informal knowledge in agricultural practices. This approach highlights the role of social capital in farm transformation.
- The government should enhance the skills of extension workers and improve the infrastructure of farmer training centres to address knowledge dissemination throughout the farmer community.

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9. APPENDIXES

Appendix 2A1. Conversion factor for number of livestock in Tropical Livestock Unit.

Animal Category	TLU
Cow & Ox	1.00
Calf	0.25
Donkey	0.50
Weaned Calf	0.34
Heifer	0.75
Sheep and Goat	0.13
Horse	0.80
Chicken	0.013
Mule	0.70

Source: Strock et al., 1991.

Appendix 2A2. **Summarized probabilities of ordered probit model in estimation of high-value farms transformation status**.

```
summarize p1oprobit p2oprobit p3oprobit
```

Variable	Obs	Mean	Std. dev.	Min	Max
p1oprobit	422	.4891476	.3486239	.0029474	.9999338
p2oprobit	422	.2871135	.1615493	.0000661	.4983907
p3oprobit	422	.2237389	.2556619	1.20e-07	.9206787

Source: Own computation using STATA version 18.

Appendix 2A3. **Test of Multicollinearity among explanatory variables used in ordered probit model .**

Variable	VIF	1/VIF
vetshr	1.67	0.600530
distmkt	1.58	0.632461
agehh	1.49	0.669697
lands	1.44	0.696354
tlu	1.43	0.700329
owbreed	1.38	0.726464
educa	1.30	0.768111
credit	1.26	0.795936
expshare	1.26	0.796648
mktbprd	1.21	0.824148
impegg	1.19	0.840420
fmsize	1.18	0.848791
herbcide	1.17	0.855938
sedsave	1.15	0.870233
fertshort	1.13	0.883350
irrigpart	1.13	0.888754
hlabor	1.12	0.891840
ldivison	1.11	0.902199
frqext	1.07	0.936094
Mean VIF	1.28	

Source: Own computation using STATA version 18.

Appendix 2A4. **Tests of the parallel regression assumption.**

	Chi2	df	P>Chi2
Wolfe Gould	28.72	19	0.070
Brant	30.40	19	0.047
score	29.42	19	0.060
likelihood ratio	31.69	19	0.074
Wald	29.52	19	0.058

Source: Own computation using STATA version 18.

Appendix 2A5. **Ordered probit model specification test.**

Ordered probit regression — Number of obs = 422; LR chi2(2) = 251.43; Prob > chi2 = 0.0000; Log likelihood = -298.70106; Pseudo R2 = 0.3381

tstatsus	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
phat	-3.234552	.8192723	-3.95	0.000	-4.840297	-1.628808
phatsq	-.1433253	.8531694	-0.17	0.867	-1.815507	1.528856
/cut1	-1.674814	.1659716			-2.000112	-1.349515
/cut2	-.3576613	.1388659			-.6298333	-.0854892

Source: Own computation using STATA version 18.

Appendix 2A6. Robustness estimation using the ordered logit model.

Marginal effects after ologit

y = Pr(tstatsus==1) (predict, outcome (Partial))					y = Pr(tstatsus==1) (predict, outcome (Medium))				y = Pr(tstatsus==1) (predict, outcome (Full))			
variable	**dy/dx**	**Std.err**	**Z**	**P>z**	**dy/dx**	**Std. err**	**Z**	**P>z**	**dy/dx**	**Std. err**	**z**	**P>z**
agehh	0.001	0.003	-0.15	0.882	0.002	0.002	0.15	0.882	0.002	0.001	0.15	0.881
fmsize	0.008	0.014	0.58	0.560	-0.005	0.009	-0.58	0.560	-0.003	0.005	-0.58	0.561
educa	0.003	0.008	0.35	0.724	-0.002	0.006	-0.35	0.724	-0.001	0.003	-0.35	0.724
lands	-0.066**	0.027	-2.49	0.013	0.044**	0.018	2.41	0.016	0.022**	0.009	2.40	0.016
ldivison*	-0.117	0.071	-1.66	0.097	0.082	0.051	1.60	0.110	0.036	0.021	1.74	0.081
fertsh~t*	0.138	0.075	1.83	0.067	-0.097	0.057	-1.72	0.086	-0.040	0.020	-2.03	0.042
tlu	-0.024***	0.006	-3.71	0.000	0.016***	0.005	3.45	0.001	0.008***	0.002	3.48	0.000
irrigp~t*	0.082	0.060	1.36	0.172	-0.054	0.039	-1.39	0.165	-0.028	0.021	-1.28	0.199
herbcide*	-0.416***	0.077	-5.38	0.000	0.322***	0.068	4.77	0.000	0.093***	0.018	5.23	0.000
sedsave*	-0.183***	0.069	-2.65	0.008	0.129**	0.052	2.49	0.013	0.054***	0.019	2.77	0.006
hlabor*	0.176***	0.067	2.63	0.009	-0.105***	0.036	-2.90	0.004	-0.071**	0.034	-2.10	0.036
creditS*	-0.175**	0.073	-2.39	0.017	0.122**	0.054	2.25	0.025	0.053**	0.021	2.52	0.012
mktbprd*	0.015	0.060	0.26	0.796	-0.010	0.040	-0.26	0.796	-0.005	0.019	-0.26	0.796
expshare*	-0.072	0.072	-1.01	0.314	0.047	0.045	1.03	0.301	0.025	0.027	0.94	0.345
frqext	-0.007	0.031	-0.21	0.833	0.004	0.021	0.21	0.833	0.002	0.010	0.21	0.833
distmkt	-0.053	0.045	-1.16	0.244	0.035	0.031	1.15	0.249	0.017	0.015	1.16	0.246
vetshr	0.114**	0.056	2.04	0.041	-0.077	0.039	-1.95	0.051	-0.037**	0.018	-2.11	0.035

(*) dy/dx is for discrete change of dummy variable from 0 to 1. Source: Own computation using STATA version 18.

Appendix 2A7. Model selection criteria using AIC and BIC.

Akaike's information criterion and Bayesian information criterion

Order Probit	N	ll(null)	ll(model)	df	AIC	BIC
.	422	-440.2895	-291.4104	21	624.8207	709.7658
Order Logit						
.	422	-440.2895	-292.4141	21	626.8282	711.7733

Source: Own computation using STATA version 18.

Appendix 2A8. Step to compute sustainability score using MFA.

Step 1. Prepare data frame.
Step 2. Create indices for each group's variables and their type.
Step 3. Run Multiple Factor Analysis (MFA).
Step 4. Visualize the result.
Step 5. Interpret the analysis.
Step 6. Statistical testing.

Appendix 2A9. Normality test for overall sustainability index.

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Overall index	422	0.99456	1.571	1.077	0.14075

Source: Own computation using STATA version 18.

Appendix 2A10. Multiple Factor Analysis (MFA)to compute environmental, economic, and social sustainability score.

```
mfa_scores <- as.data.frame(mfa_result$ind$coord)
> head(mfa_scores)
```

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
1	1.9842526	-0.52200595	1.0509464	-0.4732242	0.1489778
2	2.4295584	0.44672345	0.9195867	0.1008509	-0.7550956
3	0.5766351	-1.82308790	-0.4421614	-0.3976281	0.5496505
4	0.6293511	-0.18005082	0.5551653	-0.3650947	-0.3666808
5	1.5778618	-1.24636651	1.3708444	0.4193542	2.0102650
6	-2.4803934	-0.01730924	0.4001366	0.6843429	-0.7298854

Source: R version 4.5.1.

Appendix 2A11. MFA sustainability group contribution.

```
> sustainability_data$Total_Index <- mfa_scores$Dim.1
> mfa_result$group$contrib
```

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
Environmental	34.32330	35.866704	14.37002	15.13953	9.068449
Economic	33.51991	57.225880	53.75606	73.32907	72.665241
Social	32.15679	6.907416	31.87392	11.53140	18.266309

Source: R version 4.5.1.

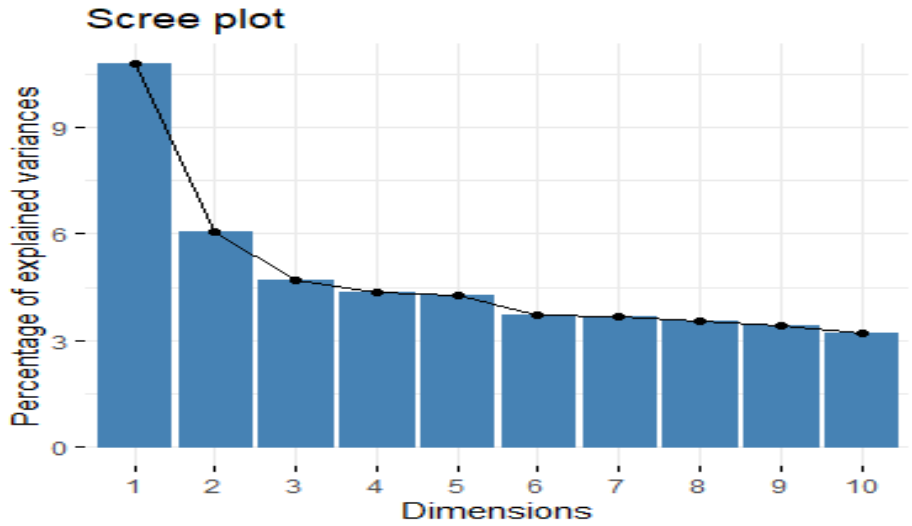
Appendix 2A12. Multiple Factor Analysis indicating variables contribution to each dimension .

```
> mfa_var_contributions <- as.data.frame(mfa_result$quanti.var$contrib)
>                          print(mfa_var_contributions)
```

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
lhvcrop	0.93813168	2.489388e+00	1.510530e-01	2.631379e+00	2.208873e-01
lveg	2.17934003	5.602637e-01	7.782771e-01	2.912048e+00	2.203746e+00
lgraz	0.70072222	3.312509e+00	3.937738e-02	8.024501e-02	2.763159e-01
freqirriga	3.42257411	3.518729e+00	2.854922e+00	2.366520e+00	9.552388e-01
nocbreed	3.55076275	9.281985e+00	2.706913e+00	7.352088e-01	7.316826e-01
TLU	4.90408728	1.429015e+00	1.043147e+00	8.016348e-02	2.365476e+00
irrigpart	4.58459192	2.137198e+00	1.638016e+00	6.790425e-01	7.122282e-01
Rowplant	0.74746250	5.410367e+00	3.332518e+00	3.692741e-01	2.049961e-01
Herbcide	1.06446769	1.620565e+00	6.106208e-03	5.853587e-01	2.591657e-01
cropsys	5.21892157	2.840287e+00	2.609124e-04	2.324604e+00	1.098347e-02
intercrp	2.85307139	2.822584e+00	1.340168e-01	1.154408e-02	3.064423e-01
Crotation	0.58327986	2.381483e-01	2.905930e-01	2.104310e-01	1.204269e-01
seed	2.11297655	7.440578e-02	5.777041e-02	2.153033e+00	6.616219e-01
anfeed	1.46290744	1.312600e-01	1.337050e+00	6.828861e-04	3.923756e-02
AvYProd	2.74393680	3.345990e-02	1.078229e+01	7.499536e+00	4.162122e-01
lnIncome	3.35904932	4.423725e+00	8.178586e-01	1.208965e+01	8.788986e-01
FCS	2.22361172	6.730324e-01	2.029365e+00	2.005732e+01	1.186101e-01
ldivison	0.92443227	1.142339e+00	1.984016e+00	8.260160e-01	3.089969e-02
milkday	5.49724868	1.793517e+01	4.945016e+00	1.379731e+00	2.024408e+00
Informal	3.09792819	7.767067e+00	3.499080e-03	1.478834e+00	2.757144e+00
formal	1.13087520	1.092978e+00	5.229639e-05	1.386266e+01	2.782232e+00
pdtlimit	0.14113423	2.972648e+00	6.726266e+00	1.124243e+00	6.699436e-01
sedmulp	1.47117818	5.512898e-01	1.767234e+01	1.254582e-01	4.134728e+00
rentbull	0.15239567	1.173927e-01	7.345842e+00	5.475409e-01	2.304797e+01
nedrent	0.02291625	1.606424e+00	2.999505e-01	2.061910e-01	3.247999e+01
mktBprd	7.33481048	6.345895e+00	2.881657e-01	3.375800e+00	9.508239e-01
pdtgard	5.27880335	1.085492e+01	3.063671e-01	5.639126e-01	1.001092e-01
crdtcontr	0.14158860	1.709548e+00	5.550377e-01	1.019217e+01	2.273274e+00
prcpGbull	0.07787007	4.884543e-01	4.137050e-01	6.752884e+00	6.186618e+00
sedsave	2.04309045	2.737946e-01	7.903539e+00	1.438727e-02	5.324792e-04
percseed	1.55015155	7.524069e-05	1.065468e+00	1.152449e+00	1.193009e+00
trainmik	3.34687169	2.205105e+00	3.266306e-02	6.110533e-01	1.146661e+00
mktinfDA	1.44225076	4.402028e-01	2.020013e+00	9.111594e-01	1.239864e-01
perption	5.36499046	1.501457e-03	2.214387e+00	1.248067e-01	9.952774e-01
sedMgap	0.17044899	5.712079e-01	1.876512e+00	5.461531e-01	2.184835e+00
comptra	0.05105156	1.178538e-01	6.465698e-01	2.665765e-01	3.207705e-01
factory	3.07388394	5.533699e-02	5.101003e+00	8.793693e-03	3.356270e+00
factlink	4.18699097	1.515505e-01	4.481533e+00	4.128591e-01	1.452760e+00
infoprice	4.29492161	1.186397e+00	4.144294e+00	2.925699e-01	2.502474e-01
network	4.11069831	2.823069e-01	1.480851e+00	6.641868e-03	7.678629e-01
confOrgf	2.44357370	1.133629e+00	4.933771e-01	4.310629e-01	2.874798e-01

Source: R version 4.5.1.

Appendix 2A13. Plotting eigen values to choose dimension.



Source: R version 4.5.1.

Appendix 3B1. Test of Multicollinearity for variables used in double hurdle model.

Variable	VIF	1/VIF
fulstatus	2.00	0.500381
mktefirg	1.84	0.542169
irrigpart	1.82	0.549805
cropsys	1.61	0.622722
expcrbrd	1.60	0.624166
tlu	1.54	0.648562
mstatus	1.51	0.663630
lands	1.49	0.673311
agehh	1.48	0.677671
impegg	1.38	0.725146
disease	1.37	0.729563
educa	1.34	0.745588
npakej	1.30	0.766661
dswzone	1.28	0.778437
mktbprd	1.27	0.787586
anfeed	1.24	0.806082
fmsize	1.24	0.808259
acmktinf	1.21	0.828170
sonwork	1.20	0.833307
trainmik	1.20	0.834883
frqext	1.16	0.860648
vlrestrct	1.16	0.863339
sex	1.15	0.866239
ldivison	1.15	0.868060
distmkt	1.15	0.868303
labrshort	1.14	0.879030
feed	1.13	0.887385
fertshort	1.12	0.888963
trustmkt	1.11	0.903208
crdt	1.09	0.921390
Mean VIF	1.34	

Source: Own computation using STATA version 18.

Appendix 3B2. Functional form of probit model specification test (linktest).

Probit regression — Number of obs = 422; LR chi2(2) = 161.75; Prob > chi2 = 0.0000; Log likelihood = -185.84611; Pseudo R2 = 0.3032

informl	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_hat	1.073687	.1442268	7.44	0.000	.7910082	1.356367
_hatsq	-.0669382	.097002	-0.69	0.490	-.2570587	.1231823
_cons	.0263072	.0881753	0.30	0.765	-.1465133	.1991276

Source: Own computation using STATA version 18.

Appendix 4C1. Distributional differences in food security score between study districts.

Food Profile	District: Ada'a Barga	Bako Tibe	Ilu	Weliso	Welmera	Total
Acceptable FC	55	67	34	32	34	222
Borderline FC	40	25	39	39	23	166
Poor FC	9	3	4	3	15	34
Total	104	95	77	74	72	422

Pearson chi2(8) = 39.1748 Pr = 0.000

Source: Own computation using STATA version 18.

Appendix 4C2. Index to compute village level farm transformational status.

$$Index\ Ratio = \frac{\sum f_i.w_i}{n}$$

Where:

f_i = frequency of the ith response

W_i = weight assigned to the i^{th} response

$\sum f_i.w_i$ = sum of all weighted responses

n = Number of questions (indicators).

After index is computed a new dummy variable is created based on summarized statistics of the index value. Then,

Index Rate

Percentiles		Smallest		
1%	1.22	1		
5%	1.55	1		
10%	1.66	1	Obs	422
25%	2	1.11	Sum of wgt.	422
50%	2.44		Mean	2.400284
		Largest	Std. dev.	.5555806
75%	2.77	3.56		
90%	3.11	3.66	Variance	.3086698
95%	3.33	3.66	Skewness	-.0231693
99%	3.55	3.67	Kurtosis	2.521612

If > 2.44 high transformation; if <2.44 low transformation status

Source: Own computation using STATA version 18.

Appendix 4C3. The joint significant of transformation status vs districts.

```
Variables that uniquely identify margins: dummyindex district_num
    . testparm i.dummyindex#i.district_num
```

```
     ( 1)  1.dummyindex#2.district_num = 0
     ( 2)  1.dummyindex#3.district_num = 0
     ( 3)  1.dummyindex#4.district_num = 0
     ( 4)  1.dummyindex#5.district_num = 0

     F(  4,   412) =   10.56
           Prob > F =    0.0000
```

Appendix 4C4. Multicollinearity Test for variables used in linear regression model.

```
estat vif
```

Variable	VIF	1/VIF
age	1.40	0.714576
lands	1.38	0.723836
educa	1.32	0.755645
tlu	1.28	0.779440
sonwork	1.21	0.826703
dummy_index	1.20	0.831169
lnincome	1.16	0.864787
irrigpart	1.15	0.868966
fmsize	1.15	0.872776
mktinfda	1.14	0.880970
sex	1.13	0.882007
frqext	1.12	0.892695
ifohelth	1.10	0.908969
distmkt	1.09	0.917859
nonfarmi	1.08	0.921673
advisefod	1.08	0.929037
Mean VIF	1.19	

Source: Own computation using STATA version 18.

Appendix 4C5. Median comparison among food consumption group.

```
    Kruskal-Walli's equality-of-populations rank test
      +---------------------------------+
      | foodconsump~e | Obs | Rank sum |
      |---------------+-----+----------|
      | Acceptable FC | 222 | 69024.00 |
      | Borderline FC | 166 | 19604.50 |
      |       Poor FC | 34 |   624.50 |
      +---------------------------------+
      chi2(2) = 330.114
         Prob = 0.0001
```

Source: Own computation using STATA version 18.

APPENDIX 4C6. One-sample Kolmogorov–Smirnov test against theoretical distribution

```
        normal ((fcs - r(mean))/r(sd))
```

Smaller group	D	p-value
fcs	0.0883	0.001
Cumulative	-0.0556	0.073
Combined K-S	0.0883	0.003

Source: Own computation using STATA version 18.

APPENDIC 4C7. Test of the Instrumental variables in the first regression.

```
. ivregress 2sls fcs ( dummy_index = mktbprd ), first

First-stage regressions

                                                      Number of obs =     422
                                                      F(1, 420)     =   48.70
                                                      Prob > F      =  0.0000
                                                      R-squared     =  0.1039
                                                      Adj R-squared =  0.1018
                                                      Root MSE      =  0.4705

------------------------------------------------------------------------------
  dummy_index | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
--------------+---------------------------------------------------------------
      mktbprd |    .324187   .0464542     6.98   0.000     .2328752    .4154988
        _cons |    .300813   .0300003    10.03   0.000     .2418436    .3597824
------------------------------------------------------------------------------
```

Source: Own computation using STATA version 18.

Appendix 4C8. Test of endogeneity.

```
. estat endogenous
  Tests of endogeneity
  H0: Variables are exogenous

  Robust score chi2(1)          =   3.8523  (p = 0.0497)
  Robust regression F(1,404)    =  3.71291  (p = 0.0547)
```

Source: Own computation using STATA version 18.

Appendix 5D1. Number of Transformational practices.

Transformational practices	Freq.	Percent	Cum.
2	30	7.11	7.11
3	18	4.27	11.37
4	14	3.32	14.69
5	33	7.82	22.51
6	25	5.92	28.44
7	52	12.32	40.76
8	72	17.06	57.82
9	48	11.37	69.19
10	38	9.00	78.20
11	35	8.29	86.49
12	26	6.16	92.65
13	17	4.03	96.68
14	14	3.32	100.00
Total	422	100.00	

Source: Own computation using STATA version 18.

Appendix 5D2. Summarized on-farm transformational practices in detail.

Percentiles		Smallest		
1%	2	2		
5%	2	2		
10%	3	2	Obs	422
25%	6	2	Sum of wgt.	422
50%	8		Mean	7.140758
		Largest	Std. dev.	3.106012
75%	10	14		
90%	12	14	Variance	9.647313
95%	13	14	Skewness	-.1537343
99%	14	14	Kurtosis	2.435679

Source: Own computation using STATA version 18.

Appendix 5D3. Multicollinearity test for variables used in negative binomial regression model.

Variable	VIF	1/VIF
extension	2.80	0.357305
fcoop	2.17	0.461812
social	1.53	0.651795
fe	1.51	0.661143
agehh	1.41	0.707021
lands	1.35	0.738146
se	1.35	0.738488
educa	1.34	0.745963
mfarmer	1.27	0.786062
training	1.17	0.851732
experi	1.17	0.858086
sonwork	1.12	0.890233
lnincome	1.11	0.898145
sex	1.09	0.916385
fs	1.09	0.921497
Mean VIF	1.43	

Source: Own computation using STATA version 18.

Appendix 5D4. Model selection based on AIC and BIC.

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
GSEM	422	-1273.14	-1494.065	45	3078.129	3260.154
Nbreg	422	-1086.476	-1036.206	17	2106.412	2175.178

Source: Own computation using STATA version 18.

Survey Questionnaire

I am Chala Hailu Hussen, a PhD student conducting a survey for my dissertation titled '**Farm Transformation Status and Sustainability in High-Value Crop and Livestock Farming: Effects on Market Participation, Food Security, and the Role of Knowledge Networks: Evidence from Smallholder Farmers in the Central Oromia Region, Ethiopia**.' This data is solely used for academic purposes to obtain my degree in Agri-Food Systems from Università Cattolica del Sacro Cuore, Italy. Therefore, I appreciate your consideration in facilitating the collection of survey data.

Name of the Respondent: _____ Code: _____ Village_____, District_____ enumerator name: _____

Household Head Characteristics

1. Age of the Household head _____years.
2. Sex of the household head 1). Male 2). Female
3. Family size: Male _____; Female _____

   3.1. The number of active labor force in the household (15-64 ages)

Age category (in years)	Male	Female
Less than 10 years		
11-14		
15-64		
>64 years		

4. Educational level in years of schooling: _____
5. Are you model farmer? (1). Yes (2). No
6. Do you have agricultural labor division among family members? (1). Yes (2). No
7. How many agricultural packages do you engaged in 2024 production year? _____

Households' Asset characteristics

1. How many hectares of land do you have? _____ ha.

   1.1. Land allocated for high value cereal crops: _____ha.

   1.2. Land allocated for vegetable production: _____ha.

   1.3. Land allocated for grazing land management: _____ha.

1.4. Land rented out: _____ha.

1.5. Land rented in: _____ha.

2. Type of livestock species and value of sale during the last 6 months (November 2023-April, 2024)

Livestock type	Total number owned	Total number sold	Total income	Purpose of sale
Oxen				
Cow				
Calves				
Heifers				
Sheep				
Goat				
Donkey				
Horse				
Mule				
Poultry				

3. Does agricultural labor is enough to conduct your farm business? (1). Yes (2). No

3.1. If your answer is 'No', what option do you use? (1). Hiring labor (2). Social cooperation (3). Land share

3.2. What factors limits for your agricultural production?

(1). Labor (2). Financial access (3). Land shortage (4). Water (5). Agricultural input supply

Objective #1. Transformational Status of High-value crop and livestock farms.

1. In which types of high value enterprises did you participate in 2023/24 for production year?

S/N	***High value enterprises***	***Indicate your answer (√)***
1	Production of Teff crop	
2	Production of Maize crop	
3	Production of Wheat crop	
4	Production of Malt barely crop	
5	Production of Chick pea crop	
6	Production of Potato crop	
7	Production of Red Onion crop	
8	Adoption of cross breed dairy cow	

9	Adoption of exotic breed dairy cow	
10	Adoption of improved egg laying poultry	
11	Sheep & bull fattening	
12	Honey harvested from modern beehives	

2. Which enterprises generate stable income for you? _____
3. Did you practice raw planting? (1). Yes (2). No

4. What methods do you use to plow your land? (1) Tractor (2) Personal oxen (3) Rented oxen (4) 'Daboo' technique.
5. How do you eliminate weeds from your cropland?
   (1) Application of herbicides
   (2) Use of family labor
   (3) Hiring labor
   (4) Cooperation from '*daboo*'

6. How many times do you use your land for cropping each year? _____ time(s).
7. Are you growing two crops through inter-cropping this year? (1) Yes (2) No
8. Which crop occupied your farm field?
   a). In year 2022/23 production Year _____
   b). In year 2023/24 production Year _____
9. Do you produce crop in cluster production mode? (1). Yes (0). No

10. How do you perceive the cluster production system? (1) Very good (2) Good (3) Fairly good
11. Did you receive an adequate quantity of fertilizer for your crops during the 2023/24 production season? (1) Yes (0) No
12. If your answer is "No," how did you manage the situation?
    (1) Switched to crops that require less fertilizer
    (2) Used homemade manure
    (3) Sowed without applying any fertilizer
    (4) Purchased from market traders (5) Applied vermicompost

13. Did you receive the preferred seed variety for your locality? (1) Yes (2) No
14. If your answer is '***No***', how did mitigate it?
    (1) Sowing locally available seeds from farmers.
    (2) Sharing seeds with other farmers.
    (3) Purchasing seeds from private seed producers or companies.
    (4) Using my own seed stock.

15. Do you save seeds for your next farming season? (1) Yes (2) No
16. How would you rate the quality of the seed variety you are currently using?
    (1) Very good
    (2) Good
    (3) Not very good

17. Why do you choose to produce high-value crops?
    (1) Because of high yield.
    (2) Because I entered into a contractual marketing agreement.
    (3) Because I have adequate land and water resources.
    (4) Because I have a plan for home food requirements.
    (5) Because the state/government encourages me to produce.
18. Do you access to agricultural market information services? (1). Yes (2). No
19. What information do you receive? (1) Product demand (2) Input price information (3) Output price information (4) All.
20. Do you follow weather forecast information for cropping? (1) Yes (2) No
21. Do you participate in irrigation farming? (1) Yes (2). No
22. How do you assess the quality of seeds for vegetable production?
    (1). I ask the seller.
    (2). I obtain information from my customer.
    (3). I do not inquire.
23. How many times in a given season produce crop using irrigation? _____times
24. Do you apply crop rotation? (1). Yes (2). No
25. What motivates you to participate in irrigation production?
    (1). awareness created by extension workers
    (2). Market driven
    (3). Own experience/ self-driven
26. For what purpose do you use crop residue? (1). Animal feeding (2). Compost preparation (3). Sale for income generation

Adoption of Cross Breed Dairy Cow and Improved egg laying poultry

1. How many cross- breed dairy cow does you have? _____.
2. From where you get? (1). I purchase from market/friends (2). A gift from family (3). I get though farmers cooperatives (4). Born via insemination
3. Experience in adoption of cross breed cow in years? _____
4. What is the level of satisfaction in milk? (1). Very high (2). High (3). Not too much high (4). Similar to local breed
5. Did you attend farmer level training on dairy production? (1). Yes (2). No
6. Which organizations more help you in dairy production?
    (1). Agricultural Research organization (2). Private agri-service dealers
    (3). Non-governmental organizations (4). Farmers' cooperative (5). Extension workers
7. Do you get adequate feed for the dairy? (1). Yes (2). No
8. If 'No' from where you get the feed? (1). On-farm production (2). Purchased from others (3). Both
9. What types of grazing system do you apply?
    (1). Open grazing on farm land (2). cutting and carrying system (3). Communal land grazing.
10. Which factors affects dairy transformation?
    (1). No cross-breed bull (2). High price to buy (purchase) improved breed
    (3). Feed availability (4). Shortage of land
11. Does labor shortage affect to manage cross-breed cow? (1). Yes (2). No
12. What types of feed is promising for better milk yield? _____
13. How often extension workers visit you in a month? _____
14. Average milk harvested per day? _____
15. Do you access to credit services? (1). Yes (2). No
16. Do you access to water to feed your cow? (1). Yes (2). No

17. For what purpose do you use cow dung? (1). Compost preparation (2) cooking (3). For sale
18. What is the average two-way walk distance from your home to veterinary clinic services? _____ hour.
19. Do you have plan to expand dairy production? (1). Yes (2). No
20. Did you adopt improved egg laying chickens/poultry? (1). Yes (2). No.
21. If '**yes**' how many egg do your collect per day? _____
22. What factors limits improved chicken production?
(1). Unavailability of breed (2). Disease problem (3). Feed problem (4). Labor shortage
23. For what purpose do you produce egg? (1). Home consumption (2). Marketing (3). For both

Objective #2. High-value crop and livestock products implication in contract market participation.

1. Do you participate in marketing of high-value farm products? (1). Yes (2). No
2. If your answer is '**Yes**' which marketing system, do you use?
   (1). Formal contract with agreements (2). Informal contract based on trust build with customer (3). Local open market
3. Who mediate you with buyers? (1). Personal (2). cooperative (3). friends
4. Are you satisfied with the incentives? (1). Yes (2). No
5. Is there legal enforcement to engage in contract marketing? (1). Yes (2). No
6. Do buyers limit volume of buying? (1). Yes (2). No
7. If 'yes', where will you sell the surplus of your produce? _____
8. Does the existing formal contract reduce the transaction cost for your product?
   (1). Yes (2). No

9. What is your perception on contract marketing system? (1). Good (2). Not good at all
10. Please mention major problem you faced with contract marketing.
(1)._____ (2)._____
(3). _____(4)._____
11 Do you participated in informal contract system? (1). Yes (2). No
12. Are there conditions in which buyers refuse to buy your products? (1). Yes (2). No
13. If 'Yes', how do you manage your product? _____
14. Does it demotivate you to supply the product next time? (1). Yes (2). No
15. Do you have social network connection to market your product? (1). (2). No.
16. Who plays key role to provide market potential information for your products?
(1). Neighbour/friends
(2). Agricultural extension workers (3). Directly connected to buyers
17. Means of product distribution.
(1). farmer transporting to buyer
(2). buyer collects at farm gate (3). Distributing via cooperative form
18. Does the informal contract marketing system build trust opportunity with your buyer?
(1). Yes (2). No
19. Does farm land size limits you're your market? (1). Yes (2). No
20. Is there complain from buyers regarding quality of your farm product?

(1). Yes (2). No

21. Is there anybody who approved quality of your products? (1). Yes (2). No
22. is there any cases you were regret to sell your product via informal contract system?
    (1). Yes (2). No
23. What you regret?
    (1). Price (2). Not searching alternative market (3). Low bargaining power
24. Do you receive agricultural market information services? (1). Yes (2). No
25. Is there any credit access encouraged by formal contract marketing? (1). Yes (0). No
26. What is the distance from your home to nearest marketing place _____hrs?
27. Do you have product packaging problem? (1). Yes (2). No

28. Answer the following questions based on 2023/24production and marketing of high value products.

S/N	Types of high-value farm products	Amount produced	Amount used consumed	Amount sold
1	Teff in quintal			
2	Wheat in quintal			
3	Malt barely in quintal			
4	Maize in quintal			
5	Potato in quintal			
6	Vegetables general in qty			
7	Milk in liter			
8	Egg in number per week			

Objective#3. The Role of high-value farm Transformation in household food security

1. How many primary school-aged children are in this household? (1). Girls_____(2). Boys_____, Total _____
2. Is there any children drop their school because of food shortage? (1). Yes (2). No
3. Do you engage in from off-farm activities? (1). Yes (2). No
4. Do you face any food insecurity in the past 5 years? (1). Yes (2). No
5. Do high value products enable you to get all food variety for your family consumption? (1). Yes (2). No

6. If '**No**', do you buy some food from market? (1). Yes (2). No
7. How do you perceive about current food production enables you to secure your food requirement?
    (1). Very good (2). Good (3). Somewhat good (4) uncertain
8. Do you have knowledge of nutritional rich food consumption? (1). Yes (2). No
9. Do extension workers train your family on healthy food production? (1). Yes (2). No
10. Do you have storage facility for perishable products (1). Yes (2). No
11. Do you purchase processed food from market? (1). Yes (2). No
12, Do you use frequently consuming animal source food? (1). Yes (2). No
13. Do health extension workers advise on consumption of healthy food? (1). Yes (2). No
14. Can you tell me annual income you get from the different sources?

(1). Income from sale of farm products _____Birr.

(2). Income from non-farm activities _____-Birr

(3). Income from remittance _____ Birr

(4). Financial assistance from donors (NGO's) _____ Birr.

15. Based on below indicators please provide your perception regarding the status of transformational activities in your village.

S/N	***Transformative practices***	***Perceived status score***			
		Nill =1	***Low=2***	***medium=3***	***High=4***
1	The extent of farmers' adoption of high-value cereal crop production in your village.				
2	The extent of farmers adopting vegetable crop production in your village.				
3	The extent of farmers adopting improved cross-breed dairy cows in your village.				
4	The extent of farmers adopting improved egg-laying poultry in your village.				
5	The extent of farmers adopting and using farm mechanization in your village.				
6	The extent of farmers' participation in irrigation agriculture.				
7	The extent of farmers participating in the marketing of high-value farms.				
8	The extent of farmers' connections to agricultural stakeholders.				
9	The extent of farmers' awareness about climate change and practices for adaptation.				

Data on Food Consumption Score

16.Could you please tell me how many days in the past one week (seven days) your household has eaten the following foods and what the main source was *(use codes at the bottom of the table, write 0 for items not eaten over the last 7 days)*

Food source codes

1*= wn production (crops, animal);* ***2****= Fishing / Hunting;* ***3****= Gathering;* ***4****= Borrowed* ;***5****= Market (purchase with cash)* ;***6****= Market (purchase on credit)* ;***7****= Beg for food* ;***8****= Exchange labor or items for food* ;***9****= Gift (food) from family relatives or friends* ;***10****= Food aid from civil society, NGOs, government, WFP etc (see the following table)*

	Food Item	*a. Number of days Eaten during last 7 days*	*b. Main Source (use Food source codes at the bottom of the table)*
16.1	**Cereals and grain:** Rice, bread / cake and / or donuts, sorghum, millet, maize, chapatti.	|__|	|__|
16.2	**Roots and tubers:** potato, yam, cassava, sweet potato, and / or other tubers	|__|	|__|
16.3	**Legumes/Nuts:** ground nuts, peanuts, sim-sim, coconuts or other nuts, beans, cowpeas, lentils, soy, pigeon pea	|__|	|__|
16.4	**Vegetables (orange, green and others):** carrot, red pepper, pumpkin, orange sweet potatoes, spinach, broccoli, amaranth and / or other dark green leaves, cassava leaves, bean leaves, pea leaves onion, tomatoes, cucumber, radishes, green beans, peas, lettuce, cabbage, etc	|__|	|__|
16.5	**Fruits:** mango, papaya, apricot, peach, banana, apple, lemon, tangerine	|__|	|__|
16.6	**Meat:** goat, beef, chicken, pork (meat consumed in large quantities not as a condiment).**Liver, kidney, heart and / or other organ meats and blood**	|__|	|__|
16.7	**Fish / Shellfish:** fish, including canned tuna, and/or other seafood (fish consumed in large quantities not as a condiment)	|__|	|__|
16.8	**Eggs**	|__|	|__|
16.9	**Milk and other dairy products**: fresh milk / sour, yogurt, cheese, other dairy products (Exclude margarine / butter or small amounts of milk for tea / coffee)	|__|	|__|
16.10	**Oil / fat / butter:** vegetable oil, palm oil, shea butter, margarine, other fats / oil	|__|	|__|
17.11	**Sugar, or sweet:** sugar, honey, jam, cakes, candy, cookies, pastries, cakes and other sweet (sugary drinks)	|__|	|__|
18.12	**Condiments / Spices:** tea, coffee / cocoa, salt, garlic, spices, yeast / baking powder, lanwin, tomato / sauce, meat or fish as a condiment, condiments including small amount of milk / tea coffee.	|__|	|__|

Source: This table is adopted from FSNA (WFP,2018) food security questionnaire.

Objective #4. The Relationship between Knowledge utilization Network and Transformational Farming Practices.

1. Are you a member of a farmers' cooperative? (1). Yes (2). No

2. For what purpose do you connect with farmers' cooperative?
   1). To be served for agricultural input (fertilizer, agro-chemicals, and seed purchase)
   2). To sell agricultural product through arrangements of contract
   3). To get information on agricultural technology
3. Are you a member of a social institution? (1). Yes (2). No
4. If your answer is "Yes" for what purpose you connect to social institution?
   (1). Reciprocal farm production
   (2). Cultural obligations
   (3). To access credit requirements
   (4). To share knowledge and information on agricultural production and marketing
5. Which one of the following is important for you to connect and receive agricultural knowledge?
   (1). Agricultural extension services
   (2). Social relation/friends/informal institutions
   (3). Farmers' cooperative
   (4). Agricultural extension and social relations
   (5). Agricultural extension and farmers' cooperative
   (6). Farmers' cooperative and social relations

6. What mode of knowledge dissemination capacitates your insight on agricultural technologies?
   (1). Informal training at farmer training centre in your village (2). Field day demonstration
7. Did you visited other places for experience sharing? (1). Yes (2). No
8. Did you share knowledge on dairy production? (1). Yes (2). No
9. Did you share knowledge on seed multiplication? (1). Yes (2). No
10. Did you share knowledge on beekeeping? (1). Yes (2). No
11. Did you share knowledge on vermi-compost production? (1). Yes (2). No
12. Did you participated and adopt cluster crop production? (1). Yes (2). No
13. Did you get the different variety of forage that you want to develop on your farm?
    (1). Yes (2). No

14. If '**yes**', how do you access it? (1). Purchase from market (2). Free obtained via farmers cooperatives (3). Free obtained from agricultural offices.

15. What types of forage species do you have on your farm?

   1). _____

   2). _____

   3). _____

   4)._____

16. Do you confident in knowledge you receive on forage development? (1). Yes (2). No
17. What factors limits you to develop forage on your farm?

(1). Land shortage (2). Labor shortage (3). Water shortage (4). Large herd size

18. Which forage variety you know that enhances milk production? _____

19. Do you multiply seed on your farm land? (1). Yes (2). No

20. If 'yes', what types of seed are you producing?

1)._____,2)._____,3)_____

21. In what form you produce seed? (1). Individual (2). cooperative

22. With whom you are coordinated to produce seed?
(1). Farmers' cooperative (union)
(2). Oromia region seed enterprise
(3). Agreement with private sector seed company

23. For what purpose do you produce the seed?
(1). Own seed demand (2). Marketing (3). Both

24. How many quintals of seed did you produced in 2023/24? _____quintals

25. Is there any certification for the success you have on seed production? (1). Yes (2). No

26. Tell me what sort of management you consider in seed production?
1). _____
2). _____
3). _____

27. Do you produce compost on your farm? (1). Yes (2). No

28. Did you get training on the preparation? (1). Yes (2). No

29. Does the training is adequate to build your skill? (1). Yes (2). No

30. Do experts supervise your vermi compost preparation? (1). Yes (2). No

31. How do you observe yield of crop applied with compost? (1). Higher difference (0). Similar with inorganic fertilizer

32. What factors limits you for sustainable preparation of compost?

1). Labor constraint 2). Large farm size 3). Dung shortage 4). Unavailability of Verm organism

33. Do you have knowledge of improving milk productivity? (1). Yes (2). No

34. Do you want to rent your bull for mate? 1). Yes (2). No

35.Do you produce high-value farm products based on market orientation (1). Yes (2). No

36. What techniques do you use to harvest your crop?
(1). Group rental of harvester (2). Individual rent (3). Reciprocal labor

37. Do you have the knowledge on how product grading affects your selling potential? (1). Yes (2). No

38. Do you have the knowledge information of urban agricultural industry? (1). Yes (2) No

39. Is knowledge utilization network help you to identify which farm enterprises combine together? (1). Yes (2). No

40. Do you think that your knowledge insists you transform farming practices?
(1). Yes (2). No

41. What is the distance in hours from your home to farmer cooperative services? _____.

42. What is the distance in hours from your home to farmers training center? _____.

43. Do you participate community level meeting regualrly? (1). Yes (2). No

Questions for Focus Group Discussion

(1). How do you describe agricultural knowledge use networking system in your village? What challenges are there?

(2). Can you elaborate opportunities and challenges related to agricultural transformation in your village.