UNIVERSITY FOR DEVELOPMENT STUDIES, TAMALE

THE EFFECTS OF SOCIAL NETWORKS ON CREDIT ACCESS AND WELFARE IN THE NORTHERN REGION OF GHANA

SEIDU ASUMAH ABDUL-RASHID

2023

UNIVERSITY FOR DEVELOPMENT STUDIES, TAMALE

THE EFFECTS OF SOCIAL NETWORKS ON CREDIT ACCESS AND WELFARE IN THE NORTHERN REGION OF GHANA

BY

SEIDU ASUMAH ABDUL-RASHID

UDS/MEC/0013/20

DISSERTATION/THESIS SUBMITTED TO THE DEPARTMENT OF AGRICULTURAL AND FOOD ECONOMICS, FACULTY OF AGRICULTURE, FOOD AND CONSUMER SCIENCES, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A MASTER OF PHILOSOPHY DEGREE IN AGRICULTURAL ECONOMICS

JUNE, 2023

DECLARATION

Student

I hereby declare that this dissertation/thesis is the result of my original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature: ……………………………. Date: ………………………..…

Name: ………………………………………..........

Supervisors'

I hereby declare that the preparation and presentation of the dissertation/thesis were supervised per the guidelines on supervision of the dissertation/thesis laid down by the University for Development Studies.

Principal Supervisor's Signature: ………………….. Date: ………………………

Name: ……………………………………………

ABSTRACT

Food insecurity persists in emerging countries as a result of low agricultural production and rising food prices. Despite the significant impact of credit on agricultural output, most smallholder farmers, particularly in rural regions, lack access to credit. Social networks have a significant impact on farmer behavior and, could influence their credit decisions. The purpose of this study was to investigate the effect of social networks on smallholder access to institutional input credit, as well as the impact of peer credit on household income and food security. The multistage sampling approach was used in this study to first purposively select two districts and then randomly sample ten villages. In all, 400 farm households were randomly sampled across the ten villages. The spatial Durbin model (SDM) and an endogenous switching regression (ESR) model were then used to analyse the data. Age, residential status, durable assets, mobile network availability, and distance to the closest source of credit are among the socioeconomic elements that influence families' decisions regarding credit, according to the results of the SDM model. The findings demonstrate that a 1% increase in the share of peers in the farmer's network with access to credit, reduces own credit access by 0.15% (endogenous effects). Similarly, most of the peer characteristics that increase peer access to credit tend to decrease the farmer's likelihood of credit access (contextual effects). The ESR results also demonstrate that an increase in the share of peers with credit, significantly increases household income by 0.9%, and their food consumption score by approximately 6.5 points. Furthermore, the treatment effect estimates for both income and food security indicate that credit users gained highly in terms of income and food consumption than non-users. This shows that credit availability and access have beneficial effects on households. It is consequently proposed that credit services be made available to these communities and that attractive loan terms be offered, such as expanding the payback time, among other things, to promote credit access.

ACKNOWLEDGMENT

First and foremost, I acknowledge God Almighty for the gift of life, my own health and that of family, and more importantly for granting me the enduring spirit that carried me through this arduous task. I also wish to express my sincere gratitude to my supervisor, Dr. Yazeed Abdul-Mumin, for his patience and guidance throughout the work, and without whose commitment this report would not have seen the light of day. My profound gratitude also goes to my family and, particularly to my sons, Farad and Hamad for their emotional support throughout the process of producing this dissertation. I wish to also thank the following people for their enormous support and encouragement; Adam Saani, Atia Sunday, and Ziblim Abdul-Mumin. I further wish to express my profound gratitude to the people who helped me in collecting the data for this study. I wish to thank my internal examiner, Dr. Isaac G. K. Ansah, as well as the external Examiner for their thorough review and suggestions provided to guide this work. Finally, my sincerest thanks go to all lecturers and colleague students at the faculty, for their diverse support and constructive criticisms during seminar presentations.

DEDICATION

I dedicate this work to my parents, Mr. Seidu Asumah Emmanuel and Madam Damata Mahama, my wife and children, and also to my siblings for their emotional and moral support throughout the study.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

1. **ADB**-Agricultural Development Bank
2. **GDP**- Gross Domestic Product
3. **IFC**-International Finance Corporation
4. **BoG**-Bank of Ghana
5. **FCS**-Food Consumption Score
6. **SDGs**-Sustainable Development Goals
7. **SSA**-Sub-Saharan Africa
8. **SAR**-Spatial Autoregressive Models
9. **SDM**-Spatial Durbin Model
10. **ESR**- Endogenous Switching Regression
11. **GSS**-Ghana Statistical Service
12. **NGO**-Non-Governmental Organization
13. **USA**-United States of America
14. **MoFA**-Ministry of Food and Agriculture
15. **IFPRI**-International Food Policy Research Institute
16. **ISSER**-Institute of Statistical, Social, and Economic Research
17. **ATT**-Average Treatment effects on the Treated
18. **ATU**-Average Treatment effects on the Untreated
19. **ROSCAs**-Rotating Savings and Credit Associations
20. **PSM**-Propensity Score Matching

CHAPTER ONE

INTRODUCTION

1.1 Background

Agriculture contributes greatly to global economic growth, particularly in sub-Saharan Africa (SSA). According to recent data from the World Bank, agriculture currently contributes about 17.78% to Ghana's GDP (World Bank, 2022). The sector also provides employment to over 36% of the country's workforce (GSS, 2019) and generates more than 45% of foreign exchange revenues (MoFA, 2017). As a result, the sector is regarded as critical to achieving the Sustainable Development Goals (SDGs), and more particularly, Agenda 2030 (FAO/ECA/AUC, 2020). In this light, increased agricultural output for example, could improve Ghana's ability to overcome extreme poverty, hunger, and malnutrition (Steiner-Asiedu et al., 2017). Although the sector's share of GDP has decreased in recent years, it is projected to grow by 7% in 2023, with a recorded growth rate of 4.6% in 2019 (MoFA, 2021).

In Ghana, 85% of farmers are smallholders who cultivate on plots less than 2 hectares; yet, they make a considerable contribution to the sector's growth and development (GSS, 2019). Despite the significant role of smallholder farmers in the agricultural sector's expansion, they are confronted with considerable obstacles that harm their welfare. Farmers often rely on the natural rainfall and its distributions, and must also contend with greater input costs and erratic weather patterns. This increases the risk associated with the industry leading to its decreased appeal, and as such makes rural poverty worse rather than better. These challenges have also contributed to the agricultural sector's ongoing fall in productivity. According to MoFA, the agricultural sector's growth over time has been ascribed to area expansion rather than higher yields (MoFA, 2017).

In addition, smallholder farmers in developing countries such as Ghana have suffered due to the climatic and global economic conditions, which makes the business of agriculture less attractive (Waje, 2020). Moreover, access to global markets is challenging for these smallholder farmers due to the stringent quality and safety criteria that they are required to meet. The most prominent and pressing of these challenges is the lack of access to financial services, especially among rural households (Dittoh, 2006; The Republic of Ghana, 2018). Adam (2018) highlighted in a case study on agricultural finance interventions in Ghana that funding is the biggest limitation to agricultural development in the country. Access to credit especially among smallholder farmers is seen as a critical tool for agricultural progress (Sekyi, 2017). It could boost the efficient application of contemporary agricultural technologies and expand the utilization of better crop types.

It is however challenging for households to access credit because of the high cost of credit, which is mostly a result of high-interest rates, high transaction costs, strict collateral requirements, and the generally unfavorable conditions for persons working in the informal sectors (Diagne, 1999). Most households are particularly unable to access formal credit or engage effectively in the formal financial systems as a result (Okurut, 2006). Additionally, supply-side problems like information asymmetry brought on by market failures, inadequate financial system regulatory frameworks, and ineffective credit management systems affect the capacity of formal financial institutions to effectively provide credit to those operating in the nation's informal sectors (Adam, 2018). These factors, along with others, account for the dominance of the informal sector, which is largely constituted by Susu collectors, savings and loans, credit unions, and micro-financial institutions (Owusu-Antwi & Antwi, 2010; Turkson et al., 2020).

The lack of proper farm records, insufficient asset portfolios, and a lack of collateral assets such as land titles and other valuable properties have all been identified as reasons why smallholder farmers are unable to obtain formal loans (Okten & Osili, 2004). Also, households' lack of access to credit has been attributed to the commercial banks' disinterest in providing loans to smallholder agricultural households (Diagne, 1999). This is related to the industry's perceived high level of risk as well as a dearth of appropriate paperwork and collateral assets required to access credit (Adam, 2018).

In Ghana, several donor organizations and other major stakeholders have implemented many interventions aimed at solving the agricultural funding crisis faced by these smallholders in the country. Notable among these donor projects include Masara N' Arziki, ADVANCE I, and ADVANCE II, to name a few (Iddrisu et al., 2018). However, most of these policies and programs could not be sustained because of the top-down approach to planning and implementation, resulting in low community ownership of these projects (Adam, 2018). The government of Ghana also implemented policy interventions to promote access to finance and increase agricultural productivity for food security and export (Sekyi, 2017).

The government through the central bank of Ghana established specialized banks such as the Agricultural Development Bank (ADB) to help address the financing needs of farmers. In the specific case of rural smallholder farmers, rural and community banks were also set up (Nair & Fissha, 2010). Also, around the same period, the government rolled into effect the Poverty Reduction Strategy (GPRS), intending to reshape the economy, generate wealth, foster growth, hasten the decrease of poverty, and safeguard vulnerable households. However, as a result of the subpar performance of these projects, the majority of the policies have fallen short of addressing the critical needs of the sector (Agboklou & Ozkan, 2022).

In addition, the Bank of Ghana launched the asset collateral registry to increase farmers access to credit by way of guaranteeing farmers and creditors through the latters' registered assets (Nkegbe, 2018). All commercial banks were additionally instructed by the BoG to devote 20% of their portfolios to the agriculture industry (Nair & Fissha, 2010). By offering farmers loans at reasonable rates, the ADB was supposed to encourage agricultural development (Dzadze et al., 2012), however, it did not fulfill this duty. This is because just 15% of the bank's total financing went to farmers, and the service coverage of the bank was biased toward urban regions with approximately 73% of its branches located there (Nair & Fissha, 2010). Due mostly to the farmers' bad repayment habits, the banks' share of financing to agriculture has also significantly decreased (Nkegbe, 2018).

The first rural bank in Ghana, founded around 1976 was aimed at addressing the issue of credit distribution among smallholder farmers in rural communities. In the period after, the banking industry expanded rapidly, with over 500 branches of these rural banks springing across many villages in the country (World Bank, 2007). According to Adam (2018), a recent Global Findex (2017) survey found that the number of people in Ghana who have accounts with mobile money providers or financial institutions increased from 62% to 69% between 2014 and 2017. Also, the average growth of financial inclusion in the country is slightly higher than the regional average of 63% for developing nations (Adam, 2018). Despite these improvements, most rural farmers continue to lack access to credit in Ghana (Sekyi, 2017). Furthermore, even though there has been an increase in the engagement of farmers in agricultural initiatives, farmer participation in credit programs is quite low, particularly among rural households (Adeoye & Ugalahi, 2017).

Furthermore, according to recent data from the Ministry of Finance (MoF), despite the improvements in access to financial services (58%) due to the digital platforms, there are still large discrepancies, particularly among the nation's rural demographics and geographic regions. For example, the five poorest regions of the nation—the Upper West, Northern, Volta, Upper East, and Brong Ahafo—are said to have the least access to financial services (The Republic of Ghana, 2018). According to earlier studies, the majority of rural households in Ghana lack access to formal credit (ISSER, 2008), which may have an impact on farmers' use of better agricultural technologies needed to increase agricultural output, as well as their motivation to commercialize their practices and engage in output markets.

Smallholder social networks and collective action groups have been recommended as alternatives for smallholder farmers to rely on rather than depend on ineffective government initiatives that do not last. These smallholder social networks could improve the interchange of resources and crucial information required to boost output and advance household welfare. The share of peers with access to credit in the farmers' network, termed as "peer credit" could have serious consequences for the farmers credit choices and welfare. In most rural communities, households utilize local tactics to boost productive capacity, share risks, and smooth consumption. These coping techniques are most commonly found in networks of friends, family, neighbors, and other community members (Fafchamps & Gubert, 2007).

In view of this, the households' social contacts may play a significant role in enhancing farmers access to finance that could support their welfare. In the literature, social networks of households have been shown in many studies to be a significant factor in facilitating the flow of information, labor, land, and credit, in addition to influencing farmers' technology adoption decisions (Bandiera & Rasul, 2006; Conley & Udry, 2010). These findings also imply that social networks may have an impact on smallholder farmers' decisions to access institutional financing in Ghana. This study intends to learn more about the effects of peer credit on household income and food security in the Northern region, as well as the role of social networks on smallholder decisions to access input credit.

1.2 Problem Statement

The majority of Sub-Saharan African (SSA) countries still struggle with food insecurity, which makes it harder for them to meet the Millennium Development Goal (MDG) of reducing global hunger by 2015 (Abdulai & Kuhlgatz, 2012). The SDG's objective of eradicating all types of malnutrition, including hunger and extreme poverty, may potentially be affected by this. Increasing agricultural productivity and supporting policies that improve food security in Africa may help achieve these goals (Steiner-Asiedu et al., 2017).

Since agriculture is the foundation of most Sub-Saharan African (SSA) economies, including Ghana's, it is crucial to combat the effects of food insecurity. Increased production could boost income and support food security. As a result, stakeholders are concerned about access to finance, which is being developed as part of mechanisms for enhancing productivity (Waje, 2020). According to a World Bank report (2019), increasing access to funds, electricity, modern technology, and irrigated land for farmers and agribusinesses to grow high-value crops could generate a trillion-dollar food industry by 2030. Credit availability and access for smallholder farmers in developing countries appear to be limited due to high information asymmetry, a lack of adequate collateral assets, and high default risk, despite evidence that credit increases productivity through improved farmer technical efficiency (Nkegbe, 2018). This could explain the sector's consistent decline in Ghana's GDP share since 2016 (World Bank, 2022).

Studies in the literature have confirmed the role of social networks in promoting information distribution and diffusion of ideas, which may have an impact on household behaviors and decisions. For instance, social networks have shown to be an important determinant of households' agricultural technology adoption decisions (Bandiera & Rasul, 2006; Conley & Udry, 2010), risk sharing (Munshi & Rosenweig, 2016), and participation in micro-finance (Banerjee et al., 2013). Social networks may therefore increase lending opportunities and credit availability, particularly for rural farmers who are on a limited budget. For instance, a farmers' social connections may increase the households' credit accessibility by providing creditors the opportunity to access them through their peers, and also offer guaranttees to lenders for their money (Hoff & Stiglitz, 1990). This could lower the cost of loan transactions while also lowering the possibility of default among borrowers due to peer monitoring.

Stiglitz (1990) discovered that social networks and group interactions greatly improve loan access among households in an earlier study. According to the study, social networks influence household credit access by providing information about borrowers to the lenders about the creditworthinesss or otherwise of potential borrowers, lowering the cost of loans, and lowering the risk of default. However, while some studies find positive impacts of social networks on access to credit and resources such as land, labor, and information (Stiglitz, 1990; Okten & Osili, 2004; Obaa & Mansur, 2016), others find results that suggest the contrary (Alio et al., 2018; Banerjee et al., 2013; Banerjee et al., 2021). According to Alio et al. (2018), households with strong social network contacts in the Soroto district of Uganda's various savings and cooperative credit unions are less likely to use credit than those with low social network contacts. Banerjee et al. (2013; 2021) also discovered that, while social networks impact significantly households' access to information, they do not have any influence on the households' decision to access credit, and communities that are exposed to microfinance lending tend to see a decline in their social network links. These disparate findings in the literature suggest that more study is needed to evaluate the link in other social circumstances.

Furthermore, the most recent studies conducted to assess the effects of local networks on credit access (Kariuki & Mdoe, 2017; Okten & Osili, 2004) have concentrated on group networks, particularly interactions within community-based organizations and farmer groups, which, according to Bramoullé et al. (2009), may cause network identification challenges due to the reflection problem. In the case of group network interactions, individuals' behavior and outcomes are influenced by the group's average outcome and vice versa, potentially resulting in perfect collinearity between the group's expected mean outcome and its mean characteristics (Manski, 1993). The social network variable in the current study was constructed in a way that permits it to have an arbitrary structure where farmers interact with different people at the village level outside group interactions (Bramoullé et al., 2009). As a result, although network transitivity was not examined, the majority of the individuals in the farmer's network is less likely to be socially linked to each other and hence cannot affect each other directly.

Additionally, studies have been conducted to look into the role of social networks on household welfare. Most of this research has found social networks to have a considerable impact on the incomes and food security of households (Jayashankar & Raju, 2020; Kang, 2019; Olarinde et al., 2020). However, Marco & Thorburn (2009), contradicts the notion that social networks significantly affect household welfare. The current study considers the role of peer credit on smallholder income and food security, which improves on the common approach of assessing the general role of network ties on incomes and food consumption based on the idea of gifts and transfers, in the form of micro-loans and food exchanges among network members (Hadley et al., 2007; Tam et al., 2014; Olarinde et al., 2020).

Additionally, because folks who own property and have successful farming businesses are often targeted for credit opportunities, and thus often have easy access to loans, the study intends to assess the role of peer credit on the welfare of those without credit, with a particular focus on their income and food security levels. So far, the impact of peer credit on smallholder incomes and food consumption is yet to be demonstrated in the literature. As a result, the current study intends to contribute to the literature by stressing how peer credit influences smallholder income and food consumption. This will improve understanding of how social networks affect household well-being, particularly among people who do not have access to finance. This could also help in the development of strategies by policymakers to raise household income and food consumption among farm households. Consequently, the study looks into how peer credit and social networks impact smallholders' credit decisions, income, and food consumption in the Northern region. The following specific research questions address this wide study topic:

1. What impact do social networks of smallholder farm households in the Northern region have on their credit decisions?
2. What is the effect of peer credit on smallholder incomes and food consumption in the Northern region?

1.3 Objectives

The overarching goal of this current study is to investigate the role of social networks and peer credit on smallholder credit access, income, and food consumption. The following specific objectives will influence the achievement of this goal:

1. To investigate how social networks impact smallholder credit decisions in the Northern region.
2. To assess the impact of peer credit on smallholder incomes and food consumption in the Northern region.

1.4 Justification of the study

Firstly, the social effects of networks in credit access could reveal whether household credit decisions are influenced by endogenous and contextual factors or correlated unobservables. This will enable stakeholders to understand the drivers that influence smallholder credit behavior and how to use credit as a way of promoting the welfare of rural farmers. For example, whether or not the features of households, the credit behavior of network members, and their characteristics or similarities in the environmental conditions encountered by farmers might all be used to improve loan decisions. This will help in the formulation of policies that target smallholder credit access and welfare.

Secondly, investigating the effect of peer access to credit on smallholder income and food consumption of households will reveal the mechanisms of monetary and food transfers among farmers, and how it affects the overall income and food security of farm households, especially those without credit access. For instance, the findings could show the nature of exchanges that are likely to exist between credit users and their network members. Studies have revealed that farmers with credit tend to be more productive (Iddrisu et al., 2018), and are more likely to raise their incomes and food security (Abdulai et al., 2018; Diagne, 1996; Nkegbe, 2018; Sekyi et al., 2020), but structural bottlenecks could limit smallholder access, and therefore researchers must consider the role of peer credit on household welfare. The current study will therefore reveal the role of peer credit in the incomes and food consumption of farmers across both users and nonusers of credit. This could enhance the formulation of policy interventions that seek to promote welfare among households. Moreover, the results will demonstrate the significance of social networks as a coping strategy for households facing the threat of food security shocks.

1.5 Limitations of the study

The few challenges that confronted this study included; firstly, the sampled villages that were surveyed for the final data collection were quite small and concentrated. While this helped to minimize the measurement errors and biases associated with sampled networks, it created a potential loss of network information by cutting off the tails of the village size distribution. Also, the random matching within the sampling procedure created the possibility of cutting off important network links that could impact the farmer's credit decisions more.

The second major limitation of this study had to do with the specification of a network boundary. The study measured farmer networks at the village level, where inter-village level interactions are not anticipated. For this reason, interaction effects are not accounted for in the final analysis. The study used village-level networks based on the view that the strength of social interactions among individuals decreases with social and geographical distance, known as the distance decay effect, which forms the basis of many spatial econometric models (Anselin, 1988). Moreover, the inter-village level interactions, if they exist were not expected to impact significantly on the outcomes of this study for two reasons; first, each of the villages represented in the sample occupied a distinct geographical area with a cluster of households, and the only likely mechanism for social interactions between these communities is the common market center at the various district capitals. However, based on qualitative evidence gathered from the field, these market centers are not likely to foster lasting social networks, and hence no significant network interaction effects across the different villages are expected. Secondly, the villages that were surveyed are far from each other with several other communities located in between them which were not part of the sample. The village-level network data collected for this study is therefore believed to capture the bulk of social interactions among farmers and reflect significantly the network structure of the area.

1.6 Organization of the study

The current study is organized into five chapters. Chapter one presents the introduction which includes background, a statement of the problem, research questions, objectives, justification, limitations, and organization of the study. The second chapter defines concepts, describes the study's conceptual and theoretical framework, and provides a review of literature on Ghana's financial system and credit markets, the impact of credit on agriculture, factors affecting farmers' access to credit, and the impact of social networks on credit access and food consumption among farm households. Chapter three highlights the methodology of the study which covers the selection of respondents, methods of data collection and analysis as well as a description of the study area. Chapter four presents the results and discussions, while Chapter five provides a summary of findings, conclusions, and recommendations from the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter outlines the definitions of concepts, presentation of the conceptual and theoretical framework of the study as well as a review of literature on the credit markets in Ghana, and the role of credit on agriculture and household welfare. The chapter further presents the definition of concepts such as social networks, credit access, and food security. Finally, the chapter highlights the empirical review of factors influencing household credit access, the effect of social networks on credit access, and the impact of social networks on household food security.

2.2 Concepts and definitions

2.2.1 Social networks

Social networks are defined as between social entities such as human beings, organizations, and even countries. These relationships are developed and sustained by interactive and stable kinship, friends, family, neighbors, or territorial ties (Kebede & Butterfield, 2009). Social networks relate to a set of actors connected by social relations or ties. Obaa & Manzur, (2016) noted that these relationships constitute an important source of information and exchange of economic resources.

2.2.2 Credit and credit access

The concept of credit has been defined variously by different scholars. Feder et al. (1990) defined credit as the capacity to obtain the capital of another, backed by the promise of future repayment. Similarly, Latifee (2003) viewed credit as a contract between two people, where one party transfers money, goods, or services to the other with the promise of future resettlement. Credit access is therefore viewed as the ability of individuals and enterprises to obtain external funds to ease cash flow problems (Osoro & Muturi, 2013). Credit access has also been defined to include the gap between the amount of credit demanded and the amount eventually supplied (Diagne, 1999; Diagne & Zeller, 2001). Nkegbe (2018) observes that agricultural credit is mostly advanced in the form of cash or in kind. However, because most households are likely to divert cash credits towards other domestic expenditure rather than invest in agriculture, in kind credits are suggested to be more suitable for enhancing agricultural production. This form of credit, known as input credit, entails the direct supply of improved seeds, agrochemicals and training services to farmers and the credit amount together with an agreed interest is paid from the produce after harvest (Iddrisu et al., 2018). In this study, credit refers to smallholder access to institutional input credit.

2.2.3 Peer credit

The refers to the share of peers with access to credit in the farmers network. This variable is weighted by the social network matrix and is therefore a weighted average of the observed credit access variable. The variable is derived by multiplying the credit access variable (C_i), by the ith row of the binary social network matrix A (Abdul Mumin & Abdulai, 2021). This is discussed more extensively in chapter three, under subsection 3.4.2.

2.2.4 Food security

One of the earliest definitions of food security came from the United Nations after the World Food Conference of 1974. Food security was described as "access by all people at all times to enough food for an active and healthy life" (Webb et al., 2006). According to Petr et al. (2010), by the end of the 1990s, there were over 200 definitions of hunger and food security. However, the definition which is widely accepted and currently used in most studies, is the one agreed upon at the food conference of 1996. Food security was defined as "a situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2010). As a result, this definition has been accepted for the current investigation.

2.3 Conceptual framework of the study

This section highlights the pathways through which social networks and peer credit may influence farmers' credit decisions as well as enhance their incomes and food security. To begin with, the mechanism of information sharing and knowledge transfer embedded in networks allow individuals to receive credit information which could enhance their credit access (Xiong et al., 2016). This is especially significant for farmers in underdeveloped nations due to market flaws and knowledge asymmetry. Smallholder farmers suffer more financial constraints, among other challenges, due to a lack of credit awareness (Okten & Osili, 2004). Therefore, farmers may likely have a higher chance of accessing loans if credit information is disseminated through these various network links.

In much the same way, current non-users of credit may also increase their chance of access to credit if existing credit users share their experiences with them and offer assurances on their behalf. This is based on the concept of credit externalities and how it may affect the probability of access to credit among farmers (Banerjee et al., 2013). For instance, an individual may be motivated by peers, individually or collectively to take up credit, especially if a substantial number of their peers have already benefited from taken up credit in the past. However, the uptake of credit among peers may impose a positive or negative externality on the household's future credit decisions. The findings in the literature have so far shown that social networks could significantly improve household credit access (Stiglitz, 1990; Okten & Osili, 2004), or reduce the probability of access to credit among households such that those that are socially connected to credit users become less likely to use credit themselves (Alio et al., 2018; Banerjee et al., 2021). According to Banerjee et al. (2013), social networks are important for educating consumers about credit, but they have little influence over how those households decide to participate in the loan market.

Moreover, to the extent that farmers with credit are more technically efficient and productive (Abdulai et al., 2018; Nkegbe, 2018), peer credit could lead to increased peer productivity and incomes, which could increase the level of transfers among households. Increased farm productivity could empower peers to make cash and material transfers to their neighbors which could increase their resource base and productive capacity and consequently result in increases in their productivity and incomes. These transfers might either allow households to spend directly on food products or lead to higher production investment, which could result in improved farm revenue and, as a result, increased food consumption. In addition, own credit access could also have beneficial effects on the income and food security of farmers by increasing the use of improved agricultural technologies in farming (Sekyi et al., 2020). However, if credit is spent directly on consumption rather than investment in production, it may result in lost of farm revenue and could compromise the long term food security of the household.

2.4 Theoretical framework of the study

To explain how interactions in social networks affect the credit decisions of smallholder farmers, this study adopted the linear threshold model based on the theory of social contagion (Granovetter, 1978). In this study, credit access among households is modeled as an outcome of the proportion of credit users and non-users in the farmer's social network, following the frameworks of Tran & Zheleva (2019). Because each farmer in the sample was assigned 15 other contacts with whom he/she may be socially connected, the threshold of people who may be activated at any particular time is between 0 and 15, therefore the threshold (θ) is equal to or greater than zero. Following the susceptible, infectious, recovery (SIR) model, the threshold of the farmer can be illustrated as follows;

$$\theta = \frac{\delta}{\psi} \geq 0 \qquad [1]$$

Where θ is the threshold of the farmer, δ is the number of activated farmers (those with credit), and ψ represents the total number of members in the farmer's social network. Based on Azzi & Cox's (1976) analysis of credit among households, indicating that credit is a function of interest rate, collateral assets, equity, and project profitability, one can conclude that the probability of a household accessing credit is a function of individual and institutional factors such as the socio-economic conditions of the household and that of their neighbors, the threshold of people within the households network that must access credit before they are activated to do so, and that also depend on the loan amount and the required collateral, interest payment, initial wealth, and project viability. This is summarized mathematically in the equation [2] as follows;

$$p(C_i) = f(X_i, C_j, X_j, \theta, L_i(r_i, K_i, W_i, G_i(k)) \qquad [2]$$

Where, $p(C_i)$ represents the probability of access to credit, X_i, is the household socio-economic characteristics, C_j, denotes the credit behavior of peers, X_j is the characteristics of peers, θ is the network threshold, L_i is the amount of credit, r_i is the interest rate, K_i is the collateral requirement, W_i is the initial wealth of the household and $G_i(k)$ represents the viability of the investment project (profitability) and k is the aggregated value of the required variable inputs, which may be equal to or greater than the loan amount (L_i).

To evaluate the impact of each of the variables on the right-hand side of the equation [2] on the probability of the farmers' credit access, one would need to partially differentiate the probability of accessing credit concerning those variables. Differentiating the probability of credit access for the households' network threshold, for example, will result in a function that increases the probability of credit access. Indicating that the higher the proportion of members in a farmer's social network who have had credit, the higher the probability of their access to credit.

2.5 Dimensions of food security

The concept of "food security" became a household name following the World Food Conference of 1974. Food security is comprised of four major pillars: food availability, food access, food usage, and food stability (FAO, 2010). The dimensions of agency and sustainability have been recently added due to the increasing impact of vulnerabilities in the global food system (HLPE, 2020). Webb et al. (2006) observed that despite the hierarchical nature of these dimensions, food availability does not necessarily guarantee access, just as food access is not sufficient to ensure effective utilization.

Food availability

According to Gregory et al. (2005), the availability dimension refers to the physical existence of food commodities for human consumption. These food items may either be from their production or purchases made from local markets or shops overseas. It is concerned with all the supply-side processes that aim to ensure universal access to sufficient, safe, and nutritious food (Gross et al., 2000).

Food access

This dimension refers to the physical, economic, and social access to food by individuals and households (FAO, 2010). The food access dimension centers on the ability of individuals and households to obtain sufficient food with the guaranteed level of quality and quantity required for a nutritious and healthy life (Barret & Lentz, 2010). Food access is a demand-side issue concerning mostly the ability of the individual to acquire food. Access to food is typically influenced by people's financial resource capability as well as current social and political issues, according to Kuwornu et al. (2013). Webb et al. (2006) noted that food access is a more difficult concept to measure compared to food availability because of its inherently multidimensional nature.

Food utilization

The third aspect of food security is food use. It describes the consumption of healthy food that satisfies dietary requirements for all members of the home (FAO, 2010). Studies have shown that food availability and accessibility do not mean that households will have safe and nutritious meals (Sen, 1981). Conte et al. (2002) show that households that have access to available foods still suffer from malnutrition as a result of improper utilization of food commodities. Food utilization is therefore much more than the availability and access to foods, it relates also to the use of clean water, proper sanitation, and healthcare. The sanitary aspect looks at the conditions under which these foods are prepared to ensure that the food is properly prepared and safe for consumption (Barret & Lentz, 2010). It focuses greater attention on the dietary quality and micronutrient consumption of individuals and households to address deficiencies associated with the inadequate intake of essential minerals and vitamins.

Food stability

Food stability ensures that households have continuous and adequate food supplies all year round without shortages. The WFP's definition of food security, which includes "at all times," indicated that all of the other elements have to exist not just for a moment, but for a sustainably extended length of time (WFP, 2008). The food security of individuals and households is therefore adversely affected when any of these indicators are compromised. To maintain long-term food security, availability, access, and usage must be consistent across time and not be affected by weather, food price fluctuations, or civil disturbances (Carletto et al., 2013). This dimension, therefore, considers the seasonality of food insecurity, which could be transitory, cyclical, or chronic. When people cannot consistently satisfy their fundamental food needs, chronic food insecurity results. This is differentiated from transitory food insecurity which relates to short-term or temporary food shortages. Cyclical food insecurity considers seasonality factors that affect the stability of food among households.

2.5.1 Food security challenges in sub-Saharan Africa

Malnutrition and food insecurity have been on the rise in emerging nations for some time. Current statistics show that between 2014 and 2018, the rate of food insecurity and malnutrition in Africa rose from 18.2% to 20%. In the same period, sub-Saharan Africa saw a growth of 20.8% to 22.8% (FAO/ECA/AUC, 2020). According to the report, as of 2018, there were approximately 239 million undernourished persons in the subregion.

In Nigeria alone, an estimated 25 million people have been reported as undernourished in 2018, representing a 180% increase in the last ten years (FAO/ECA/AUC, 2020). This means that the majority of developing countries would likely again fall short of the 2030 objective set by the Sustainable Development Goals (SDGs) for ending hunger and improving nutrition. This was the case with the Millennium Development Goal of cutting hunger in half by 2015. The only way to deal with this is if deliberate efforts are made to remove obstacles in the way of enhancing the sub-regional population's nutritional status and food security.

The occurrence of food insecurity and malnutrition in Africa has been largely attributed to environmental, economic, and political factors like climate shocks, civil unrest, and conflicts, low wages, increases in food prices, lack of access to financial services and credits, and weak market structures for both farmers and consumers (Abdulai & Kuhlgatz 2012; FAO/ ECA/AUC, 2020). According to research, smallholder farmers who have access to financing are more productive in their farming (Nkegbe, 2018), which could improve food security situations in developing nations by increasing crop yields.

2.5.2 Methods used in measuring food security

Barett (2010) described food security as an elusive concept due to the difficulty in measuring it. He noted that a single indicator cannot capture the intricacies of food security, hence the need for building an index that considers most of the food security dimensions. Different indicators have been used in measuring food security across different countries by researchers and experts (Barret & Lentz, 2010). These studies have used a variety of methods to operationalize and quantify food security as a measure of household welfare. The choice of an indicator depends on the objective of the researcher which drives the measurement decision.

The indicator used in the measurement of food security is significant because it affects how stakeholders prioritize food security initiatives in their policy decisions. For instance, past food security interventions have been on food aids and strategies to increase agricultural productivity and food supplies because of the heavy emphasis on the food availability dimension in the past. Over time, the debate about food access took center stage following Sen, (1981)'s argument about food access accounting for most food insecurity. This changed the focus of stakeholders toward the development of poverty reduction strategies, stability in food prices, and social protection policies.

The Household Consumption and Expenditure Surveys (HCESs), Household Dietary Diversity Score (HDDS), Food Consumption Score (FCS), Coping Strategies Index (CSI), and Household Food Insecurity Access Scale (HFIAS) are some of the most frequently cited measures of food security in the literature. These indicators are the most used across developing countries to measure household-level food security, focusing on one or more of the dimensions mentioned in the FAO's definition of food security (FAO, 2010). They are used to capture the extent to which there is availability, access, utilization, and stability of sufficient, safe, and nutritious food that meets the dietary needs of households (Lele et al., 2016).

The Household Consumption Expenditure Surveys (HCESs) analyzes the availability of sufficient and high-quality amounts of food. The HCESs gather information on finances, food purchases, and consumption, as well as access to essential services like housing and education. The data collection tool is given to the head of the home or any person in charge of food preparation and includes a context-specific food list. According to Fiedler et al. (2012), the questions typically concern the source, quantity, and cost of each food item ingested during the review period. According to Perez-Escamilla and Segall-Corrêa (2017), the HCESs are criticized for being too difficult to standardize across national boundaries and for failing to take into account food consumed outside the home, fed to animals, given as presents, or received in exchange for labor.

Based on the documented correlations between a quality diet and the diversity of its nutrients and calories as well as the socioeconomic position of households, the HDDS is used to quantify the socioeconomic status of families and their capacity to get food (Swindale &

Bilinsky, 2006). The respondent household answers questions based on a yes/no response to whether 12 distinct food groups were ingested in the 24 hours before data collection. If the response is yes (1), it means that the household has eaten from that particular food group; if it is no (0), it implies that the household has not. There are between 0 and 12 total responses to the 12 questions. However, there are no limits to determining whether a household has an appropriate amount of dietary diversity, so the mean score is used to track results.

The FCS takes into account the household's varied dietary habits, food consumption patterns, and the relative nutritional content of the eight food groups that comprise the diet of the household over seven days (WFP, 2008). To calculate the food consumption score, the household consumption frequencies of the various food groups over seven days are added together and multiplied by the standardized weights given to each food group. Households are then categorized as being poor, borderline, or acceptable based on their overall consumption score. Researchers and policymakers use this indicator to track household food security, identify vulnerable households, and monitor and evaluate program outcomes. The FCS offers essential dietary data for early warning assessments, particularly in emergencies (FAO, 2010).

However, these metrics have come under fire for failing to address intra-household disparities or inequities in food security (Alinovi et al., 2009). The FCS is recognized as the optimal tool for household-level inquiry because it gives adequate information on household food consumption, dietary diversity, and nutrient intake (FAO, 2010). The food consumption score (FCS), which can evaluate both the frequency of intake as well as the food types consumed by the households, has thus been used in this study. Additionally, while other measures, like the HDDS, employ unweighted food groups in their calculations, the FCS weights the various food groups according to nutrient quality. In conclusion, it has been suggested that additional tools be created to measure all four dimensions of food security as well as account for both household and individual level food security to address the intra-household disparities in food consumption (Maxwell & Smith, 1992; Alinovi et al., 2009).

2.6 The nature of farmer social networks in Ghana

Social networks are very important in the decisions and choices made by households all around the world. These networks are a crucial component of the socioeconomic structures of society and have a big impact on a range of household decisions, including the adoption of technology (Bandiera & Rasul, 2006). They may also have an impact on household credit decisions in Ghana.

Credit, information, labor, and land networks were the four main types of farmer networks found by Conley & Udry (2010) in Ghana. These networks frequently have an impact on family production choices, such as the adoption of agricultural technology. The social ties of the farmer who exchanges these resources are shown by these interconnections. For instance, credit networks are those relationships where the farmer typically exchanges credit with the other members of the network. These network connections, particularly the credit and information networks, may have a big impact on how the farmers decide to use loans.

2.6.1 Methods used in collecting network data

Studies often use two methods to gather information from social networks. the prompted recall techniques and name-generator approaches (Butts, 2008). In the former, participants are asked to recall specific people they are socially associated with. This approach is typically employed in research involving huge and intricate network datasets. For example, Perkins et al. (2018) employed this strategy to collect data on networks in their study on food security, social networks, and symptoms of depression among men and women in rural Uganda. This strategy is not suggested for big networks with numerous linkages since forgetfulness and exhaustion may cause respondents to offer false negative answers.

The roster approach includes a series of questions that ask respondents to choose from a prepared list of people to whom they are related. This is the most commonly used and favored approach for gathering data from local and interpersonal networks. Butts (2008) stated that by prompting the respondent, this strategy helps to reduce the risk of false negatives. Conley and Udry (2010) investigated the role of social networks on agricultural technology adoption in Ghana using a random matching within the sampling method based on prompted recall. This method is appropriate for assessing network impacts since it gives sufficient information on farmers and network members (Fafchamps & Gubert, 2007).

2.7 The credit market systems in Africa

There are three major sources of credit available to applicants; formal, semi-formal, and informal sources. Formal or institutional credits are provided by formal financing institutions such as commercial banks, development banks, or rural banks. The formal institutions are licensed, regulated, and controlled by the central bank (Turkson et al., 2020). According to Helmke & Levitsky (2003), the semi-formal and informal credit sectors are governed by social network structures rather than any central monetary authority. According to Owusu-Antwi & Antwi (2010), the informal sector is made up of individuals and organizations including friends, family members, moneylenders, traders, rotating savings & credit associations (ROSCA), and so forth. In most rural settings, individuals with excess financial capacity provide loans to other poor farmers to support their activities. The informal sector has therefore been a significant source of finance for households and businesses in many developing countries including Ghana (Awunyo-Vitor, 2015).

The low uptake of formal credit, especially among rural farmers can be attributed to the strict collateral requirements of banks (Asiamah et al., 2021). For this reason, formal credits are most likely to be granted to large corporations. In Kenya, Atieno (2001) noted that most formal credits are granted to big investors, with only about 30% allocated to households. The strict and regular repayment schedule under the formal financial systems further explains the dominance of the informal sector and why most households prefer loans from the informal sector despite the exorbitant interest charges on credit (Awunyo-Vitor, 2015). Although most financial institutions have increasingly extended their services to rural areas, informal lending continues to dominate because of the unwillingness of most banks to provide credit services to rural farmers who are often considered to be highly risky (Owusu-Antwi & Antwi, 2010). Most of these banks are likely to give out loans to large corporate entities because of their desire to maximize profit as well as minimize the risk associated with those in the informal sector.

2.7.1 Credit access and the role of information sharing

Across the developing world, access to credit is negatively impacted by information asymmetry due largely to the imperfections of the markets (Diagne, 1996). The major problem is the inability of lenders to obtain credible information about the risk profile of potential borrowers because of inadequate information. Xiong et al. (2016) argued that information-sharing mechanisms could help reduce adverse selection in the distribution of credit by providing knowledge of the applicant's characteristics. This could reduce the cost of credit, increase the efficiency of credit institutions in the allocation of credit and improve credit access among households. Similarly, Stiglitz, (1990) asserted that the cost of credit has been high in most developing countries due to the problem of information asymmetry, which also prevents the efficient allocation of credit. The author noted that sharing credit information could play a key role in the efficiency and delivery of financial institutions by reducing both the cost of loan processing and the time required to process loan applications.

2.7.2 Impact of credit on agriculture

Access to financing is the most significant tool for agricultural development in poor countries. It is so critical for the agricultural sector's growth and development. Dittoh (2006) assessed the effectiveness of aid for smallholder farmers in sub-Saharan Africa and noted that credit is the most needed item for farmers in developing countries. A study conducted in the Northern region and particularly, in the Kumbungu and Karaga districts, noted that maize farmers have very minimal access to credit which affects their productivity and incomes (Wiredu et al., 2010). Access to credit tends to significantly affect agricultural productivity and increases farmers' commercial behavior (Sekyi et al., 2020).

2.7.3 Credit access and household welfare

Studies suggest that the lack of access to credit among farmers could have general effects not only on production but on the incomes and general welfare of households (Iddrisu et al., 2018; Nkegbe, 2018). Households that are credit-constrained may be affected by reductions in food consumption and lower achievements in both education and health. Kuwornu et al. (2013) revealed that access to finance among households significantly increases food consumption by about 48%. This implies that credit constraints among households could have a significantly negative impact on households' food consumption. Therefore, persistent credit constraints over the life cycle of households could substantially affect their ability to mobilize capital, and that could widen the inequality gap (Hai & Heckman, 2017). It has therefore been suggested that to increase food consumption among households, credit must be made more accessible to households that need it. For instance, Sekyi et al. (2020) found access to credit as an important requirement for households to be commercially oriented, and that could have significant beneficial effects on their consumption.

2.7.4 Methodologies used in measuring credit access

There are currently two major methodologies that are used in the literature to measure credit access. First, studies rely on information about households' participation in the credit markets, such that households are deemed to have access when they participate in the credit market, otherwise, they are said to have no access. Credit is measured as a dummy, where "access" is denoted by 1; otherwise, 0. These classifications are then used in analyzing the factors that influence households' credit decisions. This approach has been mostly used in the literature across various countries to assess the demand side factors of credit access (Feder et al., 1990; Biyase & Fisher, 2017). The second approach measures credit access in terms of the amount of credit accessed. Here, households are deemed to have access when the amount of credit demanded is equivalent to the amount of credit received, otherwise, such households are said to be credit-constrained (Diagne, 1999; Diagne, 1996; Diagne & Zeller, 2001). This approach is mostly used to address the supply-side constraints placed on households, as explicitly discussed in Diagne (1999). This current study adopts the use of a dummy in measuring credit access because of the choice of the model and the desire to determine a household's probability of access to credit.

2.8 Review of analytical methods

2.8.1 Analyzing the effect of social networks

Analyzing the effects of peer credit on household income and food security may be difficult due to econometric endogeneity difficulties. This is especially relevant since social networks are established endogenously, which means that unobserved factors have a role in link formation (Manski, 1993). Various approaches have been considered in past studies to cope with network endogeneity issues originating from unobserved factors influencing the households network link formation. These unobservable factors may jointly affect farmers network formation and the outcome, which may cause bias and inconsistency in the estimates. As a result, while measuring the influence of peer credit on household welfare, it is critical to account for variables that may jointly affect both the outcome and the variable of interest (*peer credit*). Failure to do so may result in estimates that incorrectly attribute variations in household income and food security to peer credit. Furthermore, certain unobserved factors may contribute to the initial variations in the outcomes and selection (credit access) that already exist among households. Based on this, for the the selected impact model to perform optimallt, it should help to completely avoid or at least account for these selection biases (World Bank, 2010).

Manski (1993) in evaluating the identification of social network effects, observed that social network effects cannot be properly estimated using normal linear estimation techniques due to the likelihood of perfect co-linearity among the independent covariates. In this study, two key identification issues were raised, particularly in the context of a linear-in-means model; first, the difficulty in distinguishing true social impacts (endogenous and exogenous effects) from correlated effects. To explain, the endogenous effect estimates assess the impact of the average outcome of peers on the farmers' own outcomes, whiles the exogenous effects assess the impact of the average peer characteristics on the farmers' outcomes. The correlated effects estimate, on the other hand, shows the impact of unobserved factors on the outcomes of the individual farmer. The second issue was that even in the absence of correlated effects, that is, if no correlated effects were assumed, simultaneity in the behavior of group members may result in complete collinearity between the group's predicted mean outcome and its mean characteristics (*reflection problem*).

In the linear-in-means framework, individual outcomes are expressed as a linear function of own characteristics, the average outcome of the group as well as its average characteristics (Bramoullé et al., 2009). Because of its structure and link to typical simultaneous linear models, the linear-in-means model has been employed in various research on social network interactions. This model typically assumes that individuals interact in groups, and as such outside influences are not anticipated and accounted for. This notion that individuals interact in groups presents a major problem in identifying peer effects under the linear-in-means model (*ibid*). The assumptions under this model creates the impression that the population is separated into groups and that individuals are only affected by members of their group and not by those outside of it. However, most group interaction networks are unlikely to capture most types of interpersonal relationships and social network links (Bramoullé et al., 2004).

Brock & Durlauf (2002) refuted Manski's claim, stating that the results were specific to a class of linear estimators and that social network effects could be modeled in the context of other discrete choice models, specifically using non-linear estimators such as the logit and multinomial logit models as examples. Brock & Durlauf (2003) therefore used discrete choice models to investigate endogenous and exogenous effects under the assumption of no correlated effects.

As a result, most current studies have used non-linear approaches to quantify the influence of social networks on study outcomes. Alio et al. (2018), in particular, examined the association between social networks and credit consumption using the binary logistic regression model. Similarly, Wydick et al. (2011) used the multinomial logit approach to investigate the impact of social networks and community impacts on credit access among rural Guatemalan families. The methods used in these investigations, however, are unable to represent the spatial lags on the dependent and independent variables to generate endogenous and exogenous effects (Ansellin, 1988).

The method utilized in this study was influenced by the literature on spatial econometrics. Because of the spatial lag nature of both the dependent and independent variables, the spatial Durbin model was adopted in particular. The model was chosen because of its capacity to model spatial lags on both the dependent and independent variables (Anselin, 1988). The approach uses the social weight matrix to model the outcome on independent variables such as the outcome and characteristics of network members. The social weight matrix (A) in this study has an arbitrary structure that permits the interaction patterns of each observation in the sample to differ sufficiently across the network. This study looked at network relationships that are structured through undirected social networks specified by the farmer.

2.8.2 Analysing the impact of peer credit on income and food security

To investigate how treatments affect diverse outcomes, several techniques have been explored. The impact of self-selection and unobserved factors on study results has generally been disregarded (World Bank, 2010). According to Lokshin & Sajaia (2004), biased estimates that may be inconsistent and less effective could result from failing to take into account the initial differences between the treated and untreated groups, as well as unobserved and selective biases.

The conventional linear regression (OLS) model has also been used in studies to determine how treatment factors affect study outcomes by simply incorporating the treatment as a dummy in the outcome function. The effect of unobserved components, according to Abdulai & Huffman (2014), cannot be captured by such arrangements and may cause a link between the reported explanatory variables and the error term. The analysis of treatment effects using Propensity Score Matching (PSM), which compares members of the treated group to members of the control group based on observable factors, is another widely used technique. However, the matching is only done using observable characteristics, disregarding unobservable factors, based on the theory that selection bias only affects observable traits (World Bank, 2010). The PSM is therefore unreliable.

In this study, the selection variable (credit access) and peer credit are potentially endogenous in analyzing the impacts of peer credit on household incomes and food security; as a result, they need to be controlled to get accurate and reliable results. This calls for reliable tools to take into account the impact of variables that could affect smallholders' income and food security in addition to the credit decisions made by farmers and the access to credit of their peers. The full information maximum likelihood strategy has been suggested to address any potential endogeneity problems brought on by unobserved factors in light of the difficulties connected with the previous estimation methods that have been described. To generate effective and reliable estimates under an endogenous switching regression (ESR) regime, the selection and outcome models should be estimated simultaneously (Lokshin & Sajaia, 2004).

2.9 Empirical review

2.9.1 Factors affecting household credit access

Access to finance is a critical developmental concern for stakeholders in the developing countries (Waje, 2020). As a result, numerous studies have been carried out across the continent to investigate the factors that affect how easily households may acquire loans (Kedir, 2003; Diagne, 1996; Diagne, 1999; Diagne & Zeller, 2001). Nkegbe, (2018), Sekyi, (2017), Waje, (2020), Dzadze et al. (2012), Biyase & Fisher (2017), and Asiamah et al. (2021) are some more recent works in this field.

Age, sex, education, household income, household size, total landholdings, and household assets have been identified as the major socioeconomic characteristics that significantly affect households' access to credit. The availability and access to credit among households are also impacted by supply-side factors, many of which are related to the financial institutions themselves, such as interest rates, lending conditions, and distance from the institution. The decision of households to obtain credit is significantly influenced by socioeconomic parameters such as sex, age, household size, farming experience, education, farm size, hired labor, extension services, and farmer-lender distance (Owusu, 2017).

Socio-economic factors

Age of household head

In Ghana, cassava growers' access to financing was examined by Owusu (2017). The study found that the age of cassava farmers in Ghana has a significantly negative impact on their capacity to receive financing, such that getting older decreases the likelihood of getting a loan. This suggests that older farmers have a decreased likelihood of obtaining finance. The age of cassava growers specifically lowers their access to finance by around 2%. Additionally, Chen & Chivakul (2008) looked into the variables influencing credit restrictions and household borrowing in Bosnia and Herzegovina. According to the authors, access initially declines with age until a certain age is reached. According to this, the likelihood of being credit-constrained decreases up until a particular age and then increases after that. Similarly to this, Pastrapa (2009) investigated the factors that influence urban Greek household loan demand. The study discovered that age was a crucial factor in determining credit demand, with younger people being more inclined to do so than older persons. The study also showed that, while age considerably enhanced the likelihood that households would request credit, the likelihood of receiving the requested credit was decreased by unemployment or low income. The findings of Nwaru (2011), who investigated the factors influencing informal loan demand among Nigerian farmers of food crops, go counter to the idea that age has a substantial impact on credit access. Therefore, the study concluded that age had no discernible impact on obtaining credit.

Sex of household head

According to numerous research (Okurut, 2006; Barslund & Tarp, 2008), men are more credit-constrained than women. It is argued that female-headed households tend to have easy access to credit than their male counterparts. However, other research has found households headed by males to have greater access to loans than female household leaders. For instance, Biyase & Fisher (2017) discovered that men are much more likely than women to have access to formal credit in their analysis of the determinants influencing access to credit across households. Additionally, Owusu (2017) investigated the variables influencing loan availability among Ghanaian cassava farmers and discovered that men were more likely (26%) than women to have access to credit. They discussed how conventional hurdles prevent women from owning and controlling the financial resources needed to obtain loans, particularly from formal financial organizations. Due to their inability to work and generate sufficient income to repay borrowed credit, elderly female farmers in particular are significantly impacted by the distribution of credit (Doku et al., 2020). This demonstrates the inconsistent data in the literature regarding the impact of gender on households' access to credit.

Educational status

According to studies, education considerably improves a household's ability to acquire loans (Kedir, 2003; Okurut, 2006). Additionally, Biyase & Fisher (2017) discovered that households' access to credit is statistically influenced by education at all levels. However, Chen & Chivakul (2008) discovered contradictory findings about the impact of education on credit access in various nations. For example, they discovered that schooling had no discernible impact on the chance of being credit limited in the Netherlands, Bosnia, and Herzegovina, but that it generally decreased the likelihood of being credit constrained in Italy and Thailand. The report revealed that lenders do not have confidence that these people will find employment since the nature of unemployment in Bosnia and Herzegovina is designed so that the majority of educated people are unemployed.

Employment status

Biyase and Fisher (2017) explored the determinants influencing poor households' access to formal credit in South Africa using data from the National Income Dynamics Study (NIDS).

The research findings demonstrate that the probability of a household's access to credit is greatly increased by the work position of the household head. Chen & Chivakul (2008) found that whereas unemployment had no discernible impact on household credit access in the US and Italy, it significantly raised the possibility of credit limitations among Bosnian and Herzegovina households. They noted that whereas having a self-employed status did not significantly affect potential borrowers' access to credit in Bosnia, Herzegovina, and Thailand, it did significantly raise the risk of having a credit constraint in Italy, the Netherlands, and the United States. They argued that the low rate of self-employment in these nations could be responsible for the effect that was being observed.

Household income

In their study, Biyase and Fisher (2017) found that income and accumulated assets greatly increase a household's likelihood of being approved for loans. The study concludes that families' credit decisions are related to their income level, thus those with greater salaries and more assets, particularly among the working class, desire more credit. In 2020, Metseyem looked into the variables influencing households' access to credit in Cameroon. According to the study, a household's level of access to credit is highly influenced by its income. This suggests that wealthier Cameroonian households are more likely to have access to loans than poor ones. This might be especially true in formal and semi-formal institutions where lending credit to households often necessitates the use of collateral assets. The factors influencing credit access among households were also examined by Gideon & Matsuda (2015), who discovered that larger households with higher levels of productivity, savings accounts, and other strategies for diversifying their sources of income tend to have more access to credit than smaller households with insufficient production capacity to diversify their income sources and generate additional income to pay back borrowed credit.

Family size

According to studies, households with big family sizes request more loans than homes with small families do. Fanwell (2003) evaluated the variables influencing Malawian household credit demand. The findings showed a notable correlation between household spending and loan demand. The most likely explanation is that households with big family sizes spend more money and have greater levels of spending, which are linked to a higher likelihood of requesting loans. Large family households are thought to have more expenses, which leads to higher borrowing. The size of the household has a significantly beneficial impact on loan access, according to research by Gideon & Matsuda (2015) on the factors influencing credit access across households. This suggests that households with larger sizes have higher access to credit, which may be attributed to an increased desire for borrowing to meet the household's urgent needs.

Household assets

In Vietnam, Barslund & Tarp (2008) investigated formal and unofficial rural credit. They discovered that ownership of land and other forms of productive resources had a considerable impact on the demand for formal credit, whereas family size and a poor credit history had a beneficial impact on the demand for informal credit. This demonstrated that while households sought out formal credit for asset management and production, they sought out informal credit for smoothing out spending. Similarly, Quoc (2012) examined the variables influencing access to formal loans using data from 325 rural Vietnamese families. The study found that household capital endowments influence both the demand and the amount for credit by using the double hurdle and Heckman models to analyze the data. Kedir (2003) also estimated the factors affecting loan amounts and credit availability in Ethiopia using the Probit and Tobit models. He discovered that the amount of current resources and collateral assets in a household has a significant impact on credit availability.

Other community factors

Community factors, such as the distance of the community from the main town, the presence of market facilities in the village, the quality of the road network connecting the community to the city, as well as high soil fertility, could have a significant impact on household decisions to access credit, according to Metseyem (2020), who examined credit access among households in Cameroon using data collected between 2001 and 2015. Therefore, a key factor in determining credit access was household geography. The study found that households in urban areas were more likely than those in rural areas to have access to credit. According to Quoc (2012), household access to credit is significantly influenced by their distance from market hubs. Quoc (2012) discovered that household access to credit is heavily influenced by distance to market centers. Families who live close to commercial areas can need credit to engage in other sources of income.

2.9.2 Factors that influence household food security

Age of household head

The age of the household head is projected to have an impact on food security through labor supply. According to Babatunde et al. (2007), the age of a household head influences food security through the amount of labor available for food production. According to the study, younger household heads are more energetic and can grow larger farms than older ones, and hence are more likely to be food secure. Furthermore, young family heads can seek other off-farm employment and earn better wages to supplement what the home produces. However, Arene and Anyaeji (2010) discovered contradictory results, indicating a considerably favorable association between the age of the household head and the household's food security. They argue that households headed by older people are more food secure than households headed by younger people. Abdullah et al. (2017) discovered that older household heads were more food secure than younger household heads. The expected impact of this variable on food security could thus be positive or negative.

Sex of household head

Through the different responsibilities they play, the household head's sex is crucial to the family's ability to obtain food. Gender has been found to have a variable impact on household food security. Hadley et al. (2008) studied the connection between individual and household food insecurity among teenagers in Ethiopia. According to the study, boys seem to have a lower likelihood of experiencing food insecurity than girls do when they live in a household where there is food insecurity. This is related to the gender gap as well as the privileges and roles that are assigned to each gender. According to a study conducted by Abdullah et al. (2017) to analyze the determinants affecting family food security in northern Pakistan, female-headed households are more likely than men to face food insecurity due to unequal access to economic resources. This could be because most female-headed households have greater dependency ratios and are unable to contribute labor for on-farm and off-farm activities, which reduces household income. Furthermore, when compared to male family leaders, the majority of these female household heads are older and have less schooling. However, Awoyemi et al. (2023) discovered that households that are headed by males have a reduced likelihood of slipping into poor and borderline food insecurity than female-headed households. As a result, the predicted effect of sex on household food security could be either positive or negative.

Off-farm trade

Farming and livestock rearing are the primary occupations of rural families in Ghana (GSS, 2019). Farmers may participate in different occupations aside from farming to supplement their household income. These activities can have a beneficial or negative impact on household food security depending on the tradeoffs in gains (Babatunde et al., 2007). Farmers, for example, who engage in off-farm activities may earn additional revenue that they might spend on food-related things, so increasing the household's food security portfolio. According to Danso-Abbeam et al. (2023), who studied the determinants of household food insecurity and coping strategies in the Northern region, households that participate in non-farm activities are better able to cope with food security challenges than those that do not participate. Danso-Abbeam et al. (2023) concluded that households that engage in non-farm activities are better equipped to manage food security difficulties than those that do not. However, if farmers spend more time on non-farm activities and ignore their agricultural operations, and if the revenue they receive is insufficient to compensate for the lost farm income, their food security situation may deteriorate. The expected effect of off-farm activity could therefore be positive or negative.

Farm size

This is the total area of land used by the household to grow crops. According to studies, there is a correlation between farm size and both household income and food security (Jayne et al., 2005). This could be ascribed to households with big farms having higher production capacities, which could result in higher food output. This suggests that households with larger farms should have greater food security than those with smaller farms. With all else being equal, it is anticipated that this variable will have a favorable impact on food security.

Access to credit

Households mostly rely on credit, either in cash or in kind, to stabilize consumption or scale-up output. Household credit could boost welfare through either productivity or direct consumption. According to Babatunde et al. (2007), households with access to credit have a short-term boost in income, which could improve their consumption over time. Access to financing improves smallholders' ability to obtain production equipment and inputs such as knapsacks, seeds, pesticides, and fertilizers to promote agricultural production and potentially improve household food security (Okurut, 2006).

Land ownership

The land is mostly owned through outright purchase or inheritance. Studies have found land ownership to have a significant impact on rural poverty and food security. According to Jayne et al (2005), land ownership reduces the phenomenon of rural poverty and ensures improved access to food. More research demonstrates that households without access to land are more likely to experience acute food insecurity and poverty (Kyaw, 2009). Danso-Abbeam et al. (2023) investigated the determinants of household food insecurity and coping strategies in northern Ghana. According to the findings, a household's capacity to manage food insecurity is greatly impacted by the number of assets that the household has. The study concluded that households with more assets can cope with food security challenges with fewer approaches. The findings of Abdullah et al. (2017) also confirmed that the number of assets owned by households impacts significantly on food security. The assets owned by households included land, which could affect food security through its production.

Household income

In their study, Babatunde et al. (2007) discovered that a household's overall revenues from both off-farm and on-farm sources have a substantial effect on the household's food security. Arene & Anyaeji (2010) asserted that households that are gainfully employed and earn higher incomes have a higher chance of being food secured. Households that earn more incomes can increase their production capacity and can access quality foods in large quantities. Kassy et al. (2021) studied the factors affecting the food security of households in Nigeria and found income measured by household wealth index to be a significant factor influencing food security. They attributed the problem of food insecurity among households largely to poverty.

Level of education

Shaikh (2007) studied the determinants of household food security and consumption pattern of households and found education to significantly improve the capacity of individuals to process and apply information, which could affect the food security of individuals. Moreover, low educational attainment could impede a household's ability to access better job opportunities in the labor market and that could further affect the food security of households (FAO, 2002). Awoyemi et al. (2023) studied the drivers of food security in Ghana using data from the Ghana Living Standards Survey round seven (*GLSS 7*). The study also confirmed that improving access to education, specifically nutrition education could enhance the food security status of households. Similarly, Abdullah et al. (2017) found that education has a considerably favorable impact on household food consumption in their study of the determinants impacting food security in Pakistan. The findings imply that households that are highly educated are more likely to be food secure than those who are less educated

Own farm production

The total amount of food and cash crops that households produce on their farms may help the household's ability to purchase food, either directly or through the proceeds from crop sales. Quaino, (2010) found out that own food production significantly reduces the incidence of food insecurity among rural households since most of these households consume what they produce. The majority of farmers, according to Babatunde et al. (2007), sell their farm products to buy other foods for domestic consumption.

Farm experience

In a study by Feleke et al. (2003) conducted to examine the determinants of food security among farming households, the results show a significant correlation between farming experience and the food security status of farmers. Oluyole et al. (2009) discovered comparable findings in their investigation of the elements influencing the food security of cocoa farmers in Ondo State. The experience of farmers is considered based on the number of years of the household heads' engagement in farming. Hence, it is believed that more experienced farmers have more insight and ability to diversify their products to minimize the risk of food shortage. Moreover, experienced farmers may increase production by leveraging the knowledge gained through the years to manage pests and diseases.

Household size

This represents the total number of persons living in the household and eating from the same pot. A study by Feleke et al. (2003), found a significantly negative relationship between household size and food security. The study concluded that an increase in household size puts pressure on consumption rather than production, especially if most of the members are not economically active and working. This is also because most of these households have low resource capacity. Similarly, Ojogbo (2010) also noted that an increase in the number of non-working members of a household tends to increase the dependency ratio which could adversely affect the food security condition of the household.

2.9.3 Empirical evidence of the effect of social networks on credit access

Studies in the literature have provided mixed evidence regarding the relationship between social networks and household credit access. The empirical evidence presented so far is both scanty and contradictory. While some studies find a statistically strong and positive relationship between social networks and credit access, others reveal results that suggest the contrary. Moreover, the specific roles of different network types on credit access have also been a subject of debate. Some studies find strong network types such as the family to be more significant in promoting credit access, while others find weak network ties (friends, community neighbors, etc.) to have a much stronger impact on household credit access.

Zhao et al. (2021) studied the impact of complex social networks on the credit behavior of rural households in China using data from the CHFS. The study found social networks to have a statistically significant effect on the credit decisions of households, although the effects tend to differ across the different credit sources and network types. In particular, social network effects were found to be stronger in influencing household behavior towards informal credit than formal credit. Also, the effect of emotional networks on both formal and informal credit sources was stronger compared to instrumental networks.

Using data from the Indonesia Family Life Surveys (ILFS2), Okten & Osili (2004) examined the relationship between social networks and credit access in Indonesia. The study found that family and community networks have a greater impact on households' awareness of new credit institutions than credit sources that are already well-established. They concluded that social networks have a significant influence on the credit decisions of households, especially with new credit institutions. A research conducted to assess the role of family networks on household credit access in Kenya by Kariuki & Mdoe (2017) using cross-sectional data from the FinAccess Household Survey of 2016 also confirmed these results. The study found that family networks increase the likelihood of access to microcredit by reducing search and information costs, noting that the effect of family networks on credit access was much stronger among women.

Alio et al. (2018) investigated the effects of social networks on the credit utilization of members of savings and cooperative credit unions in Uganda. The study found that members with high social contacts have a lower probability of access to credit compared to those with smaller contacts. In a recent study by Banerjee et al. (2021) to examine the dynamics of social network structure in response to the emerging formal credit markets, the findings reveal that access to microcredit among households could result in decreases in network links, especially among existing ones. The study further noted that exposure to microfinance could cause network links to disappear. Preceding this study, Banerjee et al. (2013) also studied the diffusion of microfinance through social networks in India and found that despite the significant role of social networks in informing households about credit, it does not significantly influence their decision to participate in the credit markets. The evidence in the literature on social networks and credit access is therefore inconclusive, and this requires more studies to assess the link between social networks and credit access across different social settings.

2.9.4 Empirical evidence of the impact of social networks on household food security

There exist contrasting findings in the empirical literature on the effect of social networks on the food security of households. While some studies find social networks to have significant impacts on household food security, others find no evidence that households benefit from social networks in terms of their food security (Hadley et al., 2007; Jayashankar & Raju, 2020; Kang, 2019). Tam et al. (2014) studied the role of social networks as a coping strategy for food insecurity and hunger among young Aboriginal children in Canada. The study was conducted using two national datasets that included the Aboriginal Children's Survey and the National Longitudinal Survey of Children and Youth. The study revealed that while the majority of urban children in the sample cope with food insecurity by reducing the amounts of food they consume, rural children depended largely on the social support systems in the community to cope with hunger and food insecurity. The results indicate the differential role of social networks across different social settings, and that social network support could be more effective in rural areas than urban centers.

In a study to assess the effect of social networks on household welfare in Tanzania, Aker (2011) noted that social networks play a significant role in reducing household poverty. The study revealed that an increase in the social network of a household is significantly associated with a decrease in poverty, which also enhances the ability of households to increase expenditure. The study concluded that social networks help households significantly reduce poverty and improve welfare. Obaa & Manzur (2016) also conducted a study to examine social network characteristics and resource access among formerly displaced households in northern Uganda and confirmed that households with larger and more diverse social networks appear to have greater access to resources, which tend to make them more productive and less exposed to food security threats compared to those with smaller and less diverse networks.

Olarinde et al. (2020) also studied the impact of social networks on household food security among cassava farmers in Nigeria using primary data. The study found social network groups to significantly increase household food security, especially among those that make cash and labor contributions to the group. Similarly, Kaleb et al. (2017) in studying the effect of social networks on the food security of maize farmers in rural Ethiopia, found that networks that are constituted by both relatives and non-relatives at the village level provide valuable information and support that significantly improve the food security of households.

In rural Uganda, Perkins et al. (2018) also looked at the connection between social networks, depressive symptoms across genders, and food insecurity. The study was conducted using cross-sectional data. The study revealed a significantly higher correlation between the mental health of respondents and their food insecurity status. However, the study found the impact of social networks to differ significantly across gender. Social networks, for instance, were found to have a significantly higher moderation effect on the relationship between severe food insecurity and depressive symptoms in men than they did on the relationship between food insecurity and symptoms of depression in women. When compared to individuals who were on the periphery of the village social network and had a large number of poor acquaintances, this was particularly obvious among those who are deeply ingrained in the networks and have few poor links. The study concluded that the effect of social networks on household food security depends on the gender of the household head and their ability to cope with a variety of shocks that may adversely affect their food security.

However, Marco & Thorburn (2009) in their study of the relationship between income and food insecurity among residents of Oregon and the role of social support, found results that contradict the view that social networks have a positive influence on food security or contribute to reducing the incidence of food insecurity among households. The study concluded that social networks do not correlate strongly with food insecurity, and do not significantly moderate the relationship between income and food insecurity.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter presents the research methodology of the study. It highlights the profile of the study area, the design used for the study, sampling and sample size determination as well as data collection tools and techniques. The chapter further outlines the methods used in analyzing the research objectives of the study.

3.2 Study area

This study was conducted in the Northern region of Ghana. Currently, the region is made up of 16 districts, with Tamale being the regional capital and constituting about 14% of the regional population (GSS, 2021). The region has a total land area of about 25,459 sq. km. It is located between latitude $8^0 30$ and $10^0 30$ N and lies within the savannah belt of Ghana. It is bounded to the East by Togo as its international neighbor, to further south by the Savannah region, and North East region to the north. It also shares boundaries with the Oti region to the South-east (GSS, 2021). The region has a vegetation cover that is predominantly grassland with clusters of drought-resistant trees such as the baobab, shea trees, and neem trees.

The population of the region currently stands at 2,310,939, representing about 7.5% of the total population of Ghana (GSS, 2021). The data shows that the Northern region recorded the highest annual intercensal population growth rate of 3.7% compared to the national average of 2.1%, and a population density increase of 28.9 per square kilometer since the last census in 2010. The most populated city in this region is the Tamale metropolis, with a population of 374,744, followed by the Sagnarigu municipality (341,711), while Nanton has the least population of 50,767 (GSS, 2021). According to the recent population and housing census

(2021), the female population in the region (50.6%) is slightly higher than the male population (49.4%). A decline of roughly 2.8 people between 2010 and 2021 left the average household size at 5.2 people, which was nevertheless higher than the national average of 3.6 people (GSS, 2021). Also, the Tamale metropolis is the most urbanized city (100%) in the region, followed by the Sagnarigu municipality (81.6%), while the Mion district remains the least urbanized (10.4%). The majority of the people are into agriculture, with over 90% of the active age group being predominantly peasant farmers. The bulk of cereals, tubers, and groundnuts in the country are produced by the smallholder farmers in the region, with Shea nut being an important cash crop for rural women. The vast majority of the people are however poor and cannot afford basic services (GSS, 2021).

3.2.1 Profile of study area

This study was conducted in the Northern region of Ghana, using data from farm households in the Karaga and Kumbungu districts. The region is typically characterized by a mono-modal pattern of rainfall that normally starts in May and ends in October, with an average annual rainfall of 900–1000mm. The temperatures are mostly high through out the year, particularly between March and April, with an average temperature of 36 °C recorded during this period. However, during the harmattan period, notably between November and February, temperatures are generally lower. There are drought-tolerant plant species such as Shea trees and mango, which forms an important part of the people’s livelihood. The major food crops grown in the area include maize, rice, millet, sorghum, cassava, yam, groundnut, cowpea, and soybean (Wiredu et al., 2010).

In 2004, the current Karaga district was carved out of the then Gushiegu-Karaga district. It is one of the 261 Metropolitan, Municipal, and District Assemblies (MMDAs) that makeup Ghana's Northern region. The district falls in the northeastern part of the region, roughly between latitude $09^{0}30$ N and $10^{0}30$ N and between longitude 0^{0}W and 45^{0}W. The district has an elevation above sea level averaging about 228.57m (masl) and a land mass of about 2898 km^2, equivalent to about 289,800ha (MoFA, 2017). It is bounded to the north by the East and West Mamprusi, to the west by the Savelugu Municipal, and to the east by the Gushiegu Municipality. The districts' population currently stands at 114,225, with 55,677 males and 58,548 females. It has about 19,535 households and an average household size of 5.8 (GSS, 2021). The district is home to many tribes such as Mamprusis, Konkombas, Frafras, Akans, Ewes, and Ga's, but the most predominant ethnic group throughout the various villages is Dagombas.

Similarly, the Kumbungu district was also carved from the old Tolon-Kumbungu district, and its constituted as part of the new districts and Municipalities created in the year 2012 with L.I 2062. The capital of the district is located in Kumbungu. The district shares boundaries to the north with Mamprugu Moagduri, Tolon district, and north Gonja district to the west, Sagnarigu Municipal to the south, and Savelugu Municipal to the east. The district falls between latitude 10^0N and 20^0N and longitude 10^0W and 50^0W. Its elevation above sea level averaged 163.43m (masl), with a land mass of about 1,547 sq. km, which is equivalent to 174,100 ha (GSS, 2021). The estimated population of the district is 110,586, with 55291 males and 55295 females, with a total of 17,766 households and an average household size of 6.2 (GSS, 2021). The population density of the district is approximately 71.5 inhabitants/km^2, which is lower than the regional figure of 87.1/km^2.

The data for this study was collected from farmers in the Kumbungu and Karaga districts of the northern region, which are one of the operational areas of Opportunity International's input credit scheme. The Opportunity International (OISL) is a leading savings and loans institution in Ghana and is at the forefront of delivering financial services to help transform the lives of poor people. OISL was licensed by the Bank of Ghana in 2004 and has built a national branch network of 43 outlets with two-thirds of the branches in rural locations. The

Opportunity International operates an agricultural finance model which seeks to support economically active farmers in agriculture and its related businesses including farming, irrigation, agro-marketing and processing, agro equipment etc. The input credit scheme provides farm inputs to especially smallholder farmers in various areas of crop and animal production. The scheme provides to farmers inputs including fertilizer, agrochemicals, protective clothing and spraying machines as well as other weedicides, pesticides and fungicides which are mainly in liquid form. Some protective clothing provided include gloves, overalls, jackets, boots, nose masks and goggles. In addition to financing, Opportunity continues to provide training to the farmers in Good Agricultural Practices, Digital Financial Services and other Financial Literacy programs. The main crops being supported include Cocoa, Cashew, Root & Tuber, Rice, Vegetables, Maize, Oil Palm, Plantain, Pineapple, Poultry, Piggery, Livestock and Soy Bean in ten out of the sixteen regions in Ghana.

3.3 Study design

The cross-sectional survey design was employed in this study. The households were surveyed to obtain primary data about the socio-demographic characteristics of farmers and their network members, and other socioeconomic data of households such as their level of access to credit, incomes, livestock assets, and food consumption. The information was then examined to ascertain how social networks affect farmers' access to credit as well as how peer access to credit affects household income and food security.

3.4 Sampling and sample size

The multistage sampling procedure was used to first, purposively select two districts in the Northern region, based on the severity of credit limitations faced by farmers[1] and the ongoing

[1] This was based on studies by Wiredu et al, (2010). According to the survey, farmers in the Karaga and Kumbungu districts had much less access to finance than farmers in other districts in the northern region.

input credit program in the study area[2]. In the second and third stages, 10 villages were randomly sampled across the two districts, and 40 households were selected randomly in each village. The results of a study by Wiredu et al. (2010) to analyze the characteristics of maize farmers in the Northern region showed that, in comparison to other districts, farmers in the study area had a severe lack of access to financing. This could severely impact the incomes and food security of the affected farmers (Wiredu et al., 2010)[3]. The population (N) of the study is constituted by farm households in the Karaga and Kumbungu districts of the Northern region. It was therefore necessary to select a representative sample because of the cost and difficulty of surveying the entire study population (Anderson et al., 2011).

The sample size was determined using a statistical procedure that allows the results of the sampled households to be generalized for the entire population. Based on Cochran (1977) and Anderson et al. (2011), the sample size for this study was determined using the desired margin of error formula as follows:

$$e(\sigma_\rho) = Z\alpha_{/2}\sqrt{\frac{\rho(1-\rho)}{n}} \qquad [3]$$

Where e denotes desired margin of error (0.05), n is the sample size, ρ is the population proportion (0.526) (GSS, 2021), and $Z\alpha_{/2}$ is the Z-critical value (1.96) which is determined from the confidence level (95%). From equation[3], the sample size formula is deduced as follows;

$$n = \frac{\left(Z\alpha_{/2}\right)^2 \rho(1-\rho)}{e^2} \qquad [4]$$

[2] This came to light during our interaction with MoFA officers in the two districts.
[3] Wiredu et al., (2010), studied the characterization of maize producing households in Northern Ghana and noted that farmers in the Tolon/Kumbungu and Karaga districts respectively lack access to credit which affects their agricultural productivity.

Using a 5% desired margin of error, which is recommended for social science studies, particularly where the primary variable of interest is categorical (Bartlett et al., 2001). According to the Ghana Statistical Service (2021), the proportion of rural populations in the Northern region (ρ) is 52.6%. Therefore, at a 95% confidence level, which corresponds to a z-critical value ($Z\alpha/_2$) of 1.96, the estimated sample size for the study was 400 heads of households.

Table 3.1: Distribution of sampling units by districts and villages

No	Districts	Villages	Sample size
1.	Kumbungu	Zangbalung	40
		Zugu	40
		Tibung	40
		Kukuo	40
		Dulzugu	40
			200
2.	Karaga	Tong	40
		Shebu	40
		Kunang	40
		Nyong	40
		Monkula	40
			200
Total respondents			**400**

Source: Author's Computation, (2022). Note: Non proportionate sampling was used in this study based on Conley and Udry (2010). This was because, proportional sampling could have resulted in some villages having samples lower than the 15 household threshold required for the network data. Note that the 15 households are repeatedly sampled from the village sample and matched to each household in order to elicit the network data.

3.4.1 Sampling of households

The random sampling technique was used in selecting households for this study. The data for this study was collected from a survey of 400 farm households across the two (2) districts, between June and July 2022. The households were sampled, and the household head or their representatives were interviewed. Primary data was collected on the socio-demographic and socioeconomic characteristics of farmers and their network members including other farm-level information.

3.4.2 Social network data

The farmers' social network data was gathered using a technique known as random matching within the sample (Conley & Udry, 2010). This entails randomly selecting respondents from the village sample and matching them to each household in the sample. The recognized individuals from the farmer's list of contacts comprise their network members. Conley & Udry (2010) collected information on the household and their matched contacts to build various social links. Credit, land, labor and information links were found among the farmers. In this current study, the focus is on family, friends, and geographical neighbors as the social network links of the responding households. According to Fafchamps and Gubert (2007), this method has the advantage of including both household members and their peers in any randomly picked link.

In this study, 15 farmers were randomly selected from the village sample of 40 households and assigned to each household as their potential network members. Detailed information was then collected from the responding household conditioned on him/her identifying the assigned contact as their network member. Data was collected on the nature of social relationships they share i.e., family, friends, or neighbors (i.e., farm or residential neighbors). Information relating to material exchanges, if they exist and the nature of such exchanges among others were also collected. The social network of the farmer, therefore, consisted of households within the village sample that the farmer is socially connected to base on the dimensions mentioned above (i.e., ties of family, friendship, and neighborhood).

The social network variable was then constructed as a union of all these social connections based on the social and geographic indicators, i.e., the social and locational relationships that the responding farmer (i) shares with a known contact (j) (Conley & Udry, 2010). The social network variable was equals 1 if a farmer has at least one of the links, and 0 if otherwise. At the village level, a 40 x 40 social matrix was constructed based on the social network data for each village with undirected entries equal to one (1) if the respondent had any social relationships with the assigned contact (to define the link) and zero (0) otherwise. The symbol A is used to denote the symmetric matrix of the collection of 40 households randomly picked in each of the surveyed villages (Butts, 2008). The binary social weight matrix was formed using the farmer's social and geographic contacts, with entries, w_{ij}, equal to one if farmer i had any social link with the assigned contact j, and zero otherwise. The resultant spatial weight matrix A, is a 400×400 block-diagonal matrix, which is binary representing the social network of the farmer along the village networks.

3.5 Data collection

3.5.1 Data collection instruments

The questionnaire was used to collect data for the study. The instrument contained both structured and semi-structured questions. It also included closed and open-ended questions to enable households to provide further detailed information. The study relied mainly on primary data, which included the household's socio-demographic characteristics, network member's information, credit access, and food security among others. The study used these data for the generation and analysis of the results.

3.5.2 Data collection techniques

The face-to-face interview method was used to administer the questionnaires to respondents in a language that they well understood and were comfortable with. The questionnaire was pre-tested in Golinga, a community outside the study area before the actual data collection. The piloting was useful because it helped in improving the instrument by providing more clarity in the wording of questions, aligning local terms to connect key concepts, rephrasing questions deemed sensitive, determining of appropriate period per interview, and providing additional instructions where necessary.

3.6 Data Analysis

3.6.1 Assessing the effect of social networks on household credit access

The impact of social networks on the farmers' access to credit was evaluated using the spatial Durbin model (SDM). The credit access dependent variable is quantified as a binary outcome variable (0, 1), where 1 denotes families that have access to credit and 0 does not. The model calculated the influence of farmers' socioeconomic traits, average network members' access to credit, and those members' traits on the farmers' credit decisions. According to the theoretical underpinnings of this study, farmers' credit decisions should be impacted by their socioeconomic traits, as well as the typical credit behavior of their peers and other exogenous variables. The farmer's credit decisions were outlined in a spatial autoregressive framework to accomplish this. Due to the geographical interaction of the dependent and independent factors, the geographical Durbin Model (SDM), an expanded version of the Spatial Autoregressive (SAR) model, has been utilized. According to Anselin (1988), the SDM simulates spatial lags on both the dependent and independent variables. The employment of a spatial weighting matrix (A) on both the dependent and independent variables allows for the accommodation of spatial autocorrelation in both the dependent and independent variables (Bekti et al., 2013).

The objective of this study's empirical analysis is to determine how social networks affect smallholder farmers' choices regarding credit. Therefore, a spatial autoregressive framework that is founded on the idea of social imitation through network interactions is used to specify the farmer's credit decisions (Bandiera & Rasul 2006). Based on the spatial model, the farmer's credit decisions are expected to be influenced by their own characteristics (X_i), the peer outcomes (AC_i), and the peers exogenous characteristics (AX_i). The model estimates three levels of network effects: endogenous effects, exogenous effects, and correlated effects (Anselin, 1988). This method improves knowledge of whether household credit decisions are influenced by endogenous and exogenous causes or solely by correlated unobserved factors. Manski (2000) stated that disaggregating endogenous and exogenous impacts from correlated effects could have significant policy ramifications.

According to Anselin (1988), the SAR model presupposes that the autoregressive process solely affects the dependent variable. However, spatial dependencies affect both the independent and dependent variables as well. By including the spatial lag on the independent variables, the spatial Durbin model thereby addresses this flaw. Consequently, the spatial Durbin model is described as follows:

$$C = \rho AC + \beta_0 + X\beta_1 + AX\beta_2 + \varepsilon \qquad [5]$$

Where;

$$\varepsilon = \lambda A\varepsilon + u \qquad [6]$$

$$\varepsilon \sim N(0, \sigma^2 I)$$

For this study, the general form of the SDM model is rewritten as;

$$C_{ig} = \rho A_g C_{ig} + \beta_0 + X_{i,g}\beta_1 + A_g X_{ig}\beta_2 + \gamma\theta_i + \varepsilon_i \qquad [8]$$

Where $C_{i,g}$ is a binary that denotes the credit access of household i in the network g; the term $A_g C_{i,g}$ represents the credit access of network members, with its associate parameter estimate ρ, which captures the endogenous effects; $A_g X_{i,g}$ is a term that represents the exogenous characteristics of network members; θ_i is the district dummy (1 if a village is located in Karaga, otherwise 0); ε_i is the error term; the β'^s (β_1, β_2) are unknown parameters to be estimated, which capture own and contextual effects in credit access. The own effects are the effect of a farmer's socioeconomic variables on credit access, whiles contextual effects measure the effect of exogenous variables of network members on the credit access of the farmer. The terms β_0 and γ represents the intercept and district fixed effects respectively.

According to Manski (1993), endogeneity—which may be caused by link formation or correlation among the explanatory variables (selection problem)—is a fundamental topic in social network research. Research has revealed that estimations may be inconsistent and skewed if network endogeneity is not taken into account. For instance, Johny et al. (2017) examined the effectiveness of the generalized methods of moments (GMM/IV) and the ordinary least squares (OLS) in assessing network effects. The study's findings revealed that when compared to the GMM/IV, the OLS estimations were lower and more biased downward. This can be the result of the network effects causing reverse causality in the OLS estimation (Johny et al., 2017). This makes it appropriate for the current investigation to use the spatial Durbin model to assess social network effects on credit access.

3.6.3 Assessing the impact of peer credit on household income and food security

Based on the continuous nature of the dependent variable, the ESR model was chosen to examine how social networks affect household food security. The food consumption score (FCS), which is calculated using eight different food groups with standardized weights of 2, 3, 1, 1, 4, and 0.5 for each, was employed. These groups are staples, legumes, vegetables, fruit, meat, dairy, and beverage. The standard weight is multiplied by the reported value (the number of days a particular food group was consumed over the previous week), and the weighted scores for each household are then summed to get the FCS. Because it incorporates more details on a household's typical diet and consumption frequency, the FCS is favored over the household dietary diversity score (HDDS). The credit variable used in this study was measured in terms of smallholder access to institutional input credit (Iddrisu et al., 2018). Therefore, credit access was equals 1 if the farmer had access to institutional input credit, otherwise 0.

The impact of peer credit on the income and food security of smallholder farmers has been estimated using the endogenous switching regression framework in two stages: the first stage concerned the farmer's choice to access the input credit (selection equation), and the second stage involved the estimation of two regimes, with the outcomes (income and food security) for credit users and nonusers (equations 0 and 1). With the unobserved (latent) utility generated from credit expressed through observed variables, the choice of smallholder farmers to access credit was also modeled under a random utility framework (Khonje et al., 2015).

The two-step least square method, which estimates one equation at a time, and the maximum likelihood estimation methodology are the two fundamental methods used to estimate the endogenous switching regression model (ESR) (Lokshin & Sajaia, 2004). However, it is noted that the two-step least squares method is ineffective since it results in heteroskedastic residuals. Abdulai & Huffman (2014) claim that more adjustments will be necessary for this method to provide consistent standard errors. This flaw is addressed by the full information maximum likelihood estimation method, which is commonly cited in the literature. Due to this, the study employed the full information maximum likelihood (FIML) method to determine how peer credit affects smallholder farmers' income and food security.

The selection equation of the ESR model is specified as follows;

$$C_i^* = \propto Z_i + u_i \qquad [9]$$

$$C_i = 1 \text{ if } C_i^* > 0 \text{ and } C_i = 0 \text{ if } C_i^* \leq 0$$

Where C_i is a binary variable that equals 1 if household i has access to credit and 0 otherwise; $\propto$ is the vector of parameters to be estimated and Z_i is a vector of household i's socioeconomic and other farm-level characteristics that affect the households' credit decisions; u_i is the random error term assumed to be normally distributed and C_i^* is the selection function. Since the utility that derives the credit decisions of households cannot be fully observed (latent), the credit decision of the household is only observed if the latent variable is larger than zero i.e., $(C^* > 0)$. Access to credit is expected to affect the income and food security of households. Assuming that the outcome variables are expressed as a linear function of exogenous variables X_i and an endogenous selection C_i such that;

$$Y_i = \beta X_i + \delta C_i + \epsilon_i \qquad [10]$$

Where, Y_i is the outcome variable (income and food security); C_i represents the credit access of households; β and δ are parameters to be estimated; and ϵ_i is the stochastic error term. Because the credit access variable may be endogenous due to unobserved factors and sample selection bias, estimating equation [10] with the ordinary least squares (OLS) might produce bias and inconsistent estimates. Moreover, the propensity score matching (PSM) which is also commonly used may be inappropriate because the method fails to account for unobserved confounding factors in the selection. The study, therefore, employs the endogenous switching regression model to produce unbias and consistent estimates by addressing both observed and unobserved factors (Lokshin & Sajaia, 2004). With the ESR, the outcomes are modeled in two separate regimes to represent the outcomes of credit-users and non-credit users.

$$\text{Regime 0:} \quad Y_{0i} = \beta_0 X_i + \varepsilon_{0i} \quad \text{if} \quad C_i = 0 \qquad [11]$$

$$\text{Regime 1:} \quad Y_{1i} = \beta_1 X_i + \varepsilon_{1i} \quad \text{if} \quad C_i = 1 \qquad [12]$$

Where Y_{1i} and Y_{0i} represent the outcomes (incomes and food security), which are influenced by a set of independent variables (X_i); and the vector of parameters to be estimated are β_1, and β_0, which determines the magnitude and direction of the relationship between these independent variables and the outcomes; ε_{0i} and ε_{1i} represents the random error terms associated with the outcomes. Under this framework, the error terms of equations (9), (11), and (12) that is u_i, ε_{0i}, and ε_{1i} respectively are assumed to have a trivariate normal distribution, with a mean vector zero and a covariance matrix (Lee et al., 1982).

$$Cov(u, \varepsilon_1, \varepsilon_0) = \begin{bmatrix} \sigma_u^2 & \sigma_{\varepsilon_1 u} & \sigma_{\varepsilon_0 u} \\ \sigma_{\varepsilon_1 u} & \sigma_{\varepsilon_1}^2 & . \\ \sigma_{\varepsilon_0 u} & . & \sigma_{\varepsilon_0}^2 \end{bmatrix} \qquad [13]$$

Whilst, σ_u^2 is the variance of the error term in the selection equation (9); $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_0}^2$ represents the variances of the error terms in equations (11) and (12); $\sigma_{\varepsilon_1 u}$ and $\sigma_{\varepsilon_0 u}$ are the covariances of u, ε_1, and ε_0. According to Maddala (1983), because the outcome equations are not simultaneously observed, the covariance between the error terms ε_1 and ε_0 cannot be determined. Also, the mean values of ε_1 and ε_0 conditional on the selection equation is non-zero, due to the correlation between the error term of the selection equation and that of the error terms of the outcome equations in (11) and (12) (Abdulai & Huffman, 2014). Hence the expected values of the truncated error terms $E(\varepsilon_1|C = 1)$ and $E(\varepsilon_0|C = 0)$ are given as;

$$E(\varepsilon_{1i}|C = 1) = E(\varepsilon_1|u_i > -Z_i\alpha)$$

$$= \sigma_{1u_i} \frac{(\emptyset(Z_i\alpha))}{\Phi(Z_i\alpha)} \equiv \sigma_{1u_i} \lambda_{1i} \qquad [14]$$

and,

$$E(\varepsilon_{0i}|C = 0) = E(\varepsilon_0|u_i \le -Z_i\alpha)$$

$$= \sigma_{0u_i} \frac{(\emptyset(Z_i\alpha))}{(1-\Phi(Z_i\alpha)} \equiv \sigma_{0u_i} \lambda_{0i} \qquad [15]$$

The probability density function and the cumulative density function are denoted by $\emptyset(.)$ and $\Phi(.)$ respectively; λ_{1i} and λ_{0i} are the inverse Mills Ratios (IMR) generated from the selection equation with $\lambda_{1i} = \frac{(\emptyset(Z_i\alpha))}{\Phi(Z_i\alpha)}$ and $\lambda_{0i} = \frac{(\emptyset(Z_i\alpha))}{(1-\Phi(Z_i\alpha)}$, which are then included in the outcome equations (11) and (12) to correct for selection biases resulting from unobserved factors. Then equations (11) and (12) become;

$$Y_{0i} = \beta_0 X_i + \sigma_{\varepsilon 0u} \lambda_0 + \delta_{0i} \quad \text{if} \quad C_i = 0 \qquad [16]$$

$$Y_{1i} = \beta_1 X_i + \sigma_{\varepsilon 1u}\, \lambda_1 + \delta_{1i} \quad \text{if} \quad C_i = 1 \qquad [17]$$

Where, δ_{0i} and δ_{1i} are random errors with conditional zero means and constant variance. To get consistent estimates, this study used the full information maximum likelihood (FIML) technique (Lokshin & Sajaia, 2004). For proper identification under the ESR model, at least one variable (instrument) is supposed to be in the selection (Z), but does not appear in the outcome (X). This variable is needed as an exclusion constraint to completely estimate the model (Lokshin & Sajaia, 2004). However, for the instrument to be valid, it must have a considerable impact on the farmer's decision to seek finance, but not directly on household earnings and food consumption. The instrument is therefore supposed to indirectly affect the income and food security of households only through the farmer's credit access. The potential instrument used in this study is the distance of households in kilometers (km) to the nearest financial institution. This is expected to significantly influence households' credit decisions, but could only affect incomes and food security if farmers access credit.

Based on the assumptions regarding the error terms in (13) above, the derived log-likelihood function is specified as:

$$lnL = \sum_{i=1}^{N} \left\{ \left\{ C_i \left[ln\emptyset\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - ln\sigma_1 + ln\Phi(\theta_{1i}) \right] + (1 - C_i) \left[ln\emptyset\left(\frac{\varepsilon_{0i}}{\sigma_0}\right) - ln\sigma_0 + \ln\big(1 - \Phi(\theta_{0i})\big) \right] \right\} \right.$$

[18]

Where $\theta_{ji} = \frac{(Z_i\alpha + (\rho_j \varepsilon_{ji})\sigma_j)}{\sqrt{1-\rho_j^2}}$, with j= (0, 1); $\rho_1 = \left(\frac{\sigma_{1u}^2}{\sigma_u}\sigma_1\right)$ and $\rho_0 = \left(\frac{\sigma_{0u}^2}{\sigma_u}\sigma_0\right)$ being the correlation coefficients between the selection equation's error term (u_i) and the outcome equations' error terms $(\varepsilon_{1i}$ and $(\varepsilon_{0i}$, respectively. If one of the correlation coefficients (ρ_0) or (ρ_1) is statistically significant, it indicates the presence of selection bias due to unobserved factors

(Abdulai & Huffman, 2014), which will necessitate the use of an endogenous switching regression model to get consistent estimates (Maddala, 1983). If ($\rho_1 > 0$), this indicates a negative selection bias, implying that smallholders with lower-than-average outcomes are more likely to get financing, whereas ($\rho_0 > 0$), indicates a positive selection bias. Farmers will choose credit depending on the comparative advantage of accessing credit if (ρ_0) and (ρ_1) have opposite signs.

One may also predict the effect of the treatment on the treated (ATT) and the untreated (ATU) using the ESR model's coefficients. These estimates are created by calculating the predicted values of the dependent and independent variables for users and non-users in real-world and hypothetical scenarios. The seen and unobserved counterfactual results can be calculated as;

Credit users in the sample who were observed:

$$E(Y_{1i}|\, C_i = 1, X_i) = \beta_1 X_i + \sigma_{1u_i}\lambda_{1i} \qquad [19]$$

Non-credit users in the sample who were observed:

$$E(Y_{0i}|\, C_i = 0, X_i) = \beta_0 X_i + \sigma_{0u_i}\lambda_{0i} \qquad [20]$$

Users if they had decided not to use credit (counterfactual)

$$E(Y_{0i}|\, C_i = 1, X_i) = \beta_0 X_i + \sigma_{0u_i}\lambda_{1i} \qquad [21]$$

Non-users if they had decided to use credit (counterfactual)

$$E(Y_{1i}|\, C_i = 0, X_i) = \beta_1 X_i + \sigma_{1u_i}\lambda_{0i} \qquad [22]$$

Equations (19) and (20) compute the observed outcomes of users and nonusers, respectively, while equations (21) and (22) compute the counterfactuals' expected outcomes. The difference between the expected values of the outcome equations (19) and (21) is the average treatment effect on the treated (ATT). It is the gap between the expected value of the outcome for credit users and their counterfactuals (users who would not have utilized credit). The ATU is the difference between the results of equations (20) and (22), and the estimate is the difference between the expected value of the outcome for non-users and their counterfactual (that is, non-users if they had used credit).

$$ATT = E(Y_{1i}|C_i = 1) - E(Y_{0i}|C_i = 1) = (\beta_1 - \beta_0)X_i + \lambda_{1i}(\sigma_{1u_i} - \sigma_{0u_i})$$

[23]

$$ATU = E(Y_{1i}|C_i = 0) - E(Y_{0i}|C_i = 0) = (\beta_1 - \beta_0)X_i + \lambda_{0i}(\sigma_{1u_i} - \sigma_{0u_i})$$

[24]

3.7 Selectivity bias and peer credit endogeneity

The empirical specification of both the first-stage and second-stage equations of the ESR model (estimation of the selection and outcome equations) contains variables that are potentially endogenous and needs to be controlled for. For instance, the selection variable itself (credit access) and the peer credit variable in the outcome equation appear endogenous. This is because farmers with access to credit may be those with higher incomes and yield capacities, which may provide them the opportunity to acquire properties that could be used as collateral for assessing credit. Also, peer credit could be endogenous as a result of correlated unobservable factors during the network formation (Brock & Durlauf, 2002) or due to missing network information and measurement errors (Chandrasekhar & Lewis, 2016). It is also worth noting that farmers who are highly food secure may also likely be more socially connected and that could enable them to gain access to credit information through their social contacts.

To address these endogeneity concerns in the study, the two-stage control function approach and the residual inclusion technique were used as suggested by Wooldridge (2015). A first-stage peer credit model was estimated separately utilizing the same variables that explain own credit plus an instrument, in this case, the peers' household distance to credit. However, the distance variable was removed from the second stage as an exclusion limitation for estimating household income and food consumption. Table 1A in the appendix section contains the estimation of the peer credit model.

The residual of the first-stage peer credit model was plugged into the income and food security equations in the second stage to account for the possible endogeneity of peer credit (Wooldridge, 2015). By averaging out the measurement errors, this technique ensures an ideal test of the exogeneity of peer credit and enables an efficient estimate of the structural model (Wooldridge, 2015). In the selection model, household distance to the nearest source of credit was also used to instrument for credit. The purpose of using this instrument is to control for the potential endogeneity of the farmers' credit access on the outcome. This variable was therefore used because it is expected to significantly affect households' credit access but is highly unlikely to have any effect on the income and food security of households. This is because households may be reluctant in accessing credit from lenders who are located far away from them. According to Owusu (2017), the cost of transport may deter poor households from accessing credit. In addition, there is no evidence of distance to credit having any significant effect on income and food security among households. See the estimates in Tables 4.5 and 4.6.

3.8 Definition and measurement of variables

The table below depicts the definition of household and community-level variables that the researcher measured in addition to the a priori expectations.

Table 3.2 Definitions of variables

Variables	Definition and Measurement	A priori expectations
Part A: ***Socio-demographic Characteristics***		
HHAge	Age of household head (completed years)	+
HHSex	Sex of household head (1 if male, 0 otherwise)	+
HHEducation	Number of years of completed schooling	+
FarmExperience	Number of years spent in farming	+
HHSize	Household size (number of persons)	+
HLandOwnership	The total land owned by household (in acres)	+
HHDistance	Distance of household to farm (km)	+
HHIncome	Total household income (annual)	+
HHDAssets	The total value of household assets (in GHS)	+
HHLivestock	The total number of household livestock (TLU)	+
HHCredit	Access to institutional input credit	
HHMobNetwrk	Mobile network access of households	+/-
FBO_memb	Membership of an FBO	+
PeerCredit	Share of peers with access to credit (weighted average)	+
Part B: ***Community variables***		
Dist_DisCapital	Distance of the village to the district capital (km)	+/-
Acc_Tarred_road	Access to a tarred road	+
DistFinInst	Household distance to the source of credit (km)	-
Dist_Res	A dummy indicating 1 if the household resides in the Karaga district; 0 otherwise	+/-

Source: Author’s construct (2022).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

The study's findings regarding the impact of social networks on credit access, peer credit effects on smallholder income and food consumption, and the descriptive statistics on the demographic and socioeconomic characteristics of households are all presented in this chapter. These findings are discussed in the context of existing theories and other empirical research studies on social networks, credit access, and household welfare.

4.2 Descriptive statistics of households' socio-economic data

The socio-demographic and socioeconomic data collected for this study included households' domestic and farm-level information. Table 4.1 shows the descriptive statistics of farmers' and that of their network members (peers). Male-headed households dominate the study area (86%), and the average age of farmers in the sample was 40 years. The average household size in the sample was 7 persons in a household. This was found to be slightly lower than the regional average of eight people per household (GSS, 2021). Furthermore, approximately 77% of respondents are locals, with approximately 33% being migrant farmers. In addition, 39% of farmers reported experiencing shocks during the previous farming season, and 58% of families have good telecommunication networks near their homes. Furthermore, the average education of farmers was found to be very low, with an average of 2.29 years, but a high level of farming experience (22.80 years). These factors could have a considerable impact on farmers' credit decisions. When matched with those having little or no education, households with highly educated farmers may be more likely to access credit information, and could have more access to credit. From the data, 33% of farmers, and 37% of their peers have had access to credit during the period under review i.e. the 2021 planting season.

Table 4.1 Descriptive statistics of the socioeconomic information of farmers and their peers

Variable names	Farmer (*X*) Characteristics				Peers (A*X*) Characteristics			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Explanatory covariates								
HHAge	40.87	11.22	25	77	40.60	5.86	26	59
HHSex	0.86	0.34	0	1	0.85	0.22	0	1
HHEducation	2.29	3.82	0	15	2.41	6.01	0	8.2
Off-farm trade	0.23	0.42	0	1	0.24	0.48	0	1
Farm experience	22.80	10.88	0	57	22.79	5.04	10	40.7
Residential status	0.77	0.42	0	1	0.79	0.29	0	1
HHSize	7.04	2.65	3	22	7.02	1.59	4.7	13.3
HHAssociation	0.45	0.50	0	1	0.44	0.22	0	1
HDur_Asset	8.60	0.53	2084	90476	8.58	0.58	2843.20	16064.95
HHLivestock (TLU)	1.80	1.26	0	75	1.76	1.15	0	26
HLandOwnership	5.66	2.63	0	27	5.68	3.21	1.5	13.7
Farm size	5.06	1.88	2	18	5.70	1.53	1.5	9.7
Farming shocks	0.39	0.48	0	1	0.47	0.26	0	1
Health status	1.74	0.67	1	3	1.75	0.35	1	3
Dist_Res	0.5	0.50	0	1	0.49	0.50	0	1
HHMobNetwk	0.58	0.49	0	1	0.85	0.21	0	1
Dependent variables								
HHCredit	0.33	0.47	0	1	0.37	0.33	0	1
HIncome	7.90	0.69	500	20180				
Household food security	35.33	7.63	18	55				
Instruments								
DistFinInst	3.65	2.81	0.5	8	3.64	2.78	1	6

Source: Field Data (2022)

Notes: S.D. denotes normal standard deviation and the mean reports the averages

The estimated average household income (log) from both farming and non-farming sources was GHC 2,697.28. Again, the average household had durable assets (log) worth a total of GHC 5,431.659. These long-term investments included the cost of farm machinery and other residential items like motorcycles and television sets. The research also shows that just roughly 23% of the farmers who were surveyed are involved in off-farm businesses. These off-farm activities are carried out to supplement the household's resources, which may have an impact on the level of access to credit and food consumption of farmers. Among the sampled housesholds, the average food consumption score (FCS) was 35.8. Further analysis of the data reveals that small-scale farmers predominate in the region, with 83% of them cultivating on plots of land smaller than 5 acres. The average landholding of the farmers in the area was 5.66 acres-; thus this is hardly a substantial departure. This may indicate that farmers in this region find it difficult to get land for agriculture. Furthermore, even though the majority of farmers (77%) and their peers (79%) are residents of the surveyed villages, just 45% of farmers and 44% of their peers have ever belonged to a community-based organization. The implication is that farmers in this area don't participate much in group activities.

4.2.1 Descriptive statistics of social network data

Based on the social and geographical indicators of the surveyed farmers, Table 4.2 details the characteristics of the farmer's network links. These metrics have been applied to ascertain the farmers' pre-existing social ties, as per Banerjee et al. (2013). A farmer on average knows 9.85 out of the 15 people who were assigned to him/her at random. A farmer's network consists of 3.66 locational neighbors, 2.47 friends, and 1.27 family relationships on average. Additionally, the farmer is acquainted with 2.47 residents in the neighborhood and is a member of a community organization with 1.27 others. The social network variable was therefore a combination of the network links of the farmer based on family, friends and locational neighbors. Given the aforementioned definition, each farmer in the sample had an average of 7.40 social contacts among those assigned to them. The social network variable was equals 1 if at least one of these social links were present in the farmers' network, and 0 if otherwise.

Table 4.2 Descriptive statistics about farmers' social network at the village level

Information on farmers' social connectivity	Mean	S. D	Min.	Max.
The contacts known by the farmer	9.85	1.01	8	12
Network indicators (*social*)				
Number of persons who are family or relatives	1.27	1.69	0	8
Number of persons who are friends	2.47	1.70	0	8
Network indicators (*locational*)				
Number of neighbors at the residential/farm level	3.66	1.76	0	10
Number of known persons belonging to the same organization	1.27	1.69	0	8
Number of other person farmer shares weak ties in the community	2.47	1.70	0	8
Network links (social ties)				
Number of social contacts	7.40	2.53	1	13

Notes: SD, Min., and Max., denotes standard deviation, minimum and maximum values respectively. The farmer's social network measured undirected relationships defined either by farmer i or farmer j, or both. This implies that a link could exist if either the farmer or their contact indicates that they share a relationship.

4.3 Social network effects on household credit access

The SDM model estimates provide evidence of both endogenous and exogenous effects, as well as correlated effects on credit access. The endogenous effect estimates quantify the impact of average peer credit behavior on farmers' credit decisions, whereas the exogenous effect coefficients quantify the impact of average peer characteristics on farmers' credit decisions. The correlated effects estimate, on the other hand, depicts the impact of unobserved factors on smallholder farmers' credit decisions. It may also indicate the effect of unseen factors that contribute to network link formation. A district dummy was incorporated in the SDM model to account for district level fixed-effects. This is because villages within a specific district are likely to experience similar environmental circumstances which may however differ across the different districts (Wydick et al., 2011).

Table 4.3 SDM estimates of the effect of social networks on credit access

Variables	Coefficients	S. E	Z	P-value
Endogenous effects				
Average peer credit (ρ)	-0.15484*	0.08844	-1.75	0.080
Own characteristics				
HHAge	0.00799**	0.00386	2.07	0.039
Educ level	-0.00264	0.00387	-0.68	0.496
HHSex	-0.01408	0.04494	-0.31	0.754
Off-farm business	-0.02031	0.03853	-0.53	0.598
HHLandholding	-0.00498	0.00789	-0.63	0.528
Household size	0.00298	0.00468	0.64	0.524
Health status	0.01500	0.01888	0.79	0.427
Residential status	0.07123*	0.03845	1.85	0.064
Farm size	0.01138	0.01101	1.03	0.302
HD Assets	0.06199**	0.02715	2.28	0.022
HLivestock	0.00880	0.11641	0.76	0.446
Farm shocks	-0.00629	0.03050	-0.21	0.836
Farm experience	-0.00729*	0.00393	-1.86	0.064
HMNetwork	-0.12084***	0.04608	-2.62	0.009
FinDistance	-0.09198**	0.04716	-1.95	0.051
District	9.61173	-	-	-
Contextual effects				
AAge	-0.00337***	0.01080	-3.12	0.002
AEduc level	0.01562	0.01233	1.27	0.205
ASex	0.02423	0.10027	0.24	0.809
AOff-farm business	0.08991	0.12402	0.72	0.468
ALandholding	0.03862*	0.02305	1.68	0.094
AHousehold size	0.03743**	0.01935	1.93	0.053
AHealth status	0.08209	0.05581	1.47	0.141
AResidential status	0.09439	0.11391	0.83	0.407
AFarm size	-0.02038	0.02902	-0.70	0.483
AHD Assets	0.20898***	0.08459	2.47	0.013
AHLivestock	-0.02454	0.02970	-0.83	0.409
AFarm shocks	0.13938*	0.08121	1.72	0.086
AFarm experience	0.03264***	0.01096	2.98	0.003
AHMNetwork	0.00378	0.11145	0.03	0.973
AFinDistance	0.10587**	0.04585	2.31	0.021
ADistrict	-9.43745***	0.08262	-114.2	0.000
Correlated effects				
Residual effect	0.14158***	0.012288	11.52	0.000
Constant	-1.76354*	0.954787	-1.85	0.065
Model diagnostics				
Wald statistic	70.2784***			
F-statistic	2.1962***			
Log-likelihood	70.1913			
LR test SDM vs. OLS (Rho=0):	3.0650	P-value > Chi2 (1) 0.080		
LR test (WX's =0):	5.52e+04	P-value > Chi2 (16) 0.000		
No. of observations 400				

Source: Field Data (2022)

Note: Resid1 denotes the coefficient of the random error term indicating correlated effects. Variables with the prefix A denotes network variables.

In the SDM model, the coefficient of the average credit outcomes of peers (ρ), illustrates the spatial effects of networks on credit access. It measures the endogenous effects of networks on smallholder farmers' credit access. At the 10% level, the computed coefficient (-0.1548) is negative and statistically significant. According to the findings, a 1% rise in the share of peers with credit reduces farmers' credit access by 0.15%. The estimate also implies the presence of social reliance in the network, implying that households without credit may rely on their friends for social assistance, reducing their requirement for input credit. This is because farm households who get monetary or other resources from their peers may improve their resource base and increase production. Farmers' credit demands may be reduced as a result, and they may be less likely to seek financing from institutional lenders, particularly if they are risk-averse. The sociocultural practices of the individuals in the study area can also be used to explain this occurrence. Because Muslims constitute the majority of the population, the practice of paying zakat after harvest and on festive occasions may serve as an incentive for poor households to avoid taking out loans. Furthermore, most affluent farmers distribute a portion of their harvest to family members and other well-known people in the community who are not well-off. This finding is consistent with the findings of Alio et al. (2018) and Banerjee et al. (2021), who discovered that households with more network members tend to be less likely to use credit. This finding is however challenged by Wydick et al. (2011) and Okten & Osili (2004), who discovered that social networks have a significantly positive effect on household credit availability and access. They contend that members of a households social network tend to give the required information that improves the households' access to loans. However, Banerjee et al. (2013) discovered that, while households may gain credit information from their peers, they do not significantly influence households' decisions to participate in credit programs.

Furthermore, the study's findings reveal that farmers' socioeconomic factors have a major effect on their borrowing decisions. The estimated coefficients are of varying significance, and the size and direction of the effects vary substantially. Age, residential status, durable assets, farm experience, mobile network access, and the household's distance to credit are all key variables in the model. Whereas age, residential status, and durable assets have a positive impact on credit availability, farmers' years of experience, mobile network access, and the household's distance to credit impacted negatively on credit. At 5%, 10%, and 5%, respectively, the farmer's age, residential status, and durable assets were also found to be significant statistically. Also, at the level of 10%, 1%, and 5%, the farmer's experience, mobile network access, and distance to the nearest credit source were respectively found to be significant statistically.

The model results for the contextual effects of networks demonstrate that the exogenous qualities of network members have a considerable effect on the farmer's credit decisions. Peer age, peer landholding, peer household size, peer health status, peer durable assets, peer farm shocks, peer farm experience, peer distance to nearest credit source, and peer district are the exogenous peer characteristics that are statistically significant in explaining the farmer's credit access. While peer landholding, peer household size, peer health status, peer durable assets, peer farm shocks, peer farm experience, and peer distance to the nearest credit source impact positively on credit decisions of farmers, peer age, and peer district have a negative impact. These findings indicate that the exogenous qualities of peers in the network are connected to farmers' access to financing. However, the amount and direction of the association may differ. Wydick et al. (2011) discovered that peers' average education and income are connected to households' credit access in the network. They discovered that when the average education of network members increases by an additional year, it leads to increases in the likelihood of credit availability among households.

At the 1% level, the estimate of associated effects (0.14) was found to be significant statistically. This suggests that unseen or linked factors account for approximately 14% of the variation in farmer credit access. These associated characteristics may be the result of commonalities in farmers' environmental situations, which influence their lending decisions (Manski, 2000). According to Wydick et al. (2011), correlated impacts may represent a terrible weather scenario faced by all farmers in an area, forcing them to seek credit assistance from the government or a credit agency.

4.3.1 Marginal effect estimates of the SDM model

Table 4.4 shows the SDM model's marginal effect estimates. The farmers' socioeconomic characteristics tend to influence the household lending decisions as well as those of their peers (both directly and indirectly). These effects are added together to get the aggregate effect of each variable on the farmers' credit access. The direct own effects demonstrate the effect of a farmer's characteirstics on own credit access, whilst the indirect effects show the effect of the farmer's characteristics on the credit access of their peers. Similarly, the exogenous effects are also divided into direct and indirect effects, indicating the effect of peer exogenous factors on peer credit access and the effect of the peers characteristics on the farmers credit access, respectively. Specifically, the direct exogenous effects illustrate the effect of the peer variables on the credit behavior of peers, and the indirect exogenous effects show the effect of peer variables on the credit decisions of farmers.

According to the marginal effect estimates in Table 4.4, the total observed effect of age on credit access was positive and statistically significant at the level of 5%, with an estimated coefficient of 0.0080. All things being equal, this suggests that when the age of a farmer increases by one year, their likelihood of accessing credit increases by 0.8%. This suggests that older farmers tend to have greater access to credit than younger farmers. This observation is consistent with the findings of Biyase & Fisher (2017). Owusu (2017) discovered, however, that older cassava growers in Ghana have a lower probability of access to credit compared to younger farmers.

At the 10% level, the observed aggregate effect of smallholder farmers' residential status on credit access was positive and statistically significant. The computed coefficient (0.0712) suggests that being a native farmer raises the probability of credit access by 7% when compared to migrant farmers. This implies that native farmers tend to have a higher chance of obtaining credit than non-native farmers, all things being equal. This may be linked to native farmers' social reputation, as well as the likelihood of owning land resources in the community, as opposed to migrant farmers, who may be transiting and are unlikely to hold any landed property that may guarantee credit.

Furthermore, the value of a household's durable assets tends to substantially influence their decision to access credit. The computed positive coefficient of 0.0620 was significant statistically at the 5% level. This suggests that all other factors held constant, an increase in the number of durable assets owned by the household raises their probability of credit access by 6.2%. This may be related to the fact that asset ownership demonstrates a household's creditworthiness and payback capacity, which may influence lenders' decisions to advance loans to them. This result is largely consistent with the findings of Ullah et al. (2020). However, this finding contradicts the findings of Sekyi (2017) and Agboklou & Ozkan (2022), who discovered that the type of asset owned by a household affects the likelihood of credit access.

The number of years a farmer practiced agriculture was used to calculate his or her experience. At the statistically significant level of 10%, the variable's calculated marginal effect estimate was -0.0073. All things being equal, an additional year of experience gained by the farmer reduces their likelihood of obtaining credit by 0.7%. This implies that highly experienced farmers are more likely to feel confident in their capacity to manage their farms without the need for additional inputs. Furthermore, they may have the financial capacity to acquire their inputs and do not want to be taken advantage of by input creditors, who frequently charge outrageous interest due to the inherent risk. This observation sits well with the findings of Ullah et al. (2020). This observed effect, on the other hand, contradicts the findings of Chandio et al. (2021) and Agboklou & Ozkan (2022), who discovered that more experienced farmers tend to have a much higher chance of obtaining credit as a result of their efficiency in resource use and ability to increase productivity with additional resources.

Furthermore, household mobile network availability has a major impact on household credit decisions. This variable's measured total marginal effect was -0.1209, which is negative and statistically significant at the 1% level. This implies that households with greater access to mobile network coverage are 12% less likely to take advantage of the input credit. Furthermore, the distance to the nearest financial institution influences credit access among smallholder farmers. The overall marginal effect estimate (-0.0920), which is significantly negative at a level of 5%, implies that a kilometer increase in the farm household's distance from the nearest financial institution reduces the farmer's chance of access to credit by 9%. This suggests that households located further from the nearest financial institution are 9% less likely to obtain the input credit. Owusu (2017) explains that the cost of transportation which increases with distance is likely to discourage poor households from accessing credit. This result is also consistent with Adeoye and Ugalahi (2017), and Chandio et al. (2021).

Table 4.4 SDM Marginal effect estimates

Variables	Credit access		
	Direct effect (1)	Indirect effect (2)	Total effect (3)
Own characteristics			
Age	0.0092	-0.0012	0.0080**
Educational level	-0.0030	0.0004	-0.0026
Sex	-0.0163	0.0022	-0.0141
Off-farm business	-0.0235	0.0031	-0.0203
Landholding	-0.0058	0.0008	-0.0050
Household size	0.0034	-0.0005	0.0030
Health status	0.0173	-0.0023	0.0150
Residential status	0.0823	-0.0110	0.0712*
Farm size	0.0131	-0.0018	0.0114
HD Assets	0.0716	-0.0096	0.0620**
HLivestock	0.0102	-0.0014	0.0089
Farming shocks	-0.0073	0.0010	-0.0063
Farm experience	-0.0084	0.0011	-0.0073*
HMNetwork	-0.1395	0.0187	-0.1209***
FinDistance	-0.1062	0.0142	-0.0920**
District	11.1000	-1.4859	9.6141
Contextual effects			
AAge	-0.0389	0.0052	-0.0337***
AEducational level	0.0180	-0.0024	0.0156
ASex	0.0280	-0.0037	0.0242
AOff-farm business	0.1038	-0.0139	0.0899
ALandholding	0.0446	-0.0060	0.0386*
AHousehold size	0.0432	-0.0058	0.0374**
AHealth status	0.0948	-0.0127	0.0821
AResidential status	0.1090	-0.0146	0.0944
AFarm size	-0.0235	0.0032	-0.0204
AHD Assets	0.2413	-0.0323	0.2090***
AHLivestock	-0.0283	0.0038	-0.0246
AFarm shocks	0.1610	-0.0215	0.1394*
AFarm experience	0.0377	-0.0050	0.0327***
AHMNetwork	0.0044	-0.0006	0.0038
AFinDistance	0.1223	-0.0164	0.1059**
ADistrict	-10.8987	1.4589	-9.4398***

Source: Field Data (2022). Columns (1), (2), and (3) depict the direct, indirect, and total effects of own and exogenous variables on the credit decisions of smallholder farmers and their peers.

The marginal effect estimates also suggest that various peer characteristics have a considerable influence on smallholder farmers' credit selections. The observed total effect of peer age on farmer credit availability was significantly negative at the level of 1%. Holding all other covariates constant, the computed coefficient (-0.0337) demonstrates that a rise in the average age of peers reduces the chance of the farmer's credit access by 3.4%. Additionally, at a 10% level, the overall impact of peer landholding on smallholder finance availability is favorable and large. According to the computed coefficient, if all other factors remain constant, an increase in peer landholding will enhance the likelihood of the farmers accessing financing by 3.9%. Similarly to this, the size of peers' households impacted significantly how easily farmers can acquire finance. According to the estimated coefficient (0.0374), the probability of access to credit among smallholders will rise by 3.7%, all other factors being equal, if the average household size of their peers increases by one person. The average peer durable asset also exhibits a higher impact on the farmer's credit access. According to the estimate of 0.2090, significant at the 1% level, the likelihood that farmers will be able to access financing will rise by 21% if the value of their peers' durable assets rises.

Additionally, peer farm shocks have an impact on farmers' ability to access loans. According to the calculated coefficient of 0.1394, with a significance level of 10%, smallholders are 14% more likely to receive loans than their peers who encounter shocks in their farming activities. This shows that when farmers' peers are exposed to farm shocks, it may damage their ability to provide social support to their friends and network members, leading them to seek credit services to compensate for the loss of income. Furthermore, at a significance level of 1%, peer farm experience increases farmer finance access. The observed effect of this variable demonstrates that as a farmer's peers obtain an additional year of agricultural experience, the farmer's probability of access to finance increases by 3.3%. Farmers may be inspired to accept the input credit if they have faith in their peers' agricultural knowledge and want to make use of that peer support and advice to boost yields.

Finally, the proximity of the nearest financial institution to the farmer tends to affect the farmer's ability to acquire financing. At the 5% level, the calculated coefficient of 0.1059 is statistically significant. This suggests among other things that, an increase in peers' distance from the closest financial institution reduces the likelihood of the farmer accessing financing by 11%. The peer district also tends to impact highly on households' ability to acquire loans. This variable's observed effect, at the 1% level of significance, is -9.4398. The results suggest that farmers in the Karaga district are 944 percent less likely to receive finance than farmers in the Kumbungu district.

4.4 Peer credit and other determinants of household income

In this current study, the ESR model has been used to examine how peer credit affects smallholder farmers' income. Table 4.5 displays the model predictions. The household distance to the nearest source of credit was employed as an instrument in the selection model to account for credit endogeneity. The parameter estimate for this variable (-0.1130) was significant at the 5% level, indicating that the variable was important in explaining credit but it is not expected to have a direct effect on the farmers' income. In the income model, the residual from the first-stage peer credit model was also integrated into the selection based on the residual inclusion technique to control peer credit endogeneity (Wooldridge, 2015). At the 5% level, the computed coefficient (-3.7963) was statistically significant. Both of the model's coefficients have negative signs, which denotes a downward bias. The likelihood test of independent equations and the correlation coefficient are both significant at a 1% level, indicating the presence of selection and unobserved bias and demonstrating the validity of the chosen ESR model.

Also, at the significance level of 1%, the estimated correlation coefficient between the credit users' outcome and selection equation is positive. This suggests a positive selection effect such that credit users generate more money from utilizing credit than nonusers would have generated if they had not used it. According to the findings, smallholders' access to input credits is strongly linked to increases in their income levels. This is in line with the findings of Iddrisu et al. (2018), who found that smallholder farmers' earnings and output in the Northern region are significantly impacted by their access to input credit.

According to the ESR model estimates, the factors that significantly influence the credit access and incomes of users and nonusers include peer credit, landholding, health status, residential status, durable assets, livestock assets, farm shocks, mobile network access, distance to credit, peer landholding, peer health status, and peer residential status. The findings demonstrate that peer credit has a major impact on nonusers of credit, both in terms of selection and outcome. In the selection equation, the predicted coefficient of peer credit (4.60) is negative and significant at the 1% level. This demonstrates that a 1% increase in the share of peers who have credit decreases the farmers' likelihood of access to credit by 4.6%. One important element explaining away this phenomenon is the sociocultural practices of the residents of the studied location. Giving charity might make it more difficult for disadvantaged households to acquire credit given that Muslims dominate the research location.

Furthermore, the majority of prosperous farmers sometimes distribute a portion of their harvest to recognized less fortunate neighbors and family members. Obaa & Mansur (2016) discovered that social networks significantly contribute to household access to resources like land, labor, and financial support. This is in line with the findings of Alio et al. (2018), who found that households in Uganda with greater network connections to savings and cooperative credit unions had lower credit utilization rates. However, according to Banerjee et al. (2013), peers who have access to credit play a big role in educating households about credit, but they have no significant effect on whether or not those households choose to use credit.

In the model, peer credit has shown a positive effect on non-credit-using households' income. At the 1% level, the predicted coefficient of peer credit (0.9010) was likewise significant. This suggests that all other things being equal, a 1% rise in the share of peers with credit raises the farmers' income by 0.91%, especially among those without credit. It demonstrates that those who utilize credit have the propensity to give more resources to their peers who do not have access to credit than to those who also gain from using credit. As a result, the findings show that peer credit is more significant for households without credit than for those with credit. This could imply that farmers with access are already well-off and have productive resources, and hence are more likely to transfer resources to others without credit. Obaa and Mansur (2016) discovered that networks play an important role in providing households with resources such as land, labor, and financial support. The findings suggest that poor households can benefit from their credit using peers in terms of resources that can be subsequently invested in their farms or other trading activities to enhance their income levels. This is consistent with the findings of Aker (2011) and Johny et al. (2017), who revealed that households who receive social support from peers are more likely to employ income diversification measures, potentially causing a decrease in household poverty and a rise in expenditure levels.

The households' landholding is also positive and statistically significant at the 1% level, according to the findings. Based on the calculated coefficient (0.2780), farmers who own more land are 27.8% more likely to access credit than those who own less land. This is because the land is a collateral asset that may be used to guarantee the farmers' creditworthiness to creditors. This result is therefore consistent with the findings of Barslund & Tarp (2008), who discovered a positive and substantial link between smallholder credit access and land ownership in Tanzania.

Furthermore, the health status of farmers had a statistically significant effect on both the selection and outcome equations of credit users. According to the calculated coefficient of 0.4088, farmers' self-reported health, particularly those who reported being healthier than their peers, were 40.9% more likely to access credit. This is because such farmers can devote more time and care to their crops, as well as participate in other off-farm activities to create revenue that can be utilized to pay off debts even if the crops fail. However, for those who are not in good health or who are unwell, this may not be the case. As a result, it is not surprising that this variable raises credit users' income by 18.57%. Furthermore, at the 5% level, the residential status of farmers has a statistically significant estimate of 0.5581. This means that being a native farmer boosts your chances of getting credit by 55.8% more than being a migrant. This may likely be a result of locals having a higher chance than migrant farmers to own land resources and have access to credit information.

Also, the durable assets of farm households' affect their credit decisions and incomes. According to the parameter estimate (0.2127), having more durable assets boosts credit users' income by 21.3%. This estimate was positive and statistically significant at the 5% level. The income of both loan users and nonusers in the sample was positively and statistically significantly impacted by the livestock assets of families. At the 5% level, the credit users' coefficient (0.1716) was significant. This suggests that the revenue of loan users increases by 17.2% as the number of livestock assets (units) increases. For households without credit, the calculated coefficient was 0.1285 and was statistically significant at the 10% level. This demonstrates that the income of households without credit improves by 13% for every increase in the number of livestock assets (units) owned. The households' livestock holdings primarily serve as a means of generating money that may be used to pay for living expenses and to invest in business ventures. This is in line with Kedir (2003) and Quoc (2012).

Table 4.5 ESR estimates of peer credit effects on household income

	Selection (Credit access)		Outcome model (Household income)			
			Credit users		Noncredit users	
	Coefficients	Robust S.E.	Coefficients	Robust S.E.	Coefficients	Robust S.E.
HAge	0.0108	0.0245	-0.0029	0.0128	0.0044	0.0108
Education	-0.0417	0.0343	-0.0045	0.0156	0.0113	0.0156
HHSex	0.0343	0.3728	-0.0094	0.1904	0.1488	0.1512
Off-farm trade	-0.3728	0.2969	-0.1309	0.1542	-0.2219	0.1375
HLandOwnership	0.2780***	0.0773	-0.0041	0.0329	0.0239	0.0433
HHSize	0.0193	0.0358	0.0103	0.0181	-0.0029	0.0208
Health status	0.4088**	0.1797	0.1857**	0.0896	0.0794	0.0825
Residential Status	0.5581**	0.2624	0.1754	0.1572	0.0072	0.1244
Farm size	-0.0214	0.0949	0.0158	0.0432	0.0353	0.0571
HD_Assets	-0.1814	0.2316	0.2127**	0.1013	0.1285	0.0967
Livestock (TLU)	-0.2367	0.1494	0.1716 **	0.0744	0.1285*	0.0722
ACredit	-4.6046 ***	1.8099	0.6687	0.4392	0.9010***	0.2306
Farm shocks	0.6457***	0.2154	-0.2804**	0.1290	-0.0977	0.1052
Farm experience	-0.0027	0.0266	0.0010	0.0133	0.0065	0.0118
Mobile network	0.1521	0.2198	0.2526**	0.1276	0.0436	0.1099
District (Karaga=1)	0.2979	0.5852	0.1575	0.1541	0.4616***	0.1419
AAge	-0.0246	0.0564				
AEducation	-0.0654	0.0611				
ASex	-0.4998	0.7388				
AOff-farm	0.5793	0.6896				
ALandholding	-0.4063***	0.1512				
AHHSize	-0.1148	0.1073				
AHealth status	-0.7103*	0.4045				
AResid. Status	-1.1279*	0.6127				
AFarm size	0.1508	0.1664				
ADurable assets	0.1773	0.3795				
ALivestock	0.1063	0.2356				
AFarm shocks	-0.6734	0.7414				
AFarm Exp.	0.0539	0.0573				
AHMNetwork	-0.4851	0.5568				
DistFinInst	-0.1130**	0.0627				
ResidACredit	-3.7963**	1.9032	-0.5585	0.5202	-0.3483	0.3394
Constant	0.0871	5.2717	4.9178***	1.2252	8.5480***	1.0196
Model diagnostics						
Wald χ^2	36.25 ***					
Rho0	0.8486**	0.0883				
Rho1	0.1769***	0.0138				
Log-likelihood	-347.19611					
LR test of Indep. eqns.: chi2(2) = 13.56 Prob > chi2 = 0.0011						
No. of observations	281					

Source: Field Survey (2022). Note: DistFinInst denotes the distance to the nearest source of credit included in the model for identification. ResidACredit denotes the residual of the first-stage peer credit model and the variables with the A prefix denote peer variables that are likely to affect their credit.

From the selection and the second outcome equation, credit users tend to experience significant effects from farm shocks in terms of their incomes. At the 1% level, the estimated coefficient (0.6457) in the selection model was positive and statistically significant. This suggests that farmers who suffered losses or shocks during the previous farming season are 65% more likely to access credit. The calculated coefficient in the outcome equation was however negative (-0.2804), and at the 5% level, it was statistically significant. This suggests that people who use loans but have shocks in their farms are likely to see a 28% drop in their income level. This implies that credit users who are subject to farm shocks might not achieve adequate harvests that they can sell to increase profits.

Additionally, households' access to mobile network has a favorable and statistically significant effect on credit users' income. According to the findings, households that use credit are more likely to see an increase in their income by about 25% if there is adequate mobile network coverage nearby. This could be a result of the fact that households with high mobile network connectivity are more likely to get farm and market information, such as new production techniques and prices for output and input, which could help them enhance crop yields and income.

The district where a household is located also significantly and favorably affects the income of credit-less households. According to the coefficient (0.4616), households in the Karaga district that lack access to credit see a rise in their incomes of 46% when compared to families in the Kumbungu district. Peer landholding also significantly affects smallholder farmers access to credit. At the 1% level, the parameter estimate (-0.4063) is significantly negative. This suggests that a smallholder farmer's likelihood of accessing credit reduces by 41% as peers' total landholdings increase. Additionally, the coefficient of peer health was negative and statistically significant at the 10% level. This suggests that having healthy friends as opposed to those with relatively bad health reduces the likelihood of the farmers obtaining loans by 71%. Additionally, peers' residence tends to have a detrimental and statistically significant impact on a farmer's likelihood of obtaining loans. According to the predicted coefficient (-1.1279), having peers who are native residents of the village decreases the farmer's likelihood of accessing credit by 113%.

4.5 Peer credit and other determinants of household food security

In evaluating the effect of peer credit on household food security, the ESR model was also used. The selection criteria employed a 5% significant indicator of the distance to the nearest financial institution. The parameter estimate was negative, which suggests that the observed effect was biased downward. The endogeneity of peer credit in the model was also managed using the residual of a first-stage peer credit model (Wooldridge, 2015). At the 1% level, the residual parameter estimate (20.7371) was statistically significant and positive. This shows an upward bias in favor of the observed effect of peer credit on household income. The likelihood test of independent equations and the observed correlation coefficient are both statistically significant at the 1% level. This demonstrates the presence of unobserved variables that influence both the credit choices of households and their food security, making the ESR model more suitable for this investigation. The estimated parameters are thus effective and more reliable because the standard errors are robust and likewise stable.

Also, the correlation coefficient also shows that smallholder access to credit substantially improves the household's food consumption. The estimates suggests that there are positive gains on the selection, implying that households with access to credit benefit more from credit in terms of food consumption than nonusers even if they had used credit. The positive correlation coefficient between the selection equation and credit users' outcome equation (ρ_1) suggests a negative selection bias, indicating that farmers with outcomes below the mean score are more likely to access credit. Iddrisu et al. (2018) in a more recent study showed that households in the Northern region that participated in the Masara N'Ariki credit program experienced higher yields than those who did not. This supports the findings of the study in the sense that higher yields could improve smallholder household food security either through increased consumption of own production or improved income from crop sales.

Additionally, peer credit has a significant influence on the credit choices of households as well as their food consumption, particularly among those without access to credit. The peer credit variable's estimated coefficient in the selection model was (-1.42). At the 1% level, this was statistically significant. The findings show that all other things being equal, a 1% increase in the share of peers in the network who have credit reduces the farmers' likelihood of accessing credit by 1.42. This is in line with the findings of Alio et al. (2018), who found that households with a higher level of social connections, especially to credit users have a lower likelihood of using credit. The research conducted by Banerjee et al. (2013) disputes this conclusion. The study found that while credit users help educate and inform their friends about credit, they do not significantly influence the credit decisions of households.

The peer credit variable also considerably increased the food security of credit-less households at the 1% level. According to the estimate, the households' food consumption score rises by 6.6 points when there is a 1% increase in the share of peers with credit, all other things being equal. The findings also indicate that peer credit has a greater impact on non-credit users' food security than it does on credit users. This may imply that people that use credit are more likely to succeed and do not require assistance from their peers. This result is in line with several previous research in the literature (Hadley et al., 2007; Tam et al., 2014; Obaa & Mansur, 2016), which show a favorable association between social networks and household food security. Marco & Thorburn's (2009) findings, which revealed that social networks do not significantly influence household food security and do not considerably reduce the effects of the link between income and food insecurity, run counter to this conclusion.

Age, educational level, sex, off-farm trade, landholding, household size, health status, residential status, peer credit, durable assets, livestock, farm shocks, mobile network access, district dummy, peer age, peer sex, peer off-farm trade, peer landholding, peer household size, peer health status, peer farm size, peer durable assets, peer livestock, peer farm shocks, peer farm age are the significant variables in the model that affect the selection and outcomes. Both the size of the effect and the statistical significance of these variables vary greatly. The age of the household head has a considerable influence on the credit decisions of the household. At the 10% level, the parameter estimate (-0.0526) is negative and significant. This implies that an increase in the farmer's age by one year, reduces the households probability of credit access by 5.3%. This could be a result of credit providers having concerns about the elderly farmers' capacity for employment and debt repayment. Also, the nature of credit provided to the farmers, in the form of inputs, require young and energetic individuals who are more capable of working to repay the borrowed credit. This finding is similar to Waje's (2020), who discovered a strong negative connection between age and loan access among Ethiopian families.

The model results also reveal that the education of the household head influences the household's credit decisions. At the 10% level, the calculated coefficient of (0.0749) was positive and statistically significant. This implies that an additional year spent in school by the farmer, increases the households probability of accessing credit by 7.5%. This suggest that higher education raises the likelihood of access to credit, all things being equal. This also points to the fact that education may improve the households' ability to access credit information, which could increase their chances of obtaining credit. This result is consistent with previous research (Biyase & Fisher, 2017; Okurut, 2006; Kedir, 2003).

The sex of the household head has also been demonstrated to influence the household credit decisions and food consumption, particularly among those without access to credit. The selection equation's estimate was (1.1398) and statistically significant at the 5% level. The results implies that males have a higher probability of accessing credit (114%) compared to females. This suggest that male-household heads are more likely than their female counterparts to access credit. This could be due to the ownership and control of economic resources in a male-dominated society like the one under study. In most of these areas, men own and control the majority of land resources, which are frequently used as collateral for credit. Furthermore, for an input credit scheme, the most important consideration for credit suppliers is the ownership of land for crop production, which is largely held by the men. This is consistent with Biyase and Fisher's (2017) findings. However, Okurut (2006) and Barslund & Tarp (2008) discovered contradictory findings indicating that females have greater access to credit than males.

The sex of the household head was also a significant factor in determining household food consumption, particularly for those without credit. At the 5% level, the estimated coefficient (-2.87) was statistically significant and negative. This shows that male-headed households experience a decline of 2.9 in their food consumption score compared to female-headed households in the sample. This may imply that households headed by males tend to be less food secure than those headed by females, especially when they do not have access to credit. This results is consistent with other findings in the literature. For instance, Awoyemi et al. (2023) discovered that male-headed households have a lower likelihood of being food insecure than female-headed households. However, this discovery runs counter to the findings of Abdullah et al. (2017) and Hadley et al. (2008), who discovered evidence suggesting that female-headed households are less food secure than male-headed households.

Table 4.6 ESR estimates of the impact of peer credit on household food security

Variables	Selection model (Credit access)		Outcome model (Food security)			
			Credit users		Noncredit users	
	Coefficient	Robust S.E.	Coefficient	Robust S.E.	Coefficients	Robust S.E.
HHAge	-0.0526*	0.0307	0.0771	0.1288	-0.0543	0.0901
Educ	0.0749*	0.0428	0.0098	0.1492	-0.0548	0.1306
HHSex	1.1398**	0.4407	-1.8229	1.9628	-2.8769**	1.2798
Off-farm trade	-0.1434	0.3001	3.9059**	1.5255	0.4165	1.1612
HLandholding	0.3385***	0.0841	-0.1330	0.3120	-0.3612	0.4085
HHSize	0.1573***	0.0583	-0.1300	0.1860	-0.3714**	0.1816
Health status	-0.5185	0.3127	-0.7025	0.8144	-0.2801	0.7119
Resid_Status	0.7782***	0.2816	1.8641	1.4704	1.2653	1.0931
Farm size	0.1041	0.1093	-0.0771	0.4080	0.7577	0.4977
HD_Assets	0.8728**	0.3895	-0.8266	1.0506	0.6641	0.8312
Livestock (TLU)	-0.4045**	0.1629	1.8612**	0.8145	0.2318	0.6168
ACredit	-1.4245***	0.0697	3.0395	4.2176	6.5727***	2.1816
Farm shocks	0.6605***	0.2271	-5.1986***	1.2758	0.6936	0.9452
Farm experience	0.0518	0.0318	-0.1946	0.1342	0.0387	0.1003
Mobile network	0.7306**	0.3521	3.8386**	1.6887	-1.1534	1.3719
District (Karaga=1)	0.9296**	0.4352	-2.5716*	1.4374	4.1153***	1.2263
AAge	-0.0668	0.0477				
AEduc	-0.0310	0.0612				
ASex	-0.2817	0.6415				
AOff-farm	0.5643	0.6122				
ALandholding	-0.2624**	0.1274				
AHHSize	-0.0618	0.0883				
AHealth status	0.0479	0.2780				
AResid. Status	-0.9216*	0.4219				
AFarm size	0.3254**	0.1696				
ADurable assets	0.2787	0.4117				
ALivestock	-0.1481	0.1653				
AFarm shocks	0.2592	0.4965				
AFarm Exp	0.0976**	0.0488				
AHMNetwork	-0.0935	0.5123				
DistFinInst	-0.1688**	0.0803				
ResidACredit.	20.7371***	7.1197	2.3973	4.6823	0.1274	2.8974
Constant	-44.2376***	13.8522	58.9426***	11.1621	26.8867***	8.7566
Model diagnostics						
Wald χ^2	62.86 ***					
Rho0	0.3733	0.2656				
Rho1	0.7363***	0.1584				
Log-likelihood	-966.1069					
LR test of Indep. eqns.: chi2(2) = 9.47 Prob > chi2 = 0.0088						
No. of observations	281					

Source: Field Survey (2022).

Note: ResidACredit denotes the residual of the first-stage peer credit model, the variables with the A prefix denote peer variables that are likely to affect their credit.

The off-farm trade variable was also relevant in determining credit-using farmers' food security. At the 5% level, the computed coefficient (3.9059) is positive and statistically significant. From the results of the study, household heads who have access to credit and participate in off-farm activities are likely to raise the household's food consumption score by 3.90 compared to those who do not participate in off-farm activities. This implies that such farmers are more likely to earn additional cash from these activities and may utilize it to supplement their household expenses. This finding agrees with that of Babatunde et al. (2007).

The results also indicate that the landholding of the household affects their credit decisions. At the 1% level, the parameter estimate is positive and statistically significant. According to the estimated coefficient of 0.3385, an increase in the number of acreage of land owned by the household increases the farmer's probability of access to credit by 33.9%. This means that farmers that own more land are likely more than others with smaller landholdings to have access to credit. This may be attributed to the productive nature of land, and could also be used to demonstrate the farmer's trustworthiness and ability to repay borrowed credit. The land might also be used as a collateral asset to ensure the farmers' creditworthiness to creditors. This result is congruent with that of Barslund & Tarp (2008), who discovered that households that own more land are likely to have increased access to loans than those without.

Furthermore, the household size also have a significant effect on household credit choices and food security, especially among households that do not have access to credit. At the 1% level, the variable is significantly positive in the selection model. The estimated coefficient is 0.1573, indicating that adding one person to a household could increase the households likelihood of credit access by 16%. This suggests that larger households tend to have a higher demand for credit due to increases in their consumption budget compared to smaller households. The variable is also tends to significantly affect the food consumption of households. In particular, for households without credit access, the calculated coefficient (-0.3714) has the anticipated sign (negative) and is at a significance level of 5%. According to the results, an increase in the size of a household by one person, reduces the households food consumption score by 0.37. This implies that large-sized households, especially those without credit are less food secured. This maybe linked to the strain that big family numbers may place on the household's limited resources, especially when they are dependants who do not contribute to household income. This finding is largely consistent with those of Feleke et al. (2003) and Ojogbo (2010). The logical and plausible explanation is that, increasing the size of the household may impose an additional financial burden, particularly on already-stressed households, thereby worsening their food security conditions (Feleke et al., 2003).

Furthermore, the residential status of the household head influences the household's credit access. At the 1% level, the calculated coefficient of (0.7782) is positive and statistically significant. This implies that farmers who are natives tend to have an increased probability of accessing credit by 78% compared to migrant farmers. This maybe attributed to the fact that indigenous and native farmers are more likely to own land resources and have easier access to credit information from their network of family and friends in the community, which are likely to be larger compared to migrant farmers.

Also, the households durable assets significantly influence their credit choices. This variable was found to be significant in explaining household credit decisions. The estimated coefficient (0.8728) was positive and statistically significant at the 5% level, showing that an increase in the households durable assets tend to improve the probability of access to credit by 87.28%. This makes sense because the durable assets of the household might be used as collateral while simultaneously proving the farmer's creditworthiness. This result is congruent with the findings of Quoc (2012), who discovered that the total assets of households could significantly affect credit access among rural households in Vietnam. A study undertaken by Kedir (2003) to evaluate the determinants of credit access among households in the Upper West region validates these findings.

Moreover, the households livestock assets evaluated in terms of tropical livestock units for standardization tend to affect credit access and food security of households, particularly those with credit. In the selection model, the calculated coefficient (-0.4045) was negatively significant at the 5% level. This indicates that an increase in the number of livestock units owned by the household tend to reduce the probability of credit access by 40%. This demonstrates that households with more livestock assets are more inclined to sell them to meet their credit demands rather than resort to the use of credit. However, at the 5% level, the estimated parameter in the outcome model was positive and statistically significant. The coefficient for credit users (1.8612) indicates that an increase in the number of livestock units owned by the household tends to boost credit users' food consumption score by 1.9. These households sometimes rely on their livestock assets to generate money to cover household needs and to invest in productive activities.

Furthermore, agricultural shocks affect the selection and outcome equations of credit users. The estimates for the selection and the credit users' outcome are 0.6605 and -5.1986, respectively, which are both statistically significant at the 1% level. This implies that, while agricultural shocks tend to promote farmers' credit decisions, they cause a reduction in the food consumption score of credit users' by 5.2. In most cases farmers that experience farm shocks and post harvest losses in the previous season, are likely to lack the necessary inputs for the current season and may rely on credit. However, if farmers take out credit and face shocks throughout the season, they may become indebted and could be forced to cut back on their food intake.

Additionally, access to mobile networks among households tends to have a favorably significant effect on the credit decisions of credit users and their food security. According to the findings, having access to a mobile network enhances credit users' food security by 384% and farmers' likelihood of having access to credit by 73%. This implies that households with high mobile network connectivity may be more likely to obtain crucial information about new production techniques and market dynamics that may affect their loan decisions and also enable them to boost crop yields and raise their consumption levels.

Additionally, the location of the household measured in terms of the district had a significant effect on the credit choices of households and their food security. According to the findings, households in the Karaga district have a higher likelihood of accessing credit than those in the Kumbungu district. Also, residents in the Karaga district have a higher food consumption score compared to those in the Kumbungu district. The results also show that while noncredit users in the Karaga district experience an improvement in their food consumption, those with credit tend to experience a decline in their food consumption. This suggest that noncredit users in the Karaga district have a higher food consumption than noncredit users in the Kumbungu district. However, the credit users in the Karaga district have a lower food consumption score compared to credit users in the Kumbungu district. This is congruent with the finding of Awoyemi et al. (2023), who discovered that households' locations considerably influence farmers' access to food. This might be explained by the ease with which people can access marketplaces and other necessary social facilities (Nkegbe & Abdul Mumin, 2021). Kassy et al. (2021) discovered that households without as much access to markets as those with access had much higher levels of food insecurity. Finally, additional peer characteristics have a substantial impact on how families decide whether to take out loans. The majority of these factors, though, were covered in the previous section.

4.6 Impacts of credit on income and food security

The average treatment effects for the outcomes are also predicted from the ESR model. The mean outcomes of the treated households (those with credit access) and their untreated counterparts (those without credit access) are computed, along with their associated counterfactuals. The treatment group's counterfactual represents the mean outcome of households if they did not have access to credit, whereas the untreated group refers to the mean outcome of households if they did have access to credit. The net difference between the treated group's average outcome and their counterfactual yields the average treatment effect on the treated (ATT). Similarly, the net difference between the untreated group's outcome and their counterfactual yields the average treatment effect on the untreated (ATU). Table 4.7 shows how the treatment (credit access) impacts household income and food consumption.

Table 4.7: Average treatment effects of credit on household income and food security

	Mean outcomes				
Variable	Users	Non-users	Treatment effects		Effect (%)
Household income (log)	8.2024 (0.0266)	7.8187 (0.0209)	ATT =	0.3837*** (0.0362)	28.55
	8.6086 (0.0469)	8.0756 (0.0309)	ATU =	0.5333*** (0.0443)	5.61
Food consumption score (FCS)	53.4247 (0.6509)	50.8601 (0.3383)	ATT =	2.5646*** (0.6688)	26.08
	36.1778 (0.2792)	31.9917 (0.2403)	ATU =	4.1861*** (0.4088)	9.77

Source: Field Data 2022.
Note: *** denotes significance at the 1% level, and the values in the parentheses are the reported standard errors.

These estimations have generally pointed to more favorable advances in smallholder farmers' household income and food security. This means that farmers who had access to credit experienced increases in the income and food consumption of the household compared to nonusers. The average (log) income of credit users (conditional) is GHC 3,649.699, with a counterfactual income of GHC 2,486.670, yielding a net difference of GHC1,163.029. This gives the average treatment effect on the treated (ATT) for household income, which is significant at the 1% level. Also, the average income (log) of noncredit users is GHC 3,215.055, with a counterfactual of GHC 5,478.573, resulting in a net difference of GHC 2,263.517, at the statistical significance level of 1%. In terms of food security, the average food consumption score for credit users is 53.4247, with a counterfactual of 50.8601, and a net difference of 2.5646. This estimate was likewise significant at the level of 1%, demonstrating that credit users have a higher food consumption level than those without credit. For nonusers', the average food consumption score was 31.9917, with a counterfactual of 36.1178, yielding a net difference of 4.1861. This was also highly significant at the 1% level, indicating that if nonusers had access to credit, their consumption would have gone up.

The ATT estimates demonstrate that smallholder access to credit boosts credit-using households' income and food consumption by 29% and 26%, respectively. Furthermore, based on the predicted value of the ATU, households without credit would have boosted their incomes and food consumption by 6% and 10%, respectively, if credit had been used. This result supports previous research that found that access to credit can boost household income and food security. In a study of smallholder participation in the Masara N'Ariziki input credit initiative in the Northern region and its impact on production and income, Iddrisu et al. (2018) confirm similar findings. The findings demonstrated that participation in the input credit scheme by smallholders had a significant influence on productivity but not on income. According to the study, farmers who participated in the program boosted their output dramatically, but this yield level did not significantly affect farm incomes.

CHAPTER FIVE

FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

This chapter gives a summary of findings and conclusions based on the preceding chapter's results analysis. It also includes policy recommendations for credit accessibility and methods to improve the income and food security of smallholder farmers and their households, as well as recommendations for further study in the wide range of social network impacts.

5.2 Summary of findings

The study's primary goal was to analyze the impact of social networks on lending decisions made by smallholder farmers in the Northern region. The spatial Durbin model was utilized to examine and create the outcomes for this goal. The findings demonstrate that network members' credit behavior has a considerable negative impact on farmers' finance access. This shows that when the average number of peers having loan access increases, smallholder farmers are less likely to access credit. The endogenous effect estimate of 0.15, which was significant at the 10% level, indicates that as the share of peers in the farmer's network having credit increases by 1%, the farmers' probability of credit access decreases by 0.15%. The findings also reveal that farmers' socioeconomic characteristics, their peers' exogenous characteristics, and other unobserved factors influence their credit access. According to the marginal effect estimates, age, residential status, durable assets, farm experience, mobile network access, and distance to the nearest financial institution are the socioeconomic factors that significantly affect the farmer's credit access.

Furthermore, the estimates show that peer age, peer landholding, peer household size, peer durable assets, peer farm shocks, peer farm experience, peer distance to the nearest financial institution, and peer district are exogenous peer variables that significantly affect smallholder credit access. However, the amount and direction of these factors vary greatly. The marginal effect estimates reveal direct and indirect own effects, as well as direct and indirect exogenous effects, as well as the combined effect of these variables on farmer loan availability. This means that the overall impact of the farmers' characteristics on own credit and the credit access of their peers can be divided into direct and indirect effects. Similarly, the influence of peer traits on their credit access and the farmer's credit access can be divided into direct and indirect effects. The estimate of associated effects has a positive value of 0.14, with a significance level of 1%. This means that holding every other factor constant, unobserved factors account for 14% of the variation in the farmers' credit decisions. The computed coefficient's significance also shows the presence of spatial effects and that social factors have a major impact on smallholder finance availability. This validates the use of geographical modeling in evaluating smallholder credit behavior.

The study's second goal was to look at how peer credit impact the incomes of smallholder farm households in the Northern region. Due to the endogeneity of peer credit and self-selection bias, the endogenous switching regression (ESR) model was utilized for the analysis. The average treatment effects reveal that smallholder access to input credit has a considerable impact on household income. Furthermore, peer credit has a large positive impact on the income levels of households that do not have credit. However, the findings demonstrate that for credit-worthy households, the credit of their peers has no meaningful impact on their income. This could imply that there is little or no financial support exchange between these groups. The health status of household heads, durable assets, units of livestock assets owned by the household, farm shocks, mobile network access, peer credit, and geographical location or district of the household are socioeconomic factors that strongly influence household income.

The final goal of the study was to examine the influence of peer credit on smallholder farmers' food security. The study employed the food consumption score (FCS) as a proxy metric for household food security (WFP, 2008). Because of the possible endogeneity concern of the selection, as well as unobserved factors connected with the peer credit variable, the endogenous switching regression model was utilized again for analyzing this objective. According to the findings, own credit significantly impacts household incomes and food consumption. This study also finds peer credit to have a significant impact on the income and food consumption of households, particularly for those lacking access to credit. According to the computed coefficient, an increase in the share of peers with access to credit in the farmers network boosts the household food consumption level by 6.57. Furthermore, socioeconomic variables that have a major impact on household food consumption included sex, off-farm trade, household size, durable assets, units of livestock assets possessed by the household, peer credit, farm shocks, mobile network connectivity, and the household's district.

5.3 Conclusions

This study concludes that endogenous and exogenous factors, as well as correlated unobservables, significantly influence smallholder farmers' access to credit in the Northern region. The findings of the study imply that smallholder farmers' ability to access credit has a significant role in determining their income and level of food security. Therefore, this study concludes that access to credit greatly raises household income and food consumption. This is also supported by the findings of Sekyi et al. (2020). The study further finds peer credit to have a significant effect on the income and food security of smallholder farmers, particularly among those without credit. Additionally, the estimates of the treatment effects point to positive gains in the selection, showing that farmers who have access to credit experience significantly better welfare than those who do not. Despite this, the study's findings support the idea that having access to credit could be beneficial for both users and non-users in terms of how peer credit affects the well-being of households without credit. Increased peer transfers, which could be the outcome of higher peer yields and productivity improvements brought on by credit, may be responsible for this.

5.4 Recommendations

The following policy recommendations are made in light of the major issues noted in the literature and the empirical analysis in this study:

- Farmers who are less socially connected, particularly to current users, must be the focus of future credit policies by stakeholders to increase credit access among smallholder farmers. According to the empirical investigation, farmers with stronger social ties had a lesser likelihood of assessing the credit. This also corresponds to what Alio et al. (2018) discovered in Uganda. The distance of households to credit institutions was another factor that inhibited credit access among the farmers. Therefore stakeholders must ensure that credit institutions are made more available to the farmers. This could be achieved through the digital technologies that have now become available and accessible.
- To increase smallholder farmers' income and food consumption, the government should improve access to input credits through the Ministry of Food and Agriculture. However, they must put in place mechanisms to guarantee a balance between production and efficiency without jeopardizing the farmers' long-term consumption of nutritious and safe foods. Ghana's structural adjustment initiatives may have contributed to the reduction in state support for agriculture and the elimination of input subsidies, which in turn caused input prices to rise and the cost of output to rise. The government of Ghana recently implemented the Planting for Food and Jobs (PFJ) program, which has increased productivity and improved food security.

However, the gains have been undone by the recent global crisis, which has resulted in rising food inflation and a high cost of living, particularly for the poor and vulnerable. Additionally, the majority of smallholder farmers were still unable to access the PFJ's subsidy program. Studies have even called out the policy's primary flaws as the late delivery of inputs and improper targeting of the intended recipient farmers (Lambongang et al., 2019). Also, access to mobile networks was key to the income and food security of farmers. This could promote their ability to receive market information, increase their general knowledge on agronomic practices and also about current market conditions and pricing that could improve the households' food security.

- According to the empirical analysis, enhanced peer access to credit can boost smallholder farmers' income and food consumption through higher peer incomes. Policies to improve the income and food security of smallholder populations must foster social cohesiveness, peace, and harmony among these farmers. To sustain the ties among smallholders that could permit resource transfers necessary to secure their food security, the government, peace council, house of chiefs, the clergy and other relevant stakeholders must work to ensure that civil disputes and political instability are kept under control. The government must also improve access to social support services concerning health and other conditions that affect productivity. Since the majority of the farmers in the survey did not engage in any off-farm activities and as a result wasted away in the lean seasons, the one village one dam program must also be scaled up in most communities to promote off-season engagements.

To better understand smallholder access to input credit and its effects on agricultural output, potential future research projects should take a look at several other areas in addition to these policy concerns. It will be interesting to think about how the input credit markets are incorporated into the rural cash economy and the prospects of improving household incomes and consumption of safe and nutritious foods.

The literature on social networks has relied on observational data, which is limited in scope and also not available in a nationally representative dataset, such as those collected by the Ghana Statistical Service, to allow for a more dynamic analysis of the impact of changes in social network structure on household welfare outcomes. As a result, the information used for this study was limited to a small number of communities in the Northern region. As a result, ethnic heterogeneity in social network impacts could not be considered in this study's analysis.

Therefore, the focus of future research should be on accumulating enough village-level data to enable more varied analyses including ethnic heterogeneities. Further study is needed, particularly on how social networks affect household well-being among the various ethnic groups in the northern region.

Future research must therefore concentrate on social networks since they may also influence output, entrepreneurial performance, and educational results. Such initiatives must concentrate on the breakdown of the various social network characteristics and perform a thorough examination of the social network structure of farmers and how it influences household food security and dietary intake. To ensure the exogeneity of the network data, randomized control trials must be taken into consideration in network investigations. Additionally, research must examine alternative distribution channels for microfinance and other lending programs that go beyond social and geographic networks to reach smallholder farmers. Future research should also look into the effects of threshold heterogeneities and the influence of degree on the diffusion and access to microlending.

REFERENCES:

Abdulai, S., Nkegbe, P. K., & Donkoh, S. A. (2018). Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach. *Cogent Food and Agriculture*, *4*(1). https://doi.org/10.1080/23311932.2018.1512390

Abdulai, A., & Huffman, W. (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics*, 90(1), 26–43. https://doi.org/10.1353/lde.2014.0009

Abdulai, A., & Kuhlgatz, C. (2012). Food Security Policy in Developing Countries. The Oxford Handbook on the Economics of Food Consumption and Policy. 344.

Abdullah, Zhou, D., Shah, T., Ali, S., Ahmad, W., Din, I.U., & Ilyas, A. (2017). Factors affecting household food security in the rural northern hinterland of Pakistan, *Journal of the Saudi Society of Agricultural Sciences*, doi: http://dx.doi.org/10.1016/j.jssas.2017.05.003

Abdul Mumin, Y., & Abdulai, A. (2021). Social networks, adoption of improved variety and household welfare: evidence from Ghana. *European Review of Agricultural Economics*, Vol 49(1), pp. 1-32. https://doi.org/10.1093/erae/jbab007.

Adam, I. (2018). Agricultural Finance Intervention in Ghana. A Case Study: Alliance for Financial Inclusion (AFI). *Bank of Ghana*. Accra.

Adeoye, S. O., & Ugalahi, U. B. (2017). Smallholder food crop farmers' participation in the Bank of Agriculture (BOA) scheme in the Ogun state of Nigeria. *Agrosearch*, 17(2), 51-66.

Agboklou, K. E., & Ozkan, B. (2022). Analysis of rice farmers' access to agricultural credit and profitability in South Togo. *Journal of Business, Economics, and Finance* (JBEF), 12(1), 1-14.

Aker, J. C. (2011). Social Networks and Household Welfare in Tanzania: Working Together to Get Out of Poverty. *SSRN Electronic Journal*, *November*. https://doi.org/10.2139/ssrn.995941

Alinovi, L., Erdgin, M., & Donato, R. (2009). Measuring Household Resilience to Food Insecurity: Application to Palestinian Households. Rome: EC-FAO Food Security Programme.

Alio, D., Okiror, J. J., Agea, J. G., Matsiko, F. B., & Ekere, W. (2018). Influence of social networks and social support on credit utilization in the Savings and Credit Cooperatives in Soroti District, Uganda. *Journal of Agricultural Extention and Rural Development*, Vol. 10(3), pp. 54-60. Doi:10.5897/JAERD2017.0877

Anderson, D. R., Sweeney, D. J., & Williams, T. A. (2011). Statistics for business and economics (11 ed.). USA, South-Western Cengage Learning: pp 310-330.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. *Kluwer Academics*

Publishers, London. Vol. 4 Springer.

Arene, C. J., & Anyaeji, J. (2010). Determinants of Food Security among Households in Nsukka Metropolis of Enugu State, Nigeria. *Pakistan Journal of Social Sciences*, 30(1): 9-16.

Asiamah, T. A., Steel, W. F., & Ackah, C. (2021). Determinants of credit demand and credit constraints among households in Ghana. *Heliyon*, *7*(10), e08162. https://doi.org/10.1016/j.heliyon.2021.e08162

Atieno, R. (2001). Formal and informal institutions' lending policies and access to credit by small-scale enterprises in Kenya: An empirical assessment. *African Economic Research Consortium*, Nairobi.

Awoyemi, A. E., Issahaku, G., & Awuni, J. A. (2023). Drivers of household food security: evidence from the Ghana living standards survey. *Journal of Agriculture and Food Research*, Vol (13), 100636

Awunyo-Vitor, D. (2015). The informal financial market in Ghana: Factors influencing participation by maize farmers. *Savings and Development*, *39*(1), 37–58.

Azzi, C. F., & Cox, J. C. (1976). A theory and test of credit rationing: Comment. *The American Economic Review, 66 (5), pp 911-917.*

Babatunde, R. O., Omotosho, O. A., & Sholotan, O.S. (2007). Factors Influencing Food Security Status of Rural Farming Households in North Central Nigeria. Agric. J., 2(3): 351 – 357.

Baffoe, G., & Matsuda, H. (2015) Understanding the Determinants of Rural Credit Accessibility: The Case of Ehiaminchini, Fanteakwa District, Ghana. *Journal of Sustainable Development*, 8: 183.

Barrett, C. B. (2010). Measuring food insecurity. Science 327, 825–828.

Barrett, C. B., & Lentz, E. C. (2010). International Studies Compendium Project. Eds. R. A. Denemark et al. *Wiley-Blackwell,* Oxford. DOI: 10.1126/science.1182768, 825-327

Barslund, M., & Tarp, F. (2008). "Formal and Informal Rural Credit in Four Provinces of Vietnam", *Journal of Development Studies*, Vol. 44, No. 4, pp. 485 503.

Bartlett, J. E. II, Kotrlik, J. W., & Higgins, C. C. (2001). Organizational Research: Determining Appropriate Sample Size in Survey Research, *Information Technology, Learning, and Performance Journal, 19(1) pp 48*.

Bandiera, O., & Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique, Royal Economic Society Stable. *The Suntory Centre Suntory and Toyota International Centres for Economics and Related Disciplines*, *116*(514), 869–902.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341(6144), 1236498.

Banerjee, A., Breza, E., Chandrasekhar, A. G., Duflo, E., Jackson, M. O., & Kinnan, C. (2021). Changes in Social Network Structure in Response to Formal Credit Markets.

NBER Working Paper No. 28365

Bekti, R. D., Rahayu, A., & Sutikno (2013). Maximum Likelihood Estimation for Spatial Durbin Model. *Journal of Mathematics and Statistics* 9 (3) 169-174.

Biyase, M., & Fisher, B. (2017). Determinants of access to formal credit by the poor households. *Studia Universitatis Babes-Bolyai OEconomica*. Volume 62, ISSUE 1, pp. 50-60. DOI:10.1515/subboec-2017-0004

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics* 150(1): 41-55.

Brock, W., & Durlauf, S. (2002). A Multinomial-Choice Model of Neighborhood Effects. *American Economic Review*. Papers and Proceedings, 92(2), 298-303.

Brock, W., & Durlauf, S., (2003). Multinomial choice with social interactions, *SSRI Working Paper No. 2003-1*, University of Wisconsin.

Butts, C. T. (2008). Social network analysis with sna. *Journal of Statistical Software*, 24(6), 1–51.

Carletto C., Zezza A., & Banerjee R. (2013). Towards a better measurement of household food security: harmonizing indicators and the role of household surveys. *Glob Food Sec* 2, 30 –40.

Chandio, A. A., Jiang, Y., Rehman, A., Twumasi, M. A., Pathan, A, G., & Mohsin, M. (2021). Determinants of demand for credit by smallholder farmers: a farm level analysis based on a survey in Sindh, Pakistan. *Journal of Asian Business and Economic Studies*. Vol. 28 No. 3, pp. 225-240.

Chandrasekhar, A. G., & Lewis, R. (2016). Econometrics of sampled networks. *Mimeo*, Massachusetts Institute of Technology.

Chen, C. K., & Chivakul, M. (2008). What drives household borrowing and credit constraints? Evidence from Bosnia and Herzegovina. *IMF Working Paper. WP/08/202.*

Cochran, W. G. (1977). Sampling techniques. 3rd Ed. New York: John Wiley & Sons.

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, *100*(1), 35–69. https://doi.org/10.1257/aer.100.1.35

Conte, A., & Morrow, N. (2002). Rural Community and Household Food Security Profiles, Vulnerability Analysis and Mapping, *World Food Programme report*, Rome.

Danso-Abbeam, G., Asale, M. A., & Ogundeji, A. A. (2023). Determinants of household food insecurity and coping strategies in Northern Ghana. *GeoJournal* **88**, 2307–2324. https://doi.org/10.1007/s10708-022-10742-0

Diagne, A. (1996). Impact of Access to Credit on Income and Food Security in Malawi. *FCND Discussion Paper, 17.*

Diagne, A. (1999). Determinants of Household Access to and Participation in Formal and Informal Credit Markets in Malawi. *International Food Policy Research Institute, 67*(67), 1–62.

Diagne, A., & Zeller, M. (2001). Access to credit and its impact on welfare in Malawi. *Research Report of the International Food Policy Research Institute*, *IFPRI Repo*(116), 1–143. https://doi.org/10.2499/0896291197rr116

Dittoh, S. (2006), "Effective aid for small farmers in sub-Saharan Africa: *southern civil society perspective*, Ghana case study", available at: www.ccic.ca/_…/003_food_2007-01_small_ farmers_research_report_summary.pdf (accessed January 1, 2018).

Doku G. D., Obubuafo J. M. M., & Hagan M. A. S. (2020). "Access to Credit by Smallholder Female Farmers in Ho Municipality, Ghana", *World Journal of Business and Management*.

Dzadze, P., Osei Mensah J., Aidoo, R., & Nurah, G. K. (2012). Factors determining access to formal credit in Ghana : A case study of smallholder farmers in the Abura- Asebu Kwamankese district of the central region of Ghana. 4(December), 416–423. https://doi.org/10.5897/JDAE12.099

Fafchamps, M., & Gubert, F. (2007). "The formation of risk sharing networks". *Journal of Development Economics* 83(2) 326-350/

Fanwell, B. (2003). Determinants and characteristics of household demand for agricultural credit in Malawi. *Journal of World Development*, 14, 167-171.

FAO, ECA & AUC. (2020). Africa Regional Overview of Food Security and Nutrition 2019. Accra. https://doi.org/10.4060/CA7343EN.

FAO. (2010). "World Summit on Food Security." http://www.fao.org/wsfs/world-summit/ en/?no_cache=1.

Feder, G., Lau, L. J., Lin, J. Y., & Luo, X. (1990). The relationship between credit and productivity in Chinese agriculture: A microeconomic model of disequilibrium. *American Journal of Agricultural Economics*, 72 (5): 1151-1157.

Feleke, S., Kilmer, R. L., & Gladwin, C. (2003). Determinants of Food Security in Southern Ethiopia. A selected paper was presented at the 2003, *American Agricultural Economics* Association meetings in Montreal. Canada. Retrieved on 12th December, 2005 from http://ageconsearch.umn.edu/bit stream/22010/1/sp03fe02.pdf

Fiedler, J. L., Keith L., Odilia I. B., & Marc-Francois S. (2012). "Household Consumption and Expenditures Surveys (HCES): A Primer for Food and Nutrition Analysts in Low- and Middle-Income Countries." *Food and Nutrition Bulletin* 33 (3): 170–184.

Ghana Statistical Service. (2019). Ghana Living Standards Survey round 7 (GLSS7), Main Report. *Ghana Statistical Service*, 1–343. https://statsghana.gov.gh/gsspublications. php?category=MTAwMjg3Mzk3NC4zMDc=/webstats/1opr93rn57

Ghana Statistical Service. (2021). Ghana 2021 Population and Housing Census: General

Report Volume 3A. Populations of Regions and Districts.

Gideon, B., & Matsuda, H. (2015). "Understanding the Determinants of Rural Credit Accessibility: The Case of Ehiaminchini, Fanteakwa District, Ghana", *Journal of Sustainable Development*, 2015.

Granovetter, M. (1978). "Threshold models of collective behavior." *The American Journal of Sociology*, 83(6):1420-1443.

Gregory, P., Ingram, J. S. I., & Brklacich M, (2005). Climate Change and Food Security. *Philosophical Transactions of the Royal Society B-Biological Sciences*, 360 (1463): 2139-2148.

Gross, R., Schoeneberger, H., & Pfeifer H. (2000). The four dimensions of food and nutrition security: definitions and concepts. SCN News 20, 20 –25

Hadley, C., Mulder, M. B., & Fitzherbert, E., (2007). Seasonal food insecurity and perceived social support in rural Tanzania. *Public Health Nutrition*: 10(6), 544-551. DOI:10.1017/S1368980007246725.

Hadley, C., David, L., Fasil, T., & Tefara, B. (2008)."Gender Bias in the Food Insecurity Experience of Ethiopian Adolescents." *Social Science & Medicine* 66 (2): 427–438.

Hai, R., & Heckman, J. J. (2017). Inequality in human capital and endogenous credit constraints. *Review of Economic Dynamics*. http://dx.doi/org/10.1016/j.red.2017.01.001

Helmke, G., & Levitsky, S. (2003). Informal institutions and comparative politics: a research agenda. Technical report, South Bend, IN: *Kellog Institute for International Studies*, Notre Dame University.

Hoff, K., & Stiglitz, J. E. (1990). Imperfect information and rural credit markets: puzzles and policy perspectives. *World Bank Economic Review* (4) 3. 235-250

HLPE. (2020). Food security and nutrition: building a global narrative towards 2030. A report by the High-Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security, *Rome.* 1–112. www.fao.org/cfs/cfs-hlpe

Iddrisu, A., Ansah, I. G. K., & Nkegbe, P. K. (2018) "Effect of input credit on smallholder farmers' output and income: Evidence from Northern Ghana", *Agricultural Finance Review*, Vol. 78 Issue: 1, pp.98-115, https://doi.org/10.1108/AFR-05-2017-0032.

Institute of Statistical, Social and Economic Research (2008). The state of the Ghanaian economy in 2007. *ISSER*, Accra, Ghana.

IFPRI. (2002). Ghana Strategy Support Program- Smallholder Agriculture in Ghana. *International Food Policy Research Institute*. www.ifpri.org.

Jayashankar, P., & Raju, S. (2020). The effect of social cohesion and social networks on perceptions of food availability among low-income consumers. *Journal of Business Research*, *108*(July 2018), 316–323. https://doi.org/10.1016/j.jbusres.2019.10.028

Jayne, T. S., Marther, D., & Mghenyi, E. (2005). Smallholder Farming in Difficult Circumstances: Policy Issues for Africa in IFPRI (International Food Policy Research Institute): The future of small farms: Proceedings of a Research Workshop. PP.103123. Wye, UK, Washington, DC.

Johny, J., Wichmann, B., & Swallow, B. M. (2017). Characterizing social networks and their effects on income diversification in rural Kerala, India. *World Development*, *94*, 375–392. https://doi.org/10.1016/j.worlddev.2017.02.002.

Kang, X. (2019). The Impact of Family Social Network on Household Consumption. *Modern Economy*, *10*(03), 679–697. https://doi.org/10.4236/me.2019.103046

Kebede, W., & Butterfield, A. K. (2009). Social networks among poor women in Ethiopia. *International Social Work* 52(3): 357-374.

Kedir, A. (2003). Determinants of Access to Credit and Loan Amount: Household-level Evidence from Urban Ethiopia", *International Conference on African Development Archives*, Paper 64.

Kaleb, K., Mekonnen, H., Tesfaye H., & Eyob, B. (2017). *Effect of social networks on food security status : The case of maize producing farmers in Ethiopia*. *62*, 22–30.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695 706. https://doi.org/10.1016/j.worlddev.2014.09.008

Kariuki, G. K., & Mdoe, J. I. (2017). Family networks and microcredit access in Kenya. *Journal of African Political Economy and Development*, *2*(1), 125–144.

Kassy, W. C., Ndu, A. C., Okeke, C. C., & Chwike, E. (2021). Food security status and factors affecting food security in Enugu State, Nigeria. *Journal of Health Care for the Poor and Underserved*, Vol. 32(1), pp. 565-581.

Kuwornu, J. K. M., Suleyman, D. M., & Amegashie, D. P. K. (2013). Analysis of Food security status of farming households in the forest belt of the central region of Ghana. *Russian Journal of Agricultural and Socio-Economic Sciences*, 1(13)

Kyaw, D. (2009). Rural Households' Food Security and Coping Strategies to Food Insecurity in Myanmar.Institute of Developing Economies, Japan External Trade Organization.R. F. Series No. 444. PP. 78.

Lambongang M., Ansah, I. G. K., & Donkoh, S. A. (2019). Participation and yield effects of Ghana's planting for food and jobs program in Bunkprurugu-Yunyoo District. *Ghana Journal of Agricultural Economics and Agribusiness;* Vol 2(1), June 2019.

Latifee, H. I. (2003). Microcredit and poverty reduction: Experiences of Grameen operation in Asia, Grameen Trust.

Lee, L. F., Maddala, G. S., & Trost, R. P. (1982). Testing for Structural Change by D-Methods in Switching Simultaneous Equations Models. Center For Naval Analyses. Professional Paper 342.

Lele, U., William A. M., Joyce K., Meenakshi, J. V., Bharat R., Julia T., & Sambuddha G. (2016). Measuring Food and Nutrition Security: An Independent Technical Assessment and User's Guide for Existing Indicators. *Food Security Information Network*. http://www.fsincop.net/topics/fns-measurement/en/.

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3), 282–289. https://doi.org/The Stata Journal

Maddala, G. S. (1983). Limited-dependent and qualitative variables in econometrics (No. 3). *Cambridge university press*.

Manski, C. F. (2000). Economic analysis of social interactions. *Journal of Economic Perspectives*, 14(3), 115–136. http://doi.org/10.1257/jep.14.3.115

Manski, C., (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60(3), 5311-542.

Marco, D. M., & Thorburn, S. (2009). The relationship between income and food insecurity among Oregon residents: does social support matter? *Public Health Nutrition*, Vol (12) 11, pp. 2104-2112. DOI: https://doi.org/10.1017/S1368980009990243

Maxwell, S., & Smith, M. (1992). "Household Food Security: A Conceptual Review." In Household Food Security: Concepts, Indicators, Measurements: A Technical Review, edited by Simon Maxwell and Timothy R. Frankenberger, 1–72. Rome and New York: IFAD and UNICEF.

Metseyem, C. (2020). The Effect of Social Capital on Households' Access to Microcredit in Cameroon in 2001 and 2007.

MoFA. (2021). Ministry of Food and Agriculture Medium Term Expenditure Framework (MTEF) for 2021-2024 Programme Based Budget Estimates for 2021. *Www.Mofep.Gov.Gh*, *August*, 58. https://mofep.gov.gh/sites/default/files/pbbestimates/2021/2021-PBB-MOFA.pdf

MoFA. (2017). Planting for Food and Jobs: Strategic Plan for Implementation (2017-2020). *Ministry of Food and Agriculture*, Accra, Ghana.

Munshi, K., & Rosenweig, M. (2016). Networks and misallocation: Insurance, migration and the rural-urban wage gap. *American Economic Review*, 106(1), 46–98.

Nair, A., & Fissha, A. (2010). Rural banking: the case of rural and community banks in Ghana. *Agriculture and Rural Development* Discussion Paper, 48.: The World Bank. Washington DC. http://siteresources.worldbank.org/INTARD/Resources/GhanaRCBs_web.pdf.

Nkegbe, P. K. (2018). Credit access and technical efficiency of smallholder farmers in Northern Ghana: Double bootstrap DEA approach. *Agricultural Finance Review*, *78*(5), 626–639. https://doi.org/10.1108/AFR-03-2018-0018

Nkegbe, P. K., & Abdul Mumin, Y. (2021). *Impact of Community Development Initiatives* *and Access to Community Markets on Household Food Security and Nutrition in Ghana*. 1–23. www.aercafrica.org

Nwaru, J. C. (2011). Determinants of informal credit demand and supply among food crop farmers in akwa ibom state, Nigeria. *Rural and Community Development*, 6(1), 129-139.

Obaa, B. B., & Mazur, R. E. (2016). Social network characteristics and resource access among formerly displaced households in Lira, Uganda. *Disasters* 41(3):468-486.

Ojogho, O. (2010): Determinants of Food Insecurity among Arable Farmers in Edo State, Nigeria. *Agricultural Journal*, 5(3): 151-156.

Okten, C., & Osili, U. O. (2004). Social networks and credit access in Indonesia. *World Development*, *32*(7), 1225–1246. https://doi.org/10.1016/j.worlddev.2004.01.012

Okurut, F. N. (2006). Access to Credit by the Poor in South Africa: Evidence from household survey date 1995 and 2000", *Working Papers 13/2006*, Stellenbosch University, Department of Economics.

Olarinde, L. O., Abass, A. B., Abdoulaye, T., Adepoju, A. A., Adio, M. O., Fanifosi, E. G., & Wasiu, A. (2020). The influence of social networking on the food security status of cassava farming households in Nigeria. *Sustainability (Switzerland)*, *12*(13), 1–35. https://doi.org/10.3390/su12135420

Oluyole, K. A., Oni, O. A., Omonona, B. T., & Adenegan, K. O. (2009). Food Security among Cocoa Farming Households of Ondo State, Nigeria. ARPN *Journal of Agriculture and Biological*. Sciences 4:7-13.

Osoro, K., & Muturi, W. (2013). The role of micro-financial institutions on the growth of SMEs in Kenya: A case study of micro-financial institutions in Kisi Town. *The Journal of Humanities and Social Science* 16(1): 83-93. Doi: 10.9790/0837-1618393

Owusu, S. (2017). Factors Affecting Farm Households' Access to Credit in the Afigya-Kwabre District of Ghana. *International Journal of Scientific Research in Social Sciences & Management Studies | IJSRSSMS*, *2*(1), 98–113.

Owusu-Antwi, G., & Antwi, J. (2010). The Analysis Of The Rural Credit Market In Ghana. *International Business & Economics Research Journal (IBER)*, *9*(8), 45–56. https://doi.org/10.19030/iber.v9i8.611

Pastrapa, E. (2009). Estimating the determinants of loan demand: The case of Greek households. *Department of Home Economics and Ecology*. Athens, Greece: Harokopio University.

Perkins, J. M., Nyakato, V. N., Kakuhikire, B., Tsai, A. C., Subramanian, S., Bangsberg, D. R., & Christakis, N. A. (2018). Food insecurity, social networks and symptoms of depression among men and women in rural Uganda: A cross-sectional, population-based study. *Public Health Nutrition*, *21*(5), 838–848. https://doi.org/10.1017/S1368980017002154

Petr, L., Zoe C., Aurele D., Jan D., & Ivan L. (2010). Ethiopia's Food Insecurity: Europe's Role within the Broader Context of Food Flows, Climate Change and Land Grabs.

Glopolis: First edition| Prague.

Pérez-Escamilla R., & Segall-Corrêa A. M., (2008). Food security measurement and indicators. *Revista de Nutrição*. DOI: 10.1590/S1415-52732008000500003

Quaino, M. E. (2010). Food Security Implications of Women Farmers' Participation in Biofuel Crop Production in the Gomoa District. Unpublished MPhil Thesis submitted to the Department of Agricultural Economics and Agribusiness, University of Ghana, Legon.

Quoc, D.V. (2012) Determinants of household access to formal credit in the rural areas of the Mekong Delta, Vietnam. African and Asian studies, 11: 261-87.

The Republic of Ghana. (2018). National Financial Inclusion and Development Strategy. *Government of Ghana*, *November*, 1–20. https://www.cbn.gov.ng/Out/2013/CCD/NFIS.pdf%0Ahttp://www.afi-global.org/sites/default/files/publications/mfg-en-paper-national-financial-inclusion-strategy-oct-2012.pdf

Sekyi, S. (2017). Rural Households ' Credit Access and Loan Amount in Wa. *International Journal of Economics and Financial Issues*, *7*(1), 506–514.

Sekyi, S., Abu, B. M., & Nkegbe, P. K. (2020). Effects of farm credit access on agricultural commercialization in Ghana: Empirical evidence from the northern Savannah ecological zone. *African Development Review*, *32*(2), 150–162. https://doi.org/10.1111/1467-8268.12424

Sen, A. (1981), "Ingredients of famine analysis: Availability and Entitlements", *The Quarterly Journal of Economics*, Volume 93:3 August 1981, 433-464.

Shaikh, F. M. (2007). Determinants of Household Food Security and Consumption Pattern in Rural Sindh: Non-Separable Agriculture Household Model. *IUB Journal of Social Sciences and Humanities*, 5(2): 18-39.

Steiner-Asiedu, M., Dittoh, S., Newton, S. K., & Akotia, C. (2017). Ghana Zero Hunger StrategicReview.1–104.https://docs.wfp.org/api/documents/WFP0000071730/download/

Stiglitz, J., (1990). Peer monitoring and credit markets. *World Bank Economics Review*, 4 (3): 351-366.

Swindale, A., & Bilinsky, P. (2006). Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide (v.2). Washington, DC: USAID, FHI 360/FANTA.

Tam, B., Findlay, L., & Kohen, D. (2014). Social Networks as a Coping Strategy for Food Insecurity and Hunger for Young Aboriginal and Canadian Children. *Societies*, *4*(3), 463–476. https://doi.org/10.3390/soc4030463

Tran, C. & Zheleva, E. (2019). Learning Triggers for Heterogeneous Treatment Effects. In *Proceedings of the AAAI Conference on Artificial Intelligence.*

Turkson, F. E., Amissah, E., & Gyeke-dako, A. (2020). The role of formal and informal finance in the informal sector in Ghana. *Journal of Small Business & Entrepreneurship*, *0*(0), 1–24. https://doi.org/10.1080/08276331.2020.1724002

Ullah, A., Mahmood, N., Zeb, A. & Kächele, H. (2020). Factors determining farmers' access to and sources of credit: evidence from the rain-fed zone of Pakistan. *Agriculture*, 10, 586.

Waje, S. S., (2020). Determinants of Access to Formal Credit in Rural Areas of Ethiopia: Case Study of Smallholder Households in Boloso Bombbe District, Wolaita Zone, Ethiopia. *Economics*. Vol. 9, No. 2, 2020, pp. 40-48. doi 10.11648/j.eco.20200902.13

Webb, P., Coates, J., Frongillo, E. A., Rogers, B. L., Swindale A. & Bilinsky, P. (2006). Measuring household food insecurity: why it's so important and yet so difficult to do. *The Journal of Nutrition*, Vol (135), Issue 5, 1404s-1408s.

Wiredu, N. A., Gyasi, K.O., Abdoulaye, T., Sanogo, D. & Langyintuo, A. (2010). Characterization of maize-producing households in the Northern Region of Ghana. *Country Report – Ghana: CSRI/SARI – IITA, Ibadan, Nigeria. 24 pp.*

Wooldridge J. M. (2015). "Control Function Methods in Applied Econometrics." *The Journal of Human Resources* 50(2): 420-445.

World Bank (2007). World Development Report 2008: Agriculture for Development, *World Bank* Washington, D.C.

World Bank (2010). Handbook on Impact Evaluation: Quantitative methods and practices. *The World Bank*, Washington, D.C. World (Vol. 41).

World Bank (2017). World Bank data, World Bank Data Base

World Bank. (2022). World Bank national accounts data, and OECD National Accounts data files. Agriculture, forestry, and fishing, value added (% of GDP) - Ghana | Data (worldbank.org)

World Bank (2019). Enabling the Business of Agriculture. Washington D.C.

Wydick, B., Karp Hayes, H., & Hilliker Kempf, S. (2011). Social Networks, Neighborhood Effects, and Credit Access: Evidence from Rural Guatemala. *World Development*, *39*(6), 974–982.

WFP (2008). Food Consumption Analysis Calculation and Use of the Food Consumption Score in Food Security Analysis (v.1). Rome: WFP.

Xiong, H., Payne, D., & Kinsella, S. (2016). Peer effects in the diffusion of innovations: Theory and simulation. *Journal of Behavioral and Experimental Economics*, *63*, 1–13. https://doi.org/10.1016/j.socec.2016.04.017

Zhao, Q., Shen, Y., & Li, C. (2021). Credit Behaviors of Rural Households in the Perspective of Complex Social Networks. *Complexity*, *2021*. https://doi.org/10.1155/2021/9975856

APPENDICES

Appendix I: Determining factors affecting peer access to credit

Table 1A: OLS estimates of factors influencing peer credit

Variables	Coefficients	Std. Err.	t-value	p-value
Intercept	-1.9582***	0.5572	-3.51	0.001
District (Karaga = 1)	-0.5380	1.8194	-0.30	0.768
HAge	-0.0027	0.0026	-1.02	0.308
HEduc	0.0042	0.0036	1.18	0.241
HSex	0.0497	0.0402	1.24	0.218
Off-farm trade	-0.0011	0.0317	-0.03	0.973
HLandholding	0.0023	0.0085	0.27	0.790
HHSize	0.0073	0.0046	1.59	0.113
Health status	-0.0444**	0.0186	-2.39	0.018
Residential status	-0.0061	0.0294	-0.21	0.835
Farm size	0.0067	0.0111	0.60	0.550
HDurable assets	0.0461**	0.0228	2.02	0.044
Livestock assets (TLU)	-0.0096	0.0179	-0.54	0.593
Farming shocks	-0.0047	0.0250	-0.19	0.851
Farm experience	0.0023	0.0029	0.80	0.422
HMNetwork	-0.0276	0.0385	-0.72	0.474
DistFinInst	0.0672**	0.0266	2.53	0.012
AAge	-0.0180***	0.0056	-3.22	0.001
AEduc	0.0044	0.0072	0.61	0.543
ASex	0.1208*	0.0713	1.69	0.092
AOff farm trade	0.0714	0.0738	0.97	0.334
ALandholding	0.0565***	0.0143	3.94	0.000
AHHSize	0.0171	0.0113	1.52	0.131
AHealth status	0.1353***	0.0380	3.56	0.000
AResidential status	0.1117*	0.0654	1.71	0.089
AFarm size	0.0384*	0.0206	1.86	0.064
ADurable assets	0.1120**	0.0492	2.28	0.024
ALivestock	-0.0772***	0.0206	-3.75	0.000
AFarm shocks	0.3536***	0.0513	6.89	0.000
AFarm experience	0.0173***	0.0059	2.94	0.004
AHMNetwork	0.1449**	0.0704	2.06	0.041
ADistFinInst	-0.0575***	0.0268	-2.14	0.033
Model diagnostics				
Adj. R^2	0.64			
F test	15.85			
Prob.> F	0.000			

Notes: $***$ $p < 0.01$, $**$ $p < 0.05$, and $*$ $p < 0.1$

Appendix II: Household survey questionnaire

University for Development Studies

Faculty of Agriculture, Food and Consumer Sciences

Department of Agricultural and Food Economics

Impacts of Social Networks and Peer Credit on Credit Access, Income, and Food Security of Farm Households in the Northern Region

Introduction

Good day Sir/Madam

Thank you for talking to me. We are surveying to examine the impact of social networks on credit access and the food security of households. More specifically, the study intends to assess the effect of credit information links and peer credit on household credit access and food security. The information gathered will aid in the write-up of an MPhil thesis in Agricultural Economics at the University for Development Studies, Ghana. The whole interview will take about an hour and your participation is by choice. All information provided including your name, identity, and other personal responses will be kept strictly confidential.

Do you wish to participate in this survey? 0= No 1= Yes

Survey identification

Questionnaire number: ______________ Name of enumerator: _________________

Date of interview: __________________ Start time (24hr Clock): _______________

Location

1. District name: __________________ 4. District code: ___________

2. Name of community: ____________ 5. Community ID: _________

3. Head of Household (name): ____________ 6. Household ID: __________

Section A: Socio-demographic characteristics

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
What is the age of the household head? ___	What is the sex of the household head? 0=F 1=M	What is the educational level of the household head? (*no. of completed years of schooling*) ___	What is the religion of the household head? Codes A4	Was this your religion since birth? 0=No 1=Yes	If not, when did you join your current religion? ____	What religion does members of the household practice? Codes A4	What is the marital status of the household head? Codes A8	What is the main occupation of the household head? Codes A9	If farming, for how long has the household head been engaged in farming? _____	What type of farming does the household head do? 0=Small scale 1=Large scale	What is the literacy status of the household head? Codes A12

Codes A4

0. No religion
1. Islam
2. Christianity
3. Traditional
4. Other (specify) ________

Codes A8

0. Never married
1. Married
2. Separated
3. Divorced
4. Widowed
5. Other (specify)_____

Codes A9

1. Farming (crop and /or livestock)
2. Formal employment
3. Casual labor
4. Non-farm business (trade, shops etc.)

Codes A12

0. Illiterate (cannot read and write in any language)
1. Literate (can read and write in any one language)

Please complete this table on household and household head's social issues

No.	Questions	No.	Questions	No.	Questions
A13	What is the residential status of the household head? 0=Migrant 1=Native	A22	Does the household head hold any position of authority in the village? 0=No 1=Yes	A31	Does the household have access to television or radio services? 0= No 1=Yes
A14	If migrant, for how long has the household head lived in the village? ___	A23	Does any member of the household hold any position of authority in the village? 0= No 1= Yes	A32	Does the community have access to strong telecommunication coverage? 0=No 1=Yes
A15	Does the household head have a royal lineage? 0 =No 1 =Yes	A24	What is the size of the household? _____	A33	Did you experience the sudden death of any household/family member in the last 5 years? 0 =No >>A33 1 =Yes
A16	Has any of the parents of the household head or spouse held any important position of authority in the traditional or political system? 0=No 1=Yes	A25	Did you or any member of the household undertake any lumpy expenditure (such as the construction of the house and/or room) in the last 5 years? 0 =No 1 =Yes	A34	If yes, how many times did you experience this in the past 5 years? _________ (times)
A17	Was the household head born in this community? 0= No 1=Yes	A26	Has the household head changed location in the past …...? 5 years? 0=No 1=Yes 10 years? 0=No 1=Yes	A35	Did you experience a long period of sickness of a household member which led to his/her death in the last 5 years? 0 =No 1 =Yes
A18	Did the household head grow up in this community? 0=No 1=Yes >>A20	A27	Did you experience any shock or loss in your farming activities in the last 5 years? 0 =No >>A31 1 =Yes	A36	What is your state of health compared to others that you know? 1. Poor 2. Average 3. Above average
A19	If not, how long has the household head been in this community? ______(years)	A28	If yes, which of the following did you experience? 1 =Weather shocks 2 =bush/wildfires 3 =Other (specify)___	A37	Does the household head belong to any farmer-based organization (FBO) or any type of group in the village? 0=No 1=yes
A20	Do you own a mobile phone? 0=No 1=Yes	A29	If yes, how regular is the incidence of these shocks/losses? 1 =Very regular 2 =Regular 3=Occasional	A38	Do you belong to any other community-based association? 0=No 1=Yes
A21	How many mobile networks do you use? ______	A30	Is there an ICT Centre in the community? 0=No 1=Yes	A39	If yes, how many associations are you a member of? _____

Please complete this table on household and household head's social issues

A40	Have you ever used a mobile phone either belonging to you or someone else to seek market information? 0=No 1=Yes	A47	Do you have strong mobile phone reception around the location of your household? 0=No 1=Yes	A54	Do you attend association meetings? 0=No 1=Yes
A41	If yes, how many times in the 2020/21 season? _____	A48	What was the value of the property? _______	A55	How many times did you attend meetings in the 2020/21 season? _____
A42	Have you ever used your mobile phone to borrow money? 0=No 1=Yes	A49	What is the distance from your household to the nearest financial institution? _____(km)	A56	Do you occupy any leadership positions within the association? 0=No 1=Yes
A43	How much did you borrow? ______	A50	What is the distance from your farm plot to the nearest financial institution? ____(km)	A57	Did you inherit any property (s) from a deceased family member? 0=No 1=Yes
A44	Have you ever used your phone to seek or give financial information? 0=No 1=Yes	A51	What is the distance to the district capital? ________	A58	What was the nature of the property? Codes A58
A45	Do you have a market or at least periodic markets in the community? 0=No 1=Yes	A52	What is the distance from your house to the nearest market center? _____	A59	Did you use any of the inherited property as collateral for credit? 0=No 1= Yes
A46	What ethnic group does the household belong to? Codes A46	A53	What language (s) do members of the household mostly speak? Codes A63	A60	Did you contribute to acquiring the property? 0=No 1=Yes

odes A53

Dagbanli	7. Likpakpa	13. Chekosis
Nanunli	8. wali	14. Mamprusis
Gonja	9. Sissala	15. Kasem
Hausa	10. Gruni	16. Nankan
Bimoba	11. Ga	17. Twi
Dagaare	12. Ewe	18. Other ____

Codes A46

1. Dagombas	7. Kassenas	13. Chekosis
2. Nanumbas	8. Nankan	14. Konkombas
3. Gonjas	9. Akans	15. Kusasis
4. Hausas	10. Ewes	16. Gas
5. Bimobas	11. Mamprusis	17. Grunsi
6. Dagaabas	12. Sissalas	18. Other _____

Codes A58

0. Land
1. House
2. Tractor
3. Thresher
4. Harvester
5. Other (specify) _____

Section B: Information on household income, financing, and expenditure

Please indicate the annual income earned from the following sources:

	Source of income	Amount/GHC
B1	Annual income from the sale of farm produce/crops	
B2	Annual income from the sale of livestock	
B3	Annual income from non-farm activities	
B4	Gifts and remittances	
B5	Aid (from NGO/Gov't)	
B6	Annual income from farm labor activities	
B7	Others	

Please indicate which of the following applies to you:

	Finance	Response
B8	Does the household normally save food for consumption in the following year? 0=No 1=Yes	
B9	Does the household head save money regularly? 0=No 1=Yes	
B10	Does the household head hold a bank account? 0=No 1=Yes	
B11	Does the household head hold other financial assets 0=No 1=Yes	
B12	Does the household head borrow money often to meet household expenditures? 0=No 1=Yes	

Please indicate the household expenditure on the items listed below:

	Expenditure item	Expenditure/GHC
B13	How much did you spend on food in a normal month?	
B14	How much did you spend on other non-food items in a regular month?	
B15	Other expenditures (e.g. funerals, remittances, gifts, weddings, etc. over the past year?	

Section C: Livestock and other household assets (Please I will like to ask you about your livestock and other household assets)

		Cattle	Sheep	Goat	Pigs	Poultry	Oxen/donkeys	others
C1	Do you own any of these animals in the household?	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes
C2	If yes, how many does the household own?							
C3	How many in all do you own?							
C4	How many did you sell in the 2020/21 season?							
C5	At what price did you sell most of this? (GHS)							
C6	How many did you buy in the 2020/21 season?							
C7	At what price did you buy most of this? (GHS)							
C8	Do you seek veterinary services for them? 0=No 1=Yes							
C9	If yes, how much did you spend over the last 12 months? GHS							

Please provide information about your household assets

#	Asset/Item	Do you have an item? 0=No 1=Yes	If yes, how many in all?	If you were to sell it now, what will be the per-unit price? (GHS)
1	Cutlass			
2	Hoe			
3	Knapsack			
4	Irrigation pump/kit			
5	Radio			
6	Cell phone			
7	Television			
8	Bicycle			
9	Motorcycle			
10	Car/motor-king/kia			
11	Bullock/donkey			
12	Thresher			
13	Tractor			
14	Mechanized sheller			
15	House			
16	Other ____			

Section D: Information on household credit needs and access

Please I will like to ask about your credit needs and access during the 2020/21 season

D1	During the last season, did you run into liquidity challenges as far as financing production? 0=No 1=Yes	D8	Did they require collateral before granting the loan? 0=No 1=Yes
D2	If yes, did you apply/ask for any formal loan to finance production? 0=No 1=Yes	D9	What did you use as collateral? Codes D9
D3	If yes, were you granted? 0=No 1=Yes	D10	Did you use any other form of credit during last year's cropping season? 0 No 1 Yes
D4	Where did you access the credit? Codes D4	D11	What was the nature of the credit? Codes D10
D5	How much did you apply for? _______(GHS)	D12	If cash, how much interest did you pay on the loan? __________(GHS)
D6	Were you given all you applied for? 0=No 1=Yes	D13	If input credits, in what form did you repay/expected to repay the loan? Codes D10
D7	If not, how much were you given? __________(GHS)	D14	If you did not take up formal credit, why? Codes D13

Codes D4

1. Friends or relatives
2. Local moneylenders
3. Banks
4. NGOs (specify)_______________
5. Nonbank financial institution (including MFI)
6. Input dealers
7. Out grower
8. FBO
9. Digital lending e.g Momo etc
10. Others (specify) _________

Codes D9

1. Land
2. Building
3. Livestock
4. Household asset
5. Farm produce
6. Other (specify) ________

Codes D10

1. Informal credit (cash)
2. Input credit (ploughing, seeds, fertilizer etc.)

Codes D13

1. Unavailability of credit opportunities
2. Lack of collateral
3. Lack of access to credit information
4. No one to provide guarantee your credit application
5. Other (specify) ____________________

Section F: Information on household food consumption (Consumption module)

Please answer the following questions in your capacity as the person responsible for food provision/preparation in the household in the past 4 weeks/one month.

F1. How many days in the last 7 days did members of your household eat the following foods?

	Food groups (definitive)	Food item (examples)	Days eaten in the last week (0-7 days)	Weight (definitive)	FCS (No. of days X weight)
1	Main staples	Maize, maize porridge, rice, sorghum, millet pasta, bread, and other cereals		2	
		Cassava, potatoes and sweet potatoes, other tubers, plantains			
2	Pulses	Beans, peas, groundnuts, and cashew nuts		3	
3	Vegetables	Vegetables leaves		1	
4	Fruit	Fruits		1	
5	Meat and fish	Beef, goat, poultry, pork, eggs, and fish		4	
6	Milk	Milk yogurt and other dairies		4	
7	sugar	Sugar and sugar products, honey		0.5	
8	Oil	Oils, fats, and butter		0.5	
9	Condiments	Spices, tea, coffee, salt, fish powder, and small amounts of milk for tea.		0	

Section G: Information on household head's social networks: (S/E= Sought or Exchange)

Contact Name/ID	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12
	Do you know this person? 0=No>> next contact 1=Yes	For how long have you known him/her?	Did you S/E credit information? 0=No 1=Yes	No. of times in the past 12 months? ____	What was the nature of the information? Codes G5	Did you S/E food products with this person? 0=No 1=Yes	How did you obtain the food from this person? Codes G7	No. of times in the past 12 months? ___	What was the value of the said exchange? _____	Did you S/E cash? 0=No 1=Yes	What was the amount? ____GHS	What was the nature of the exchange? Codes G12
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												
11												
12												
13												

Section G: Information on household head's social networks: (S/E= Sought or Exchange)

Contact Name/ID	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12
	Do you know this person? 0=No>> next contact 1=Yes	For how long have you known him/her?	Did you S/E credit information? 0=No 1=Yes	No. of times in the past 12 months? ____	What was the nature of the information? Codes G5	Did you S/E food products with this person? 0=No 1=Yes	How did you obtain the food from this person? Codes G7	No. of times in the past 12 months? ___	What was the value of the said exchange? _____	Did you S/E cash? 0=No 1=Yes	What was the amount? ____GHS	What was the nature of the exchange? Codes G12
14												
15												

Codes G5

1. Available sources of credit
2. Location of credit facility
3. Interest charge on loans
4. Loan requirements

Codes G7

1. Gift
2. Purchase on credit
3. Food donation
4. Barter or trade
5. Purchase with cash
6. Exchange for labor
7. Other (specify) ________

Codes G12

1. Credit
2. Gift
3. Both

Household head's network of family and friends/neighbors

G13	G14	G15	G16
Do you know anyone from? MoFA, NGO, or any external agency? 0=No 1=Yes	How long have you known him/her? ______	Have you ever sought or received any information from him/her? 0=No 1=Yes	If yes, how often? Codes G16

Codes G16

1. Daily
2. 2-3 times weekly
3. Once weekly
4. Seasonally
5. Monthly
6. Yearly

I will like to ask about the social and proximal issues between you and your matched contacts

Contact ID	G17 How do you know this person? Codes G17	G18 What is the sex of contact? 0=Female 1=Male	G19 Have you ever visited his/her home and vice versa? 0=No>> G21 1=Yes	G20 If yes, number of visits per month to his/her home? ___	G21 Where does he/she live? Codes G21	G22 How long did you have to travel to see this person? (km/meter)	G23 Has he/she ever obtained credit? 0=No 1=Yes	G24 In general, do you discuss important matters with this person? Codes G24	G25 In general, do you exchange other resources? Codes G25
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									
11									
12									
13									
14									
15									

Codes G17

1. Parent
2. Child
3. Sibling
4. Grandparent
5. Grandchild
6. In-law
7. Other relative
8. friend
9. Same family lineage
10. Neighbor
11. Attend same church/mosque
12. Belong to same association
13. Professional/business colleague
14. Other (specify)__________

Codes G21

1. Next house/neighbor
2. Neighbor of my neighbor
3. Neither my neighbor nor my neighbor's

Codes G24

0. Never
1. Rarely
2. At times
3. Often
4. Always

Codes G25

0. No
1. Cash
2. Land
3. Plowing/digging
4. Fertilizer
5. Information
6. Crop finance/loan
7. Seeds
8. Pesticides
9. weedicides
10. Advice
11. Other_____

Plot ID	H1 What is the total size of this plot?		H2 What portion of the land has been cultivated? __	H3 What is the status of the remaining portion? Codes H3	H4 If rented, how much did you receive whether in cash or kind? ___	H5 Which crops were cultivated on this plot in the 2020/21 season? Codes H5	H6 Where is the farm located? Codes H6	H7 What is the distance of the farm from your home (*no. of minutes in walking*)?	H8 What is the trend in soil fertility on this plot over the last 10 years? Codes H8	H9 How did you obtain this plot, or gain the right to farm on it? Codes H9	H10 For how long have been farming on this land? ___	H11 What did you use in plowing this land? Codes H11	H12 How much did it cost you to plow this farm? ___
	Size	Unit of measure Codes H1											
1													
2													
3													
4													
5													
6													

des H3

Allow land to fallow
Give out to someone else to farm
3. Rent out to an outsider

Codes H11

1. Tractor
2. Drought animal
3. Hand

Sec

Codes H4

1. Maize	7. Cowpea
2. Rice	8. Groundnut
3. Millet	9. Cotton
4. Sorghum	10. Yam
5. Cassava	11. Vegetables
6. Fruits	12. Others ___

Codes H6

1. Within homestead
2. Outside the homestead but within same village
3. Outside the homestead, in different village

Codes H8

1. Infertile
2. Increase in fertility
3. Remains the same
4. Decrease in fertility

Codes H9

1. Owner	5. Allocated free of charge
2. Purchased	6. Begged
3. Inherited from deceased family member	7. Borrowed
4. Tenant /rented (cash or kind)	8. Other (specify) ________

Codes H1

1. Acres
2. Hectares
3. Poles

Please I will like to ask about your input applications during the 2020/21 farming season

Plot ID	II1	II2	II3	II4	II5	II6	II7	II8	II9	II10	II11	II12	II13
	What quantity of seeds did you apply on this farm? (kg)	What variety of seeds did you apply on this farm? Codes II2	Where did you obtain the seeds planted on this farm? Codes II3	If purchased, what quantity was purchased for this farm? (kg)	How much did you pay for the purchased seeds on this farm?	Did you apply fertilizer on this farm? 0=No 1=Yes	Which type did you apply on this farm? Codes II7	What was the quantity applied on this farm? (kg)	What was the price per bag?	Did you apply pesticides? 0=No 1=Yes	Which types did you apply? Codes II11	What quantity did you apply on the farm? (liters/kg)	How much did you spend on pesticides
1													
2													
3													
4													
5													
6													
Other													

Plot ID	II14	II15	II16	II17	II18	II19	II20
	Did you apply weedicides? 0=No 1=Yes	Which types did you apply? Codes II15	What quantity did you apply on this farm? (liters)	How much did you spend on weedicides? (GHS) __	Did you apply green manure to this plot? 0=No 1=Yes	Did you apply animal manure on this farm? 0=No 1=Yes	Did you apply compost on this farm? 0=No 1=Yes
1							
2							
3							
4							
5							
6							
Others							

Codes II2

0. Local
1. Improved

Codes II11-II15

0. None
1. Powder/ condemn
2. Sarosate (specify) _____

4. Fungicide
5. Tintani
6. Other

orage
ers
nput dealer
sed from market

6. Local seed
7. Extension officers
8. NGO

Codes II7

1. Fertilizer: NPK (15-15-15)
2. Fertilizer: ammonium sulphate (SA)
3. Fertilizer 23-10-5 (Actyva)
4. Other compound fertilizer

Section J: Information on farm labor

Please I will like to ask about your farm labor during the 2020/21 cropping season

Family labor			Hired labor				Communal labor		
J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
In general, did you use family labor during the 2020/21 farming season? 0=No 1=Yes	If yes, how many? __	If yes, how many days did they spend on the farm?	In the last farming season, did you use hired labor on your farm? 0=No 1=Yes	If yes, how many? __	If yes, how many days did they spend on your farm? ___	What was the total cost incurred on hired labor? ____	Did you use communal labor on your farm during the last farming season? 0=No 1=Yes	If yes, how many?	If yes, how many days did they spend on your farm? __

Section K: Harvesting, storage, and marketing

Plot ID	K1		K2	K3		K4	K5	K6	K7	K8	K9	K10	K11	K12	
	What was the number of crops harvested on this plot for the 2020/21 season?		Did you experience crop losses during harvesting on this field? 0=No 1=Yes	How much of the crop was lost in total? ____		What type of storage do you use for your crops? Codes K4	Did you sell any of your crops? 0=No 1=Yes	If yes, how did you obtain information about existing market conditions? Codes K6	What was the quantity sold since harvest in 2020/21?	How much did you sell most of the crops per unit?	Where did you sell most of the crops? Codes K9	What is the distance to the nearest market for crops sold at the market? (km)	What was the cost of transporting to the market?	Did you incur additional costs at the market and how much?	
	No.	Unit of measure Codes K1		No.	Unit of measure Codes K1									0/1	Amt.
1															

2															
3															
4															

Plot	K13	K14	K15	K16						
	When did you sell most of your harvest? Codes K13	What was the main reason for these sales? Codes K14	What was the nature of the crop? Codes K15	Did you purchase any crops for household consumption during this year? 0=No 1=Yes						
				K17	K18	K19	K20	K21	K22	K23
				If yes, what crop did you buy?	What quantity of those crops did you buy?	Where did you buy most of these crops? Codes K19	If in the market, what is the distance to the purchase point? (km)	Did you ask about the market conditions before buying? 0=No 1=Yes	If yes, through what means did you acquire that information? Codes K22	At what price did you buy those crops? (GHS)

Codes K4

0. Do not store
1. Mud granary/silo
2. In bags at home/farm
3. In a warehouse
4. Store under ground
5. Pots
6. Other (specify) ____________

Codes K6/ Codes K22

0. Did not sought for any market information
1. Telephone/cell phone
2. Radio/TV
3. Traders
4. Newspaper
6. Extension officer
7. NGO's
8. FBO's
9. Digital platforms
10. Other _______

Codes K9/ Codes K19

1. On the farm
2. Community markets
3. Markets outside the community

Codes K15

0. Staple crop
1. Cash crop

Codes K13

1. Before cultivation or immediately after harvest
2. When household faces cash constraints
3. When crop prices increase/ expected to fall in the near future
4. When there are excess stocks

Codes K14

1. Buy food
2. Buy inputs
3. Medical care
4. Child education
5. Buy clothes
6. funerals
7. Buy household necessities
8. Pay back loan
9. Marriage
10. Build a house
11. Other (specify) ______

Codes K1

1. Kg
2. Bowls
3. Basin
4. Tubers
5. Maxi bag
6. Mini bag
7. Other (specify) ____