DETERMINANTS OF RURAL HOUSEHOLDS' ACCESS TO CREDIT AND ITS IMPACT ON HOUSEHOLDS' FOOD SECURITY AND CROP PRODUCTIVITY: EVIDENCE FROM ETHIOPIA

M.SC. THESIS

BY

AMANUEL NIGUS

JUNE, 2025

ADDIS ABABA, ETHIOPIA

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A THESIS SUBMITTED TO DEPARTMENT OF ECONOMICS, COLLEGE OF BUSINESS AND ECONOMICS, SCHOOL OF POST GRADUATE STUDIES, ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR MASTER OF SCIENCE DEGREE IN FINANCIAL ECONOMICS.

DECLARATION

I, Amanuel Nigus, hereby declare that this research paper entitled " Determinants of rural households' access to credit and its impact on households' food security and crop productivity: Evidence from Ethiopia" is my original work and it has not been submitted for BA or MSc degree in any other university, and all sources of material used for this thesis have been duly acknowledged.

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SUPERVISOR'S APPROVAL SHEET

This is to certify that the thesis work entitled "Determinants of rural households' access to credit and its impact on households' food security and crop productivity: Evidence from Ethiopia" submitted in partial fulfillment of Masters of Science degree in financial economics is worked by Amanuel Nigus under my supervision. Thus I recommend the thesis to be submitted to the department for defense

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We, the undersigned members of examiners of thesis defense by Amanuel Nigus, have read and evaluated his MSc thesis entitled "Determinants of rural households' access to credit and its impact on households' food security and crop productivity: Evidence from Ethiopia" and examined the candidate for presentation. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement for the degree with _____corrections.

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ACKNOWLEDGEMENT

All things are accomplished with the willingness of almighty God and nothing happen without him. I thank my God and his mother with my sinful body. My next special and heartfelt gratitude goes to my advisor **Gebeyehu Manie (PhD)** for his intensive genuine advice, suggestions, guidance and constructive comments to improve the quality of this paper.

I have also been blessed with the constant moral support of my family especially my mother and father. They have always been there for their prayers, love, and support, and for understanding why I could not call you all every day. For me throughout the study and my life; and this day would not have been possible without them. I have no word to express my mom.

My equal special appreciation goes to my friends **Hussien Ali (MA) & Zigale Yirsaw (M.Sc.)** for their unlimited encouragement and comments provided since the inception of the paper in problem identification. All have much contribution in spending for their priceless contribution in my work. Finally, I want to express my grateful thanks to all those who participated in the fruitfulness of the study.

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ACRONYMS

ADLI ----------Agricultural Development Lead Industrialization

AEMFI----------Association of Ethiopian Microfinance Institutions

AIMS----------Assessment impact of Microfinance Service

BoARD ----------Bureau of Agricultural and Rural Development

CIMMYT ----------International Maize and Wheat Improvement Center

CSA---------- Central Statistical Agency of Ethiopia

DKAE----------Daily Calorie per Adult Equivalence

DDS----------Dietary Diversity Score

ESRM---------- Endogenous switching regression model

FAO----------Food and Agricultural Organization

GAP----------Global Agricultural Productivity Report

GDP---------- Gross Domestic Product

IDA---------- International Development Associations

MDGs---------- Millennium Development Goals

MFIs----------Microfinance Institutions

NGO----------Non-governmental Organization

RCT----------Randomized Controlled Trial

SDGs----------Sustainable Development Goals

UNDP---------- United Nation Development Program

WFP----------World Food Program

ABSTRACT

This study examined the determinants of rural households' access to credit and its impact on household's food security and crop productivity in rural Ethiopia. To this end it employed a secondary data of 1524 rural households participated on the 2021/22 socio-economic survey accessed from the World Bank data base. Households' food security status was measured by dietary diversity score and daily calorie consumption per adult equivalence. As to econometric methodology, binomial logistic regression model was used for identifying factors affecting households' credit access, while endogenous switching regression model was employed for examining the impact of access to credit on food security and crop productivity (yield) outcomes. The study revealed that access to credit is very low in rural Ethiopia in which only 7.2% of sample households have managed to get credit access. Moreover, the result of binomial logistic regression model indicated that age of household head, monthly income, livestock size, distance from nearest market center and access to extension services are key determinants of rural households access to credit in the study area. Results of average treatment effect indicate that access to credit significantly boosts teff and maize productivity in the study area. However, despite significantly enhancing improved seed and chemical fertilizer adoption, it is not found to have impact on food security. It emphasizes the need for complementary interventions to address broader household welfare, ensuring that agricultural gains translate into sustainable food security outcomes for rural households of Ethiopia.

Key Words: Credit Access, Endogenous Switching regression, Food Security, Ethiopia

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Access to credit is a foundation of worldwide efforts to enhance food security and crop productivity for rural households (Salima et al., 2023a). Globally food security remains a critical global challenge, with severe hunger rising for the sixth successive year and affecting roughly 295 million people in 2025, driven by conflict, climate extremes, and economic shocks (World Bank, 2025). The issue is exacerbated by stagnation of agricultural productivity growth – which is essential for feeding a growing population amid climate disruptions –in low-income countries, partly due to underinvestment in smallholder farming systems (GAP, 2023). Moreover, liquidity constraints extremely limit smallholders' capacity to invest in yield-enhancing technologies: only 18-24% of small-scale farmers globally access formal credit, impeding adoption of improved seeds, irrigation, and climate-resilient practices (FAO, 2024a).

Africa, despite having abundant arable land resources, faces disproportionate food insecurity burdens, hosting over 60% of the world's acutely hungry population (World Bank, 2025). It is due to structural barriers include fragmented financial systems, with only 10-15% of rural households accessing formal credit due to collateral requirements, banking exclusion, and underdeveloped rural infrastructure (Gonfa et al., 2025). Moreover, climate volatility further strains agricultural livelihoods, for example, prolonged droughts in Eastern Africa has caused severe food insecurity and crop yield (Aryal et al., 2021; Ackerl et al., 2023). The region faces severe challenges, with approximately one in five Africans experiencing hunger due to low crop yields, weak economic growth, and climate-induced disruptions like droughts and floods (Wang et al., 2025).

Ethiopia, despite building one the rapidly-growing economies in sub-Saharan Africa, remains heavily dependent on agriculture, which employs over 70% of the population and contributes approximately 34% to the country's GDP (World Bank, 2022). In spite of having such economic landscape, rural households face persistent challenges, including low agricultural productivity, food insecurity, and limited access to financial services. Moreover, smallholder farmers, who constitute 95% of Ethiopia's agricultural sector, often operate on fragmented plots with minimal

mechanization, relying on rain-fed systems which make them highly vulnerable to climate shocks (FAO, 2021). These structural bottlenecks perpetuate cyclical poverty, in which, in 2021/22, nearly half of the rural population in Ethiopia was in extreme poverty (Goshu et al., 2024). In this context, improving access to credit among rural households has emerged as a crucial intervention to enhance agricultural investment, productivity, and resilience (Gebeyehu et al., 2019; Girma, 2022).

Microfinance institutions (MFIs) have obtained prominence in Ethiopia as tools for poverty reduction and rural development (Chomen, 2021). Since the 1990s the government has promoted MFIs to bridge the gap left by formal banking systems (Assefa et al., 2013), which serve less than 15% of rural populations (Lakew & Azadi, 2020). By 2020, more than 30 MFIs have been operating in Ethiopia, disbursing loans to nearly 10 million clients, predominantly in agrarian communities (National Bank of Ethiopia, 2021a). However, access remains uneven, with studies highlighting disparities influenced by gender, education, landholding size, and social networks (Tesiso et al., 2023). For instance, women-headed households are 1.5 times less likely to receive a loan than men-headed households are (Tassew, 2023) due to collateral requirements and sociocultural biases (Mengstie & Singh, 2020). Such barriers undermine the potential of microcredit to boost equitable development. Moreover, Ethiopian women face significant financial exclusion, with only 35% of them having access to formal financial services compared to 48% of men (Awol, 2025).

Despite being central focus of academic research, the relationship between credit access and food security is a contested area. While some studies argue that microfinance enables households to invest in productive assets, diversify income sources, and smooth consumption during bad seasons (Mengstie, 2022; Boltana et al., 2023) others caution that high-interest rates and rigid repayment schedules may exacerbate indebtedness, forcing families to sell productive assets or reduce food expenditures (van Rooyen et al., 2012). In Ethiopia, where 22.2% of the population is undernourished (Wiemers et al., 2024), understanding how credit interacts with household food security is vital. For example, a longitudinal study in Amhara region found that microcredit participation increased dietary diversity, but only among households with pre-existing irrigation access (Baye et al., 2019). This suggests the need for undertaking nationwide conditions.

Crop productivity, a key determinant of rural livelihoods, is similarly linked to credit accessibility. Smallholders often lack capital to purchase improved seeds, fertilizers, or machinery, resulting in significant yield gaps (Zerssa et al., 2021; Senbeta & Worku, 2023). Microcredit can theoretically alleviate these constraints, yet evidence from Ethiopia is mixed. For instance, a study in Oromia showed that access to credit resulted in high crop productivity by adopting high-yield varieties (Lelisho & Lelisho, 2024). Conversely, there are also studies which indicated that those rural households are diverting the credit they obtained to immediate consumption needs due to liquidity crises (Regasa et al., 2021). Such contradictions emphasize the need to examine the impact of access to credit on crop productivity.

Ethiopia's policy environment further shapes credit dynamics. Agricultural Development-Led Industrialization (ADLI) strategy and Growth and Transformation Plans (GTP I/II) of the government prioritize agricultural financing, yet implementation gaps persist. For example, while the Rural Financial Intermediation Program (RUFIP) enhanced MFI outreach, only 35% of smallholders report sufficient access to seasonal loans (MoA, 2022). Moreover, the expansion of group-lending models which are designed to reduce default risks—often excludes the poorest households, who are deprived of social capital to join liability groups (Bahng, 2013). Recent reforms, such as the National Financial Inclusion Strategy (2021–2025), aim to address these gaps through digital financial services and gender-targeted products (National Bank of Ethiopia, 2021b). However, their effectiveness remains untested in Ethiopia's heterogeneous rural contexts.

Although extensive studies are conducted on the issue, critical gaps still exist. Most studies concentrates on either credit determinants or impacts, neglecting the bidirectional relationships between access, food security, and productivity. Furthermore, most of those studies focus on a specific geographical area. Hence, this study addresses these gaps by employing a holistic framework to assess credit access determinants and its impact on food security and crop productivity using contexts from multiple regions in Ethiopia.

1.2 Statements of the Problem

Rural households' in Ethiopia, which are 76.84% of the country's population (World Bank, 2023), remain trapped in a cycle of low agricultural productivity and severe food insecurity. Despite the expansion of microfinance institutions (MFIs) as a policy tool to reduce poverty, still

more than 40% of rural households lack access to formal or semi-formal credit (Mulatu, 2021; Gelata & Han, 2024). This exclusion continues despite evidence that agricultural investment—enabled by credit—could reduce yield gaps and improve food security (Boltana et al., 2023; Berhanu et al., 2021). Hence, the critical problem this study addresses is the uneven and often ineffective penetration of microfinance services in rural Ethiopia, which limits their potential to transform livelihoods, enhance food security, and improve crop productivity.

While MFIs have expanded nationally, access remains uneven. Factors such as gender, land size, and proximity to financial institutions disproportionately exclude vulnerable groups. For example, women, who manage 30–50% of smallholder farms, face systemic barriers: only 35% of female-headed households secure loans, compared to 48% of male-headed households (Awol, 2025). Similarly, landless or near-landless households are frequently deemed "high-risk" by MFIs, perpetuating poverty traps (Balana et al., 2020). These disparities raise urgent questions about which factors most critically determine access to credit and how exclusionary practices compromise Ethiopia's development goals.

Moreover, the impact of credit on food security and productivity is inconsistent and poorly understood. While some studies report positive outcomes, such as increased dietary diversity and adoption of improved seeds (Boltana et al., 2023; Berhanu et al., 2021; Gebeyehu et al., 2019; Elemineh et al., 2020), others find negligible or even negative effects. For instance, in drought-prone regions, households often divert loans to consumption smoothing rather than agricultural investment, leading to debt cycles without productivity gains (Regasa et al., 2021). This controversy indicates that contextual factors like agro-ecology, market access, and climate resilience can mediate credit impacts, yet existing studies overlook these variables holistically.

Furthermore, Ethiopia's policy frameworks prioritize agricultural credit but fail to address structural mismatches. For example, the rigidity of loan products (e.g., fixed repayment schedules) doesn't go with the seasonal and unpredictable nature of smallholder farming (Fentahun et al., 2018). Similarly, group-lending models, intended to reduce default risks, often exclude marginalized households lacking social capital (Bahng, 2013). Compounding this, digital financial services—touted in the National Financial Inclusion Strategy (2021–2025)—remain inaccessible to more than 75% of rural populations due to poor infrastructure and low

digital literacy (National Bank of Ethiopia, 2021b). These systemic obstacles suggest a disconnection between policy ambitions and on-the-ground realities.

In addition to these, notable studies in Ethiopia (e.g. Kiros & Meshesha, 2022; Boltana et al., 2023; Waje, 2020; Berhanu et al., 2021; Elemineh et al., 2020; Bahiru et al., 2023; Ahmed et al., 2017; Teshome & Tegegne, 2020; Fikire & Emeru, 2022) focused on specific geographical areas. However, a comprehensive national level analysis is quite important so as to understand the issue at large. Therefore, this study is pioneering which tries to assess determinants of rural households' credit access and its impact on food security and crop productivity, specifically maize and teff, in Ethiopia using the 2021/22 national socio-economic survey.

1.3 Objectives of the study

1.3.1 General objective

The general objective of this study is to investigate determinants of rural households' access to credit and its impact on households' food security and crop productivity in Ethiopia.

1.3.2 Specific objective

Under the umbrella of the general objective, the study specifically aims to:

- Identify determinants of rural households' access to credit in Ethiopia.
- Examine the impact of access to credit on rural households' food security in Ethiopia.
- Investigate the impact of access to credit on teff and maize productivity in Ethiopia.

1.4 Scope and Limitation of the Study

This study aims to identify determinants of rural-households access to credit and its impact on households' food security and crop productivity in Ethiopia. It specifically tried to address the credit's impact on food security outcomes as well as teff and maize productivity. To this end, it is primarily based on a cross-sectional data of the 2021/22 national socio-economic survey data. The study encompassed 1524 sample rural households---which are found to have complete data on access to credit---across nine regions (administrations) of Ethiopia namely: Afar, Amhara, Oromia, Somali, Benishangul Gumuz, SNNP, Gambela, Harari and Dire Dawa.

As to limitations of the study, it would be best if there was a possibility to undertake the study using longitudinal data by incorporating the 2018/19 survey round. However, data

inconsistencies were discovered and so that only the most recent survey data of 2021/22 were employed. Moreover, the number of sample households which responds they had access to credit is fewer relative to the overall sample size used in the study. Thus, it would be even better if those households with credit access were nearly approximate with those which didn't have access to credit. Furthermore, it would be interesting if households' food security outcomes were measured by standard indicators such as food consumption score (FCS) and food insecurity access scale (FIAS).

1.5 Significance of the study

Microfinance institutions have been providing credit for rural smallholder households for more than three decades now. However, determinants and impact of such credits on rural livelihood and productivity outcomes remains controversial. Hence, this study aims to investigate rural households' access to credit and its impact on households' food security and crop productivity in Ethiopia. Thus, it is quite important to identify those factors which determine rural households' access to credit and their food security and productivity outcomes. Besides to this, the findings of the study is expected to be useful as a stepping stone for related studies that will be undertaken within the thematic area. In addition to this, the study will have important inputs to development policy via shading lights for policymakers regarding rural finance, access to credit, food security and crop productivity in rural Ethiopia.

1.6 Organization of the Study

This thesis is organized into five main chapters. The first chapter deals with introductory part of the research which includes background of the study, statement of the problem, research questions, and objectives of the study, scope of the study, limitation of the study and significance of the study. The second chapter reviews detailed literatures that provides broader view on conceptual and theoretical perspectives and empirical literature on the effect of microfinance rural households' livelihood and crop productivity. Subsequently, methodologies of the thesis; includes study area description, sampling procedure, source of data, methods of data collection, data analysis, definition dependent and explanatory variables with its expected sign are discussed in the third chapter. Then, the fourth chapter presents the results of data analysis, and discussion. Finally conclusions and possible policy recommendations are discussed in the fifth chapter.

CHAPTER TWO: LITRATURE REVIEW

2.1 Theoretical Literature Review

2.1.1 Definition and evolution of microfinance

Microfinance is broadly defined as financial services—including microloans, savings accounts, insurance, and payment systems—targeted at low-income individuals and small businesses excluded from traditional banking systems (Ribeiro et al., 2022). Rooted in the principle of financial inclusion, its core objective is to empower marginalized populations, particularly in developing economies, by providing access to capital for entrepreneurial activities and risk management. Early iterations of microfinance can be traced to informal community-based systems, such as rotating savings and credit associations (ROSCAs) in Africa and "tandas" in Latin America, which emphasized collective financial support. The modern conceptualization, however, emerged in the 1970s with Muhammad Yunus's pioneering work in Bangladesh, where the Grameen Bank demonstrated that small, collateral-free loans could spur self-sufficiency among impoverished communities, particularly women. Yunus's model, which emphasized group lending and social collateral, became a blueprint for global microfinance institutions (MFIs), blending ethical lending practices with financial sustainability (Ribeiro et al., 2022) .

The evolution of microfinance reflects both institutional innovation and critical debates about its efficacy. Historical precedents include the 19th-century German credit cooperatives, which enabled rural farmers to shift from subsistence grain farming to capital-intensive dairy production by pooling resources. These cooperatives operated without subsidies, relying on member ownership and minimal regulation—a model that foreshadowed contemporary MFIs' emphasis on decentralized financial systems (Duong & Nghiem, 2022). By the late 20th century, organizations like ACCION International and FINCA expanded microfinance globally, incorporating services such as micro-insurance and financial literacy programs. However, the sector's commercialization sparked controversy, as for-profit MFIs like Mexico's Banco Compartamos faced criticism for high interest rates and mission drift, prioritizing profitability

over poverty alleviation. Academic studies further revealed mixed outcomes: while microloans improved household resilience and consumption smoothing, they often failed to generate transformative income growth or address structural inequalities.

Recent theories and literature emphasize a nuanced understanding of microfinance's role. Randomized controlled trials (RCTs) highlight that impacts vary by context, with benefits such as increased female empowerment and business diversification offset by limited scalability in saturated markets (Cull et al., 2009). Innovations like flexible repayment schedules, grace periods, and asset-based lending have shown promise in aligning loan structures with borrowers' cash-flow cycles. Meanwhile, bibliometric analyses identify three dominant research themes: (1) socioeconomic impacts, (2) MFI performance metrics, and (3) financial innovation's role in poverty reduction. Scholars argue for holistic approaches that integrate microfinance with broader development initiatives, such as education and healthcare, to address multidimensional poverty. Contemporary models also stress the importance of leveraging local financial ecosystems, recognizing that traditional systems like trade credit and kinship-based lending already serve many unbanked populations.

2.1.2 Microfinance landscape in Ethiopia

Since its introduction in 1995 Ethiopia's microfinance sector has emerged as a critical tool for financial inclusion, targeting low-income populations, smallholder farmers, and micro-entrepreneurs that are underserved by traditional banking systems. As of 2025, the country hosts over 30 microfinance institutions (MFIs), which collectively serve millions of clients, focusing on microloans, savings programs, and insurance products (Desai, 2025). These institutions operate under a regulatory framework overseen by the National Bank of Ethiopia (NBE), which mandates minimum capital requirements and governance standards to ensure stability and accountability. The Digital Ethiopia 2025 strategy has further catalyzed the integration of digital financial services, with mobile money platforms like Telebirr (launched in May 2021) and Safaricom's M-Pesa (introduced in August 2023) expanding access to financial services. It emphasizes leveraging technology to expand outreach, particularly in rural areas where 70% of the population resides. Mobile money platforms and agent banking networks are increasingly bridging the gap, enabling farmers and small businesses to access credit and manage transactions digitally (International Finance Corporation, 2025). Despite progress, challenges persist,

including high operational costs, limited financial literacy, and regional disparities in service accessibility.

Digital innovation is reshaping Ethiopia's microfinance ecosystem, driven by partnerships between MFIs, fin-tech firms, and international organizations. For instance, the International Finance Corporation (IFC) and Kifiya Financial Technology launched a project in 2025 to digitize financial services for one million smallholder farmers, combining digital profiling with agent training to facilitate loans and payments in remote areas. This aligns with Ethiopia's Digital Agriculture Roadmap (2025–2032), which integrates microfinance into broader agricultural value chains to enhance productivity and food security. Similarly, mobile wallet adoption has surged, with platforms like Telebirr enabling MSMEs to formalize transactions and build credit histories. However, infrastructure gaps—such as unreliable electricity and internet connectivity—hinder scalability, particularly in agrarian regions. MFIs are also grappling with balancing social missions against financial sustainability, as evidenced by debates over interest rates and repayment flexibility (Desai, 2025).

The sector faces structural challenges, including a "missing middle" where micro-entrepreneurs are too large for microloans but too small or risky for commercial banks. Studies highlight that 85.3% of Ethiopians lack access to formal financial services, forcing many to rely on informal credit networks (World Bank, 2021). Recent academic research underscores governance issues: board diversity and capital adequacy positively impact MFI performance, while liquidity constraints and non-performing loans strain profitability. Furthermore, Ethiopia's high inflation (28% in 2023) and foreign exchange shortages exacerbate operational risks, complicating loan affordability and currency stability (Joseph, 2025). To address these barriers, stakeholders advocate for blended finance models, combining public subsidies with private investments, and policies that incentivize MFIs to prioritize underserved demographics, such as women-led enterprises.

Policy reforms and international collaboration are pivotal to the sector's future. The government's Home-Grown Economic Reform Agenda (2019) and banking liberalization efforts aim to attract foreign investment and modernize financial infrastructure, including the establishment of the Ethiopian Securities Exchange in 2025. These measures are expected to enhance MFIs' access to capital markets and foster innovation in products like micro-insurance

and green finance. However, regulatory uncertainties, bureaucratic inefficiencies, and political instability in some regions remain risks. Moving forward, Ethiopia's microfinance landscape will depend on harmonizing digital transformation with inclusive policies, ensuring that growth translates into poverty reduction and equitable economic participation.

2.1.3 The role of microfinance on rural development

Microfinance has emerged as a pivotal tool for fostering rural development, particularly in low-income countries where traditional banking services are often inaccessible to the poor. By providing small loans, savings accounts, insurance, and other financial services, microfinance institutions (MFIs) enable rural households to invest in income-generating activities, improve their living standards, and build resilience against economic shocks. In regions like Ethiopia, where agriculture employs over 60% of the population, microfinance supports smallholder farmers and entrepreneurs, contributing to poverty alleviation and economic growth (World Bank, 2023). Recent studies highlight microfinance's role in enhancing access to education and healthcare, thereby improving quality of life in rural communities (Salih, 2024). Moreover, microfinance often targets women, who constitute a significant portion of the rural poor, promoting gender equality and social inclusion. This multifaceted impact underscores microfinance's potential as a catalyst for sustainable rural development, though its effectiveness depends on local conditions and implementation strategies.

One of the primary ways microfinance contributes to rural development is by providing credit to individuals and groups excluded from formal financial systems. This access enables rural entrepreneurs to start or expand small businesses, creating employment opportunities and increasing household incomes. For instance, when micro-loans combined with education, insurance, and micro-savings, significantly improved the financial performance of rural businesses, with regression models showing over 70% explanatory power for profits and sales growth (Gyimah et al., 2024). In agricultural communities, microfinance supports the purchase of inputs like seeds, fertilizers, and equipment, leading to increased crop productivity and food security. The Asian Development Bank's 2007 evaluation of the Rural Microfinance Finance Project in the Philippines demonstrated that microfinance can reduce poverty and enhance income levels among the rural poor, particularly when using models like the Grameen Bank approach (Kondo, 2007). Additionally, microfinance fosters financial inclusion by offering

savings and insurance products, helping households manage risks and build assets over time, which is critical in volatile rural economies.

Microfinance's impact extends beyond economic benefits to social and human development. By targeting women, microfinance empowers them to engage in economic activities, enhancing their decision-making power and social status. A 2023 report from Chaitanya India noted that microfinance has been effective in addressing poverty among vulnerable populations, particularly women, in rural India, where agriculture employs 42.6% of the workforce (Kumar Dey, 2015). Programs like India's Jeevika initiative have reduced reliance on informal moneylenders, who often charge exorbitant interest rates, thereby improving financial stability (M & Bhavani, 2023). Furthermore, microfinance enables households to invest in education and healthcare, as evidenced by a 2024 study that found improved access to these services in rural communities (Salih, 2024). In Ethiopia, where microfinance institutions like Oromia Credit and Saving Share Company serve millions, these social benefits are crucial for breaking cycles of poverty and fostering inclusive development.

Despite its benefits, microfinance faces challenges that can limit its impact on rural development. High interest rates, necessary for MFIs to achieve financial sustainability, can burden borrowers and lead to over-indebtedness, as noted in a 2023 analysis. The effectiveness of microfinance is also constrained by the lack of complementary services, such as financial literacy training, agricultural extension, or infrastructure development. For example, the Asian Development Bank emphasized that successful microfinance programs require careful targeting and implementation to reach the poorest households (Kondo, 2007). In Ethiopia, challenges like limited digital infrastructure and low financial literacy hinder microfinance outreach, with 85.3% of individuals lacking bank or mobile money accounts (EFTCorp., 2025).

2.1.4 Theories of access to credit

2.1.4.1 Classical Theories of Access to Credit

i) **Asymmetric Information Theories:** It occurs when lenders lack sufficient information to assess borrowers' creditworthiness, leading to adverse selection and moral hazard. Adverse selection happens when lenders cannot distinguish between low-risk and high-risk borrowers, resulting in higher interest rates that deter low-risk borrowers. Moral hazard arises when borrowers take on more risk knowing that lenders bear the cost of

default. In rural Ethiopia, where formal credit histories are scarce and legal enforcement is weak, these issues significantly restrict credit availability (Stiglitz & Weiss, 1981). Microfinance institutions (MFIs) attempt to mitigate these challenges through innovative lending models, but information asymmetries remain a persistent issue even in group-based lending (Ahlin & Townsend, 2007).

ii) **Credit Rationing Theory:** It was formalized by Stiglitz and Weiss (1981), explains why lenders might limit credit supply despite high demand (Stiglitz & Weiss, 1981). Raising interest rates can attract riskier borrowers, leading lenders to ration credit to avoid losses. In Ethiopia, this phenomenon restricts rural households' ability to invest in agriculture, affecting productivity and food security (Besley, 1994). While microfinance has expanded credit access, high transaction costs and correlated poverty factors among borrowers can still constrain its effectiveness (Cull et al., 2009).

2.1.4.2 Modern Theories and Innovations

i) **Institutional Theories and Group Lending:** It emphasizes the role of alternative financial institutions like MFIs in addressing credit market failures. Group lending, where loans are given to groups rather than individuals, reduces risks through joint liability and peer monitoring. This model has been successful in Ethiopia, with MFIs like Oromia Credit and Saving Share Company (OCSSCo) serving rural populations effectively, achieving repayment rates above 98% (De Aghion & Morduch, 2000). Social capital theory complements this approach, suggesting that community trust can substitute for collateral, though its effectiveness depends on the strength of local social networks (De Aghion & Morduch, 2000). Recent advancements in digital finance, such as mobile banking platforms like Telebirr, are further expanding outreach by reducing transaction costs and overcoming geographical barriers, aligning with Ethiopia's Digital Ethiopia 2025 strategy (Kumar & Asmare, 2024).

ii) **Financial Inclusion Frameworks:** It advocate for integrating credit with other financial services such as savings, insurance, and payments to enhance economic stability and reduce inequality (Demirguc-kunt et al., 2008). These frameworks emphasize that limited access to finance is linked to income inequality and slower economic growth (Galor & Zeira, 1993). Addressing financial exclusion through integrated approaches, such as

combining credit with agricultural extension services and digital literacy training, is crucial for long-term development in Ethiopia (EFTCorp, 2025). Modern perspectives suggest that more developed financial systems are associated with lower inequality over time, highlighting the importance of inclusive financial policies (Demirgüç-Kunt et al., 2008).

2.1.5 Concept of food security and its measurement

Food security is a cornerstone of global development, particularly in regions like Ethiopia, where rural households face critical challenges in accessing sufficient and nutritious food. This review synthesizes recent literature to elucidate the concept of food security and the methodologies used to measure it, focusing on their application in developing contexts. Drawing on academic journals and reports from international organizations, the review explores the multidimensional nature of food security, the tools and indicators used for its measurement.

2.1.5.1 Defining Food Security

The concept of food security was formalized at the 1996 World Food Summit, which defined it as a state "when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996). This definition underscores four core dimensions namely: (i) Availability, (ii) Access, (iii) Utilization, and Stability. While availability denotes physical presence of sufficient food quantities, achieved through domestic production, imports, or food aid (Barrett, 2010), access represents individuals or households ability to obtain food through purchasing power, own production, or social transfers (Coates, 2013). Moreover, utilization indicates the proper biological use of food, encompassing nutritional quality, safety, and cultural acceptability, as well as factors like health and hygiene that affect nutrient absorption (Manikas et al., 2023). Finally, stability depicts the consistency of availability, access, and utilization over time, ensuring resilience against economic, climatic, or conflict-related shocks (FAO, 2023)

Recent literature expands this framework by proposing additional dimensions, such as sustainability and agency, to address environmental concerns and individual empowerment in food systems (Wahbeh et al., 2022). Related concepts include nutrition insecurity (encompassing care, health, and hygiene), undernourishment (caloric deficiency), hunger (recurrent lack of

access), and hidden hunger (micronutrient deficiencies affecting approximately 2 billion people globally) (Barrett, 2010). These distinctions are critical in contexts like Ethiopia, where chronic and transitory food insecurity coexist due to reliance on rain-fed agriculture and vulnerability to climate shocks.

2.1.5.2 Measurement of Food Security

Measuring food security is inherently complex due to its multidimensional and latent nature, requiring a combination of quantitative and qualitative indicators across various scales (national, regional, household, and individual). Recent literature highlights a range of tools and indicators, each addressing specific dimensions and purposes. At the national level, food security is often assessed using methods such as Prevalence of Undernourishment (FAO, 2023), Share of Food Expenditure by the Poor (Jones et al., 2013), Relative Dietary Supply Index (Jones et al., 2013), Domestic Food Price Volatility (FAO, 2023): Global Hunger Index (GHI) (Grebmer et al., 2023) and Global Food Security Index (GFSI) (EIU, 2022). As this study is at household level, standard food security measurement scales at household level are presented as follows:

i) **Household Food Insecurity Experience Scale (HFIES)**: It measures the frequency and severity of food access issues, such as worrying about food shortages or reducing meal sizes, validated in contexts like Sub-Saharan Africa (Coates et al., 2007).
ii) **Household Dietary Diversity Score (HDDS)**: It is a simple count of the variety of food groups a household consumed, linked to nutritional outcomes like child stunting (FAO, 2011).
iii) **Food Consumption Score (FCS)**: It assesses diet quantity and quality by combining the frequency of consumption with the nutritional significance of food groups (WFP, 2024).
iv) **Household Hunger Scale (HHS)**: It is a simpler scale focusing on severity of hunger, designed for cross-cultural comparability (Ballard et al., 2011).
v) **Coping Strategies Index (CSI)**: It measures the frequency and severity of coping behaviors (e.g., borrowing food, eating less preferred foods) during food insecurity (Maxwell et al., 2008).

A systematic review of 78 articles found that household-level calorie adequacy is the most frequently used indicator (22% as a sole measure), followed by dietary diversity-based (44%)

and experience-based (40%) indicators. However, only 13% of studies captured utilization, and 18% addressed stability, with just three publications measuring all four dimensions (Manikas et al., 2023).

2.1.5.3 Recent Developments in Food Security Measurement

Recent literature highlights several advancements in food security measurement, reflecting the evolving nature of the concept. One of those measurements provides vulnerability and resilience dimension for the concept is the Vulnerability to Food Insecurity Index (VFII). It assesses the likelihood of households becoming food insecure, while resilience measures evaluate the capacity to withstand shocks (Ibok et al., 2019). For example, dynamic panel data modeling has been used to quantify resilience (Manikas et al., 2023). Moreover**,** the 2024 State of Food Security and Nutrition in the World report introduces a new methodology to measure financing for food security and nutrition, emphasizing the need for increased and efficient funding to address SDG 2 targets (FAO, 2024b). There is also the UK Food Security Index which employs nine indicators (e.g., production-supply ratio, agricultural productivity) to monitor year-on-year changes, highlighting the importance of tailored approaches (DEFRA, 2024). Furthermore, recent studies propose adding sustainability as a dimension, linking food security to environmental and climate resilience (Wahbeh et al., 2022).

2.1.5.4 Challenges in Measuring Food Security

Despite these advancements, measuring food security faces several challenges. One of the major challenge is data limitation in which high-quality, timely data are often unavailable especially in low-income countries like Ethiopia, limiting the accuracy of measurements (Manikas et al., 2023). Balancing simplicity and comparability with contextual detail is also challenging. Household-level data are less resource-intensive but may miss intra-household disparities, while individual-level data are more precise but costly (Jones et al., 2013). The underrepresentation of utilization (13%) and stability (18%) in studies highlights a gap in comprehensive measurement (Manikas et al., 2023). Furthermore, ensuring measurement tools are precise, dependable, accurate, and context-grounded requires both quantitative and qualitative validation methods, such as ethnographic studies and cognitive interviewing (Coates, 2013).

Table 2. 1: Summary of key food security measurement indicators

Indicator	Description and Relevance
Prevalence of Undernourishment	Estimates caloric deficiency using food balance sheets, used for global SDG monitoring (FAO, 2023).
Global Hunger Index (GHI)	Combines undernourishment, child stunting, wasting, and mortality for cross-national comparisons (von Grebmer et al., 2023).
Global Food Security Index (GFSI)	Uses 58 indicators across affordability, availability, and quality/safety, relevant for policy analysis (EIU, 2023).
Household Food Insecurity Access Scale (HFIAS)	Measures food access experiences, validated in Ethiopia and other Sub-Saharan contexts (Coates et al., 2007).
Food Consumption Score (FCS)	Assesses diet quantity and quality, widely used in humanitarian settings (WFP, 2023).
Household Dietary Diversity Score (HDDS)	Measures dietary variety, linked to nutritional outcomes in rural Ethiopia (FAO, 2011).
Coping Strategies Index (CSI)	Quantifies coping behaviors during food insecurity, relevant for crisis contexts (Maxwell et al., 2008).

Source: Author (2025)

2.1.6 Theories of crop productivity

Crop productivity, defined as the yield or output of crops per unit of land (typically measured in tons per hectare), is a cornerstone of global food security, economic development, and environmental sustainability. In developing countries like Ethiopia, where agriculture employs over 60% of the population and is a primary source of livelihood, enhancing crop productivity is critical for poverty reduction, food security, and resilience to environmental challenges (World Bank, 2023). This review explores classical and modern theories, factors influencing

productivity, recent innovations, challenges, and future directions, with a focus on their relevance to Ethiopia's agricultural context.

2.1.6.1 Classical Theories of Crop Productivity

i) **Liebig's Law of the Minimum**: It was developed by Justus von Liebig in the 19th century, and it states that plant growth is constrained by the nutrient or resource in shortest supply, even if all other essential factors are abundant (Liebig, 1847). For example, if a soil lacks sufficient magnesium, yields will be depressed regardless of nitrogen or phosphorus availability (Crop Nutrition, 2023). This theory, often illustrated by the barrel analogy where the shortest stave limits capacity, has guided the development of mineral fertilizers to replenish soil nutrients, significantly increasing yields in modern agriculture (Humintech, 2023). In Ethiopia, where soil degradation is a major issue, Liebig's Law underscores the importance of balanced nutrient management to optimize crop productivity.

ii) **Total Factor Productivity (TFP)**: In agricultural economics, TFP measures the efficiency with which inputs such as labor, land, capital, and materials are converted into outputs (Wikipedia, 2023). TFP accounts for technological progress and efficiency gains beyond individual input increases, such as those achieved during the Green Revolution through high-yielding varieties and mechanization (World Bank, 2007). In sub-Saharan Africa, low TFP is a proximate cause of low aggregate productivity, highlighting the need for technological and institutional interventions to boost crop yields (Taylor, 2023).

2.1.6.2 Modern Theories of Crop Productivity

Modern theories emphasize sustainability, technology, and resilience to address contemporary challenges in agriculture.

i) **Sustainable Intensification (SI)**: It aims to increase crop yields without expanding agricultural land or degrading natural resources, integrating practices like conservation agriculture, improved crop varieties, and efficient nutrient management (Pretty et al., 2011). SI enhances ecosystem services such as soil health, biodiversity, and water

quality, making it highly relevant for Ethiopia, where land degradation and climate variability threaten productivity (Rockström et al., 2017). Research suggests SI can increase yields while reducing environmental impacts, though its adoption requires policy support and farmer training (CIMMYT, 2020).

ii) **Precision Agriculture**: This approach leverages technologies like GPS, sensors, drones, and data analytics to optimize input use (e.g., water, fertilizers, pesticides), reducing waste and environmental impact while maintaining or increasing yields (Godfray et al., 2010). Precision agriculture is gaining traction in developing countries, though its application in Ethiopia is limited by infrastructure and cost barriers (Foley et al., 2011).

iii) Climate-Smart Agriculture (CSA): It is a kind of agriculture which integrates sustainable practices with climate change adaptation and mitigation, promoting resilient crop varieties, water-efficient irrigation, and reduced greenhouse gas emissions (Rockström et al., 2017). In low-latitude regions like Ethiopia, where climate change is projected to reduce crop diversity and yields, CSA is critical for maintaining productivity (Heikonen et al., 2025).

2.1.6.3 Factors Influencing Crop Productivity

Crop productivity is affected by a number of factors such as biophysical, socioeconomic, and policy factors. Biophysical factors consist of soil quality, water availability, climate conditions, and pest and disease management. Fertile soils with adequate organic matter, proper pH, and good structure support higher yields. Soil degradation, prevalent in Ethiopia, limits productivity (Foley et al., 2011). Moreover, adequate and timely water supply is crucial, particularly in Ethiopia's rain-fed agricultural systems (Tilman et al., 2011). Temperature, rainfall, and sunlight also influence crop suitability, with climate change posing new challenges (Heikonen et al., 2025). In addition to this effective control is essential to maintain crop health and yield (Godfray et al., 2010).

Other crucial factors affecting crop productivity are socioeconomic factors including labor and capital, technology adoption and access to well-functioning market. Access to labor and financial resources determines investment in inputs and technologies (World Bank, 2008). Likewise, improved seeds, machinery, and irrigation systems boost productivity, but adoption is limited by

cost and knowledge (Godfray et al., 2010). Proximity to markets and infrastructure also play an indispensable role as it affects farmers' ability to sell produce and access inputs (Bustos et al., 2013)

Lastly, but not least, policy and institutional factors are also quite critical for crop productivity. It includes government policies such as subsidies, research, and extension services which can enhance productivity, while restrictive policies can hinder it (World Bank, 2008). Moreover, secure land rights encourage long-term investments in soil conservation (Foley et al., 2011). Furthermore government extension services and credit facilities, such as microfinance, are also pivotal for smallholder farmers (Bustos et al., 2013).

2.1.6.4 Challenges of crop productivity in Ethiopia

Ethiopian agriculture is facing a number of challenges on its way for achieving sustainable crop productivity. One of the major challenges is climate Change in which rising temperatures and erratic rainfall threaten yields, with projections indicating a 10–31% shift in crop production outside climatic niches under 2°C warming (Zenda, 2024). Developing resilient varieties and adaptive practices is essential. The other major challenge is resource scarcity such as water scarcity, soil degradation, and biodiversity loss which require sustainable land management practices like no-till farming (Foley et al., 2011). Besides to this, sustainability is also another in which balancing productivity with environmental conservation demands significant investment in research and infrastructure (Godfray et al., 2010). Likewise, high transaction costs and limited infrastructure restrict smallholder farmers' access to modern technologies, necessitating interventions like microfinance (Bustos et al., 2013).

2.2 Empirical Literature Review

This section synthesizes recent empirical studies on the determinants of access to credit and its impact on food security and crop productivity, specifically for teff and maize, among rural households in Ethiopia. The review is organized into three sections: (1) determinants of access to credit, (2) impact of access to credit on food security, and (3) impact of access to credit on teff and maize productivity. Each section draws on peer-reviewed studies and institutional reports to provide a comprehensive overview, focusing on evidence from Ethiopia and beyond. The review aims to address key findings of existing studies and discover gaps in the literature.

2.2.1 Determinants of access to credit

Access to credit is a foundation for rural households in Ethiopia, where smallholder farming dominates agricultural production. Recent studies identify several socio-economic and institutional factors that determine whether rural households can access formal credit, reflecting the challenges of financial inclusion in a predominantly agrarian economy. A study by Waje (2020) in Boloso Bombbe District, Wolaita Zone, utilized a probit regression model to analyze data from 312 households, finding that age, educational level, cooperative membership, access to extension services, saving habits, collateral, connections with local leaders, and livelihood diversification significantly influence credit access. The study indicated that older and more educated household heads are more likely to secure credit due to their experience and ability to navigate financial systems. Moreover, cooperative membership facilitates access by linking farmers to microfinance institutions, while extension services provide critical information on credit opportunities. Similarly, Tesiso et al., (2023) analyzed determinants of credit access in Bilate Zuria District, Sidama Region, using a cross-sectional dataset from 385 households and logistic regression. Only 34.5% of households are found to have credit access. The study revealed that gender, marital status, collateral, lending procedures, group lending, high interest rates, distance to credit institutions, number of dependents, and limited availability of microfinance institutions were significant determinants. It also underscores the need for gender-inclusive credit programs and improved access to microfinance in remote areas.

In addition, another study by Kiros & Meshesha, (2022) examined factors affecting formal credit access among 299 smallholder farmers in Basona Worana District, Amhara Region, using logistic regression. The study revealed that only 24.1% of participants accessed formal credit in the study area. Significant determinants included age, sex of household head, family size, extension contacts, off-farm income, interest rates, lending procedures, group lending, and rapid repayment periods. Furthermore, the study highlighted that simplifying lending procedures and reducing repayment pressures could enhance credit access. Chaka & Komicha (2017) also explored factors influencing credit access in Doba and Karsa districts, Oromia Region, using household survey data. It showed that education, age, income, land size, livestock ownership, distance to financial institutions, and cooperative membership were key determinants. The study emphasized the need for expanding financial services to remote areas and improving financial literacy so as to increase credit access in the study area.

Furthermore, Lemessa & Gemechu (2016) investigated credit access determinants in Jibat District, West Showa Zone, using survey data and econometric models. It indicated that education, family size, land size, livestock ownership, distance to credit institutions, and cooperative membership significantly influenced credit access in the study area. The study suggested that enhancing awareness of credit services and supporting cooperative structures can improve access. Another study by Yehuala (2008) analyzed factors affecting formal credit access in Metema Woreda, North Gondar Zone, using household survey data. The study indicated that age, education, land size, income, collateral and cooperative memberships were significant determinants. It also underscored that addressing collateral constraints and promoting financial inclusion through cooperatives is a critical steps for enhancing access to credit in the study area.

Table 2. 2: Summary of empirical literatures on determinants of access to credit

Study	Key Findings	Methodology
Waje, (2020)	Age, education, membership, extension, saving, collateral, local connections, diversification	Probit regression
Tesiso et al., (2023)	Gender, marital status, collateral, lending procedures, group lending, interest rates, distance, dependents	Logistic regression
Kiros & Meshesha, (2022)	Age, sex, family size, extension, off-farm income, interest rates, lending procedures, group lending, repayment period	Logistic regression
Chaka & Komicha (2017)	Education, age, income, land, livestock, distance, membership	Econometric models
Lemessa & Gemechu, (2016)	Education, family size, land, livestock, distance, membership	Econometric models

Source: Author (2025)

2.2.2 Impact of access to credit on households' food security

Food security still remains a pressing challenge for rural livelihoods in Ethiopia. The impact of credit access on food security is mixed, with studies showing both positive and negative outcomes depending on context and usage. Below is a review of some recent studies exploring the relationship between credit access and food security.

A study by Boltana et al., (2023) assessed the impact of credit utilization on food security in Offa District of Southern Ethiopia, using a multi-stage sampling of 352 households and propensity score matching. It revealed that credit access increased households' daily calorie intake by 248.53 Kcal/capita/day, indicating a positive impact on food security. The study finally underscored that credit from microfinance institutions can enhance food security, particularly in drought-prone areas, by enabling agricultural investments. Moreover, using 360 sample households, a study by Berhanu et al., (2021) examined the impact of credit access on smallholder households food security in Jimma zone of southwest Ethiopia using propensity score matching. It indicated that microcredit utilization has generated a positive and significant impact on household food security. The study also emphasizes the need for scaling out services of microcredit institutions should target improving financial literacy of the rural poor and their current financial need on the basis of other resources such as land and livestock they owned with the ultimate goal of ensuring household food security. Another study by Sani & Kemaw, (2019) examined food insecurity and coping strategies in Assosa Zone, Western Ethiopia, using data from 276 households. It found that households with credit access were more likely to adopt coping strategies like selling assets, suggesting a complex relationship with food security.

Beyond Ethiopia, Kehinde & Kehinde, (2020) investigated the impact of credit access and cooperative membership on food security of rural house- holds in south-western Nigeria, using 300 sample households. The study's result of propensity score matching (PSM) and augmented inverse-probability weighting model (AIPW) revealed that access to credit improved households food security through increasing daily per capita consumption by 1,496 kilocalories. Furthermore, Salima et al., (2023b) examined the impact of access to either formal or informal credit on household food security in a credit-constrained developing country context of Malawi. By employing the Endogenous Regime Switching (ERS) approach and the Tobit regression model, the study indicated that although access to formal credit improves household food security, access to informal credit worsens food security within the context.

Table 2. 3: Summary of empirical literature on impact of credit access on food security

Study	Key Findings	Methodology
Boltana et al.,	Increased calorie intake by	

(2023)	248.53 Kcal/capita/day	Propensity score matching
Kehinde & Kehinde, (2020)	Increase the food security of rural households	binary logit model, propensity score matching (PSM) and augmented inverse-probability weighting model (AIPW
Salima et al., (2023a)	Improved households food security	Endogenous Regime Switching (ERS) approach and the Tobit regression model
Berhanu et al., (2021)	Improved households food security	Propensity score matching
Sani & Kemaw, (2019)	Mixed impact via coping strategies	Food insecurity index, Tobit model

Source: Author (2025)

2.2.3 Impact of access to credit on households' teff and maize productivity

Teff and maize are staple crops in Ethiopia, critical for food security and economic livelihoods. Credit access can enhance productivity by enabling farmers to invest in improved inputs and technologies. Below is a review of recent studies that explore the impact of access to credit on teff and maize productivity.

A study by Gebeyehu et al. (2024) evaluated the impact of credit on maize productivity in Hababo Guduru District, oromia region of Ethiopia using a cross-sectional survey of 260 households and propensity score matching. It revealed that credit access increased maize productivity by 26.6% through enhanced use of improved seeds (37.4%), fertilizer (47.8%), and hired labor (33.6%). It also pointed out that credit is crucial for overcoming capital constraints and adopting yield-enhancing technologies. Moreover, Ahmed et al., (2017) measured the impact of improved maize varieties on productivity in East Hararghe Zone using propensity score matching and stochastic frontier analysis. It revealed that access to credit facilitated the adoption of improved varieties, significantly increasing maize productivity. Finally, the study emphasized that credit programs should support technology dissemination to enhance maize yields.

As to credit access's impact on teff productivity, Fikire & Emeru, (2022) investigated technology adoption for teff production in Minjar Shenkora Woreda, Amhara region of Ethiopia using data from 362 households and multinomial logistic regression model. The study indicated that access to credit was a key determinant of technology adoption, which is critical for improving teff

productivity. It also asserted that credit programs should focus on supporting modern technology adoption for sustainable teff production. Abate et al. (2021) also examined the impact of technology adoption on teff productivity in North Shewa Zone, Amhara region, Ethiopia using data from 395 households and multinomial logit models. It indicated that access to credit significantly influenced technology adoption, leading to higher teff productivity, especially with combined fertilizer and seed use. It also emphasizes that credit programs should prioritize technology adoption to maximize teff yields.

Another study by Elemineh et al., (2020) investigated technology adoption and teff productivity in Basso Liben District using a cross-sectional survey of 190 households and multivariable regression. The study indicated that credit access increased teff productivity (26.18 vs. 20.47 quintals/hectare) and the likelihood of technology adoption by 3.141 times. It underscored that credit is a key enabler of technology adoption and productivity gains in teff production. Moreover, Teshome & Tegegne (2020) also analyzed factors influencing the adoption of improved teff varieties in Kobo District using a double-hurdle model and data from 150 households. The study also indicated that access to credit was a significant determinant of adoption decisions, indirectly enhancing teff productivity. It emphasized that credit can support the adoption of improved varieties, boosting teff yields.

Table 2. 4: Summary of empirical studies on impact of credit access on teff and maize productivity

Study	Crop	Key Findings	Methodology
Gebeyehu et al., (2019)	Maize	26.6% productivity increase	Propensity score matching
Ahmed et al., (2017)	Maize	Increased productivity via variety adoption	Propensity score matching, stochastic frontier
Elemineh et al.,(2020)	Teff	26.18 vs. 20.47 quintals/hectare, 3.141x adoption	Multivariable regression
Abate et al. (2021)	Teff	Increased productivity via technology adoption	Multinomial logit
Teshome & Tegegne, (2020)	Teff	Indirect impact via variety adoption	Double-hurdle model

(Fikire & Emeru, 2022)	Teff	Increased productivity via technology adoption	Multinomial logit

Source: Author (2025)

This review highlights the critical role of credit access in supporting rural households in Ethiopia. Key determinants of credit access include age, education, cooperative membership, and asset ownership, with barriers like gender disparities and geographical isolation limiting inclusion. Credit access generally improves food security by increasing calorie intake and supporting agricultural investments, though its effectiveness depends on productive fund use. For crop productivity, credit significantly boosts maize yields and indirectly enhances teff productivity through technology adoption.

2.3. Conceptual framework of the Study

The conceptual framework of this study is depicted below (see figure 1) based on the assumption that the determinants of rural households' credit access and its impact on food security and crop productivity. Following Boltana et al., (2023) and Tesiso et al., (2023) factors which can affect households access to credit are categorized into demographic, socio-institutional and economic factors. Then access to credit is linked with food security and crop productivity through channels such as income diversification, consumption smoothing, agricultural investment and input acquisition etc. Food security outcome is measured by households dietary diversity score (DDS) and daily calorie consumption per adult equivalence (DKAE). Then crop productivity is indexed by households Teff and Maize productivity. Both Teff and Maize productivity is measured as the number of kilograms produced per hectare.

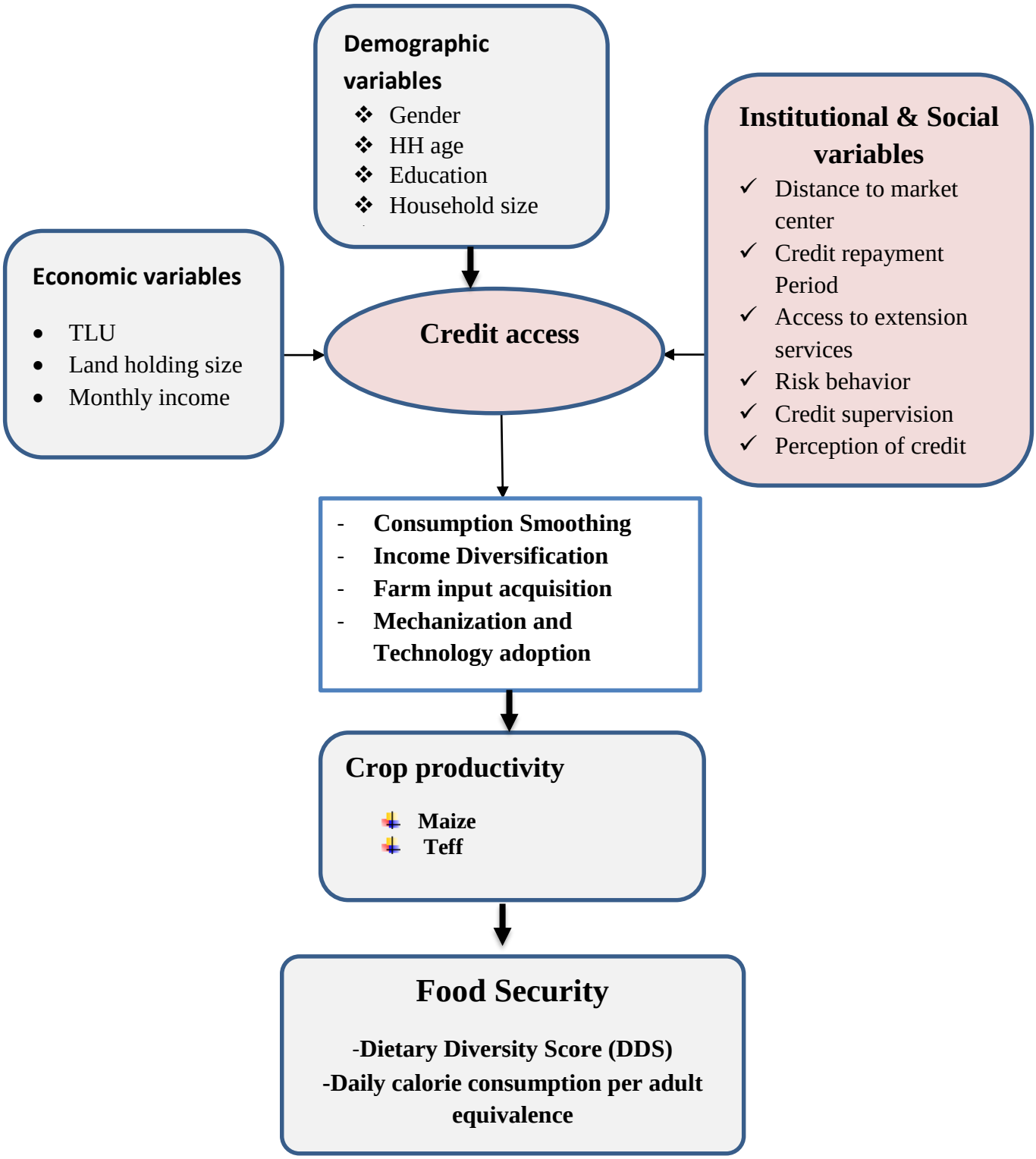

Figure 2. 1: Conceptual framework of the study

Source: Own synthesis based on literature review (2025)

CHAPTER THREE: METHDOLOGY OF THE STUDY

This chapter presents the basic methods and materials which are used to address the stated research objectives of the study. Hence this section discusses about description of the study area, sampling techniques, sample size determination, data sources and methods of data analysis techniques that are employed for the study.

3.1 Description of the Study Area

This study was conducted in Ethiopia, which is a landlocked country in the horn of Africa. In terms of administration, it is sub-divided into 12 regional states and 2 city administrations. Its diverse topography spans highland plateaus, the Great East African rift valley, and lowland arid regions, fostering varied agro-ecological zones. The country's capital, Addis Ababa, serves as a political and economic hub, while its population exceeds 120 million, making it Africa's second-most populous region (CSA,2023)

Despite rapid urbanization in recent decades, approximately 79% of the population remains rural, depending predominantly on subsistence agriculture (World Bank, 2022). This sector employs over 70% of the workforce and contributes roughly 35% to GDP, underscoring its centrality to livelihoods and economic stability. Dominated by smallholder subsistence farming, it concentrates on producing staple crops such as teff, maize, and sorghum while coffee—Ethiopia's major export item---fuels foreign exchange earnings. Nevertheless, the sector faces challenges from climate variability, soil degradation, and limited access to financial services, and reliance on rain-fed systems, which curbs productivity despite its crucial role in food security and livelihoods.

3.2. Research Design and Approach

This particular study employed a quasi-experimental technique which encompasses rural households which have access to credit (Yes) and those households which don't have access (No). Hence, the total sample households used in this study are categorized into: treatment groups (credit user households) and control groups (non- user households).

3.3 Data Type and Sources

So as to attain the objectives of this study quantitative type of data was used. This study is primarily depended on secondary data sources. Specifically, the empirical data for this particular

study is the 2021/22 national socio-economic survey which is obtained from micro-data library of the World Bank. In addition to this, relevant information from peer-reviewed journals as well as national and international reports from the World Bank database, which are chosen for their reliability and relevance, was used (World Bank, 2021/22).

3.4 Methods of Data Collection

Secondary data for this study were obtained from pre-existing sources such as government and institutional reports, academic literature, international organizations (e.g. World Bank and FAO). The empirical data were accessed from the World Bank database and it was organized properly to align with the stated objectives of the study. Households that which needs aggregation were carefully aggregated. Moreover, all secondary data were accessed in compliance with open-access policies or institutional permissions. In addition to this, sensitive demographic data were anonymized and aggregated to protect confidentiality.

3.5 Sampling Technique and Sample Size Determination

According to the World Bank database 2142 sample rural households—from nine regions/administrations---were participated on the 2021/22 national socio-economic survey. We don't have the information as to the sampling technique that was followed to select those 2142 households for the survey. However, the final empirical survey data indicated that out of those 2142 rural households, it's only 1524 households which revealed that whether they do have access to credit or not. Since the center of this study is access to credit, therefore, we purposively selected those 1524 rural households. Those 1524 rural households are distributed across eight regional states and one city administration (Dire Dawa) as depicted in table 3.1.

Table 3. 1: Distribution of rural sample households of the study across regions

Regions	Number of Sample Households	Percentage
Afar	22	1.4%
Amhara	242	15.8%
Oromiya	340	22.3%
Somali	42	2.9%
Benishangul	95	6.2%
SNNP	391	25.6%
Gambela	138	9.1%
Harari	161	10.6%
Dire Dawa	93	6.1%
Total	1524	100%

Source: Author (2025)

3.6 Methods of Data Analysis

This study employed both descriptive and econometric statistical techniques to answer the stated research objectives. Particularly the descriptive analysis makes use of different charts, mean, standard deviation, frequencies distribution, percentages and chi- square test, F-test as well as t-test while the econometric analysis is mostly devoted to impact evaluation techniques like average treatment effects and endogenous switching regression models. The whole methodology of the model is discussed below.

3.6.1 Model specification

3.6.1.1 Determinants of rural households' credit access

A binomial logistic regression model was used to identify the major factors which determine the rural households' credit access. To specify the binomial logistic regression model, suppose that, from the regression model.

$$Y_i = X\beta + U_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

$\boldsymbol{Y_i}$ represents the i^{th} household's status as to access to credit and it takes the value 1 if the household has access to credit and it takes the value 0 otherwise. Moreover, $\boldsymbol{X\beta}$ is a vector of parameter and explanatory variables, while $\boldsymbol{U_i}$ is the random disturbance term. Now, according to (Gujarati, 2003), $\boldsymbol{Y_i}$ follows logistic distribution and, hence, a particular household's probability to get access to credit, usually known as probability of success, can be expressed as

$$P_i = \frac{e^{Y_i}}{1 + e^{Y_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

If P_i is household's probability of getting access to credit, the probability that a particular household not to get access to credit, usually known as probability of failure, can also be represented as

$$1 - P_i = \frac{1}{1 + e^{Y_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Now taking the ratio of household's probability of getting credit access (probability of success) to household's probability of not getting credit access (probability of failure) gives as the odds ratio which is denoted as

$$\frac{P_i}{1 - P_i} = e^{Y_i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

Now if we take the natural logarithm of the odds ratio we automatically arrive at the logistic regression model, which is given as

$$L_i = ln\left(\frac{P_i}{1 - P_i}\right) = Y_i = X\beta + U_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

Moreover, this logistic model (L_i) is not only linear in explanatory variables but also it is linear in parameters.

3.6.1.2 Impact of access to credit on households' food security & crop productivity

In impact estimation, several methods have been used like OLS, logit, probit and propensity score matching (Nuttall and Houle, 2008). In this study access to credit is the treatment variable. Keeping this in mind, analyzing the impact of access to credit on selected outcome variables (*rural households' food security and crop productivity*) is the major aim of this study. For this purpose, commonly used models of OLS and probability models (logit and probit) can give

consistent estimates if assumption of no endogeneity holds. But in this study outcome variables may affect households' access to credit and there may be simultaneity (i.e., bidirectional relationship) and the likelihood of getting access to credit is not randomly given. This indicates there is sample selection bias besides endogeneity. Thus, it needs an estimation technique which both accounts for sample selection bias and endogeneity problem. For tackling these issues, Propensity score matching (PSM) technique and endogenous switching regression are commonly used. However, PSM has a serious limitation that leads to the existence of unmeasured confounding variables and biased results (Nuttall and Houle, 2008). Rather than using PSM, endogenous switching regression is recommended in the literatures (Shiferaw et al., 2014b; Abdulai & Huffman, 2014; Manda, 2016b; Workineh et al., 2020). Therefore, to correct the section bias and control unobserved farm and household characteristics, endogenous switching regression is the most appropriate thus; it has been employed for this study.

Specification and estimation of binomial endogenous regression model follows a two-step procedure. Before examining the impact of access to credit on the outcome variables it is necessary to identify factors determining households' access to credit. Thus, the first stage involves identification of factors affecting households' access to credit as well as estimation of inverse mills ratio terms for controlling the possible endogeniety and sample selection bias. For this purpose we used the binomial probit regression model, which is nearly similar with that of the binomial logistic model we specified in section 3.6.1.1., as it provides more precise estimates than the logistic model (Gujarati, 2003).

Then so as to control sample selection and endogeneity bias, it is necessary to incorporate a selectivity correction term usually known as inverse mills ratio ($lambdas$) in the second stage of estimation (Greene, 2012). By doing so we used a least square estimation on the second-stage of the endogenous switching regression model (Shiferaw et al., 2014a). Assuming those households with no credit access ($Z = 0$) is our reference category, following different literature the outcome equation adjusted for inverse mills ratio terms is specified as follow:

$$\begin{cases} Regime\ 1(\ for\ credit\ user): Y_{1i} = \Gamma_1 X_{1i} + \Theta_1 \hat{\lambda}_{1i} + U_{1i} \quad if\ \ Z = 1 \\ \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \ldots\ldots (3.6) \\ Regime\ 2(for\ CF\ non - credit\ user):\ Y_{2i} = \Gamma_2 X_{2i} + \Theta_2 \hat{\lambda}_{2i} + U_{2i} \quad if\ \ Z = 0 \end{cases}$$

Where Y_{ji} is outcome variables U_{ji} is independently and identically distributed mean zero and constant variance random disturbance term, X_{ji} is a vector of different socio-economic characteristics of households, $\Gamma_j \; and \; \Theta_j$ are parameters to be estimated and $\hat{\lambda}_{ji}$ is the inverse mills ratio which is derived from the selection equation in the first stage.

Furthermore, the binomial endogenous switching regression model can also be used to derive the average treatment effect (ATE) which compares the expected value of the outcome variables (*rural households' food security and crop productivity*) among credit user and non- user households. It both indicates the actual and counterfactual effect of treatment variable on the outcome variables. Following the work of Manda, (2016a); Abdulai & Huffman, (2014), and Shiferaw et al., (2014a) average treatment effect is estimated as follow:

The actual expected value of outcome variables for households with credit access is given by:

$$E\left(Y_{1i} \mid Z = 1; X_{ji}, \hat{\lambda}_{ji} \right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. \ldots \ldots .. \ldots \ldots . (3.7)$$

The actual expected value of outcome variables for households with no credit access is given by:

$$E\left(Y_{2i} \mid Z = 0; X_{1i}, \hat{\lambda}_{1i} \right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (3.8)$$

The counterfactual expected value of outcome variables for households with credit access is given by: (credit user if they would not use) is given by:

$$E\left(Y_{1i} \mid Z = 0; X_{ji}, \hat{\lambda}_{ji} \right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots . (3.9)$$

The counterfactual expected value of outcome variables for households with no credit access is given by: (if non- user of credit would use) is given by:

$$E\left(Y_{2i} \mid Z = 1; X_{1i}, \hat{\lambda}_{1i} \right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (3.10)$$

Now the average treatment effect on the treated (ATT) is determined as the difference between equation 3.7 and equation 3.9 as follow:

$$ATT = E\left(Y_{1i} \mid Z = 1; X_{ji}, \hat{\lambda}_{ji} \right) - E\left(Y_{1i} \mid Z = 0; X_{ji}, \hat{\lambda}_{ji} \right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (3.11)$$

Similarly, the average treatment effect on the untreated (ATU) will be determined as the difference between equation 3.8 and equation 3.10 as follow:

$$ATU = E\left(Y_{2i} \mid Z = 0; X_{1i}, \hat{\lambda}_{1i}\right) - E\left(Y_{2i} \mid Z = 1; X_{1i}, \hat{\lambda}_{1i}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.12)$$

3.7 Definition of Variables and Working Hypothesis

This section presents major variables used in the study and the research hypothesis.

3.7.1 Outcome variables

This study has three major outcome variables namely (a) access to credit (b) food security (c) crop productivity.

(a) Access to credit: It is a binomial dummy variable which takes the value 1 for those household with access to credit and it takes 0 otherwise.

(b) Food security: It is a continuous variable which is measured by dietary diversity score (DDS) and daily calorie consumption per adult equivalence (DKAE). While DDS indicates the number of food items a household eats within 24 hours before the survey out of 12 possible food items, DKAE depicts each household's daily calorie consumption per adult equivalence.

(c) Crop productivity: It represents productivity of land among teff and maize producer households. While teff productivity represents the amount of teff a particular teff in kilograms producer household produces per a single hectare of land, maize productivity on the other hand indicates the mount of maize in kilograms a particular maize producer household produces using a single hectare of land.

3.7.2 Explanatory variables

Age of household head: it is a continuous variable which is measured in years. Since it raise rural households' experience, it is highly likely to have a positive effect on access to credit and other outcome variables of this study. Hence, this study hypothesized that, age is positively associated with the likelihood of access to credit, food security and crop productivity.

Age squared: It is a continuous variable which represents a simple square of age of household head. This study hypothesized that it is negatively associated with access to credit, food security and crop productivity in the study area.

Gender of household head: It is a categorical variable which assumes 1 if a household is male headed and 0 otherwise. (Tesiso et al., 2023) indicated that gender of household head increases

the likelihood of access to credit. Thus this study hypothesized that male headed households are more likely to get access to credit and to have high food security status and crop productivity.

Marital status: it is a categorical variable which assumes 1 if a household head is married and 0 otherwise. (Boltana et al., 2023) indicated that married households are highly likely to secure credit access. Hence, this study hypothesizes that married households are more likely to get access to credit than their counterparts.

Household Size: It is a continuous variable which depicts the number of individuals which are living in a household. (Boltana et al., 2023) and (Tesiso et al., 2023) revealed that households with higher size are more likely to get credit access. Hence, this study hypothesized that a rise in household size increases the probability of getting access to credit. Moreover, it is expected to negatively affect food security and crop productivity.

Land size: It is a continuous variable that shows cultivated land size of a household in *hectare.* Land size is found to have a highly positive significant influence on households access to credit (Boltana et al., 2023). Thus, this study also hypothesized that cultivated land size is positively associated with the probability of getting access to credit and it has also a positive effect on food security and crop productivity.

Average monthly income: It is a continuous variable which indicates average monthly income of a household in Birr. As raise in income makes most things possible, this study hypothesized that average monthly income is negatively associated with households' access to credit. Because, it is most probably those households with insufficient income which seek to get access to credit from microfinance institutions. Moreover, it is hypothesized that, average monthly income is positively linked with food security and crop productivity.

Amount of Livestock Owned: It is a continuous variable that shows livestock amount of a household in tropical livestock unit using tropical conversion factor. Following (Tesiso et al., 2023) this study hypothesized that tropical livestock unit raises households probability of getting access to credit.

Distance to *the nearest* market center: It is a continuous variable that shows the distance of a nearest market from a house of a household in kilometers. This study hypothesized that distance to nearest market decreases the likelihood of getting access to credit.

Distance from the nearest major road: Like that of the previous variable, it is a continuous variable that shows the distance of a nearest major road from a house of a household in kilometers. It is also expected to negatively influence households' likelihood of getting access to credit.

Educational status of household head: it is a dummy variable which takes the value 1 for those household heads which are literate and takes 0 otherwise. As education is a quite important tool, this study hypothesized that it will positively affect household's probability of getting access to credit.

Access to extension service: It is a categorical variable that assumes 1 if a household has access to extension services and 0 otherwise. This study hypothesized that those households which get access to credit are more likely to get credit access and have higher food security status and crop productivity.

Table 3. 2: Summary of explanatory variables, their symbols and expected signs

Variables	Symbol	Scale of Measurement	Expected sign	Source
Age of household head	Age_of_HH	Continuous	+	(Boltana et al., 2023)
Age Squared	Age_Square	Continuous	_	(Boltana et al., 2023)
Gender of household	Gender	Dummy (1 if male and 0 otherwise)	+	(Boltana et al., 2023)
Marital Status	Marital_Status	Dummy (1 if married and 0 otherwise)	+	(Tesiso et al., 2023)
Household Size	hh_size	Continuous	+	(Boltana et al., 2023)
Land Size	LandSizeHectare	Continuous	+	(Tesiso et al., 2023)
Average Monthly Income	Monthly_Income	Continuous	_	(Tesiso et al., 2023)
Tropical livestock unit	TLU	Continuous	+	(Boltana et al., 2023)
Distance from the nearest market center	dist_market	Continuous	_	(Tesiso et al., 2023)
Distance from the nearest major road	dist_road	Continuous	_	(Tesiso et al., 2023)
Education(Dummy)	EducationDummy	Dummy (1 if literate and 0 illiterate)	+	(Tesiso et al., 2023)
Extension Service Participation	Extension_Service_Participation	Dummy (1 if a household participates and 0 if not)	+	(Boltana et al., 2023)

Source: Author (2025)

CHAPTER FOUR: RESULTS AND DISCUSSION

This chapter is devoted to data analysis and discussion of the study. First, descriptive analysis of sample households that are related to their socio-economic characteristics as well as status of credit access is discussed. Second, estimation of results and discussions regarding determinants of access to credit as well as its impact on food security and crop productivity is presented.

4.1 Socioeconomic characteristics of sample households

Table 4.1 below indicates socio-economic characteristics of sample households in the study area. As shown in the table the average age of household head of sample households is 46.6 years with a minimum and maximum age of 18 years and 97 years respectively suggesting that most household heads in the area lies at productive age group. Moreover the average household size of sample households is 5.21 (approximately 5 persons) while average monthly income is ETB 9184.2 with a minimum and maximum of ETB 684.4 and 137653.8 respectively. In addition to this, as table 4.1 indicate, the average land size and tropical livestock unit of sample households in the study area is 1.64 hectare and 3.94 units respectively. The result suggests that average land size and tropical livestock unit of the study area is approximate to the national average of 1 hectare and 4.6 units respectively.

Table 4. 1: Characteristics of sample households: Continuous variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Age of household head	46.6	14.82	18	97
Household size	5.21	2.19	1	13
Land Size	1.64	1.77	0.00074	7.84
Livestock Owned	3.94	4.45	0	51.75
Distance to the nearest market	68.88	59.53	1.9	291.5
Distance to the nearest major road	9.19	10.69	0	61.3
Average monthly income	9184.2	8181.6	684.4	137653.8

Source: Author (2025)

Table 4.2 below indicates the characteristics of sample households in the study area related to a number of categorical variables. As clearly indicated, of those households which have access to credit 86.3% (95) are male-headed while the rest 13.7% (15) are female headed households. In addition to this 86.3% (95) of those households which have access to credit are married while there remaining 13.7% (15) are unmarried. With regard to educational status, 43.7% (48) of households which have access to credit are literate which can read and write, whereas the rest 56.3% (62) are illiterates. Furthermore, the result demonstrates that only 37% (564) of sample households participate in or have access to extension services which indicates that the majority of sample households in the study area either don't participate in or have no access to extension services. The results also show that 73.6% (81) of sample households which have access to credit have participated in extension services. Moreover, of those households which don't have access to credit 65.9% (931) don't have participated in extension service which implies that there is some sort of connection between getting access to credit and participation in extension service. The significant χ^2 result associated with marital status and participation in extension service also suggests that these factors can affect getting access to credit among rural farm households in the study area.

Table 4. 2: Characteristics of sample households: Categorical Variables

Variables		Credit Access(Yes)		Credit Access(No)		Chi-square Test(χ^2)
		Amount	%	Amount	%	
Gender of household head	Male	95	86.3	1135	80.2	2.43
	Female	15	13.7	279	19.8	
Marital status	Married	95	86.3	1084	76.7	5.48**
	Unmarried	15	13.7	330	23.3	
Educational Status	Illiterate	62	56.3	799	56.5	0.0008
	Literate	48	43.7	615	43.5	
Participation in extension service	Yes	81	73.6	483	34.1	68.23***
	No	29	36.4	931	65.9	

Source: Own household survey (2021) ** and *** indicates statistical significance at less than 5% and 1% level of significance respectively.

Table 4.3 below demonstrates mean comparison test of continuous variables between sample households which do have access to credit and those households which don't have. For this purpose T-test was used in which a significant t-value indicates there is a significant mean difference between two groups. Hence, except for land size and tropical livestock unit, for all continuous variables, the test result is found to be statistically insignificant indicating that there is no significant mean difference between the two groups. It suggests that these variables can't affect farm households' access to credit in the study area. The statistically significant result in land size and tropical livestock unit, however, indicates there exist a significant mean difference in land size and tropical livestock unit between those households which have access to credit and which don't. The result further implies that access to credit may be attributed to land size and tropical livestock of those rural households in the study area.

Table 4. 3: Mean comparison test of some variables between credit users and non-users

Variable	Credit Access (Yes) (n=110)	Credit Access (No) (n=1414)	
	Mean	Mean	t-test
Age of household head	45.98	46.67	0.47
Household size	5.34	5.21	-0.63
Land size	2.13	1.6	-3.04***
Livestock size (in TLU)	5.32	3.83	-3.39***
Distance to the nearest market	60.9	69.5	1.45
Distance to the nearest major road	9.8	9.14	-0.61
Average monthly income	8079.29	9270.13	1.47

Source: Author (2025) *** denotes statistical significance at 1% level of significance.

Table 4.4 presents the regional distribution of access to credit among rural farm households in the study area. It indicates that majority of households which have access to credit are from Amhara region (53.6%) which is followed by Oromiya (29.1%) and Benishangul Gumz (9.1%). Out of all sample households for this study, Afar, Somali, Gambela and Dire Dawa are found to be regions with no household having access to credit. Table 4.4 further shows that out of all

sample households (1524) only 7% (110) have managed to get access to credit which may be due to the fact that there is poor financial inclusion in the country and absence of credit platforms which is tailored to those rural farm households. It might also be attributed to strict credit policies of those few micro-finance institutions which are nowadays promoted to formal banks which further deprive those households from getting access to credit.

Table 4. 4: Regional distribution of access to credit among rural households in the study area

Region	Accessed Credit		No Credit Access	
	Number	Percent	Number	Percent
Afar	0	0	22	1.5
Amhara	59	53.6	183	12.9
Oromiya	32	29.1	308	21.8
Somali	0	0	42	2.9
Benishangul	10	9.1	85	6
SNNP	8	7.3	383	27.1
Gambela	0	0	138	9.7
Harari	1	0.9	160	11.6
Dire Dawa	0	0	93	6.5
Total	110	100	1414	100

Source: Author (2025)

4.2 Food security characteristics of sampled households

Food security status of sample households is assessed based on dietary diversity score (DDS) and daily calorie consumption per adult equivalence. While DDS signifies the number of food items a household eats out of 12 different food items within 24 hours, DKAE denotes household's daily calorie consumption per adult equivalence. Table 4.5 indicates that the average DDS of sample households in the study area is 4.32 with a minimum and maximum value of 1 and 12 respectively. It suggests that households' food security status is low in terms of consuming varieties of food items. Moreover, the results indicate that the average daily calorie consumption per adult equivalent is 2897.64 kilocalories with a minimum and maximum value of 34.4 and 20289.89 respectively. It denotes that the average DKAE in the study area is higher than that of

the common standard of daily 2200 kilocalories per adult equivalence which further implies that in terms of calorie consumption households' food security status is relatively better.

Table 4. 5: Food security indicators of sampled households in the study area

Food Security Indicators	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Dietary Diversity Score(DDS)	4.32	2.5	1	12
Daily Calorie consumption per Adult Equivalence (DKAE)	2897.64	2053.1	34.4	20289.89

Source: Author (2025)

Table 4.6 presents the regional distribution of food security status of sample households across different regions of Ethiopia. It demonstrates that, on average, sample households from Somali region have the highest (7.31) dietary diversity score which are followed by Harari (5.79) and Benishangul (5.26). In terms of daily calorie consumption per adult equivalence, households from Harari region comes first (3328.2) and are fooled by SNNP (3248.7) and Benishangul (3061.2).

Table 4. 6: Food security indicators (averages) across regions in the study area

Regions	**Food Security Indicators**	
	Dietary Diversity Score(DDS)	Daily Calorie consumption per Adult Equivalence (DKAE)
Afar	4.63	1810.6
Amhara	3.39	2853.4
Oromia	4.1	2778.95
Somali	7.31	2250.12
Benishangul	5.26	3061.2
SNNP	4.08	3248.7
Gambela	4.27	2521.1
Harari	5.79	3328.2
Dire Dawa	3.79	2166.26

Source: Author (2025)

4.3 Determinants of access to credit in the study area

Table 4.7 presents the result of binomial logistic regression model which is employed to identify determinants of households' access to credit in the study area. The estimation result shows that households' participation in extension service, tropical livestock unit, monthly income, marital status, age of household head and distance from the nearest market center are major determinants of access to credit in the study area.

Table 4. 7: Determinants of access to credit: Result of binomial logistic regression

Variables	Coefficient	Std. err.	z	P>z	Marginal Effects
Age of household head	.09	.052	1.73	0.083*	.00412
Age Squared	-.0009	.0005	-1.82	0.07*	-.00004
Gender of household	-.17	.38	-0.45	0.65	-.0082
Marital Status	.66	.36	1.81	0.07**	.026
Household Size	-.042	.056	-0.74	0.46	-.0019
Land Size	.085	.056	1.50	0.13	.0039
Average Monthly Income	-.00004	.00002	-2.20	0.03**	-2.19e-06
Livestock in Tropical livestock unit	.053	.021	2.48	0.013**	.0024
Distance from the nearest market center	-.004	.0021	-1.82	0.07*	-.00018
Distance from the nearest major road	.005	.01	0.54	0.59	.00025
Education(Dummy)	-.07	.23	-0.31	0.75	-.0033
Extension Service Participation	1.65	.23	7.25	0.000***	.098
_cons	-5.38	1.28	-4.19	0.000	
Number of obs = 1,524		Prob > chi2 = 0.0000			
LR chi2(12) = 93.74		Pseudo R2 = 0.1186			

Source: Author (2025) ***, ** and * indicates statistical significance at 1%, 5% and 10% level of significance respectively.

As shown in the table 4.7, estimates of marginal effects indicates that participation in extension service increases households probability of getting access to credit by 9.8% and the result is statistically significant at 1% level of significance. This could be attributed to the fact that participation in extension service can improve households' knowledge and skills, raise access to information about available credit options and enhance social capital of those households which fosters networks with other farmers cooperatives and agricultural officers. The result is also in line with the findings of Waje (2020) and Balana et al. (2020).

The result also indicates that a unit raise in tropical livestock unit (TLU) enhances households' likelihood of getting access to credit by 0.2%. This could be mainly because of the fact that livestock plays an indispensable role in income generation and repayment capacity which makes highly likely for lenders to extend credit for those households. Moreover, when households get married their likelihood of getting access to credit raises by 2.6% and it is statistically significant at 5% level of significance. This may be due to lenders perception that married households are less likely to default on loans as they do have family responsibilities. Additionally, married couples are highly likely to accumulate more assets which can serve as collateral to secure loans. The result is congruent with the findings of Deyganto (2022) and Kuuwill et al (2024).

Furthermore, the result also indicates that as age of household head increase by one year, on average, probability of getting access to credit raises by 0.4%. This may be as a result of consistent income and established carriers, which older household heads are more likely to have, that is favored by borrowers. Moreover, this arises from the fact that age brings greater experience regarding financial literacy and discipline for older household heads making them more convincing to lenders. The result also indicates that households distance from the nearest market center is negatively associated with households' likelihood of getting access to credit. It may be because of the reason that distance can hinder access to credit through physical inaccessibility, reduced economic opportunities and limited information which is even more aggravated by lenders reluctance to serve households living in remote areas. Finally, and surprisingly, monthly income of households is found to be negatively and significantly associated with probability of getting access to credit in the study area. This may be attributed to reduced need for credit by higher-income households which rely less on credit. The result also is accounted for targeted credit programs, in some regions, which provides subsidized loans

designed specifically to help lower-income households. Another possible reason could be higher-income households' greater financial literacy, more savings and diversified income sources which reduces the likelihood of borrowing from small and microfinance institutions.

Table 4. 8: Result of odds ratio estimation

Variables	**Odds ratio**	**Std. err.**	**Z**	***P > z***
Age of household head	1.09	.056	1.73	0.08
Age Squared	.99	.0005	-1.82	0.07
Gender of household	.84	.32	-0.45	0.65
Marital Status	1.93	.71	1.81	0.07
Household Size	.95	.054	-0.74	0.46
Land Size	1.09	.061	1.50	0.13
Average Monthly Income	.99	.00002	-2.20	0.028
Livestock in tropical livestock unit	1.05	.022	2.48	0.013
Distance from the nearest market center	.99	.002	-1.82	0.07
Distance from the nearest major road	1.005	.01	0.54	0.59
Education(Dummy)	.93	.213	-0.31	0.75
Extension Service Participation	5.22	1.19	7.25	0.000
_cons	.004	.005	-4.19	0.000

Source: Author (2025)

Table 4.8 presents odds ratio estimates of the binomial logistic regression model. The odds ratio estimates denote the ratio of probability of getting access to credit to not getting credit access. The result indicates that households which participate in extension service are 5.22 times more likely to get access to credit. Moreover, a unit increase in tropical livestock unit make households 1.05 times more likely to get access to credit. In addition to this, when households get married they are 1.93 times more likely to get access to credit. Similarly as age of household head increase by one year, on average, households become 1.09 times more likely to get access to credit. This could be attributed to paramount farm experiences those farm households could obtain at higher ages.

4.4. Impact of access to credit on Teff and Maize yield

For this study, impact assessment of credit access on teff productivity is based on 358 producers, while the impact assessment on maize productivity is based on 832 maize producers in the study area. While teff productivity denotes the amount of teff in kilograms a particular household produce produced per a hectare of land, maize productivity represents the amount of wheat in kilograms produced per hectare. Estimation results and discussion as to teff and maize productivity is presented in the following section.

Following similar procedure estimates of average treatment effects (ATE) are calculated for examining the impact of credit access on cop productivity (Maize and Teff) and the result is presented in table 4.10. The results indicated that there is strong statistical evidence that access to credit enhances teff and maize productivity in the study area. It is because of the fact that access to credit increases the likelihood of adoption of improved inputs and practices, leading to yield gains. Moreover, access to credit breaks farmers' financial constraints and enables them purchase fertilizers, high-quality seeds and pesticides which directly increase crop yields. Credit access also support productivity in terms of facilitating timely operations such as timely planting, weeding, and harvesting, which are pivotal for maximizing teff and maize yields.

Based on estimates of the average treatment effects (ATE) in table 4.10, it has been revealed that access to credit increases teff productivity in the study area by 3.93 times and the result is statistically significant at 1% level of significance. The result is in line with the findings of (Elemineh et al., 2020) and (Belay, 2021). As to maize productivity, the result demonstrated that access to credit raises maize productivity up to 5.7 times which is also statistically significant at 1% level of significance. is in line with the findings of (Diamoutene & Jatoe, 2021) and (Assouto & Houngbeme, 2023).

Table 4.9: Impact of access to credit on crop productivity: Estimates of average treatment effect (ATE)

Crop productivity	**Credit Access**					
	Yes (n=110)			No (n=1414)		
	Actual	Counterfactual	**ATT**	Actual	Counterfactual	**ATU**

Teff productivity (kilogram per hectare)	2423.01	615.78	**1807.23*****	674.43	2075.1	**-1400.67*****
Maize productivity (kilogram per hectare)	3583.7	625.13	**2958.57*****	724.62	3661.14	**-2936.52*****

Source: Author (2025) *** indicates statistical significance at 1% level of significance.

4.5 Impact of access to credit on households' chemical fertilizer use

Furthermore, this study has tried to examine the impact of access to credit on households chemical fertilizer use. Chemical fertilizers use denotes the total amount of chemical fertilizers (such as DAP, Urea and NPS etc.) a household has used on its farmland per kilograms. Likewise the section 4.3 and 4.4, the study has used endogenous switching regression model taking marital status as a valid instrument. Then, the result of average treatment effects (ATE) is provided in table 4.10.

The result indicated that credit user households have on average used 238.6 kilogram of chemical fertilizers, while non-user households used 64.6 kilograms. The result of average treatment effect further indicates that access to credit has increase farmers chemical fertilizer use by 94% and the result is also statistically significant at 1% level of significance. The finding is also in line with the studies of Regassa et al (2023) and, Tesfay and Moral (2021).

Table 4. 9: Impact of access to credit on chemical fertilizer use: Estimates of average treatment effect (ATE)

	Credit Access					
	Yes (n=110)			No (n=1414)		
	Actual	Counterfactual	**ATT**	Actual	Counterfactual	**ATU**
Chemical Fertilizer Use (Per	238.6	122.9	115.7*******	64.6	161.1	-96.5***

Kilograms)						

Source: Author (2025) *** indicates statistical significance at 1% level of significance

4.6 Impact of access to credit on households' improved seed adoption

This study has also identified the impact of access to credit on households' improved seed adoption in the study area. Unlike the previous one, this time, the outcome variable (improved seed adoption) is binary. Thus, taking distance to the nearest market center as an instrument, a selectivity adjusted binomial probit regression was used in the second-stage estimation of ESR. Then, households' likelihood of adopting improved seed is estimated and then, estimates of the average treatment effect (ATE) is predicted as shown in table 4.11.

ATT indicates the difference between credit user households' likelihood of adopting improved seed while having credit access and the likelihood of adoption if they wouldn't have access to credit. The result indicates that credit access has raised likelihood of access to credit by 56% and the result is also statistically significant. It suggests that access to credit has significant potential of enabling farm households to purchase agricultural inputs like improved seed. The result is similar with the findings of Kehinde (2021) and NasereIdin et al (2023).

Table 4.11: Impact of access to credit on improved seed adoption: Estimates of average treatment effect (ATE)

	Credit Access					
	Yes (n=110)			No (n=1414)		
	Actual	Counterfactual	**ATT**	Actual	Counterfactual	**ATU**
Likelihood of Improved Seed Adoption	0.78	0.5	0.28***	0.29	0.64	-0.35***

Source: Author (2025) *** indicates statistical significance at 1% level of significance

4.7 Impact of access to credit on households' food security

To identify the impact of access to credit on households' food security, as mentioned in the methodology section, binomial endogenous switching regression (ESR) is used. It is a two-step procedure which involves binomial probit regression, in the first step, and then OLS estimation, in the second stage, which is adjusted for inverse mills ratio derived from the first stage estimation. Before estimating ESR a falsification test is used to identify variables that make the outcome equation identified. Following Di-falcao et al., (2011) distance to nearest market is used as selection instrument since it significantly affect access to credit but doesn't affect food security status of those households which don't get access to credit. Then with the exclusion of selection instruments and inclusion of inverse mills ratio from the first stage, ESR (second-stage) is estimated for each regimes and, finally, average treatment effect for treated and untreated households is calculated.

Table 4.12 presents the average treatment effect of access to credit for those households which get access to credit (treated) and those which don't (controlled). It also signifies the average treatment effect for both actual and counterfactual cases. The actual cases illustrates the average predicted food security status(in terms of DKAE and DDS) for both treated and controlled households while the counterfactual shows the average predicted food security status if those households which get access to credit wouldn't get and if those households which don't get access to credit would get. Finally, as indicated in methodological section, average treatment effect for the treated households (ATT) and average treatment effect for the untreated households (ATU) are estimated as the different between actual and counterfactual cases.

Table 4.12: Impact of access to credit on food security: Estimates of average treatment effect (ATE)

	Credit Access					
Food Security Indicators	Yes (n=110)			No (n=1414)		
	Actual	Counterfactual	**ATT**	Actual	Counterfactual	**ATU**
DKAE	2952.8	2847.3	**105.5**	2893.4	3731.5	**-838.1*****
DDS	4.02	4.06	**-0.04**	4.35	3.87	**0.48**

Source: Author (2025) *** indicates statistical significance at 1% level of significance

Table 4.9 indicates that daily calorie consumption per adult equivalence (DKAE) of households which get access to credit is increased by 3.7% (105.5) while their dietary diversity score (DDS) is decreased by 0.9% (-0.04). However, the result appeared statistically insignificant. Moreover, it's been observed a 28.9% fall in daily calorie consumption per adult equivalence of households which didn't get access to credit and the result is also statistically significant at 1% level of significance. It suggests that those households would have better food security status had they manage to get credit access. In general, despite showing some implication of improving it, access to credit is not found to have a significant effect on rural households' food security status in the study area. The result is in line with the findings of (Annim et al., 2011) and (Salima et al., 2023a).

CHAPTER FIVE: SUMMARY, CONCLUSION AND POLICY IMPLICATION

This chapter presents summary, conclusion and policy implications of the study. Hence, firstly, a brief summary of the study is presented and it is followed by conclusion and policy implication of the study.

5.1 Summary

This study is devoted to examine determinants of rural household access to credit and its impact on food security and crop productivity as a case study from rural Ethiopia. It was based on 1524 sample rural households which are composed of nine different regions states of Ethiopia. Identifying factors affecting rural households' access to credit, examining the impact of access to credit on food security and investigating the impact of access to credit on maize and teff productivity were the major objectives of the study. To this end it employed the 2021/22 socio-economic survey data obtained from World Bank data base. Households' food security status was measured by dietary diversity score and daily calorie consumption per adult equivalence. Moreover, teff and maize productivity of those households were measured by the number of kilograms those teff and maize producers produce per hectare. Regarding econometric methodology, binomial logistic regression model was used for identifying factors affecting households' credit access, while endogenous switching regression model was employed for examining the impact of access to credit on food security and crop productivity outcomes.

The study indicated that only 7.2% of those sample households have access to credit, of whom 53.6% are from Amhara region and 29.1% are from Oromia region. The result of binomial logistic regression model also revealed that age of household head, monthly income, livestock size, distance from nearest market center and access to extension services are key determinants of rural households access to credit in the study area. Specifically, estimates of the marginal effects showed that when households participate in extension services their likelihood of getting access to credit increases by 9.8%, while estimates of the odds ratio also suggested that those households with extension service access are 5.22 times more likely to get access to credit than their counterparts. Furthermore, as to impact of credit access on household's food security outcomes, despite showing some positive results, this study found that credit access has not significant impact on households' food security in the study area. Unlike food security, the study

results indicated that households' credit access has increased teff productivity by 12 times while it also enhance maize productivity by 4.7 times.

5.2 Conclusion

A number of recent scientific studies present concrete arguments reflecting critical role of access to credit for sustaining rural livelihoods and agricultural productivity. However, in rural Ethiopia, this study concluded that access to credit among farm households is very low. Majority of households in rural Ethiopia are deprived off access to credit. In general, this is attributed to the country's financially exclusive environment especially among rural households and marginalized groups such as women and elderly. And specifically, as revealed by this study, this low credit access is accounted for age of households head, marital status, monthly income, land size and access to extension services. Most importantly, this study showed that access to extension service is pivotal for rural households on their way of securing credit from microfinance institutions. While access to credit significantly boosts teff and maize productivity, its lack of impact on food security underscores the need for complementary interventions to address broader household welfare, ensuring that agricultural gains translate into sustainable food security outcomes for rural households of Ethiopia.

5.3 Policy Implication

Based on its key findings, this study has forwarded the following policy recommendations:

- Enhancing credit accessibility for younger and unmarried household heads: Since age and marital status affect credit access, it is better to have targeted microfinance programs that are tailored to younger and unmarried household heads. This program may include flexible loan terms, low collateral requirements, or financial literacy training to build creditworthiness, ensuring broader access to credit for these demographics.

- Expanding agricultural extension services to boost credit uptake: Since access to extension services is a key factor behind access to credit, scaling up these services to reach more rural households is quite important. Policies could foucus on increasing the number of trained extension workers, integrating financial literacy into extension programs, and using mobile technology to deliver advice, hence linking farmers to credit opportunities.

- Designing credit programs to enhance crop productivity: It involves efforts such as encouraging microfinance institutions to provide tailored agricultural loans with favorable terms such as low interest rates to promote investments in high-quality inputs, irrigation, or mechanization specifically targeting teff and maize producers.

- Addressing food security through complementary interventions: As credit access is not significantly affecting food security, it is important to complement credit programs with direct food security interventions such as subsidized input programs, crop insurance or safety net initiatives such as food-for-work schemes. Such kinds of efforts can stabilize household food access while credit continues to drive productivity gains.

Room for further research

This study mainly employed a cross-sectional data. However, for impact assessment studies of this kind cross-sectional data is not the best option. Thus further studies shall employ panel data so that impacts of such interventions are well understood. Moreover, future studies that can be conducted all over Ethiopia shall consider the usage of sufficient sample size both for treated and controlled households corresponding to population sizes of regions or administrations involved.

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APPENDICES

A) Stata result of the binomial logistic regression model

Coefficients

```
. logit Access_to_Credit Age_of_HH Age_Square Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_m
> arket dist_road EducationDummy Extension_Service_Participation

Iteration 0:   log likelihood = -395.07854
Iteration 1:   log likelihood = -357.12722
Iteration 2:   log likelihood = -348.28971
Iteration 3:   log likelihood = -348.20985
Iteration 4:   log likelihood =  -348.2097
Iteration 5:   log likelihood =  -348.2097

Logistic regression                                     Number of obs =  1,524
                                                        LR chi2(12)   =  93.74
                                                        Prob > chi2   = 0.0000
Log likelihood = -348.2097                              Pseudo R2     = 0.1186
```

Access_to_Credit	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Age_of_HH	.0900846	.0519753	1.73	0.083	-.0117851	.1919543
Age_Square	-.0009276	.0005099	-1.82	0.069	-.001927	.0000718
Gender	-.1712166	.3804364	-0.45	0.653	-.9168582	.5744251
Marital_Status	.6616785	.3657825	1.81	0.070	-.055242	1.378599
hh_size	-.0421638	.0569854	-0.74	0.459	-.1538533	.0695256
LandSizeHectare	.0853569	.0567226	1.50	0.132	-.0258175	.1965312
Monthly_Income	-.0000478	.0000217	-2.20	0.028	-.0000903	-5.27e-06
TLU	.0530885	.021371	2.48	0.013	.0112022	.0949748
dist_market	-.0039554	.0021769	-1.82	0.069	-.008222	.0003113
dist_road	.0054726	.0101375	0.54	0.589	-.0143965	.0253417
EducationDummy	-.0716325	.2289368	-0.31	0.754	-.5203404	.3770755
Extension_Service_Participation	1.652735	.2278906	7.25	0.000	1.206077	2.099392
_cons	-5.389019	1.284789	-4.19	0.000	-7.907159	-2.87088

Odds Ratio

```
. logit Access_to_Credit Age_of_HH Age_Square Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_m
> arket dist_road EducationDummy Extension_Service_Participation, or

Iteration 0:   log likelihood = -395.07854
Iteration 1:   log likelihood = -357.12722
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Iteration 3:   log likelihood = -348.20985
Iteration 4:   log likelihood =  -348.2097
Iteration 5:   log likelihood =  -348.2097

Logistic regression                                     Number of obs =  1,524
                                                        LR chi2(12)   =  93.74
                                                        Prob > chi2   = 0.0000
Log likelihood = -348.2097                              Pseudo R2     = 0.1186
```

Access_to_Credit	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Age_of_HH	1.094267	.0568748	1.73	0.083	.9882841	1.211615
Age_Square	.9990728	.0005094	-1.82	0.069	.9980749	1.000072
Gender	.8426391	.3205706	-0.45	0.653	.3997731	1.776109
Marital_Status	1.938043	.7089021	1.81	0.070	.9462561	3.969337
hh_size	.9587127	.0546327	-0.74	0.459	.8573978	1.071999
LandSizeHectare	1.089106	.0617769	1.50	0.132	.974513	1.217173
Monthly_Income	.9999522	.0000217	-2.20	0.028	.9999097	.9999947
TLU	1.054523	.0225362	2.48	0.013	1.011265	1.099631
dist_market	.9960525	.0021683	-1.82	0.069	.9918117	1.000311
dist_road	1.005488	.0101931	0.54	0.589	.9857067	1.025665
EducationDummy	.9308729	.2131111	-0.31	0.754	.5943182	1.458014
Extension_Service_Participation	5.221238	1.189871	7.25	0.000	3.340355	8.161206
_cons	.0045664	.0058669	-4.19	0.000	.0003681	.0566491

Note: **_cons** estimates baseline odds.

Marginal effects

```
. mfx

Marginal effects after logit
      y  = Pr(Access_to_Credit) (predict)
         =  .04804338
```

variable	dy/dx	Std. err.	z	P>|z|	[	95% C.I.	]	X
Age_of~H	.00412	.00236	1.75	0.081	-.000504		.008745	46.622
Age_Sq~e	-.0000424	.00002	-1.84	0.066	-.000088		2.9e-06	2393.3
Gender*	-.0082179	.01913	-0.43	0.668	-.045722		.029286	.807087
Marita~s*	.0260163	.01231	2.11	0.035	.001885		.050147	.773622
hh_size	-.0019284	.0026	-0.74	0.459	-.007034		.003177	5.21785
LandSi~e	.0039038	.00259	1.51	0.132	-.001174		.008981	1.64068
Monthl~e	-2.19e-06	.00000	-2.26	0.024	-4.1e-06		-2.9e-07	9184.18
TLU	.002428	.00098	2.48	0.013	.00051		.004346	3.94417
dist_m~t	-.0001809	.0001	-1.83	0.067	-.000375		.000013	68.8898
dist_r~d	.0002503	.00046	0.54	0.590	-.000659		.00116	9.19685
Educat~y*	-.0032629	.01039	-0.31	0.754	-.02363		.017104	.435039
Extens~n*	.098417	.01509	6.52	0.000	.068838		.127996	.370079

(*) dy/dx is for discrete change of dummy variable from 0 to 1

B) Results of Endogenous Switching Regression: Second Stage

```
. reg Daily_Kcal_per_Adult_Equivalce Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist
> _road EducationDummy Extension_Service_Participation mills1 if Access_to_Credit == 1,robust

Linear regression                               Number of obs     =        110
                                                F(11, 98)         =       3.18
                                                Prob > F          =     0.0010
                                                R-squared         =     0.4394
                                                Root MSE          =     2103.3
```

Daily_Kcal_per_Adult_Equivalce	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	-16.35234	13.68933	-1.19	0.235	-43.51836	10.81369
Gender	-833.3286	712.3394	-1.17	0.245	-2246.943	580.2857
Marital_Status	-1621.699	1169.681	-1.39	0.169	-3942.893	699.4955
hh_size	-553.5283	170.2697	-3.25	0.002	-891.4229	-215.6336
LandSizeHectare	-151.0495	141.7668	-1.07	0.289	-432.381	130.2821
Monthly_Income	.3058808	.1041105	2.94	0.004	.099277	.5124847
TLU	71.88589	67.88966	1.06	0.292	-62.83893	206.6107
dist_road	-14.86263	16.17889	-0.92	0.361	-46.96912	17.24386
EducationDummy	-3.200407	347.7993	-0.01	0.993	-693.3968	686.996
Extension_Service_Participation	-355.5136	1615.756	-0.22	0.826	-3561.929	2850.902
mills1	13.85312	1633.295	0.01	0.993	-3227.367	3255.073
_cons	6637.485	5146.976	1.29	0.200	-3576.521	16851.49

```
. reg Daily_Kcal_per_Adult_Equivalce Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist
> _road EducationDummy Extension_Service_Participation mills2 if Access_to_Credit == 0,robust

Linear regression                               Number of obs     =      1,414
                                                F(11, 1402)       =      27.91
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2836
                                                Root MSE          =     1698.5
```

Daily_Kcal_per_Adult_Equivalce	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	3.129436	3.446929	0.91	0.364	-3.632258	9.89113
Gender	-445.351	188.7991	-2.36	0.018	-815.7101	-74.99188
Marital_Status	425.9362	197.3603	2.16	0.031	38.78288	813.0896
hh_size	-415.5904	26.18924	-15.87	0.000	-466.9648	-364.2161
LandSizeHectare	65.89209	30.36419	2.17	0.030	6.32796	125.4562
Monthly_Income	.0824115	.0203467	4.05	0.000	.0424983	.1223247
TLU	71.68412	14.49593	4.95	0.000	43.24807	100.1202
dist_road	6.133571	3.47226	1.77	0.078	-.6778142	12.94496
EducationDummy	67.60374	95.30123	0.71	0.478	-119.3446	254.5521
Extension_Service_Participation	1432.774	324.1585	4.42	0.000	796.8859	2068.662
mills2	5489.452	1475.234	3.72	0.000	2595.548	8383.356
_cons	3946.284	250.5903	15.75	0.000	3454.711	4437.856

```
. reg DDS Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road EducationDummy Extens
> ion_Service_Participation mills1 if Access_to_Credit == 1,robust

Linear regression                               Number of obs     =        108
                                                F(11, 96)         =       0.74
                                                Prob > F          =     0.6975
                                                R-squared         =     0.0788
                                                Root MSE          =     1.9195
```

DDS	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	-.0131158	.0161061	-0.81	0.417	-.0450861	.0188545
Gender	-1.151787	1.699199	-0.68	0.500	-4.52467	2.221095
Marital_Status	.0772508	1.553891	0.05	0.960	-3.007199	3.161701
hh_size	.1063583	.1087102	0.98	0.330	-.1094298	.3221464
LandSizeHectare	.0916185	.1748837	0.52	0.602	-.255523	.4387599
Monthly_Income	.0000415	.0000645	0.64	0.521	-.0000865	.0001696
TLU	.0092902	.0767732	0.12	0.904	-.1431035	.1616839
dist_road	.0010424	.0137567	0.08	0.940	-.0262645	.0283493
EducationDummy	-.0147459	.4459973	-0.03	0.974	-.9000436	.8705519
Extension_Service_Participation	.1641651	1.482757	0.11	0.912	-2.779084	3.107414
mills1	-.3092109	2.018702	-0.15	0.879	-4.316303	3.697881
_cons	4.79983	4.694517	1.02	0.309	-4.518712	14.11837

```
. reg DDS Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road EducationDummy Extens
> ion_Service_Participation mills2 if Access_to_Credit == 0,robust

Linear regression                               Number of obs     =      1,394
                                                F(11, 1382)       =       7.45
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0931
                                                Root MSE          =     2.4325
```

DDS	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	-.0067757	.0048067	-1.41	0.159	-.016205	.0026535
Gender	-.4883603	.2230943	-2.19	0.029	-.9260004	-.0507203
Marital_Status	.5457601	.213544	2.56	0.011	.1268547	.9646655
hh_size	-.0092473	.034357	-0.27	0.788	-.0766448	.0581503
LandSizeHectare	.0080913	.0522387	0.15	0.877	-.0943845	.1105671
Monthly_Income	.000071	.0000249	2.85	0.004	.0000222	.0001199
TLU	.0311386	.0181035	1.72	0.086	-.0043747	.066652
dist_road	-.0105174	.0059212	-1.78	0.076	-.0221329	.0010981
EducationDummy	.2228209	.1543356	1.44	0.149	-.0799365	.5255782
Extension_Service_Participation	.5358166	.3691843	1.45	0.147	-.1884057	1.260039
mills2	4.409184	1.793157	2.46	0.014	.8915811	7.926788
_cons	4.301993	.3682418	11.68	0.000	3.579619	5.024366

```
. reg Maize_Productivity Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road Educat
> ionDummy Extension_Service_Participation mills1 if Access_to_Credit == 1,robust

Linear regression                               Number of obs     =         91
                                                F(11, 79)         =       0.74
                                                Prob > F          =     0.6976
                                                R-squared         =     0.2249
                                                Root MSE          =      14655
```

Maize_Productivity	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	-52.67111	80.36929	-0.66	0.514	-212.6422	107.3
Gender	2513.968	5314.893	0.47	0.638	-8065.061	13093
Marital_Status	-1148.928	6301.941	-0.18	0.856	-13692.63	11394.77
hh_size	841.3856	642.0753	1.31	0.194	-436.6332	2119.404
LandSizeHectare	-4111.76	1558.476	-2.64	0.010	-7213.829	-1009.691
Monthly_Income	.2090023	.3976317	0.53	0.601	-.5824638	1.000468
TLU	642.5053	417.61	1.54	0.128	-188.7267	1473.737
dist_road	-201.6602	127.0816	-1.59	0.117	-454.6097	51.28928
EducationDummy	2362.132	3225.827	0.73	0.466	-4058.716	8782.98
Extension_Service_Participation	-3412.947	6541.221	-0.52	0.603	-16432.92	9607.029
mills1	-6508.781	9198.406	-0.71	0.481	-24817.75	11800.19
_cons	18477.86	20512.67	0.90	0.370	-22351.58	59307.31

```
. reg Maize_Productivity Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road Educat
> ionDummy Extension_Service_Participation mills1 if Access_to_Credit == 0,robust

Linear regression                               Number of obs     =        741
                                                F(11, 729)        =       3.69
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0350
                                                Root MSE          =     3958.9
```

Maize_Productivity	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	6.429857	9.843427	0.65	0.514	-12.89499	25.7547
Gender	-236.7071	370.8273	-0.64	0.523	-964.724	491.3098
Marital_Status	-112.7026	321.2458	-0.35	0.726	-743.3798	517.9746
hh_size	65.3803	42.55921	1.54	0.125	-18.17294	148.9335
LandSizeHectare	-391.7115	168.8203	-2.32	0.021	-723.1434	-60.27953
Monthly_Income	.0064057	.0286831	0.22	0.823	-.0499056	.0627169
TLU	57.83262	30.26478	1.91	0.056	-1.583917	117.2492
dist_road	11.35672	25.47242	0.45	0.656	-38.65134	61.36478
EducationDummy	392.5543	208.8637	1.88	0.061	-17.49183	802.6004
Extension_Service_Participation	-983.8097	479.5432	-2.05	0.041	-1925.26	-42.35937
mills1	-974.1548	1095.647	-0.89	0.374	-3125.154	1176.844
_cons	2829.983	1917.404	1.48	0.140	-934.31	6594.275

```
. reg Teff_Productivity Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road Educati
> onDummy Extension_Service_Participation mills1 if Access_to_Credit == 1,robust

Linear regression                               Number of obs     =         68
                                                F(11, 56)         =       0.79
                                                Prob > F          =     0.6495
                                                R-squared         =     0.2744
                                                Root MSE          =     9820.6
```

Teff_Productivity	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	5.036379	87.56259	0.06	0.954	-170.3726	180.4453
Gender	-6048.091	4426.266	-1.37	0.177	-14914.97	2818.786
Marital_Status	11183.39	6549.74	1.71	0.093	-1937.319	24304.09
hh_size	358.877	539.9807	0.66	0.509	-722.8342	1440.588
LandSizeHectare	-2524.581	973.883	-2.59	0.012	-4475.503	-573.6587
Monthly_Income	-.2727136	.5146821	-0.53	0.598	-1.303746	.7583185
TLU	1101.603	726.7174	1.52	0.135	-354.1868	2557.393
dist_road	4.608718	121.0244	0.04	0.970	-237.8324	247.0498
EducationDummy	2778.671	2181.243	1.27	0.208	-1590.883	7148.225
Extension_Service_Participation	6776.161	10383.11	0.65	0.517	-14023.71	27576.03
mills1	9009.687	14736.55	0.61	0.543	-20511.17	38530.54
_cons	-23942.05	32509.1	-0.74	0.465	-89065.6	41181.5

```
. reg Teff_Productivity Age_of_HH  Gender Marital_Status hh_size LandSizeHectare Monthly_Income TLU dist_road Educati
> onDummy Extension_Service_Participation mills1 if Access_to_Credit == 0,robust

Linear regression                               Number of obs     =        290
                                                F(11, 278)        =       3.84
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1302
                                                Root MSE          =     1393.9
```

Teff_Productivity	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age_of_HH	3.080916	5.376116	0.57	0.567	-7.502151	13.66398
Gender	433.1951	422.9665	1.02	0.307	-399.4288	1265.819
Marital_Status	-771.9782	542.507	-1.42	0.156	-1839.922	295.9652
hh_size	-39.27853	34.3511	-1.14	0.254	-106.8998	28.34277
LandSizeHectare	-267.7386	87.10232	-3.07	0.002	-439.2024	-96.27469
Monthly_Income	.0488008	.0192924	2.53	0.012	.010823	.0867785
TLU	-5.655638	18.08271	-0.31	0.755	-41.25206	29.94078
dist_road	18.34272	11.55625	1.59	0.114	-4.406146	41.09159
EducationDummy	-67.41431	154.7698	-0.44	0.663	-372.0838	237.2552
Extension_Service_Participation	-868.7647	376.9712	-2.30	0.022	-1610.845	-126.6842
mills1	-1445.592	598.7129	-2.41	0.016	-2624.179	-267.0053
_cons	4150.169	1463.816	2.84	0.005	1268.597	7031.741

C) Post-estimation tests

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. vif
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Variable	VIF	1/VIF
mills2	6.41	0.155925
Extension_~n	4.78	0.209183
Marital_St~s	1.81	0.552614
Gender	1.68	0.596826
TLU	1.62	0.616037
Monthly_In~e	1.32	0.759873
hh_size	1.30	0.767993
LandSizeHe~e	1.30	0.769374
EducationD~y	1.27	0.788916
Age_of_HH	1.24	0.808333
dist_road	1.10	0.911992
Mean VIF	2.17	