EFFECTS OF SOCIAL NETWORKS ON HOUSEHOLD FOOD CONSUMPTION AMONG SMALLHOLDER FARMERS IN KISII AND NYAMIRA COUNTIES, KENYA

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DECLARATION

This thesis is my original work and has not been presented for the award of a degree in any other University.

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DEDICATION

To my parents, Mr Evans Mbugua and Mrs Jane Mbugua, for your prayers, support and showing me the right ways of life. To my loving husband, Jack, for being my best friend, greatest support, and strongest motivation. To my sons, Kian and Ivan, for putting my world into perspective.

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ACRONYMS AND ABBREVIATIONS

ADDA	Agriculture and Dietary Diversity in Africa
ATE	Average treated Efects
AR	Anderson-Rubin test
AWSC	African Women's Studies Centre
BMLE	German Federal Ministry of Food and Agriculture
BMI	Body mass index
Bt	*Bacillus thurigiensis*
EUT	Expected Utility Theory
FAO	Food and Agriculture Organisation of the United Nations
HDDS	Household Dietary Diversity Score
Ibid	In the same source
IFAD	International Finds for Agricultural Development
IFPRI	International Food Policy Research institute
IQ	Intelligence Quotient
KHDS	Kenya Demographic and Health Survey
KSHS	Kenya shillings
LPM	Linear Probability Model
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PEM	Protein energy malnutrition
PhD	Doctor of philosophy
QAP	Quadratic Assignment Procedure
RUT	Random Utility Theory
SDG	Sustainable Development Goals
SSA	Sub Saharan Africa
UNICEF	United Nations Children's Fund
US	United States
WFP	World food Programme
WHA	World Health Assembly's
WHO	World Health Organization

ABSTRACT

Malnutrition is a major burden worldwide. One strategy for curbing malnutrition is through food and nutrition policies that promote both sufficient calorie intake and dietary diversity. However, effects of shocks and lack of nutrition knowledge have led to consumption of insufficient quantity and poor quality diets respectively. In absence of formal institutions to offer nutrition education and insurance against shocks, social networks act as an informal insurance and a channel for individuals to obtain new nutrition information.

Literature has mixed findings on the insurance role of social networks, while information on the role of social network in improving dietary diversity is scarce. This study evaluated effects of idiosyncratic shocks on social network formation; the effects of social networks in insuring household food consumption against idiosyncratic shocks; factors influencing formation of nutrition information network and effects of such networks on household dietary diversity.

The study was undertaken in Kisii and Nyamira counties of Kenya and data was collected using semi-structured questionnaires. A two-stage sampling procedure was used to identify the sample, farmer groups were first sampled and then households were sampled from the selected farmer groups. Two rounds of data were collected, the first round between October and December 2015, and the second was round between October and December 2016. A total of 824 and 745 farmers were interviewed in the first and second rounds respectively.

A dyadic linear probability model was used to evaluate the effects of shocks on the formation of financial and non-financial networks as informal risk sharing strategies. Findings showed that kinship, geographical proximity, education and age are important determinants of both financial and non-financial links, while health shocks influences formation of financial links.

The effects of health shocks on food consumption and also the effects of social networks in insuring food consumption against health shocks were estimated using a fixed effects model. The finding showed that health shocks have a negative and significant effect on purchased food but not on total food consumption. The results further indicate that financial credit networks have positive and significant effect in insuring food consumption against health shocks.

Lastly, factors influencing nutrition information link formation, and the effects of such networks on household dietary diversity in Kenya were estimated using Probit and Poisson regression models respectively. The results indicate that education level and the number of neighbours positively affect the probability of having a nutrition information network. Further, the average household dietary diversity of an individual's network members has a positive effect on the dietary diversity of the individual. Furthermore, education level of an individual's network members, household size, wealth status and farm size also have a positive effect on household dietary diversity.

The study concluded that social networks play a risk sharing role and insure food consumption against idiosyncratic shocks, though the social networks don't provide full risk sharing against health shocks. Therefore, policy makers would make policies, for the public sector to create safety nets that complement the ones formed by the smallholders, to enhance resilience to shocks sharing. Additionally, there is need to implement nutrition education programs targeting to improve the quality of diets. Such programs can use social networks as pathways through which nutrition information flows and would also widen nutrition information networks among smallholder farmers. Most importantly, the programs can take advantage of the social multiplier effect generated by the endogenous network effects.

CHAPTER ONE

INTRODUCTION

1.1 Background

While malnutrition is a global problem, it is more prominent in sub-Saharan Africa (SSA) and Asia (IFPRI, 2016). Malnutrition exhibits itself in the form of undernourishment, micronutrient deficiency and over-nutrition (Gomez *et al*., 2013). Undernourishment and micronutrient deficiency are particularly common in the rural areas of SSA (FAO, 2015). Undernourishment is insufficient consumption of food to meet dietary energy requirements (FAO, 2009). Micronutrients deficiency, also referred as "hidden hunger" is insufficient intake of micronutrients (such as vitamin A, iodine, zinc and iron) or essential vitamins and minerals (USAID *et al.,* 2009).

Undernourishment is majorly caused by protein energy malnutrition (PEM), which is insufficient intake of energy giving foods and proteins. According to FAO (2015), PEM is categorised as consumption of less than 1600-2000 calories per person per day. It results to retarded physical and mental growth and diseases. SSA countries are not able to meet the minimum caloric requirement. According WHO (2015), the per capita supply of calories has remained stagnant in most of the SSA and has reduced in the countries that are in economic transition.

In Kenya, 60 percent of the population is unable to meet the recommended calories intake per day (Mohajan, 2014). In Kisii and Nyamira Counties, the interest area of the study, 47 percent of the total population, went all day without food while 36 percent slept hungry in 2014 (African Women's Studies Centre (AWSC), 2014). The eating patterns has resulted to consumption of insufficient calories within the populations in the counties.

Micronutrient deficient is referred to as “hidden hunger” because, the signs and symptoms of micronutrients deficiency may not be always obvious but causes sometimes, lifelong health challenges and mental impairment (USAID *et al.,* 2009). For example, while lack of vitamin A has no symptoms, it can cause blindness, compromised intellectual development in children and reduced immunity which can lead to early deaths. Lack of enough iron in the body cause anaemia which can cause death and also compromises mental development.

Vitamin A, iron, iodine and zinc deficiencies are among deficiency that result to major health problems among children below five years and pregnant and lactating women (Bain *et al.,* 2013). In SSA, 48 percent of children below 5 year have Vitamin A deficiency and about 50 percent pregnant women have iron deficiency (WHO 2013). In Kenya, regardless of the ongoing camping which targets giving Vitamin A capsule to children below 5 after every six months, there are still high levels (80 percent) of vitamin A deficiency in children (KNBS *et al.,* 2015). Iron deficiency causes anaemia in 36 percent of children below 5 years and 42 percent of pregnant (KNBS *et al.,* 2015).

Anthropometric measures are one of the proxies that are used to assess the severity of undernourishment and micronutrients deficiency. The measures give indicators such as stunting, underweight, wasting and body mass index (BMI). These indicators have shown that the prevalence of malnutrition is high in SSA where about 39 percent of the children under five years of age are stunted, 24 percent are underweight and 10 percent are wasted (WHO, 2010). Stunting and underweight are more prominent in East Africa while wasting is highest in West Africa (Akombi *et al.,* 2017).

In Kenya, the situation is not different from the rest of SSA. Kenya is still one of the 36 countries that make up 90 percent of the global burden of under-nutrition (Black *et al.,* 2008). According to the Kenya Demographic and Health Survey (KDHS) (2014), 26 percent of children under five are stunted, 11 percent are underweight and 4 percent wasted. Particular, in Kisii and Nyamira Counties, 25.5 percent of all the children in both Nyamira and Kisii are stunted, and a further 9.6 and 8.4 percent are underweight in the two counties respectively (KHDS, 2014).

To address the challenge of malnutrition, Ruel (2003a) suggested that food and nutrition policies should consider both sufficient calorie intake and diversification of diets. Insufficient calories intake causes malnutrition due to deficient or imbalanced intake of nutrients for proper tissue and organ function (WHO, 2018). Diversification of diets on the other hand, has positive correlations with nutrient density and adequacy of diets of people or groups of people such as women and children (Arimond *et al.,* 2010; Kennedy *et al*., 2007a) hence, it is key in curbing malnutrition.

Consumption of sufficient calories in a household is dependent upon the household's food supply. One of the major factors that adversely affect availability and access to enough quantity and quality of food is shocks that affect household incomes and food supply (Fafchamps, 2010). These shocks come in form of death, acute illness and loss of a job of household members, natural calamities or adverse changes in input and output prices (Wossen *et al.,* 2016). These shocks affect food supply through, reduced household incomes and food production due to constrained family labour (in case of sickness and death), bad weather, and price fluctuations.

Given that the effects of the shocks depend on ability of the household to insure itself, farmers need to have both the access and the wherewithal to insure themselves. This presupposes that such households have access to financial and insurance markets (Islam and Maitra, 2012). Unfortunately, financial and insurance markets in many rural areas of SSA are either missing or poorly developed, causing increased food insecurity and poverty (Karlan *et al.,* 2014). This has led to extensive reliance on informal insurance strategies (Cervantes-Godoy *et al.,* 2013).

Consumption of diversified diets is dependent on several major drivers among them nutrition knowledge (Kuchenbecker *et al.,* 2017; Ragasa *et al.,* 2017). According to Murendo et *al.* (2018), nutrition education, particularly child feeding and child care information, has been shown to have a positive effect on household's, children's and women's dietary diversity However, according to Odini (2014), one of the greatest challenges in the rural areas of SSA, is that the flow of information through formal channels, is limited. Consequently, the limited access to nutrition information has led to low dietary diversity and persistent malnutrition (Murendo et *al.,* 2018).

Use of social networks is one of the informal strategies that have been widely used by households to overcome market failures (inefficient circulation of goods and services in a free market) and substitute for poorly performing institutions (Adelman, 2013). In absence of formal insurance against idiosyncratic and covariate shocks smallholder farmers in SSA rely on social networks, among other strategies, to insure themselves against shocks (Debebe *et al.,* 2013). Additionally, social networks also play an important role as a source of information in cases where flow of the information through formal channels, is limited (Chuang and Schecheter, 2015).

Marin and Wellman (2011) define social networks as an informal structure made up of actors (individuals or groups of people) that are connected to each other through socially-meaningful relations such as family, friends, trust-based relations, and/or information sharing relations. The actors in a network are referred to as the nodes while the relations are the links. The relations in a network are pathways through which material resources and information are mainly transferred within the networks (Berman, 2007; Lauber *et al.*, 2008; Maerten and Barret, 2012).

Transfers of material resources, such as loans and gifts within networks play a risk-sharing role (Bramoulle and Kranto, 2007). Moreover, transfer of information through social interactions within networks lead to social learning, which enable individuals to obtain new information which may in turn influence their decisions (Bandiera and Rasul, 2006). There is therefore a need to understand whether and how social networks can be harnessed as a way of curbing malnutrition through insuring household food consumption against shocks, which leads to sufficient food supply, and improving household dietary diversity through nutrition information flow within social networks.

In Kenya, social networks have potential in promoting adoption of technologies and food security. Hogset, (2005) argues that the adoption of improved natural resource management techniques in Kenya is influenced by information network and not through materials transferred within the networks. Thuo *et al.* (2014) emphasizes that information transferred within social networks influences adoption of improved groundnut varieties in Kenya. Additionally, Lamb (2011) using qualitative analysis indicate that there is a positive correlation between food acquisition networks and food security of households in Kenya.

1.2 Statement of the Problem

There is a growing body of literature that shows how social networks, as informal insurance strategies, have helped households insure their food consumption against shocks (De Weerdt and Dercon, 2006; Kinnan and Townsend, 2012; Di Falco and Bulte, 2013; Wossen *et al.,* 2016). The results have presented mixed findings postulating that the insurance roles of network depend on the types of network and the network structures that are different within different communities.

Moreover, several recent studies have examined the role of information networks in improving different agricultural and financial outcomes. For example, Muange and Schwarze (2014) found positive effect of agricultural information network on adoption of improved crop varieties in Tanzania. Mekonnen *et al.* (2018) found the agricultural information network had a positive influence on banana productivity in Ethiopia, while Murendo *et al.* (2018) found that financial information networks had a positive effects on mobile money use in Uganda. However, the role of nutrition information networks in improving household dietary diversity in Kenya is not known.

Broadly, farmers have been known to form social networks, but whether such networks have any effect on food consumption and/ or dietary diversity among small holder farmers in Kenya and particularly in Kisii and Nyamira Counties, is not known. This study fills the gap by providing information and evidence on whether social networks can be used to insure households against shocks as well as improve their dietary diversity in an effort to curb malnutrition in Kisii and Nyamira Counties, Kenya.

1.3 Purpose and Objectives of the study

The purpose of this study was to evaluate the effect of social networks on household food consumption among smallholder farmers in Nyamira and Kisii counties of Kenya.

The specific objectives study were:

i. To evaluate the effect of idiosyncratic shocks on the formation of credit and food sharing networks in Kisii and Nyamira Counties.

ii. To evaluate the effect of credit and food sharing networks in insuring household food consumption against idiosyncratic shocks in Kisii and Nyamira Counties.

iii. To assess the effect of nutrition information networks on household dietary diversity amongst smallholder farmers in Kisii and Nyamira Counties.

1.4 Hypotheses

The hypotheses tested were that:

i. Idiosyncratic shocks have no influence in the formation of credit and food sharing networks amongst smallholder farmers in Kisii and Nyamira Counties.

ii. Credit and food sharing networks have no effect in insuring household food consumption against idiosyncratic shocks amongst smallholder farmers in Kisii and Nyamira Counties.

iii. Nutrition information networks have no effect on household dietary diversity amongst smallholder farmers in Kisii and Nyamira Counties.

1.5 Justification for the Study

At 53 percent, malnutrition is the single greatest contributor to the mortality of children under five in Kenya (Kamenwa, 2017). Nearly 30 percent of Kenya's children are undernourished while another 26 percent are stunted (Kamenwa, 2017) and 25 percent of households have low dietary diversity (Smith *et al.*, 2006). Consumption of sufficient calories and improved dietary diversity (which is a proxy for dietary quality), are important factors in curbing malnutrition (Ruel, 2003a). Thus, the need for research to inform policy on ways to curb malnutrition through consumption of diversified diets and sufficient calories.

Insurance of food consumption against shocks and nutrition education are important strategies of improving quantity and quality of diets. Given the missing or malfunctioning formal institutions to achieve these, social networks can be an important informal strategy through their risk sharing and social learning roles (Pachucki *et al*., 2011). Therefore, understanding the role that social networks play in mitigating food shocks and improving dietary diversity can help to inform nutrition practitioners and policy makers on how to harness social networks while designing policies and strategies aimed at curbing malnutrition.

The study was carried out in Kisii and Nyamira counties where, despite high agricultural productivity, high levels of malnutrition are still prevalent. For example 25.5 percent of all the children in both Nyamira and Kisii were stunted, and a further 9.6 and 8.4 percent are underweight in the two counties respectively (KHDS, 2014). Malnutrition in this region is caused by food shortages which have been partly attributed to the shocks induced on food and incomes by covariate and idiosyncratic risks (Otiso *et al.*, 2016) and low dietary diversity (Frempong and Annim, 2017).

The results of therefore study will contribute to achieving the United Nations' second sustainable development goal (SDG) that aims at ending hunger, attaining food security and enhanced nutrition (FAO *et al.*, 2015). They will also address the food security agenda of Kenya's Vision 2030 (Government of Kenya, 2007) and food security pillar of the Kenya's Big 4 Agenda by recommending policies on harnessing social networks to improve diet quality and household food consumption. Lastly, the study will contribute to the scientific knowledge by enlarging the scanty literature on the linkages between social networks, dietary diversity and food shocks in Kenyan households.

1.6 Organization of the thesis

The rest of the thesis is organized into five chapters. Chapter two presents a general review of the literature. Chapter three presents the first paper that addresses the first objective of this thesis entitled *'Social networks and ex post risk management among smallholder farmers in Kenya'*. Chapter four addresses the second objective and presents the second paper entitled *'Effects of social network in insuring household food consumption against idiosyncratic shocks'*. Chapter five presents the third paper, *'Effect of social networks on household dietary diversity: evidence from smallholder farmers in Kenya'*, which addresses the third objective. Lastly Chapter six presents a general summary, conclusions and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Malnutrition in Kenya

In Africa, Kenya is the only country that is on course to meet all five World Health Assembly's (WHA) maternal and child nutrition targets endorsed in 2012–2013 (IFPRI, 2015). These targets, are measured by tracking stunting, wasting, and overweight among children under five; anaemia in women 15–49 years of age, and rates of exclusive breastfeeding for infants younger than six months of age (IFPRI, 2015). However, even with such progress, malnutrition is still a major public health problem in Kenya that needs urgent attention (Kamenwa, 2017).

Malnutrition is a condition leading to poor body performance and clinical outcomes due to a deficiency or imbalance of energy, proteins, and other nutrients (Stratton *et al.,* 2003). The major cause of malnutrition is lack of sufficient food (both in quantity and quality). For instance, over ten million people in Kenya suffer from chronic food insecurity and poor nutrition and 2-4 million people need emergency food aid at any specific time (Kamenwa, 2017). Malnutrition can be categorised as protein-energy malnutrition and micronutrients deficiency.

Protein-energy malnutrition is a nutritional deficiency caused by either inadequate energy (caloric) or protein intake. It majorly affects children below five years, leading to stunting and underweight in children when mild and to marasmus, kwashiorkor or marasmic-, kwashiorkor when severe (Ayaya et al., 2004). Protein-energy malnutrition affects the physical and mental development of children even in their later years (Kwena and Baliddawa, 2012). According to (KDHS, 2014), its prevalence in Kenya stands at 26 % stunting and 14 % underweight in children below five years.

Micronutrient deficiency is also a major contributor of malnutrition probably second after protein energy malnutrition. Vitamin A and iron deficiency are among the micronutrients deficiency that lead to significance health problems in Kenya (Othoo et al., 2014). On one hand, Vitamin A deficiency (VAD) is a leading cause of blindness in children who are below five years of age and also affects birth outcomes in pregnant women (Oyunga *et al.,* 2016). In Kenya, around 80 percent of preschool-aged children and 17 percent of pregnant women in Kenya are deficient in vitamin A (WHO, 2009).

On the other hand, iron deficiency is the leading cause of anaemia mostly in children who are below three years and pregnant and lactating women (Stephen *et al.*, 2018). The Iron deficiency anaemia among pregnant women can lead to premature birth, low birth weight, and maternal mortality while it reads to retarded growth and development in children (Abu-Ouf *et al.*, 2015). There is prevalence of iron deficiency in Kenya with 69 percent of preschool-aged children and 55 percent pregnant women having iron-deficiency (WHO, 2008). There is therefore, a need to come up with policies that will help in overcoming the challenge of malnutrition by enhancing access of sufficient quantities and quality food in Kenya.

Literature suggest several ways of dealing with the problem of malnutrition. According to Deckelbaum *et al*. (2006), under-nutrition and micronutrient deficiency can be dealt with efficiently by linking agriculture to human nutrition. This is because agriculture is the principal supplier of calories and fundamental nutrients and is currently the most crucial source of income for 80 percent of the world’s poor (IFPRI and ILRI, 2010). Deckelbaum *et al*. (2006) argues that efficiency in agriculture production and increased farm diversity would lead to increased food supply and improved dietary diversity respectively.

Empirical research has shown positive linkages between farm diversity and dietary diversity among smallholder farmers (Jones *et al.,* 2014; Sibhatu, *et al.,* 2015). This means that increased farm diversity could be used as a tool to reduce malnutrition by increasing the dietary diversity of the farming households. Additionally, Cassidy *et al.* (2013) argues that if food was grown solely for direct human consumption, the available food calories would increase by about 70 percent which could feed 4 billion people, more people than the projected world population growth of 2- 3 billion.

However, according to Berners-Lee *et al,* (2018) for the agricultural food systems to be efficient and sustainable, first, food production must be adequate, in quantity and quality, to provide food without adverse environmental impacts. Secondly, food distribution must also be efficient to make sure quality food with adequate nutrition is available to all (Berners-Lee *et al.,* 2018). In Kenya, inequalities in the caloric intake are pronounced. For instance, the poorest 10 percent consume on average 918 calories per day (slightly above half of daily requirement) while the wealthiest 10 percent consume on average 3,330 calories (twice the daily requirement) (Kamenwa, 2017). Thirdly, socio-economic status must be equitable to allow every consumer to access adequate food for a healthy diet (Berners-Lee *et al.,* 2018). Lastly, consumers need to be informed so that they can make informed decisions on consuming healthy diets (*ibid*).

Hence, the challenge of malnutrition cuts across sectors and the solution requires effective collaboration of different sectors (Oshaug and Haddad, 2002). However, in most developing countries, nutrition is placed in one Ministry, for example, in Kenya, nutrition is placed under the Ministry of Health. There is a need for a multi-disciplinary approach to solving malnutrition. To achieve food and nutrition security, incentives should be put in place cross-ministerial policies and programs (Oshaug and Haddad, 2002).

2.2 The concept of social network

Social networks consist of a set of actors connected through social relationships such as blood relations and friendships (Garton *et al.*, 1997). A social network dataset is defined by actors and relations (links) through which material goods and information are exchanged between the actors (Hanneman and Riddle 2005). The simplest form of a social network is a “dyad”. A dyad defines the relationship between two connected actors in which one actor (the one whose network is being studied), is called the “ego” while his match or partner is referred to as the “alter” (Smith and Christakis, 2008).

Social network analysis involves analyzing the relations (ties) among individuals or groups or institutions. It highlights the significance of the organization of the network as well as the quality of the relations among actors in the networks (Caniels and Romijn, 2008). The organizational characteristic of a social network is related to the number (network size) (Muange *et al.,* 2015) and importance (centrality) of the links in a network, and their closeness or connectedness (Jackson, 2011).

The quality of relations between actors mainly focuses on the strength of connections (strength of the network links) between different actors (Granovetter, 1973), which, in turn, is measured by the emotional strength of the link (Granovetter, 2005), duration of the relationship between different actors (Son and Lin, 2012) or the frequency of contact between different actors (Fu *et al.*, 2013; Murendo *et al.,* 2018). Strong network ties define relations among individuals who are emotionally connected within a social network (i.e, kinship, friendship, and neighbourhood). Weak ties, on the other hand, define relations that link a network to the society at large.

Social networks have been useful in studying the general behaviour of individuals as well as their decisions and choices (Granovetter, 2005). Such decisions are influenced by either social learning (new information) or social influence (imitation) within the networks. The outcome of such decisions could be improved firm productivity, health and nutrition, and profitability (Borgatti *et al*., 2009; Kimura, 2011). Social networks also act as an informal risk sharing strategy through resource transfers within the networks (Munshi and Rosenzweig, 2016). The risk sharing networks are very useful because they act as an informal insurance especially in the rural communities where insurance and financial markets are either missing or poorly developed (Karlan *et al.,* 2014).

Social networks were first described by Durkheim (1895). Writing about "social facts", Durkheim (1895) describe social networks as phenomena that are formed by the interactions of individuals, yet constitute a structure that is independent of any individual actor. Social network analysis was first applied to educational psychology and child development, where children in school were found to associate with other children who had similar intelligence quotient (IQ) as theirs (Almack, 1922; Wellman, 1926; Bott, 1928). These studies however raised issues such as how to link attributes (such as IQ) with network interactions and the difference between observed and self-reported patterns of interactions.

Social networks gained currency in economic sociology and anthropology after the 1950s. The research gave attention to various network concepts including the strength of weak ties and "small worlds". The network also became central in research on social capita. For example, Granovetter (1973) carried out research on the strength of weak ties and argued that weak ties are more important in politics or employment seeking than strong ties because weak ties connect individual to many more others.

There has been a resurging interest in the application of the social network concept in agricultural economics in the recent past. This is partly due to the believe that social networks could be useful in information dissemination channels through social learning particularly among smallholder farmers in rural areas where formal infrastructure is poorly developed or completely missing (Odini, 2014). In addition, social networks could also serve as platforms for providing informal insurance against risks in the rural areas characterized by incomplete or missing markets (Karlan *et al.,* 2014).

Accordingly, the concept of social network has been applied to evaluate the adoption of agricultural technologies, agricultural productivity and financial decisions among small holder farmers. For example Maertens and Barrett, 2013 and Muange and Schwarze, 2014 focused on effects of agricultural information networks on adoption of *Bacillus thurigiensis* (Bt) cotton and improved varieties respectively and found positive effects of social network. Van den Broeck and Dercon, (2011), Muange *et al.* (2015) focused on agricultural productivity of banana and sorghum respectively, they both found positive effects of social network on the productivity. Murendo *et al.* (2018) evaluated effects of social networks on adoption of mobile money among smallholder farmers in Uganda and found positive effects of social networks.

The concept of social networks is also increasingly being applied to investigate the role of social networks in risk sharing among smallholder farmers who are vulnerable to covariate and idiosyncratic risks. Most of the studies have focused on the role of social networks in insuring household food and non-food consumption against shocks among small holder farmers. For example, Fafchamps and Gubert (2007) and De Weerdt and Fafchamps (2010) evaluated the risk sharing role of social networks in the presence of shocks. They both found that social networks insures households against health shocks.

2.2.1 Measurement of social networks

Identifying and measuring social networks is not an easy task. The process is riddled with challenges including how to select an appropriate reference group (i.e., actors to be studied) as well as how to identify the actors that make up an individual's network. In empirical work, the first of the two challenges is addressed by use of full networks, partial (snow-balling) or personal (ego-centric) network methods (Hanneman and Riddle, 2005).

The full network approach involves a census of all the study subjects. Information about each actor's relations with all other actors is collected with the aim of describing the properties of the entire social network in a selected population (Lucas and Mayne, 2013). The limitations of this approach is that it is both costly and time-intensive and hence of limited practical use in large target populations. Additionally, a census of a small population increases the chances of falsely truncating the social networks being studied (Maertens and Barett, 2013). Because the current study targeted a large population, this approach could not be employed.

The partial networks method involves collecting information from part of the population (Lucas and Mayne, 2013). The networks so captured result from snowball sampling where a principal actor(s), who are purposively selected, are required to mention some or all of their relations with other actors (Hanneman and Riddle, 2005). The identified actors are then asked to mention their relations. The same process is repeated until there are no new actors being mentioned (*ibid.*). This method is mostly used when targeting a sub-sample of subjects in a large population. The main weakness of this method is that it results in a non-representative sample of the target population thus making it difficult to make inferences from the results (Maertens and Barett, 2013). It could therefore not be applied in this study.

Recent literature (such as, Bandiera and Rasul, 2002; Boahene *et al.*, 1999; Conley and Udry, 2001; Miguel and Kremer, 2003) has challenged both full and partial social network analysis approaches by indicating that individuals do not depend on the entire population to form meaningful relations. Rather, these authors note, individuals depend on diminutive personal social networks which do not essentially correspond to geographic borders. The personal social network approach involves sampling of the focal actors (ego) who then identify the actors (alters) that they are connected to (Hanneman and Riddle, 2005). Therefore, this study employed the personal social network approach to understand how personal networks affect risk management and dietary diversity of the ego.

The use of the personal social network approach requires information on an individual's social network. This poses the second challenge of identifying the actors that make up an individual's network. Three approaches have been suggested in the literature to define an individual's social network, i.e., direct enquiry method, matches within-sample, and random matching within sample (Fafchamps and Gubert, 2007; Tatlonghari *et al*., 2012).

In direct enquiry, one can ask the ego to mention a fixed number of individuals or, in some cases, unlimited number that s/he has ties with (Bandiera and Rasul, 2006; Tatlonghari *et al*., 2012). The weakness of this approach is that if the survey limits the number of ties that the individual can list, truncation bias occurs in estimates of individual's behaviour (Momeni, 2017). Additionally, individuals are likely to name only the relations with whom they have strong social network ties thereby ignoring those with whom they have weaker ties, again resulting in biased estimates of network properties (Momeni, 2017).

To make sure that both strong and weak network ties are captured, the ‘matches within-sample’ method has been proposed (Santos and Barrett, 2008). In this method, each study subject is asked about their relationship with all others in the sample (Santos and Barrett, 2008). This method is time-intensive especially when dealing with a large sample. To overcome the time challenge, random matching within sample method could be used where every individual in the sample is matched with only a particular number of individuals who are randomly selected from the sample (Conley and Udry, 2010). This approach however, falsely shortens the social network and results in biased estimates of behaviour (Chandrasekhar and Lewis, 2011).

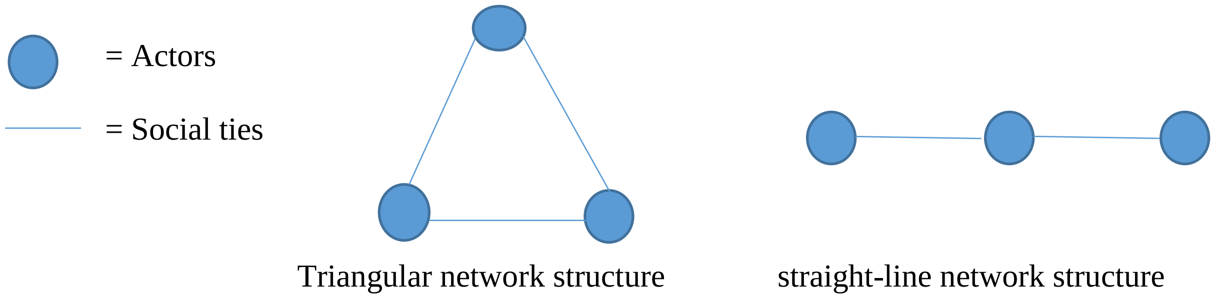
Despite its limitation, this study employed a modified matches within sample method suggested by Munshi (2004). The modification involved clustering household into farmer groups where each respondent was matched with all members of their group, instead of being matched with everybody in the whole sample. This helped in reducing the intensity of the time needed and also reduced the chances of truncating the networks. Smallholder farmer groups were used as sub-samples of the whole sample where actors were asked about their relationship with all the actors in the famer groups instead of all the actors in the whole sample.

2.2.2 Theories explaining social networks

The concept of social network is anchored in the body of literature referred to as the economic sociology. Economic sociology posits four basic components of social networks based on their social significance, structural, resource, normative and dynamic components (Davern, 1997). It argues that the magnitude of impacts of social networks depends on the actors’ position in the network structure, the resources accessible to actors within the networks, the rules and norms guiding the networks and also the changes in the network over time.

The structural component defines the geometric shapes formed by the connections (ties) of different actors within the network as well as the strength of the ties (Davern, 1997). Figure 1 presents networks structure. Assuming that actors are connected with lines which represent social ties, three actors connected to each other will form a triangle while two actors will from a straight line (Figure 1). The different network shapes influences the social impact of the networks and hence they explain the differences in the level of exchange within the networks (Markovsky *et al.*, 1993). For instance, an actor connected to different actors in a straight line has a stronger network position relative to others while no body has strength advantage in a triangular network structure.

Illustration: Example of network structures



Adopted from Davern, 1997

Figure 1. Network structure

The resource component involves the distribution of resources that differentiate people with the same structural network positions (Davern, 1997). It focuses on non-structural resources that are available to actors through network ties such as gender, ability, class, knowledge etc. An actor connected to several actors who have high-status has more resources than the one connected to low-status actors only (Davern, 1997). Useem (1984) applied the resource component to study how they influence interlocking dictatorship in United States while Stanton-Salazar and Sanford (1995) focused on how information resources within social network influenced reproductive inequalities among high school students in Mexico.

The normative component refers to the norms, rules and sanctions that control the conduct of the actors in a network (Coleman, 1990). The normative characteristics influence the process of exchange within networks. Network exchange thrives where there is trust among the network members, effective rules that govern the networks and effect sanctions to enforce the rules (Davern, 1997). This explains why some sections of the society performs better than others. Lastly is the dynamic component which defines changes of networks over time. It is the least studied component of social networks yet it can give good insight on social network processes (Davern, 1997). It assumes that social networks are dynamic because actors create and dissolve network ties over time. Hallinan and Williams (1987) studied networks over time by studying the stability of interracial friendship among high school students where they found that individual characteristic were the strongest determinant of stable interracial friendships.

Several theories explain the formation and the impacts of social networks. Theories that explain the formation of network ties include rational self-interest and social exchange (Monge and Contractor, 2003) while those that explain the functioning (impacts) of social networks include social learning theory and economic theory of insurance (Bandura, 1977; Arrow, 1964). The existence of a multitude of theories underpinning the social network concept suggests lack of consensus on one single theory that explains formation and functioning of networks in totality.

Rational self-interest theories assume that individuals form relations with others or organizations either to maximize utility or minimize transaction costs (Katz *et al.*, 2004). Self-interest theories include social capital and transaction cost theories (*ibid*). The social capital theory assumes that individuals form social networks as an investment in social capital in expectation of utilizing social resources to maximize return on investment (Coleman, 1990; Lin, 2001).

Transaction cost theory assumes that organizations' networks can activate interpersonal communication networks which increase access to non-public information leading to reduced transaction costs (Henningsen *et al.,* 2013). Another assumption is that trust, cooperation and reciprocity involved in these networks reduce transaction costs and reduce opportunistic behaviour (Andriani, 2013). A weakness of self-interest theories is that they ignore altruism among the network members while literature argues that altruism and social network are interconnected (Curry and Dunbar, 2011).

A second family of theories from which social networks perspectives are drawn is social exchange and dependence theories. Based on these theories, the formation of social networks is based on the sharing of material resources and information between actors in a network (Monge and Contractor, 2003). The purpose is to establish social relations based on the actor's capability to reduce dependence on other individuals from whom they need resources and increase the reliance of others to whom they can offer resources (Katz *et al.,* 2004). These theories ignore the costs forming networks which include cost of enforcement, overcoming information asymmetry and moral hazards as well as conflicts (Fafchamps and Gubert, 2007). The costs are important aspect of network formation since rational individuals form networks after analysing the cost of enforcement within the networks.

As earlier indicated, social learning and economic theory of insurance are some of the theories that explain how social networks function. Bandura's (1977) social learning theory posits that individuals learn through observation, imitation and through other peoples' experiences. The learning is enhanced by social interactions within the network. Such interactions influence the attitudes, behaviour and performance of network members through social learning and social influence (Young, 2009; Hogset and Barrett, 2010; Mekonnen *et al.,* 2018).

Social learning enables individuals to obtain new information or affirm the already available information (Ruef, 2002). Such information shapes their opinions and attitudes directly or indirectly and, in turn, influences their decisions (Munshi, 2008; Conley and Udry, 2010). Therefore social learning is important in influencing different outcomes within households. According to Easley and Kleinberg (2010), social influence is an outcome of imitation through observations where individuals change their behaviour to conform to the observed behaviour of other individuals in their networks. One weakness of this theory is that it is only applicable when studying the effects of social networks where information is exchanged; it is not applicable where material resources are transferred within social networks (Munshi, 2008).

Lastly is the economic theory of insurance proposed by Arrow in 1964. The theory explains the risk sharing tendencies among individuals within a group. It posits that in a community where there are institutions that help in pooling risk to achieve Pareto optimality, consumption across the households in the community will be equalized. This implies that risk-sharing interactions will help the household to mitigate specific shocks, which ultimately balances the marginal utility of consumption across households in the community.

The application of the economic theory of insurance on social networks analysis assumes that given the poorly functioning formal risk-sharing institutions, social networks become an informal institution through which risk is shared (Islam and Maitra, 2011). Thus, financial and non-financial social transfers act as insurance to household with the social network. One of the weaknesses of applying the economic theory of insurance on social networks is its limited assumption that the only important transfers within networks are financial and non-financial gifts and loans (De Weerdt and Dercon, 2006; Munshi and Rosenzweig, 2016). It therefore does not regard the transfer of information within the networks.

2.2.3 Theoretical approaches for self-interest, social learning and insurance

This study used self-interest family of theories as the basis for the formation of social networks. Following Fafchamps and Gubert (2007), the study argued that individuals form social networks when the benefit accruing from the network outweigh the costs (Fafchamps and Gubert 2007). Ideally, the cost of maintaining a network link increases with social and geographical distances (Fafchamps and Gubert 2007). However, in a situation where the risks is correlated the more similar individuals are, the probability of forming a risk-sharing link increase as the social and geographical distances increase (Fafchamps and Gubert 2007).

Consumption smoothing was based on the economic theory of insurance which has been applied by Islam and Maitra (2012), Debebe (2013) and Wossen *et al.* (2016). The study argued that transfer of material resources insures network households against exogenous idiosyncratic shocks such as illnesses, death and job loss. It was assumed that food gifts and financial assistance (e.g., loans) that individuals shared within their networks would insure the household against food consumption shocks.

The social learning theory was used to explain the impact of social networks on dietary diversity. Several other studies such as Van den Broeck and Dercon (2011) and Muange and Schwarze (2014), have used the theory to explain how farmers acquire information within networks and how the information affects their adoption decisions. Mekonnen *et al.* (2016) used the theory to explain how social networks affect farm productivity. It was assumed that farmers acquire nutrition information or even imitate the feeding habits of their network members with whom they share nutrition information, which would, in turn, influence their own dietary diversity.

2.3 Review of past related studies

Several studies have explored the formation of different types of social networks. The networks that have mostly been studied include information and material (financial and non-financial) networks. The formation of material networks has mostly focused on networks within which financial gifts and loans and labour are transferred. Empirical studies have argued that transfers of such materials within networks play a risk-sharing role.

For instance, Fafchamps and Lund (2003) studied the effects of income and expenditure risk on formation of financial gifts, informal loans and labour transfer networks in the rural Philippines. The study used panel data and a fixed effect model to study the risk sharing networks. They found that income and expenditure shocks have a strong effect on gifts and informal loans implying that the shocks are insured by the networks. This study used panel data and fixed effects model unlike the current study which uses cross section data and Linear Probability Model (LPM) to study formation of risk sharing networks.

Fafchamps and Gubert (2007) studied the effect of income and health risks on formation of financial gifts and informal loans transfer networks in Philippines. The study used dyadic Logit to do the analysis and found that health shocks had an effect on financial gifts and informal loans networks formation while income shocks had no effect, suggesting that the networks are formed to only insure health shocks but not income shocks. They attributed this to farming households investing in other diversification strategies to insure themselves against income shocks such as off farm activities. This study used a similar theoretical approach but the current study used dyadic logit while the current study uses dyadic LPM.

De Weerdt and Fafchamps (2010) also studied the effect of income and health risks on formation of financial gifts and informal loans transfer networks in Tanzania using dyadic Logit. De Weerdt and Fafchamps (2010) reported that financial gifts- and informal loans-networks do not insure people from health shocks. The study argued that this could be suggestive of risk sharing based on altruism or social norms. The study used a similar theoretical approach with the current study, however it used a dyadic Logit while the current study uses dyadic LPM.

Several other studies have focused on the risk sharing role of social networks. Particularly, the effects of shocks on household consumption, and role of social networks in insuring household consumption against the shocks. For example, Wossen *et al.* (2016) focuses on the effects of covariate and idiosyncratic shocks on household consumption and the insurance role of social capita against the shocks in rural Ethiopia, using panel data. Fixed effect estimates indicated that shocks had a negative effect on total consumption (both food and non-food consumption). Further, the study found evidence of consumption smoothing through use of social capital as sources of informal insurance. The current study uses panel data and a similar model but the main focus is health shocks and food consumption only.

Similarly, Islam and Maitra (2012) estimated the effects of health shocks on household consumption and whether access to microcredit insures households against the shocks in Bangladesh. The study used panel data and estimated a fixed effects model. The results indicated that access to microcredit had a mitigating effect such that households that had access to microcredit did not have to sell their livestock when the experienced a health shock. The current study also uses fixed effects model and focuses on health shocks. However the current study focuses on the insurance role of informal credit and not formal credit (microcredit).

Genoni (2012) studied the effect of illness on food and non-food consumption and the consumption smoothing through transfer from relatives in India. They found a negative effect of illness on consumption. They estimated a fixed effect model using panel data. They also found out that households that experience shocks usually increase their labour supply and receive more transfer from relatives who live far from the household resident to mitigate the effects of the illness. The current study similarly uses fixed effect, but focuses on the consumption smoothing effect of informal loans and food sharing instead of transfers from relatives.

Kinnan and Townsend, (2012) studied the effects of kinship and financial networks on smoothing consumption in the presence of cash flow fluctuation in Thailand. They use panel data to estimate fixed effects model. The results showed that financial networks helped in smoothing consumption while the kinship network did not have any effect. The current study uses a similar approach and same model with this study. However the current study focuses on the smoothing effect of informal financial and food networks while the study under review focused on formal financial networks and kinship ties.

Di Falco and Bulte (2013) also studied the effect of kinship networks on the adoption of self-protection measure against weather shocks that affect household consumption in Ethiopia using a Probit model. Contrary to the expectations, they reported a negative effect of social networks on consumption smoothing due to free riding which reduces motivation of self-protection against shocks. This study focused on applying social networks as an *ex ante* strategies of dealing with weather shocks that affect household consumption while the current study focuses on effects of social network as an *ex post* strategies of dealing with effects of health shocks on household consumption.

The literature on the effect of information-related social networks has mainly concentrated on agricultural technology adoption, agricultural productivity, financial decisions, and health. For example, Muange and Schwarze (2014) assessed the effects of agricultural information on adoption of improved maize and sorghum varieties in Tanzania. The study employed average treatment effect (ATE) method. The results indicated that information networks influenced adoption of improved sorghum varieties but not maize. The while the study under review focused on agricultural information networks, the current study focuses on the effect of nutrition information networks on dietary diversity using Poisson method.

Murendo *et al.* (2018) evaluated the adoption of mobile banking among farmers in Uganda using conditional logistic regression. The study reported positive effect of the size of networks on adoption of money banking with the effects being more pronounced in richer households. The study expanded the application of social networks to financial decisions. The current study borrowed the theoretic approach and applied social networks in food and nutrition. However, the current study but uses a Poisson regression to estimate effect of social network on household dietary diversity scores.

Van den Broeck and Dercon (2011) and Mekonnen *et al.* (2018) assessed the effect of social networks on agricultural productivity in Tanzania and Ethiopia respectively. They both used Ordinary least squares (OLS). Van den Broeck and Dercon (2011) found that the effect of social networks depended on the type of network with social learning in kinship networks improving the productivity of banana while friendship and neighbourhood networks did not. In Mekonnen *et al.* (2018), farm productivity in Ethiopia was positively influenced by social networks. The current study adopts the theoretical approach of these studies, it however uses a Poisson regression unlike these two studies which used OLS.

In application of social network in the field of health, Oster and Thornton (2012) assessed the peer effect on uptake of menstrual cups in Nepal using panel data. The study used fixed effect logit model and reported that having a friend with access to a menstrual cup increase their usage. This study focused on friendship networks and their effect on adoption of menstrual cups while the current study focused on nutrition information network and their effect on household dietary diversity. This study and the current one are based on social learning theory.

Marquez *et al.* (2014) assessed the effect of network composition and interactions among actors on health-seeking behaviour (having yearly medical check-up, not taking alcohol, completely avoiding fast food, and having the recommended time for leisure physical activity and sleep) among adults in California. The study used multivariate logistic regression and found that size of network was positively associated with meeting the recommended time for leisure physical activity. The study focused on relationship of social network with health seeking behaviour while the current study focused on relationship of social network with food and nutrition. The two studies used different models for analysis, Marquez *et al.* (2014) used multivariate logistic regression while the current study uses Poisson regressions.

2.4 Summary

The foregoing review of literature reveals that most of the empirical studies on risk-sharing networks have focused on either financial or non-financial risks with no comparison of both aspects. Yet such comparisons would give a better understanding of the risk-sharing roles of material networks. Most of these studies have used dyadic probability models such us dyadic Logit and dyadic Probit, given that dyad is the unit of analysis in the social network formation data. The current study used dyadic linear probability models to estimate formation of food sharing and credit networks.

Studies on the role of social networks in household consumption smoothing in the presence of idiosyncratic and covariate shocks have had mixed results probably due to studying different types of networks and shocks. Therefore, more research focusing on different networks and different types of shock could enrich the growing social networks literature and perhaps lead to a better understanding about what specific networks insures what particular shocks within a defined context. Majority of such studies have used panel data and fixed effects models which is also the case in in the current study.

Studies on effects of social networks within the agricultural sector, have largely focused on agricultural information networks and their effect on technology adoption and productivity. Evidence on effects of nutrition information networks and their effect on household dietary diversity is virtually missing. Different studies have used different model depending on the nature of the outcome variable in question. Studies on adoption have widely used logit regressions while those on productivity have used OLS. This study uses Poisson regressions to estimate effects of social networks on dietary diversity since the household diversity score is a count data.

This study therefore contributes to the literature on the linkages between social networks, dietary diversity and food shocks in Kenyan households. Such information would help in identifying how social networks can be harnessed into improving the quality and quantity of food consumption among small holder farmers. This would lead to food and nutrition security and reduce malnutrition in the rural areas.

CHAPTER THREE

SOCIAL NETWORKS AND *EX POST* RISK MANAGEMENT AMONG SMALLHOLDER FARMERS IN KENYA[1]

Abstract

Smallholder farmers in developing countries are vulnerable to idiosyncratic and covariate risks. These risks affect their welfare through the shocks they impose on income, assets, health and food supply. To cope with such shocks, smallholder farmers have extensively relied on informal risk management strategies such as social networks due to poorly developed or missing formal insurance markets. Social networks play a risk-sharing role through transfers (loans and gifts) within the networks. This study evaluates the factors influencing the formation of financial and non-financial networks, as informal insurance strategies, using cross-sectional data collected from 815 households in Kenya and analysed using a dyadic linear probability model. The results show that kinship, geographical proximity, education and age of the respondents are important determinants of both financial and non-financial links. Additionally, the results reveal that health shocks are correlated with the formation of financial links. The findings suggest that financial links play a risk-sharing role when farmers are faced with health shocks. The study concludes that financial networks act as insurance against idiosyncratic health shocks.

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3.1 Introduction

Smallholder farmers in developing countries are vulnerable to idiosyncratic (household-level) and covariate (community) risks (Harttgen and Günther, 2006). Idiosyncratic risks arise from death or/ and acute illness, loss of a job and unemployment while covariate risks are caused by natural calamities such as bad weather conditions as well as adverse changes in input and output prices (Cervantes-Godoy *et al.* 2013). The two types of risks affect the welfare of the farmers through the shocks they impose on incomes, assets, health and food supply (Pinstrup-Anderson *et al.*, 2001; Fafchamps, 2010; Murendo *et al.*, 2011).

To cope with the shocks, the smallholder farmers can reduce risks *ex ante* or they can cope with the resulting shocks *ex post*. According to Lekprichakul (2009), *ex ante* strategies are taken before risky occurrences take place to evade, transfer or minimize risks or exposure to risks. Cervantes-Godoy *et al.* (2013) further argue that the most common *ex ante* strategies among smallholder farmers include diversification of economic activities, accumulation of savings and assets to cater for the absent credit markets, limited adoption of risky technologies and participation in informal saving institutions.

Ex post strategies are undertaken after the shocks have occurred to mitigate their effects on the welfare of smallholder farmers (Lekprichakul, 2009). *Ex post* strategies include adjustment of farming efforts and labour sources, migrating, selling assets, borrowing, reducing consumption or relying on their social networks (Cervantes-Godoy *et al.*, 2013). Formal risk management approaches are however not easily available to most farmers especially smallholders in developing countries due to the poorly developed or absent formal insurance institutions, leading to extensive reliance on informal strategies (Cervantes-Godoy *et al.*, 2013).

Use of social networks is one of the informal strategies that have been widely used by households to overcome market failures and substitute for poorly performing institutions (Adelman, 2013). A social network is a structure made up of actors (individuals or groups of people) that are connected to each other by socially meaningful relations such as family ties, friendship, trust-based relations and/or information sharing relations (Wellman and Berkowitz, 1988; Marin and Wellman, 2011). The actors in a network are referred to as the nodes while the relations are the links. The relations are the pathways through which information, money, goods or services flow among the actors in the network (Maertens and Barret, 2012).

In the absence of formal insurance, smallholders mitigate effects of shocks by developing informal mutual insurance arrangements among themselves (Fafchamps and Lund, 2003; Bramoulle and Kranto, 2007). Through the informal insurance, the needy are assured of survival and are aware that reciprocity is expected from them in future (Ligon *et al.*, 1997). Empirical studies have argued that such informal insurance arrangements are done through provision of soft loans and gifts within the networks, which play a risk-sharing role (De Weerdt and Dercon, 2006; Munshi and Rosenzweig, 2016).

Most empirical evidence on risk sharing networks has focused either on financial or non-financial risk sharing networks, but not both in the same setting as is the case in this study. For instance, Fafchamps and Lund (2003) focused on financial gifts, informal loans and labour transfer links as income and expenditure risk sharing networks. Fafchamps and Gubert (2007) and De Weerdt and Fafchamps (2011) studied financial gifts and informal loans transfer links as income and health risk sharing networks. Although a study like Matous *et al.* (2013) studied social and geographical determinants of financial and non-financial networks, their study did not capture the risk-sharing aspects of the networks studied.

This study evaluates the factors influencing formation of credit (financial) and food sharing (non-financial) networks and tests whether the networks help farmers deal with idiosyncratic income and health shocks *ex post*, in Kisii and Nyamira counties in Kenya. The findings of this study address a fundamental question of ‘does the formation of non-financial networks, in fact, overlap with the formation of financial networks, and are they formed as an insurance to health and income shocks.

The rest of this study is organized as follows; study methods which explain data sources and the study’s theoretical and empirical approaches are discussed in section 3.2. The results are discussed in section 3.3 while the conclusions and policy implications of the study are discussed in section 3.4.

3.2 Study methods

3.2.1 Theoretical framework

The decision to form a risk-sharing network can be modelled using discrete choice models. Such models can be based on two theories: random utility theory (RUT) and expected utility theory (EUT). The two theories assume that given a set of alternatives, individuals choose the alternative that gives the highest utility (Batz *et al*., 1999; Debertin, 2002). RUT assumes that choices are made in an environment with no uncertainties in the outcome, such that the preferences of the outcome are revealed. On the other hand, EUT is applied when choices are made amidst uncertainties and therefore preferences are stated (Polak and Liu, 2006). Thus, for the case of EUT, the outcomes of the choices made are not known, implying that, individuals can only expect the outcome.

Given that risk-sharing networks are not a totally new concept to farmers, this study assumes that the preferences for the outcome (risk sharing) are already known. Therefore, the decision to form food-sharing links in the case of this study is founded on the RUT. According to Fafchamps and Gubert (2007), a link is expected to be formed if its benefits are more than the cost of maintaining it such that:

$L_{ij} = 1 \; if \; B(d_{ij}, 1) - B(d_{ij,}0) - C(d_{ij}) + e_{ij} > 0$, and 0 otherwise………………….... (3.1)

where $L_{ij} = 1$ denotes the presence of a link between individuals *i* and *j*, while $L_{ij} = 0$ means otherwise; d_{ij} is the geographical and social distance between individuals *i* and *j*. $B(d_{ij}, L_{ij} = 1) - B(d_{ij,}L_{ij} = 0)$ is the net benefit from forming the link while $C(d_{ij})$ represents the cost of sustaining the link, and e_{ij} is the error term. The study uses geographical distance and socioeconomic factors such as blood relation, age, education income, farm size and gender to measure the social distance between farmer *i* and *j* (Van den Broeck and Dercon, 2011; Muange *et al.*, 2014; Mekonnen, 2016).

The cost of maintaining the link (cost of enforcement, overcoming information asymmetry and moral hazard) is expected to increase with social and geographical distance. (Fafchamps and Gubert, 2007). Consequently, it is expected that individuals would mostly form links with people who are similar to them (McPherson *et al.*, 2006) and also those who are geographically closer to them. However, in a situation where the risk is correlated the more similar individuals are, then the probability of forming a risk-sharing link would increase as the social and geographical distances increase. In such cases, individuals mostly form links with others who are different or geographically far from them to maximize the benefits of the networks (Fafchamps and Gubert, 2007).

3.2.2 Analytical issues in network analysis

The fundamental unit of analysis in social networks is a dyad, which defines the relationship between a pair of connected actors (Shafie, 2015). Therefore, social network analysis leads to regressions which are dyadic in nature. Estimating dyadic regression raises two challenges namely; identification and inference.

According to Fafchamps and Gubert (2007), the problem of identification occurs due to the nature of the independent variables in dyadic regressions. The variables, which include characteristics of the links between individuals *i* and *j* (w_{ij}) and also the attributes of the nodes (individuals in the network) *i* and *j* (x_i and x_j), must be specified in a symmetrical way to make sure the effects of (x_i, x_j) on the outcome, Y_{ij}, is the same as effects of (x_j, x_i) on Y_{ji} (Fafchamps and Gubert, 2007).

However, specifying the regressors in a symmetrical manner depends on the nature of the dyadic relationship, whether it is directional, such that $Y_{ij} \neq Y_{ji}$ for all *i* and *j* or not directional such that $Y_{ij} = Y_{ji}$ for all *i* and *j* (Fafchamps and Gubert, 2007). The nature of the relationship helps in determining the form in which the regressors enter the regression. On the one hand, if the dyadic relationship is not directional such that, $Y_{ij} = Y_{ji}$ for all *i* and *j*, then regressors $x_i - x_j$ and w_{ij} should enter the equation as absolute values. In such a case the model is specified as:

$$Y_{ij} = \alpha + \beta_1|x_i - x_j| + \beta_2(x_i + x_j) + |w_{ij}| + u_{ij} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.2)$$

On the other hand, if the relationship is directional such that $Y_{ij} \neq Y_{ji}$ for all *i* and *j*, the regressors $x_i - x_j$ and w_{ij} enter as actual values as specified:

$$Y_{ij} = \alpha + \beta_1(x_i - x_j) + \beta_2(x_i + x_j) + w_{ij} + u_{ij} \quad (3.3)$$

Another consideration when solving the problem of identification is the distribution of nodes degree (the number of links an individual has with other individuals in the network). Fafchamps and Gubert (2007) argue that, in cases where all individuals have the same degree, the combined level effects (β_2) cannot be identified due to the dyadic nature of the observations, meaning that only the effects of the differences between the observations (β_1) can be estimated.

The challenge of statistical inference relates to the standard errors of dyadic regressions (Fafchamps and Gubert, 2007). In dyad analysis, it is expected that *i* and *j* may have similar attributes, which leads to the problem of non-independence of residuals. The literature proposes various methods to correct for this correlation to achieve robust standard errors. One is using the estimation procedure assuming independence of errors and then adjusting the standard errors after the estimation (Fafchamps and Gubert, 2007). The adjustment is done by clustering the standard errors in two dimensions, i.e., the dimensions of both individuals *i* and *j* (Cameroon *et al.* 2011).

An alternative method of correcting for correlated standard errors is through permutations in a non-parametric procedure called Quadratic Assignment Procedure (QAP) (Hubert and Schultz, 1976). QAP relies on bootstrapping and corrects the p- values directly instead of correcting the standard errors (Krackhardt, 1988). This study follows the first approach which besides adjusting the standard errors, also corrects for heteroscedasticity.

3.2.3 Empirical model

Because the dataset collected on both food sharing and credit networks in this study was undirected, the expectation was that $Y_{ij} = Y_{ji}$ for all i and j. However, there were discordant responses meaning $Y_{ij} \neq Y_{ji}$ for all i and j as is also observed in other studies (e.g., see De Weerdt and Fafchamps, 2011; Liu *et al.*, 2011). To deal with the discordant responses, the study assumed that farmers reported their desire to link (not the existing networks) as opposed to assuming bilateral or unilateral link formation process.

This assumption is supported by the findings of Comola and Fafchamps (2014) who observed that the desire to link is the most appropriate model to interpret self-reported risk-sharing network formation processes. The relationship studied in this study was therefore assumed to be directional and hence the actual values for the regressors (regressors $x_i - x_j$ and w_{ij}) were used. Additionally, the degree computed for each *i* was different, hence the combined level effects were included as regressors.

Following Fafchamps and Gubert (2007), equation 3.1 was then specified further as follows:

$$Y_{ij} = \alpha + \boldsymbol{\beta}(x_i - x_j) + \boldsymbol{\partial}(x_i + x_j) + \boldsymbol{\gamma} w_{ij} + u_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

where Y_{ij} is the link between *i* and *j*; x_i and x_j are the attributes of *i* and *j*, $\boldsymbol{\beta}$ is a vector of coefficients that measure the effects of the differences in attributes *i* and *j* while $\boldsymbol{\partial}$ is a vector of coefficients that estimate the combined level effects of the attributes of *i* and *j* on Y_{ij}. w_{ij} are the characteristics of the link between *i* and *j* (such as relations and geographical distance between *i* and *j*), and u_{ij} is the error term.

Equation (3.4) was estimated using a linear probability model (LPM). One limitation of LPM is that it can yield probabilities that are below zero or above one which is against the probability. However, this was not the case in this study, the probabilities ranged between 0.2 and 0.8. According to rule of thumb, LMP would then fit well since the probabilities are not on the extremes (close to zero or close to one) (Horrace and Oaxaca, 2006). To address the challenge of non-independence of dyadic observations, the standard errors were adjusted by clustering them in two dimensions (two-way clustering), i.e., at *i* and *j*'s level to allow for error variance correlation (Cameron *et al*., 2011; Petersen, 2009).

A major challenge of this study was the reverse causality between health shock and social networks. While the study initially hypothesized that risk-sharing networks are formed to respond to health shocks in accordance with Fafchamps and Lund (2003) and De Weerdt and Fafchamps (2011), several studies have reported the effect of social networks on health outcomes. For example, Nagayoshi *et al.* (2014) and Chang *et al*. (2017) found that social networks reduce the incident of stroke and coronary heart disease among both men and women in the United States.

Given that our health shock variable includes acute sickness whose incidence is influenced by social networks, the study could not infer causality. The literature suggests the use of an instrumental variable or a lag of the endogenous variable to deal with possible endogeneity. However, given the challenge in availability of panel data and lack of a strong instrument for health shocks, this study could not infer causality in the model that includes health shock as an independent variable. The study, therefore, discusses the association of social and geographical distances for each pair of farmers who are linked by relationships of sharing agricultural produce and potential financial support.

3.2.4 Data sources and sampling

The study used primary data, collected in Kisii and Nyamira counties, using a household survey. These are high potential production areas with agricultural activities taking the largest share of the arable land in both counties. On average Nyamira county receives 1600 mm of rainfall annually, while Kisii receives an average of 1,500mm. Despite a high agricultural potential in the two counties owing to reliable rainfall, food insecurity has been reported partly due to the shocks induced on food and incomes by covariate and idiosyncratic risks (Otiso *et al.,* 2016).

A two-stage sampling procedure was used to select the respondents. In the first stage, 94 registered farmer groups (71 from Kisii and 23 from Nyamira) were listed. Considering the number of groups in each county as a proportion of the total groups' listed, simple random sampling was used to select 48 groups (32 from Kisii and 16 from Nyamira Counties). In the second stage, simple random sampling was also used to select 20 group members. In cases where the groups had 20 or less than 20 members, they were all selected. In total, 824 respondents (557 in Kisii and 267 in Nyamira) were interviewed.

To collect social network data, each of the 824 respondents was paired with all the other members in the group, including those members that had not been sampled for cases where groups had more than 20 members. However, the analysis used matches that were part of the sample only, since information on group members that were not sampled was not available. Nine observations were dropped from the analysis because the respondents did not answer the network questions resulting in a sample size of 815 as opposed to 960 observations and a total of 13,318 dyads.

3.2.5 Key Variables and their Measurement

The dependent variables in this study were the food sharing and credit links between two farmers measured as a binary variable taking a value of 1 if *i* and *j* had a link and zero if no link was reported. To capture food-sharing networks, the following question was asked to farmer *i*; *"Did you lend or borrow agricultural produce (food) from [NAME of farmer j?]".* To capture the credit networks, the farmers were asked, *"If you suddenly needed money, would you ask [NAME of farmer j] to lend it to you?"* The food networks were the actual networks while the credit networks were potential networks. This is because it was difficult to collect information on the actual credit network since it proved sensitive particularly for the borrowers. If the answer to both questions was yes, then farmer *i* was considered to have a link with farmer *j*, otherwise they did not.

The formation of risk-sharing networks is influenced by the information flow across the agents, trust, norms and the capacity to enforce the network institution (De Weerdt, 2002). One of the crucial variables with regard to the formation of risk-sharing networks is kinship. It is important in imposing norms and trust because family members are in a position to punish each other in case of misconduct, which reduces the cost of enforcement within the networks (De Weerdt, 2002).

Another important variable is geographical distance (Fafchamps and Gubert, 2007). Neighbours are expected to have a smooth flow of information if the geographical distance between them is short, which enhances the formation of risk-sharing networks. In this study, kinship was defined as the blood relationship between dyad members while being neighbours was defined if their farms bordered each other. The two were measured as binary variables where, 1 indicated kinship or neighbours and 0 indicated otherwise.

The social distance between agents also influences the formation of risk-sharing networks (Fafchamps and Gubert, 2007). For example, the correlation of income flow within a dyad affects the formation of risk-sharing networks. Agents with weakly-correlated incomes are in a better position to form an insurance network as opposed to their counterparts to maximize the benefits of risk sharing (De Weerdt, 2002). Income was therefore included as an explanatory variable in food sharing and credit network formation equations. It was measured by summing both off-and on-farm annual incomes for the households.

Education, age and gender were also included as proxies for social distance because networks are also structured along age-groups and education levels and gender of the agents (Muange *et al.*, 2014; Mekonnen, 2016). The expectation is that such networks are formed by households that are similar to each other with regard to education and age in order to reduce the cost of enforcement.

Lastly, Fafchamps and Gubert (2007) and Fafchamps and Lund (2003) argue that risk-sharing networks are also formed to respond to shocks. Therefore, the networks could be formed purposively as a way of dealing with shocks, and particularly idiosyncratic shocks since they do not affect an entire network (Bramoullé and Kranton, 2007). This study used health shocks to measure idiosyncratic shocks because health shocks are among those that have a severe effect on the welfare of smallholder farmers. To measure health shocks, data were collected by asking a farmer whether any member of the respective household had suffered acute illness in the 12 months preceding the survey. If they responded “yes”, then the household was considered to have suffered health shocks.

3.3 Results and discussions

Table 3.1 presents the characteristics of the sampled farmers. On average, the farmers were middle-aged, with primary level of education. Women formed the majority (62 percent) of the farmers involved in farmer groups and farming was the main occupation for 86 percent of the farmers in the study area. On average, farmers in Kisii and Nyamira Counties owned small parcels of land (1.62 acres) due to the high population density. The average annual household total income (on-farm plus off-farm income) was Kenya Shillings 133,000. Sixty percent of the farmers experienced idiosyncratic health shocks where at least one of the family members had suffered from acute illness.

Table 3.1 Social economic characteristic of smallholder farmers in Kisii and Nyamira.

Variables	**Mean**	**SD**	**min**	**Max**
Age (years)	46.51	12.52	18.00	79.00
Education (years)	8.67	3.68	0.00	17.00
Farm size (acres)	1.62	1.26	0.06	9.74
Income (Kshs)	133,074	90,606	600	376,459
	Number	**percent**		
Gender (1= male 0=otherwise)	321	38		
Occupation (1= farmer 0= otherwise0	706	86		
Marital status (1=married 0=otherwise)	619	75		
Relationship with head (1-head 0=otherwise)	502	60		
Credit networks (1=Yes 0= No)*	2030	15		
Food sharing networks (1=Yes 0= No)*	1068	8		
Acute illness (1=Yes 0= No)	491	60		
Observations	*815*			

*The total number of the networks were out of the total dyads (13,318) and not the 815 households.

Table 3.2 provides a comparison of the average differences and sums of socio-economic characteristics between paired farmers (*i* and *j*) who reported food sharing and credit networks and those who did not. The food-sharing and credit networks were present in eight and 15 percent of all the dyads respectively.

Table 3.2 Descriptive statistic of variables used in dyadic regressions

Variable	Food networks			Credit networks		
	Yes n=1068	**No n=12256**	**Diff.**	**Yes n=2030**	**No n=11288**	**Diff.**
	Mean	Mean	Mean	Mean	Mean	Mean
Difference in:						
Age (years)	-1.56	0.14	-1.70***	-0.39	0.07	-0.46
	(0.46)	(0.15)		(0.34)	(0.15)	
Education (years)	-0.10	0.01	-1.11	-0.44	0.08	-0.52***
	(0.15)	(0.05)		(0.10)	(0.05)	
Income (000' Ksh)	-3.95	0.32	4.27	-11.29	2.00	13.29***
	(3.639)	(1.07)		(2.59)	(1.12)	
Health shock	0.00	-0.00	-0.00	0.04	-0.01	-0.04***
	(0.02)	(0.01)		(0.01)	(0.01)	
Sum of:						
Age (years)	91.99	93.27	-1.28**	94.06	93.01	1.06**
	(0.58)	(0.18)		(0.44)	(0.44)	
Education (years)	16.81	17.37	-0.60***	17.3	17.3	-0.04
	(0.17)	(0.05)		(0.13)	(0.05)	
Income (Ksh)	253.08	266.89	13.82***	274.78	264.17	-
	(4.27)	(1.23)		(3.16)	(1.28)	10.61***
Health shock	0.81	0.79	-0.02	0.84	0.78	-0.05***
	(0.02)	(0.01)		(0.02)	(0.01)	
Gender (1=male 0=	0.64	0.76	-0.12***	0.81	0.74	0.07***
otherwise)	(0.02)	(0.01)		(0.01)	(0.02)	
Occupation (1= farmer	1.77	1.72	0.05***	1.72	1.73	-0.01
0=otherwise)	(0.02)	(0.01)		(0.01)	(0.01)	
	percent	**percent**	**Chi2**	**percent**	**percent**	**Chi2**
Kinship (1= blood relation between *i* and *j* 0=otherwise	30	20	60.94***	33	19	196***
Neighbor (1= *i* and *j* fields border each other 0=otherwise)	24	4	804***	16	4	535***
Differences in:						
Gender (1=*i* and *j* have different gender 0=otherwise)	29	37	29.01***	30	38	42.38***
Occupation (1=both *i* and *j* are not farmers 0=otherwise)	20	24	11.64***	24	24	0.03

Notes: *, **, *** denote significance at the, 10%, 5%, and 1% levels, respectively; SE= standard errors at the mean

The results indicate that the mean of differences in age between paired farmers that mentioned a food-sharing link, and those that did not, were significantly different at the 1 percent level (Table 3.2). The difference was lower between matches that mentioned food-sharing links, implying that food links are likely to be mentioned between matches that had a smaller age difference. Furthermore, the mean of the sum ages was also significantly different at the 5 percent level. The mean of sum of age between matches who mentioned the links was lower, suggesting that food sharing links are likely to be formed between younger farmers than between older farmers. The same was also true for the credit links.

The mean of sum of years of education and income between the dyads that reported a food sharing link, and those who did not, were significantly different. The mean sum of both education and income between matches that mentioned the link was lower, implying food sharing links are more likely to be formed between less educated farmers and low income . The mean sum of income of the matches that mentioned a credit link was higher, implying that credit links are more likely to be formed between farmers with higher incomes which is plausible because they have some money to share with others in their link.

Differences in the mean difference of education, income and health shocks between paired farmers who mentioned and those who did not mention a credit link were significantly different at one percent level (Table 3.2). Matches were more likely to mention credit links if their education and income differences were smaller but were likely to mention the credit link if their differences in health shocks were larger. The sums of health shocks were also significantly different, with the mean sum of health shock for matches that mentioned a credit link being higher, implying that credit links are more likely to be formed between farmers with higher health shocks.

The average sum of the gender dummy is significantly different between farmers who reported food sharing links and credit links and those who did not at 1 percent level (Table 3.2). Those who did not mention the link had a higher average sum, suggesting that matches with more males were less likely to report food sharing. Those who mentioned credit links had higher mean sum indicating that more males were more likely to form credit links. Additionally, the mean of the sum of the occupation dummy between farmers who reported food sharing link and those who did not, was significantly different at 1 per cent level. The mean of sum for those who mentioned the link was higher, implying that matches with more farmers were more likely to mention food-sharing link.

The percentage of dyads whose main occupation of both individuals was not farming was lower in matches that reported a food sharing link, implying the links were likely to be reported in matches where both individuals were farmers. Similarly, the percentage of the matches comprising opposite gender was lower in matches that mentioned both a food and credit link. These findings suggest that food-sharing and credit links were likely to be formed in matches where both farmers were of the same gender.

The percentage of matches where the paired farmers had blood relations was higher among the farmers that reported a food sharing link and also credit link, suggesting that both links were more likely to be formed if the two individuals had blood relations. Similarly, the percentage of matches where both farmers were neighbours was higher among the farmers who mentioned both links. This implies that both links were more likely to be formed if the paired farmers were neighbours.

Table 3.3 presents the results of the LPM, estimating the factors which influence formation of the credit and food sharing networks. To understand whether farmers form financial and non-financial networks to share income risk, the variables income and occupation were included as part of the regressors. Income alongside other dependent variables is endogenous hence an instrument, number of working adults in a household, was used (the results in Appendix 3A indicate that the variable was a strong instrument). The expectation was that farmers form a network with people who have a negatively correlated income with theirs and also different occupation to maximize the benefit of idiosyncratic income risk sharing. However, the results indicate that the income difference and occupation difference were not significant in the formation of both financial and non-financial networks. The finding is consistent with that of Fafchamps and Gubert (2007).

Table 3.3 Effect of income shocks on formation of financial and non-financial networks

Variables	Credit networks		Food sharing networks	
	Coefficients	**SE**	**Coefficients**	**SE**
Differences of:				
Income (predicted)	-0.014	0.027	-0.035^{*}	0.020
Age	-0.001^{**}	0.000	-0.001^{***}	0.000
Education	-0.003	0.002	0.001	0.002
Gender	-0.048^{***}	0.009	-0.017^{***}	0.006
Occupation	-0.012	0.012	-0.012	0.008
Sum of:				
Income (predicted)	0.004	0.021	-0.016	0.016
Age	0.000^{***}	0.000	-0.001^{**}	0.000
Education	0.000	0.002	0.001	0.002
Gender	0.018	0.012	-0.004	0.007
Occupation	-0.016	0.015	0.001	0.010
Relationships				
Neighbour	0.302^{***}	0.029	0.294^{***}	0.024
Kinship	0.085^{**}	0.016	0.023^{**}	0.010
Constant	0.026	0.453	0.467	0.346
Observations(dyads)		*13318*		

Notes: Dependent variable; Food sharing / credit network (1=presence of network 0 =otherwise);*, **, *** denote significance at, 10 %, 5%, and 1% levels, respectively; SE= clustered standard errors at two dimensions (*i* and *j*). P-values were generated though t test.

Age differences had a negative and significant effect on both food sharing and credit links at the 1 percent level (Table 3.3). These effects suggest that food and credit links are more likely to be formed within age groups perhaps because of different lifestyles which might moderate social interactions across groups. Van den Broeck and Dercon (2011) and Mekonnen (2016) found similar results but the result is at odds with De Weerdt and Fafchamps (2011), implying that the effect of age on social network formation may depend on type of network.

An increase in sum of age reduces the probability of reporting a food sharing link but increases the probability of forming credit links. Older people are, therefore, less likely to report a food sharing link but are more likely to report a credit link. This finding suggests that older people, do not form food sharing networks, because they probably have less dependants or more ways of accessing food, compared to younger farmers while on the other hand, they form credit links.

Gender difference was negatively correlated with existence of both credit and food sharing links, implying that farmers of the same gender are more likely to form both links than those of different gender. The results are supported by those of Van den Broeck Dercon (2011) and Mekonnen (2016), but contradict those of Dweerdt and Fafchamps (2010). This contradiction could imply that the effects of gender on network formation depend on the type of network being studied. As expected, farmers with blood relation (kinship) were likely to report both credit and food sharing links compared to their non-related counterparts. This finding is similar to that reported by Muange *et al.* (2014) and Mekonnen (2016). Similarly, farmers whose farms bordered each other were more likely to mention a food link than their counterparts who did not share farm boundaries. Maertens and Barret (2012) found similar results with information links. This implies that food sharing networks are structured along geographical and social distance.

Given the in significant results on income and occupation in formation of both financial and non-financial links, it is evident that the links don't serve idiosyncratic income risks sharing roles. In the next analysis the study broadens our definition of risk and include health shock. Equation 3.4 was then re-estimated, replacing the predicted income with health shock and the results are shown in Table 3.4.

Table 3.4 Effect of health shocks in formation of financial and non-financial networks

Variables	**Credit networks**		**Food sharing networks**	
	Coefficients	**SE**	**Coefficients**	**SE**
Differences of:				
Health shock	0.011**	0.005	0.000	0.004
Age	-0.001***	0.000	-0.001***	0.000
Education	-0.004***	0.001	-0.001***	0.001
Gender	-0.047***	0.007	-0.018***	0.004
Occupation	-0.011	0.012	-0.014	0.008
Sum of:				
Age	0.000	0.000	0.004***	0.000
Education	0.001	0.001	-0.001	0.001
Gender	0.019***	0.006	-0.009***	0.004
Occupation	-0.016	0.012	0.002	0.008
Health shock	0.012**	0.005	0.003	0.003
Relationships				
Kinship	0.086***	0.009	0.026***	0.007
Neighbour	0.301***	0.020	0.291***	0.018
Constant	0.110***	0.036	0.124***	0.023
Observations (dyads)		*13318*		

Notes: Dependent variable; Credit/Food sharing / network (1=presence of network 0 =otherwise);*, **, *** denote significance at, 10 %, 5%, and 1% levels, respectively; SE= clustered robust standard errors

In Table 3.4, correlations are reported, given the reverse causation between social network and health outcomes. This shows that farmers' health shock differences are positive and significantly correlated with the formation of credit networks but do not influence the formation of food-sharing networks. This suggests that farmers whose household members have acute sickness are likely to form financial networks with households that do not have a member with acute sickness. The finding, therefore, suggests a health risk-sharing role of the financial networks, which is consistent with Fafchamps and Gubert (2007).

The health shock sum is also positively and significantly correlated with the formation of credit links at the 5 percent level (Table 3.4). Increasing the sum of the health shocks increases the probability of reporting a credit link. The links are therefore, more likely to be reported between farmers who have experienced health shock. This could be explained by the fact that individuals who have not experienced health shocks may not need insurance since they feel less vulnerable to the shocks. This further suggests that farmers are likely to form credit networks to insure themselves against health shocks. The finding agrees with Saidi (2015) who reported that financial gifts are used as an insurance against idiosyncratic risks.

The rest of the findings are consistent with the earlier findings, with additional education differences and gender sum significantly correlated to the formation of both links as well. Education difference between the paired network members had a negative and significant (1 percent level) correlation with the formation of both food sharing and credit links. Farmers form the links with others who have similar levels of education; hence, financial and non-financial links are structured along education levels. This finding is supported by earlier studies such as Jaimovich, (2011), Maertens and Barret (2012) and Muange *et al.* (2014).

The sum of male dummy has a negative correlation with food sharing links and appositive correlations with the formation of credit links. This indicates that the more males there are in a match the less the likelihood to report a food sharing link. The finding implies that food sharing networks are more likely to be mentioned between two females than between two males or a male and a female farmer. The finding is plausible because women are more capable than men in terms of allocating and using resources in a way that improves food availability of their families (Ibnouf, 2009). It can therefore, be concluded that women are more likely to take the informal insurance, to safeguard their families against food shocks.

Contrary to the findings of the formation of food sharing networks, the more males there are in a match, the more the likelihood to report a credit link. This implies that credit networks are more likely to be mentioned between two males than between two females or a male and a female farmer. This is consistent with Mekonnen (2016) who found that information sharing networks were more likely to be formed between male than female or male and female farmers. This could imply that men borrow more than women probably because they usually own more resources than women in Africa making the credit worth (Doss *et al.,* 2015).

All the significant variables in the formation of credit networks and food-sharing links (age difference, education difference, age difference, neighbourhood and kinship) indicate that geographical and social proximity are key drivers of network formation. This could be because proximity facilitates easier monitoring and enforcement of institutions within social networks. Additionally in case of risk sharing, like in case of health risk sharing, the proximity makes it easier to give and receive help in case of health shocks.

3.4 Conclusions and policy implications

This study evaluated the factors that influence formation of food sharing (non-financial) and credit (financial) networks among smallholder farmers in Kisii and Nyamira counties. Cross-sectional data from 815 farmers were analysed using a dyadic LPM. The results show that age, gender and education were the node characteristics that significantly influenced formation of both food sharing and credit networks. Kinship and geographical distance, and health shock are also important attributes in the formation of food sharing networks.

The study concludes that the formation of financial and non-financial network is determined by geographical and social proximity. Proximity facilitates easier monitoring and enforcement of institutions within social networks, making it easier to give and receive help in case of a risk shock. Given the correlation between health shock and credit link formation, there is an indication that financial links are formed to serve a risk-sharing role when farmers are faced with health shocks, but not to cope with idiosyncratic income risk. Non-financial links are neither formed to serve income nor health risk sharing purpose. However, other than the risk-sharing role of the financial networks, the formation of the two networks is almost similar. This means that not all kinds of risks are insured within all types of social networks.

Therefore, financial and non-financial networks are likely to exist between farmers who are geographically and socially close to each other probably to reduce the cost of maintaining the link which expected to increase with social and geographical distance. While the study cannot infer causality, the findings suggest that informal financial networks could be harnessed as an informal way to insure farmers against health shocks. Thus, any program aiming at helping farmers in dealing with idiosyncratic health shocks can benefit from such networks. There is however a need for a causality analysis on the same to give evidence on whether health shocks influence formation of financial networks.

CHAPTER FOUR

EFFECT OF SOCIAL NETWORKS ON HOUSEHOLD FOOD CONSUMPTION SMOOTHING IN THE PRESENCE OF IDIOSYNCRATIC SHOCKS: INSIGHTS FROM RURAL KENYA

Abstract

Idiosyncratic health shocks are one of the major shocks affecting smallholder households. Lack of formal mechanisms to cope with the shocks has led to increased food insecurity and poverty particularly in developing countries. Social networks have been one of informal strategies that have been widely used by households to smoothen their consumption in the presence of the shocks. This paper examine the effects of health shocks on food consumption and also the role of social networks in insuring food consumption against health shocks. The paper uses panel data collected from 719 smallholder farmers in Kisii and Nyamira counties. Fixed effects estimates shows that health shocks have a negative and significant effect on purchased food while they have no effect on total food consumption. The results further indicates that financial credit networks have positive and significant effect in insuring food consumption against health shocks. The paper concludes that health shocks affect purchased food consumption adversely while total food consumption is not affected by health shocks because reduction in purchased food due to health shocks is probably compensated for by gifts. Financial credit networks plays an insurance role against health shocks in purchased food consumption.

4.1 Introduction

Smallholder farmers in developing countries are often vulnerable to idiosyncratic and covariate shocks (Di Falco and Bulte, 2013). Idiosyncratic shocks, defined as shocks that affect particular individuals or households, result from death or acute illness, loss of a job, and unemployment (Wossen *et al.*, 2016). Covariate shocks affect an entire community and are caused by natural calamities as well as adverse changes in input and output prices (Cervantes-Godoy *et al.*, 2013).

Idiosyncratic shocks are the most common shocks within households, and health shocks are among the major idiosyncratic shocks (Wagstaff and Lindelow, 2010). The effect of such shocks depends on the ability of a household to insure themselves against the shock, which is crucially related to the household's access to finance and insurance markets (Islam and Maitra, 2012). Further, the shock effects are more severe in rural areas of developing countries where formal credit and insurance markets are either absent or poorly developed (Cervantes-Godoy *et al.*, 2013). Even in cases where financial institutions are available, collateral requirements are unattainable by most smallholder farmers and costs charged for the services are high (Ayyagari *et al.*, 2017). This makes it difficult for smallholder farmers to access credit markets to insure themselves against shocks.

Lack of formal insurance against unexpected shocks by smallholders has led to reduced food consumption, among other problems (Dercon and Christiansen, 2011). Such households are therefore forced to rely on informal coping mechanisms to smoothen their consumption. Informal strategies that have been adopted by smallholder farmers include transfers from relatives and other social networks, selling assets and livestock, or reducing consumption, depending on the type of shocks (Yilma *et al.*, 2014).

Social networks have been widely used by households in developing countries as an informal strategy to overcome insurance and credit market failures (Adelman, 2013). For example, it has been shown that smallholders form informal mutual insurance arrangements within their social networks to enable them cope with unexpected shocks (Bramoulle and Kranto, 2007). The informal insurance provides for those in need, if future reciprocity is expected (Ligon *et al.,* 2002). Informal insurance arrangements are done through transfers of loans and gifts within networks, which play a risk-sharing role (Munshi and Rosenzweig, 2016).

To design meaningful interventions for addressing idiosyncratic risks faced by smallholder households, it is important to understand whether or not such households are fully insured by the informal mechanisms of coping with shocks. It particularly remains an open empirical question as to what extent smallholder households are able to insure their food consumption against health shocks through financial and non-financial transfers within their social networks.

There is a growing body of literature on the use of informal insurance strategies by households to insure their consumption against shocks (e.g. Islam and Maitra, 2012; Yilma *et al.,* 2014; Wossen *et al.,* 2016). Most of these studies have evaluated the effects of past shocks on household consumption and the extent to which informal insurance strategies cushion household's consumption against the shocks. However, there are mixed findings on the effects of both health shocks and informal insurance (social networks) on household consumption. For example, Wossen *et al.* (2016) reported that health shocks, drought and market shocks have a negative effect on total consumption in rural Ethiopia. Similarly, Islam and Maitra (2012) and Genoni (2012) reported a negative effect of health shocks on household consumption in Bangladesh and India respectively. However, Galiano and Vera-Hernández (2008) demonstrated positive effects of health shocks on consumption in rural Colombia.

The literature on whether or not households smoothen consumption using informal insurance when faced with exogenous shocks has little consensus. Whereas some studies have found evidence of consumption smoothing through informal insurance in social networks (Kinnan and Townsend, 2012; Wossen *et al.,* 2016), others have reported insignificant or negative results (Di Falco and Bulte, 2013). To contribute to the growing literature on the role of social networks as an informal insurance strategy on household food consumption smoothing, this study examined the effect of health shocks on food consumption. It also evaluated the effect of financial and non-financial social networks on household food consumption as an insurance against idiosyncratic health shocks in rural Kenya.

The rest of the paper is organized as follows: the methods describing data sources, theoretical and empirical approaches of the study are discussed in section 4.2. The results of econometric analysis are discussed in section 4.3 while conclusions and policy implications of the study are presented in section 4.4.

4.2 Study Methods

4.2.1 Theoretical framework

In economics literature, consumption smoothing is nested in the theory of insurance developed by Arrow (1964). The theory argues that in a community/state where there are institutions that help in pooling risk to achieve Pareto-optimality, then consumption across households in the community will be equalized. This implies that risk-sharing institutions will mitigate household-specific shocks and balance the marginal utility of consumption across households within the community/state. Thus, testing for the level of consumption insurance is a test for the validity of Pareto optimal consumption whose allocation is derived from the social planner's problem.

Following Islam and Maitra (2012), and given a village setting, the central social planner solves the following maximization problem:

$Max \sum_i \sum_t \sum_v C_{itv}\ \mu_{iv}\pi_v\rho^t u(C_{itv}: \theta_{itv})$ …………………………………………….. (4.1)

subject to:

$\sum_i C_{itv} = \sum_i y_{itv}\ \forall t, s$ …………………………………………………………………….. (4.2)

where π_v is the probability of village v, $\forall v$ *=1, 2…, V*; C_{itv} is amount of household consumption, y_{itv} is household income, μ_{iv} is the time-invariant Pareto-weight associated with household i $\forall i$ = 1….., *N*, and *N* is the total number of households in the village. Lastly, θ_{itv} includes factors that change with tastes. The utility function can take various forms. Following Islam and Maitra (2012), an exponential utility function and is given as follows:

$u(C_{itv}: \theta_{itv}) = -\frac{1}{\alpha}\ exp\{-\alpha(C_{itv} - \theta_{itv})\}$ …………………………………………….. (4.3)

The first order conditions for equation 4.3 are specified as follows:

$\Delta C_{itv} = \Delta C^a_{tv} + (\Delta\theta_{itv} - \Delta\theta^a_{tv})$ ……………………………………………………….. (4.4)

where $\Delta C^a_t = \frac{1}{N}\sum_i C_{itv}$ represents and $\Delta\theta^a_{tv} = \frac{1}{N}\sum_i \theta_{itv}$.

Equation (4.4) implies that the full consumption insurance of an individual household, C_{itv} in village, υ, depends on village-level consumption, C^a_{tv}.

4.2.2 Empirical framework

To achieve the objectives of the study, the effect of health shocks on food consumption were first estimated. A framework that captures the effect of social networks as an informal insurance mechanism that can insure food consumption against idiosyncratic health shocks was introduced next. Equation 4.4 was empirically specified as follows (Islam and Maitra, 2012):

$\Delta C_{ivt} = \propto_0 + \beta S_{ivt} + \delta X_{ivt} + \gamma\Delta C^a_{vt} + \varepsilon_{ivt}$ ……………………………………… (4.5)

where ΔC_{ivt} is the change in real consumption of household *i* in village υ at time *t*, C^a_{vt} is the change in consumption of village v at time t, S_{ivt} is the health shock faced by household *i* in village v at time t, and X_{ivt} is a vector of the characteristics of household i in village v at time t. In a situation where there is full insurance, $\gamma = 1$ and $\beta = 0$ such that, the health shocks have no effect on household food consumption.

Ravallion and Chaudhuri (1997) however, argue that, testing whether $\gamma = 1$ and $\beta = 0$ would give biased parameter estimates whenever a component of village-level food consumption in the household consumption changes due to insurance market failure. They suggest the inclusion of village fixed effects in place of village consumption while treating time as a fixed effect as follows.

$$\Delta C_{ivt} = \propto_0 + \beta S_{ivt} + \delta X_{ivt} + \gamma_v + \mu_t + (\gamma_v \times \mu_t) + \varepsilon_{ivt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.6)$$

where γ_v and μ_t are village and time fixed effects respectively; all other variables are as previously defined.

In this study, data were collected from members of a farmer group. Therefore, farmer group level was used as opposed to village level. Accordingly, Equation 4.6 was modified following Wossen *et al.* (2016):

$$\Delta ln\left(\frac{C_{it}}{H_{it}}\right) = \propto_0 + \beta S_{it} + \delta X_{it} + \mu_t + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.7)$$

where C_{it} is the real food consumption of household *i* at time *t*, H_{it} is the household size, S_{it} denotes health shocks faced by the household *i* at time *t*, X_{it} is a vector of household characteristics such as age, education and gender of household head, farm size, wealth and household size, while μ_t is the time-variant fixed effects. The assumption is that the error term is uncorrelated with all observations of X_{it} for household *i* over time and that the error term is independent and identically distributed.

One of the challenges of estimating Equation 4.7 is that the health shocks could be endogenous such that some shocks that affect consumption (e.g., flooding) may also cause illness (Wossen *et al.*, 2016). Our identification strategy heavily depended on the assumption (which was later validated) that, given our measurement, health shocks could be regarded as being non-persistent and unpredictable (Wossen *et al.*, 2016). Moreover, using the fixed effects estimation removed any time-invariant unobserved variables that could simultaneously affect both consumption and health shocks.

To validate our assumption that health shocks were unpredictable and non-persistent, the study assessed whether households that experience health shocks in the present period are more likely to experience health shocks in future following Morduch (1995):

$$S_{it} = \alpha_i + \beta S_{it-1} + \gamma X_i + \varepsilon_{it} \quad \text{(4.8)}$$

In the next steps, the study estimated the effect of social networks on household consumption smoothing against health shocks as follows:

$$\Delta ln\left(\frac{C_{it}}{H_{it}}\right) = \propto_0 + \beta S_{it} + \delta X_{it} + \theta Z_{it} + \mu_t + \varepsilon_{ijt} \quad \text{(4.9)}$$

where Z_{it} denotes social network variables, which include credit and food-sharing networks.

Social networks could be potentially endogenous in Equation 4.9, such that unobservable factors that affect social networks may also influence consumption directly. The endogeneity problem was dealt with by use of panel data. Use of fixed effects model removed potential endogeneity attributable to the unobserved time-invariant variables Wossen *et al.* (2016). However, the authors acknowledge that identification might still be a challenge with social networks in case where unobserved time-varying variables influence both social network formation and food consumption. A time dummy was also included to control for heterogeneity.

To assess whether households with larger network sizes were better-placed in insuring their food consumption against exogenous shocks, Equation 4.9 was modified by adding an interaction term between health shocks and social network size as follows:

$$\Delta ln\left(\frac{C_{it}}{H_{it}}\right) = \propto_0 + \beta S_{it} + \gamma(S_{it} \times Z_{it}) + \delta X_{it} + \theta Z_{it} + \mu_t + \varepsilon_{ijt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.10)$$

The coefficient of the interacted variable (γ) measures the effects of social network size in insuring food consumption against health shocks. If $\gamma > 0$ then the social network size effect is positive.

The above equations could be estimated using the first difference, the fixed effects or a random effects model. According to Woodridge (2006), the fixed effects and first difference parameter estimates and their statistical properties are identical when *t*=2. In this study, a Hausman-specification test was used to select the most appropriate between a fixed effects and a random effects model. The null hypothesis that the random effects model is consistent was rejected at 0.005 level of significance. The study therefore reports the results of the fixed effects model.

4.2.3. Data sources and sampling

This study uses primary data, which was collected from Kisii and Nyamira Counties of Kenya. In spite of high agricultural productivity potential in the two counties, there are high levels of food insecurity, which have been partly attributed to the shocks induced on food and incomes by covariate and idiosyncratic shocks (Otiso *et al.*, 2016). Therefore, there is need to understand informal mechanisms which farmers use for smoothing food consumption in the presence of such shocks.

A two-stage sampling procedure was used to select the households. A complete list of existing farmer groups in Kisii and Nyamira obtained from Africa Harvest Biotech Foundation International, a non-profit organization that was implementing projects in the region, was used as a sampling frame. In the first stage, 48 farmer groups (32 from Kisii and 16 from Nyamira) were selected using simple random sampling with a probability proportional to the total number of groups existing per county. In the second stage, simple random sampling was used to select 20 households from each group. In cases where the groups had less than 20 households, all the households were interviewed.

The data were collected in two rounds: the first round between October and December 2015 while the second one run between October and December 2016. A total of 824 farmers were in interviewed in 2015 and 746 in 2016. However, in 2015, 9 farmers did not answer questions on social networks, shocks and food consumption sections, which were of interest to this study. Moreover, in 2016, only 719 farmers answered questions on the three sections mentioned above. This study therefore uses a balanced panel of these 719 observations.

To collect social networks data, the sampled farmers were asked questions about their links to all members of their farmer group. The questions concerned different kinds of information (nutritional, agricultural) and resources (food, money, inputs) they shared and their social and geographical proximity (relationships, neighbours, frequency of talking) in the 12 months preceding the survey. This paper used the data collected from pairs of group members that were part of the sample only because social network information on those that were not in the sample was unavailable.

4.2.4 Measurements of variables of interest

The food consumption data were collected for about 140 food items using a household 7-day recall approach (Hernández-Cordero et al., 2015) in which respondents were asked to recall and mention all the food items they had consumed in the last 7 days. The data on the source of food items consumed in the household (own-production, purchase or gifts) were also collected. Food consumption was separated into two categories: total food consumption which included purchased food, own-production and gifts, and purchased food. This study measured food consumption by the quantity of money (Kenya Shillings) used to purchase the food (Dercon and Krishnan, 2000). Food consumption from own-production and gifts were valued using prevailing market prices.

Health shocks were used to measure idiosyncratic shocks. This is because health shocks are one of the major shocks that have severe negative effect on smallholder farmers in developing countries (Wagstaff and Lindelow, 2010). Health shocks reduce household income and productive assets due to missed working days by sick member(s) and use of the available income on hospital bills and hence household consumption (Islam and Maitra, 2012).

To measure health shocks, data were collected by asking a farmer whether any member of the household had suffered acute illness in the past 12 months that led to a huge reduction in income and asset ownership. Using self-reported illness in measuring health shocks has a high potential for measurement error because what is termed "healthy" differs from one individual to another. In this case, Islam and Maitra (2012), recommend the use of long-term health shock measures as opposed to short-term measures. This study captured illnesses that affected members of households during 12 months prior to the survey, a commonly used "long-term" health shock measurement approach (De Weerdt and Dercon, 2006 and Wossen *et al*., 2016).

To capture food-sharing networks, the following question was asked to farmer *i*; *"Did you lend or borrow agricultural produce (food) from j?)* On the other hand, to capture the credit networks, a question, *"If you suddenly needed money, would you ask [NAME] to lend it to you?"* If the answer to both questions was yes, then farmer *i* was considered to have a social link with farmer *j*. Food networks were the actual networks while the credit networks were potential networks. This is because it was difficult to collect information on the actual credit network since it proved sensitive particularly for the borrowers. Following Wossen *et al.* (2016), network size was computed by summing the total number of the individuals (*j*) who were mentioned to either have food sharing or credit networks with *i*.

A wealth index was computed using assets owned by a household. A Principal Components Analysis (PCA) was used to assign weights to different assets. Following Langyintuo and Mungoma (2008), the assigned weights were then used to compute wealth index applying the following formula:

$$W_j = \sum_{i=1}^{k} b_i \; (a_{ij} - x_i)/s_i \qquad (4.11)$$

where W_j is wealth index, b_i is the weight assigned to each of the *k* assets on the PCA, a_{ij} is the value of the *k*th asset for the *i*th household, $\boldsymbol{x_i}$ is the mean of the *k*th asset over all households and s_i is its standard deviation.

4.3 Results and discussion

Table 4.1 presents demographic characteristics of the respondents in Kisii and Nyamira counties. On the average, farmers were middle aged (48 years in 2016) with an average of 9 years of formal education. A majority of the farmers were female. The households had an average of 6 members in 2015 and 5 members in 2016 and owned 1.6 acres and 1.5 acres of farming land in 2015 and 2016 respectively. The decline in household size could be attributed rural urban migration due to diminishing farm sizes in the two counties.

Table 4.1 Social economic characteristics of smallholder farmers in Kisii and Nyamira

Variable	2015		2016	
	Mean	**SD**	**Mean**	**SD**
Real total food consumption (Kshs)	2986.00	1418.72	2892.29	1346.47
Per capita total food consumption (Kshs)	601.40	388.65	607.61	468.61
Real purchased food consumption (Kshs)	1515.84	1000.20	1480.96	893.54
Per capita purchased food consumption (Kshs)	309.79	246.27	300.96	207.40
Health shock (1=Yes 0= No)	0.39	0.49	0.14	0.34
Food sharing network(1=Yes 0= No)	0.52	0.50	0.61	0.49
Food sharing network size (Number)	1.35	2.34	4.20	7.42
Credit network(1=Yes 0= No)	0.82	0.38	0.85	0.36
Credit network size (Number)	2.48	3.23	2.63	3.10
Age (years)	46.89	12.40	48.06	12.47
Education (years)	8.57	3.66	8.56	3.62
Gender (1= Male 0 =otherwise)	0.37	0.48	0.38	0.47
Household size (Number)	5.60	2.07	5.49	2.05
Land size (acres)	1.59	1.25	1.45	1.20
N		*719*		*719*

Thirty nine percent of the households experienced health shocks in 2015 while only 13 percent did in 2016 (Table 4.1). On average, the food-sharing network size was one person in 2015 and four people in 2016 while the average network size for credit network was two and three individuals in 2015 and 2016 respectively. The increase in the proportion of people having credit and food-sharing networks from 52 percent in 2015 to 61 percent in 2016 and the network sizes can be explained by the high rate of health shocks in 2015 given that social networks are often used as an *ex post* risk-management strategy (Cervantes-Godoy *et al.*, 2013).

The average real total food consumption in a week was KShs 2,986 and 2,892 in 2015 and 2016 respectively while average real household food consumption from purchases was KShs 1,516 in 2015 and slightly lower at KShs 1,481 in 2016. On the other hand, the average per capita total food consumption was KShs 600 in both years while that of purchased food consumption in 2015 and 2016 was KShs 310 and KShs 301 respectively (Table 4.1). The lower purchased food consumption in 2016 could have been caused by the increased proportion of people having credit and food sharing networks and the network sizes.

Before starting the regression analysis, the a test was done to see whether or not the health shocks were persistent in order to validate our assumption that health shocks are unpredictable and non-persistent (Islam and Maitra, 2012). Current health shocks were regressed against their lagged values using a fixed effects logit model and the results presented in Table 4.2. The results indicate that lagged health shocks did not have any significant effect on their current values. This implies that households that experienced health shocks in period *t-1* were not more likely to experience health shocks in period *t*.

This finding suggest that the health shocks experienced by the sample households were not persistent and therefore could not be predicted, thus validating our earlier assumption. Otherwise, when the health shocks are persistent, households might invest in other expensive *ex ante* food consumption smoothing strategies such as crop diversification and off-farm labor supply. In such a case, our analysis would (wrongly) show that health shock do not affect food consumption.

Table 4.2. A test for the persistence and predictability of health shocks

Variable	Fixed effects
Health shock(*t-1*)	0.349
	(8.72)
Constant	-2.008
	(74.49)
Prob>Chi-square	*0.968*
N	*1483*

Numbers in parenthesis represent robust standard errors at the mean. Dependent variable is health shock (binary variable with health shock=1 and zero otherwise).

Table 4.3 shows the effect of social networks on purchased food consumption as an informal insurance against health shocks. Model 1 shows that health shocks have a negative effect on consumption that is significant at 5% level. Further, the results show that health shocks reduced the household's per capita consumption by 10 per cent. This finding is consistent with those of Genoni (2012) and Wossen *et al.* (2016) who also found that health shocks had an adverse effect on consumption in Ethiopia.

Table 4.3 further presents the effect of social network in insuring the purchased food consumption against the negative health shock effect by examining the interaction between social networks and health shocks. The variance inflation factor test revealed that the model did not suffer from multicollinearity after introduction of the interaction variables (VIF was below 2.5). Model 2 was estimated without controlling for other confounding factors while model 3 controlled for them. In both models the results were similar.

Table 4.3. Effect of social networks on Insuring purchased food consumption against health shocks in Kisii and Nyamira

Variable	No controls	With social network	With all controls
	1	2	3
Health shock	-0.102**	-0.163**	-0.155***
	(0.05)	(0.065)	(0.059)
Credit network size		-0.005	-0.002
		(0.006)	(0.006)
Food sharing network size		0.001	0.001
		(0.004)	(0.003)
Health shock*credit network size		0.026**	0.021**
		(0.012)	(0.011)
Health shock*food sharing network size		-0.006	-0.003
		(0.013)	(0.013)
Age			-0.003
			(0.010)
Education			0.001
			(0.014)
Gender			-0.356**
			(0.149)
Household size			-0.188***
			(0.018)
Land size			-0.002
			(0.023)
Wealth index			0.023
			(0.016)
Constant	63.812	67.026	103.298
	(61.40)	(63.710)	(63.959)
Time fixed effects	Yes	Yes	Yes
Hausman *(Prob>F)*			0.005
Prob>F	*0.123*	*0.258*	*0.000*
N	*1483*	*1438*	*1438*

Notes: **, *** denote significance at 5%, and 1% levels, respectively; numbers in parenthesis represent robust standard errors at the mean. Dependent variable is natural log of per capita purchased food consumption.

The results in model 2 and 3 show a positive and significant effect of the interaction between health shocks and credit (financial) networks while the direct effect of health shock on food consumption was still negative but statistically significant (Table 4.3). This finding suggests that the financial networks had a mitigation effect though, they did not offer full insurance given that the health shocks still affected purchased household consumption negatively. The finding implies that the larger the household's credit network size the greater is its ability to insure its purchased food consumption against health shocks. Kinnan and Townsend (2012) and Wossen *et al.* (2016) reported similar results in Thailand and Ethiopia respectively. However, the interaction between food-sharing networks and health shocks was not statistically significant.

The results further indicate that purchased food consumption was influenced by other factors such as the gender of household head. Households headed by a female had higher per capita consumption than those headed by males. This finding is expected because women in Africa have been shown to have more capability in allocating and utilizing resources in a way that enhances food availability of their households relative to their male counterparts (Ibnouf, 2009). Therefore, the households where the major decision maker is female are more likely to have higher per capita consumption of food, *ceteris paribus*.

The size of the household had a negative effect on purchased food consumption at one percent significance level (Table 4.3). This suggests that households with fewer members have higher per capita consumption. This is plausible because when more people are eating from the same resources, there is a possibility that individual members may not get enough to eat relative to the case in households with fewer members. Aidoo *et al.* (2013) made a similar finding in Ghana

The study also evaluated the effect of social networks on total consumption (purchased food, food gifts and own-production) smoothing in the presence of health shocks. The first stage of analysis involved estimating the effect of health shocks on total food consumption (see Table 4.4). The analysis in this section did not include food-sharing networks because the total food purchase captures food gifts which are mostly transferred within social networks particularly among friends and relatives.

Table 4.4. Effect of social networks in insuring total food consumption against health shocks in Kisii and Nyamira

Variable	**No controls**	**With social network variables**	**With all controls**
	1	2	3
Health shock	0.014	-0.001	0.010
	(0.038)	(0.049)	(0.045)
Credit network size		-0.008	-0.004
		(0.006)	(0.005)
Health shock*credit network size		0.006	0.000
		(0.009)	(0.008)
Age			0.012*
			(0.008)
Education			0.001
			(0.013)
Gender			-0.007
			(0.110)
Household size			-0.149***
			(0.015)
Land size			0.017
			(0.018)
Wealth index			0.017
			(0.014)
Constant	10.625	9.022	65.665
	(47.935)	(48.069)	(47.205)
Time fixed effects	Yes	Yes	Yes
Hausman *(Prob>F)*			0.029
Prob>F	*0.906*	*0.746*	*0.000*
N	*1483*	*1438*	*1438*

Notes: **, *** denote significance at 5%, and 1% levels, respectively; Numbers in parenthesis represent robust standard errors at the mean. Dependent variable is natural log of per capita total food consumption.

The results show that, contrary to expectation, health shocks had no effect on the total food consumption unlike in the case of purchased food consumption where health shocks negatively influenced food consumption (see Table 4.3). The results is finding implies that the reduction in purchased food consumption due to health shocks is probably compensated for by food gifts which are part of the total food consumption. Therefore, the study cannot reject the positive role of social networks even in the case of total food consumption given that some of the food gifts were transferred within social networks. These findings are consistent with those Asfaw and Von Braun (2004) who reported a negative effect of health shocks on purchased food consumption but not on total food consumption in Ethiopia.

As in the case of purchased food consumption, the household size had a negative effect on total food consumption (Table 4.4). This implies that households with fewer members have higher per capita total food consumption. This could be because, when more people are eating from the same resources, there is a possibility that individual members may not get enough to eat relative to the case in households with fewer members. Aidoo *et al.* (2013) made a similar finding in Ghana

Additionally, the age of the household head had a positive but weakly significant effect on total food consumption suggesting that households with older heads enjoyed higher per capita food consumption contrary to *a priori* expectation. The positive correlation between age and total per capita food consumption could be attributed to (i) experience in dealing with shocks over time (ii) smaller household sizes [i.e., fewer mouths to feed given that the children have already moved out or (iii) remittances from grown up children who support them. Foster (2015) found similar results in a study of how food expenditure varies with age in United States.

4.4 Conclusion and recommendations

This study evaluated the effect of social networks on food consumption smoothing in the presence of health shocks. The study used panel data collected in two rounds in 2015 and 2016. A fixed effects model was estimated first to assess the effect of health shocks on both purchased and total household food consumption and to examine the effect of social networks in smoothing food purchases and total household food consumption in the presence of health shocks. This was done by introducing an interaction variable between health shocks and network size in the first model.

The results indicated that health shocks had a negative and significant effect on purchased food but no effect on total food consumption. Further, the interaction between financial networks and health shocks had a positive and significant effect on purchased food consumption while the direct effect of health shocks was negative but statistically significant. However, the interaction between health shocks and food-sharing networks had no significant effect purchased food consumption.

Based on these findings, the study draws the following conclusions. First, health shocks adversely affect purchased food consumption. However, total food consumption is not affected by health shocks because the reduction in purchased food due to health shocks is probably compensated for by food gifts. Second, financial networks play an insurance role against health shocks in purchased food consumption. Third, there is a potential positive role of social networks in insuring total food consumption against health shocks because most of the food gifts that reduce the negative effect of health shocks on total food consumption are exchanged through food-sharing or other social networks such as friendship and kinship ties.

The study therefore found social networks to act as an indispensable food safety net in times of adversity and particularly when rural households were confronted by insidious health shocks. For example, financial credit networks helped smallholders to reduce the effect of health shocks against food consumption, though they did not totally remove the effects of the shock. Food gifts captured in total food consumption also insured farmers' food consumption against health shocks to an extent that the shocks did not have any effect on the total food consumption, meaning they provided full risk sharing opportunities against health shocks.

Smallholder communities seem to be efficient in providing food safety nets amongst themselves through use of social networks. However in some cases, (for example in case of credit networks), these safety nets do not provide full risk-sharing opportunities against health shocks. It would be advisable, therefore that policymakers provide food safety nets that complement community-driven initiatives in order to enhance the effectiveness of indigenous risk-hedging strategies. They should also provide the safety nets through utilizing the most efficient networks that offer full risk sharing against shocks (such as food gifts in this study's case) to harness maximum benefits from social networks.

CHAPTER FIVE

EFFECT OF SOCIAL NETWORKS ON HOUSEHOLD DIETARY DIVERSITY: EVIDENCE FROM SMALLHOLDER FARMERS IN KENYA

Abstract

Nutrition knowledge, an important driver of household dietary diversity, can be improved through access to nutrition information. However, in many rural areas, the formal flow of nutrition information is limited. Social networks could play an important role as an informal source of such information. This paper evaluates the determinants of nutrition information link formation as well as the effect of such information networks on household dietary diversity in Kenya. The paper used cross-sectional data collected from 713 farmers in Nyamira and Kisii counties and employed Probit and Poisson regression models. The results show that the level of education and the number of neighbours have a positive effect on the probability of having a nutrition information network. Further, a unit increase in average household dietary diversity score of an individual's network members led to a 7.6 percent increase in the household dietary diversity score, implying the existence of endogenous effects of social networks on dietary diversity. These results suggest that farmers' social networks could be used as a complementary tool for effective delivery of nutrition education targeting enhanced nutritional quality.

5.1 Background

Despite increased food production globally, malnutrition still remains a major problem and particularly in Africa and Asia (IFPRI, 2014; UNICEF *et al.,* 2015). The term 'malnutrition' comprises three aspects of undernourishment, micronutrient deficiency and over-nutrition (Gomez and Ricketts, 2013). According to Suryanarayana (2013), most policies tackling malnutrition in developing countries are biased toward consumption of sufficient calories with little emphasis on nutrition quality. However, Ruel (2003a) posits that nutrition policies should not only consider sufficient calorie intake but also diversified diets because an increase in dietary diversity reduces the proportion of malnourished people (Darapheak *et al*., 2013)

Defined as the number of different food groups eaten by an individual or household over a given reference period, dietary diversity has been used as a proxy for dietary quality (Ruel, 2003b). Studies have shown that dietary diversity is positively correlated with nutrient density and adequacy of diets of people or groups of people (Kennedy *et al*., 2007a; Steyn *et al*., 2006a). For example, Ogle *et al.* (2001) show that women with a food group diversity of at least eight (out of a maximum of 12 groups) have significantly higher nutrient adequacy ratios for energy, protein, vitamin C, and zinc than women with a lower food group diversity. A high dietary diversity has also been associated with better nutritional status of children (Arimond *et al.,* 2010; Arimond and Ruel, 2002).

High dietary diversity is therefore key in achieving household food and nutrition security (Steyn *et al*., 2006b; Kennedy *et al.,* 2009). However, in Kenya, 25 percent of households have low dietary diversity (Smith *et al.,* 2006). Children are the most affected with 42 percent having low dietary diversity (Mbogori, 2013). According to Rah *et al*. (2010), the low dietary diversity has been a major cause of stunting in Kenya especially in children under five years.

Several studies identify nutrition knowledge as one of the key drivers of dietary diversity (Mbogori, 2013; Aberman *et al.,* 2015; Ragasa *et al.,* 2017). However, according to Odini (2014), in many rural areas, the formal flow of information, including nutrition information, is low. In contexts where formal information institutions often underperform, social networks can play an important role as a source of information (Chuang and Schecheter, 2015). Social interactions in such networks often lead to social learning due to peer effect and imitation (Hogset and Barrett, 2010).

Several studies have examined the effect of social networks on a variety of outcomes such as adoption of agricultural technologies (Maertens and Barrett, 2013; Thuo *et al.,* 2014; Muange and Schwarze, 2014), agricultural productivity (Van den Broeck and Dercon, 2011; Muange *et al.,* 2015; Mekonnen *et al.*, 2018), health, (Oster and Thornton 2012; Martire and Frank, 2014) and financial decisions (Banerjee *et al.,* 2013; Murendo *et al.,* 2018). However, studies focusing on the effect of social networks on dietary diversity are largely lacking.

Moreover, even though an extensive literature on the determinants of household dietary diversity exists (Langat *et al.*, 2013; Taruvinga *et al.,* 2013; Sibhatu *et al*., 2015), such studies have not investigated the effect of social networks on household dietary diversity. Hence, while the relationship between dietary diversity and economic resources has been well established, the effect of social networks as a potential informal source of nutrition information is not well understood. This study aims to fill this gap by evaluating the factors influencing the formation of nutrition information links and the effect that such networks have on household dietary diversity.

5.1.1 Determinants of social learning within networks

The effectiveness of learning within social networks depends largely on the structures and other characteristics of the networks. Some of the important network structures with regard to social learning are network size (Muange *et al.,* 2015), strength of the networks (Granovetter, 1973), and network behaviour (Manski, 1993). Additionally, social resources entrenched in one's network are important network characteristics that enhance social learning within social networks (Murendo *et al.,* 2018).

Network size, defined as the number of links an individual has in a network, has been found to affect the quality and quantity of information within networks (Zhang *et al.,* 2012). Therefore, individuals with large network sizes should have better outcomes (Maertens and Barrett, 2013; Muange *et al.,* 2015). However, according to Munshi (2011), individuals endogenously assign themselves into the networks, leading to endogenous network size, which might yield a spurious network effect.

The quality and process of information diffusion within networks also depend on the strength of social ties (Granovetter, 2005). Strong ties are referred to as relations among individuals who are emotionally connected within a network while weak ties are acquaintance relations that link a network to the society at large (*ibid.*). Other measures of the strength of social ties include the duration of friendship (Son and Lin, 2012) and the frequency of contact (Fu *et al.,* 2013; Murendo *et al.,* 2018). Ruef (2002) and Fu *et al.* (2013) argue that both strong and weak ties are important because, network members with strong ties have regular meetings and discussions (helps in confirming information that people are already aware of) while those with weak ties rarely meet but exchange diverse and new information when they meet. However, Granovetter (1983) argues that strong ties limit people to only gathering information that they already know therefore affecting social learning negatively.

Another important characteristic of the social networks that influences social learning is the network behaviour in an individual's network. Manski (1993) argues that social network behaviour can influence the behaviour of an individual. Van den Broeck and Dercon (2011) attribute this tendency to social externalities. For example, if the average productivity of a network increases as a result of new technology adoption by a few network members, then network members' individual productivity also improves.

Lastly, social resources embedded in an individual's network such as wealth, education and gender of the network members, influence information flow and access within a network (Song and Chang 2012). When an individual interacts with network members belonging to high social or economic status, they are likely to gather quality information and knowledge through social learning. Such knowledge may lead to the adoption of new technologies and products (Zhang *et al.,* 2012; Murendo *et al*., 2018) and/or improved productivity (Van den Broeck and Dercon, 2011; Mekonnen *et al.,* 2018).

5.2 Study Methods

5.2.1 Analytical framework

The analysis in this paper is based on Bandura's (1977) social learning theory which posits that individuals learn through observation, imitation and through other peoples' experiences. Learning is enhanced by social interactions within the network. Such interactions influence the attitudes, behaviour and performance of network members through social learning and social influence (Young, 2009; Hogset and Barrett, 2010). Social learning is enhanced by interactions and links which enable individuals to obtain new information that may in turn influence their decisions directly or indirectly (Bandiera and Rasul, 2006; Munshi 2008; Conley and Udry 2010).

On the other hand, social influence is an outcome of imitation through observation. In this case, individuals change their behaviour to conform to observed behaviour of other individuals in their networks without necessarily having accurate information about the behaviour (Hedström *et al.,* 2000; Easley and Kleinberg, 2010). Based on the foregoing arguments, this paper assumes that as individuals interact through nutrition information networks, they learn, observe and use other people's experiences to improve the quality of their diets, after assessing the consequence and effectiveness of their actions. Hence, in this paper, nutrition information networks are considered as one pathway through which people change their behaviour with regard to household dietary diversity.

5.2.2 Empirical model

The first step in the analysis was to estimate the factors influencing formation of nutrition information network. Following Van den Broeck and Dercon (2011), the relationship between nutrition information network and personal and household characteristics was captured in as probit model given the nature of the data which was normally distributed:

$$S_i = \alpha_0 + \alpha_1 X_i + \alpha_2 N_i + \varepsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5.1)}$$

where, S_i is a dummy variable equal to 1 if the ith individual has at least one nutrition information link and 0 otherwise, X_i is the personal and household characteristics of the ith individual (these include age, education, gender, occupation household size and farm size), N_i represents network characteristics that individual *i* could possibly draw nutrition information from (such as the number of neighbours and kin's members in one's information network), and ε_i is the error term which assumes a poisson distribution.

To estimate the effects of nutrition information networks on dietary diversity, the paper followed Manski (1993) who argues that individuals in the same group behave similarly due to endogenous, exogenous and correlated effects. Endogenous effects refer to the tendency of an individual's behaviour to vary with the overall behaviour of the network. Exogenous effects are the tendency of an individual's behaviour to vary with the observable characteristics of the network members, while correlated effects refer to the propensity of individuals in the same group to behave similarly because they have similar individual characteristics or institutional environments. Following Mekonnen *et al.* (2018), the empirical model was specified as follows:

$$Y_{ikt} = \beta_0 + \beta_1 \bar{Y}_{-ikt} + \beta_2 \bar{X}_{-ikt} + \beta_3 X_{ikt} + \beta_k + \varepsilon_{ikt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5.2)}$$

where Y_{ikt} denotes household dietary diversity score for individual i's household belonging to network *k* at time *t*, $\bar{Y}_{-ikt}$ captures the endogenous effects, measured by average behaviour of the network members of network *k* excluding *i* at time *t*, $\bar{X}_{-ikt}$ denotes the exogenous effects which are measured by the average observable characteristics of the network (*k*) members excluding *i* at time *t*, β_k denotes correlated effects measure by location (County), X_{ikt} denotes personal characteristics of individual i (such as age, gender, education, occupation, wealth status, farm size, household size), while ε_{ikt} is the error term. Therefore, $\beta_1 \neq 0$, $\beta_2 \neq 0$ and $\beta_k \neq 0$ suggest presence of endogenous, exogenous and correlated effects respectively.

This study used average household dietary diversity of the network members as the measure of endogenous network effects. Endogenous effects have been found to have a positive effect on outcomes such as adoption of new technologies (Mekonnen *et al.*, 2018; Murendo *et al.*, 2018). Therefore, an increase in household dietary diversity within the network is hypothesized to increase individual i's household dietary diversity.

Exogenous effects were controlled using share of weak ties, education and age of the network members and share of females in an individual's network. Zhang *et al.* (2012) and Thuo *et al.* (2014) show that weak ties are important since they influence the quality and diversity of information within networks. The share of females in an individual's network was used, given the important role that women play in a household's dietary diversity (Ibnouf, 2009; Sraboni *et al.,* 2014). The paper controlled for correlated effects by including a county (location) dummy.

According to Röper *et al.* (2009) and Song and Chang (2012), the level of education of network members influences the ability of an individual to acquire information. It was therefore hypothesized that the four variables (education and age of the network members, share of females, and share of weak ties) had a positive effect on household's dietary diversity. Because household dietary diversity score is count data, the error term was assumed to follow a Poisson distribution leading to a Poisson regression.

A key challenge in estimating the endogenous effects is the simultaneity bias problem which, in this case, arises when the network behaviour influences an individual's behaviour and in turn the individual's behaviour influences the behaviour of the network (Manski, 1993). Manski (2000) suggests two ways of solving this problem. One approach is to introduce dynamisms in the model and assume a lag in the diffusion of the endogenous effect such that the individual's behaviour is related to lag value of network's average behaviour. The other approach is the use of an instrumental variable that directly affects the outcome of some but not all network members.

Following the first suggestion by Manski, dynamism was introduced in the model as a change in mean household dietary diversity rather than the levels of lagged average household dietary diversity of the network as proposed by Mekonnen *et al.* (2018). This approach is useful in controlling for time-invariant characteristics. It also reflects past trends in the dietary diversification behaviour of respondent, which is likely to be correlated with present ones. Therefore, equation (5.2) was re-specified as follows:

$$Y_{ikt} = \beta_0 + \beta_1 \Delta \bar{Y}_{-ik} + \beta_2 \bar{X}_{-ikt} + \beta_3 X_{ikt} + \varepsilon_{ikt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5.3)$$

5.2.3 Data sources

The study used primary data, collected in Kisii and Nyamira counties of Kenya, using a semi-structured questionnaire. Despite high agricultural productivity in the two counties, there are high levels of malnutrition. For example, 26 percent of all the children in both Nyamira and Kisii are stunted; 4 and 2 percent of all children in Nyamira and Kisii respectively, are wasted, while 10 and 8 percent of all children in Nyamira and Kisii respectively are under weight (KHDS, 2014). There was, therefore, need to understand other ways, beside agricultural productivity, of improving dietary diversity in the counties.

A two-stage sampling procedure was used to select the households. A complete list of existing farmer groups in Kisii and Nyamira was used as the sampling frame. At the first stage, 48 farmer groups (32 from Kisii and 16 from Nyamira) were selected using simple random sampling with a probability proportional to the total number of groups existing per county. At the second stage, simple random sampling was used to select 20 households from each group. In cases where the groups had less than 20 households, all the households were interviewed. In total, 824 households (557 in Kisii and 267 in Nyamira) were interviewed.

The data were collected in two rounds: the first between October and December 2015, and the second between October and December 2016. In the first round, 815 answered the social network section the social network and seven day food recall sections, while 713 farmers answered the sections in second round. To assess the determinants of having nutrition information link, the study used data from the second round. To analyse the effects of social network on dietary diversity, the study used data from the two rounds where a sub-sample of only those farmers who had nutrition networks in both survey rounds, which included 462 households.

5.2.4 Measurement of Variables

To collect social networks data, the sampled farmers were asked questions about their links to all (those interviewed or not) members of their farmer group. The questions concerned the different kinds of information they shared (i.e., nutrition and agriculture information), and their social and geographic proximity (relationships, neighbours,). Data on the frequency of talking, sharing agricultural inputs and outputs was also collected. The reference period for all the questions was the 12 months preceding the survey. The analysis in this paper, however, used pairs of group members that were part of the sample only, since the social network information on those that were not sampled was unavailable.

To capture nutrition information networks, the following question was asked to respondent (farmer group member) *i*; "*Did you share nutrition information with farmer j?*" If the answer was yes then farmer *j* was considered to be a member of farmer *i*'s network. Following Comola and Prina (2017) and Banerjee *et al.* (2013), the paper assumed that the information networks were undirected, such that, a link existed if either *i* or *j* reported having shared nutrition information.

Several network variables were computed and used to capture different network effects. Following Van den Broeck and Dercon (2011) and Mekonnen *et al.* (2018), the average network behaviour was measured by the change in the average household dietary diversity score of the network members in each individual's network constructed using panel data. An individual's (*i*) network size was computed by summing the total number of individuals (*j*) who the individual (*i*) had mentioned to have shared the nutrition information with (Mekonnen *et al.,* 2018; Murendo *et al.,* 2018).

The share of weak ties was measured by the proportion of weak ties in a household's social network. Following Fu *et al.* (2013) and Murendo *et al.* (2018), the frequency of talking among network members was used to measure the strength of links between farmers. The farmers were asked, "*How often did you talk with j?*" The answers were categorize into *"very often, often, sometimes and rarely".* If a farmer had a link with individuals whom they talked very often or often, the link was defined as a "strong tie" while if the they talked sometimes or rarely, it was considered as a "weak tie". The proportion of the weak ties in a household's network was considered to be the share of weak ties.

The share of females was measured by the proportion of female network members in a household's social network. This was given by the dividing the sum of female members (in an individual's network) with the total number of the individual's network members. On the other hand, network education was measured by summing the number of network members who had post primary education (more than 8 years of formal education). All these variables were computed using the second round of dataset except for the average household dietary diversity score of the network members. The latter was computed using the networks mentioned in the first round of data collection.

A wealth index was computed using the type and number of assets owned by a household. The Principle Components Analysis (PCA) was used to assign weights to different assets. Following Langyintuo and Mungoma (2008), the assigned weights were then used to compute wealth index applying the following formula;

$$W_j = \sum_{i=1}^{k} b_i \ (a_{ij} - x_i)/s_i \qquad (5.1)$$

where W_j is wealth index, b_i is the weights assigned to (k) assets on the PCA, a_{ij} is the value of the *k*th asset for the *i*th household, $\boldsymbol{x_i}$ is the mean of the *k*th asset over all households and s_i is its standard deviation.

The household dietary diversity score was computed using a seven day recall food consumption data. The score was computed based on the FAO's guidelines (FAO, 2007) which proposes that household dietary diversity is composed of 12 food groups (cereals, roots and tubers, vegetables, fruits, meat, poultry and offal, eggs, fish and sea foods, pulses, legumes and nuts, milk and milk products, oils and fats, sugar and honey, miscellaneous). All the foods consumed within a household in the seven days were grouped into the 12 food groups. Dietary diversity score was then constructed by summing all the food groups consumed within the household in the seven days. Household dietary diversity score was a count data hence use of Poisson model.

5.3 Results and discussion

Table 5.1 presents the social-economic characteristics of sampled farmers in Kisii and Nyamira counties. Most of the farmers were middle aged (48 years) and on average had post primary school level of education. Farming was the primary occupation for a majority of the farmers who on average owned 1.5 acres of land. Seventy six percent of the farmers had at least one nutrition information link within the farmer group.

Table 5. Socio-economic characteristics of smallholder farmers in Kisii and Nyamira

Variable	Mean	SD	min	max
Age (years)	47.93	12.54	22	84
Education (years)	8.57	3.63	0	17
Farm size (acres)	1.46	1.20	0	11
Number of kin members in the group	3	4.27	0	17
Number of neighbors in the group	1	1.21	0	16
	Number	**percent**		
Gender (1= male 0=otherwise)	268	38	0	1
Occupation (1= farmer 0= otherwise)	576	81	0	1
nutrition information networks (1= Yes 0= otherwise)	540	76	0	1
N	*713*			

Table 5.2 shows results of the determinants of having nutrition information networks. The factors influencing formation of nutrition information networks in the two study sites were years of formal education and number of neighbours that a respondent had. Accordingly, an extra year in school increased the probability of forming a nutrition information network by 0.011 percent. This is plausible because educated farmers are probably more knowledgeable on nutrition information and are likely to give and/or gather nutrition information from/to a wider network.

Table 5.1 Factors influencing the formation of nutrition information networks in Kisii and Nyamira

Variables	Marginal Effects	Std. Err.
Gender	0.025	0.034
Age	-0.002	0.002
Education	0.011^{**}	0.005
Household size	0.000	0.009
Land size	-0.002	0.010
Occupation	0.065	0.052
N umber of neighbours	0.031^{**}	0.016
Number of kin’s member	-0.002	0.005
Observations	713	

Notes: ** denotes significance at 5% level; the standard errors are robust, adjusted for clustering at farmer group level. The dependent variable=1 if one has at least one nutrition information link 0= otherwise.

Having an extra neighbour within the farmer group increased the probability of forming a nutrition information network by 0.031 percent (Table 5.2). This means that farmers can rely on their neighbours to gather nutrition information. The finding is consistent with Van den Broeck and Dercon (2011) who also reported that farmers depended on neighbours and family members for advice on adoption of agricultural technologies in Tanzania.

To assess the effect of nutrition information networks on households' dietary diversity, a sub-sample (those who reported nutrition information networks) of the total sample was used. To test whether the sub-sample was any different from the sample that was not included in the analysis, a Chow test was conducted which showed that the two sub-samples were not different implying the sub-sample was representative of the whole sample (Appendix 5A).

Table 5.3 presents descriptive statistics of sub-sample (of respondents who had a nutrition information link) and definition of variables used in the Poisson regression model. The mean dietary diversity score was 10 out of 12 food groups. On average, farmers had about three nutrition information links with 64 percent of the link being females. There was a positive change in the average household dietary diversity score of an individual's network between the two survey rounds. On average, about two members of an individual's network had post primary education and the average age of the network members was 48 years. Moreover, 21 percent of network members mentioned by an individual were connected by weak ties.

Table 5.2 Descriptive statistics of variables used in Poisson regression

Variable	Definition	Mean (n=462)	SE
Dependent variable			
Household dietary diversity	Household dietary diversity score (HDDS)	9.73	0.06
Independent variables			
Social network			
Change in average household dietary diversity	Change in the average household dietary diversity score of the households in the individual's social networks (2015-2016)	0.11	0.06
Network education level	Sum of individuals with post-primary1[2] education in an individual's network	1.5	0.08
Network age	Average age in years of group members in an individual's network	48.25	0.41
Share of females	proportion of females in an individual's network	0.64	0.02
Share of weak ties	Proportion of weak ties in individual's network	0.21	0.02
Network size	Number of group members an individual share nutrition information.	2.90	0.13
Household characteristics			
Gender	Gender of the household head (1=Male, 0=female)	0.37	0.02
Age	Age of household head (years)	47.31	0.58
Occupation	Occupation of household head (1=farming, 0=otherwise)	0.83	0.02
Education level	Education level of household head (1=post primary, 0=otherwise)	0.60	0.02
Household size	Size of the household (number of members)	5.50	0.09
Farm size	Size of farm (acres)	1.46	0.06
Wealth index	Index constructed using household's asset	0.08	0.10
County dummy	County in which the household belong (1=Kisii, 0=otherwise)	0.66	0.22

[2] Completed the first 8 years of formal education in Kenyan education system

The results of the Poisson regression estimating effects of social networks on dietary diversity are presented in Table 5.4. The average household dietary diversity score of network members had a positive and significant effect on the household dietary diversity of an individual farmer. A unit increase in average household dietary diversity score of an individual's network members will lead to a 7.6 percentage increase in the household dietary diversity score. This is indicative of the existence of social learning within nutrition information networks.

Table 5.3 Effect of nutrition information networks on household dietary diversity among smallholder farmers in Kisii and Nyamira

Variable	Marginal Effects	SE
Information network variables		
Change in average HDDS	0.076**	0.037
Sum post-primary education	0.076**	0.033
Average age	0.011*	0.006
Share of females	0.253	0.190
Share of weak ties	-0.229	0.170
Household characteristics		
Gender of household head	0.173	0.127
Age of household head	-0.011**	0.005
Occupation of household head	-0.207	0.131
Education of household head	-0.122	0.113
Household size	0.080**	0.032
Wealth index	0.065**	0.031
Farm size	0.153***	0.051
County dummy	-0.112	0.136
N	*462*	

Notes: *, **, *** denote significance at 1%, 5% and 1% levels, respectively; SE= clustered standard errors (to control for fixed group effect).

The results imply that nutrition information networks have an endogenous effect on household dietary diversity. This could be from social learning from members of the network or imitating eating habits of network members which may lead to eating improved diets. This finding is supported by earlier studies that reported positive endogenous network effects on technology adoption (Van den Broeck and Dercon, 2011; Mekonnen *et al.*, 2018; Murendo *et al.*, 2018)) and agricultural productivity (Van den Broeck and Dercon, 2011; Mekonnen *et al.*, 2018).

The average education level of the nutrition network members had a positive effect on household the dietary diversity of individual farmer, which was significant at five percent. A unit increase in the number of network members with post-primary education increased the household dietary diversity score by 7.6 percent (Table 5.4). Educated networks members are likely to have more nutrition information which when shared, it would lead to consumption of quality foods. The results are comparable to those of Basu and Foster (1998) and Van den Broeck and Dercon (2011) who found that the number of literate members of a network had a positive effect on the productivity of individual network members in Tanzania.

The effect of the average network age was positive, but weakly significant. Additionally, the rest of the exogenous variables, namely, share of females and weak ties in the information networks did not have any significant effect on the household dietary diversity score. These results suggest that the only exogenous effects that influence the behaviour of individuals in the nutrition-information networks are those associated with education level. On the other hand, the county dummy is not significant, suggesting absence of correlated effect on the household dietary diversity score.

Other significant factors included household size, wealth and farm size all of which had a positive and significant (at least at the 5 percent level) effect on household dietary diversity score (Table 5.4). Households with bigger farm sizes consumed more food groups (Table 5.4). This could be explained by the fact that farmers mainly consume what they grow on their farms, implying that they are likely to grow more diverse crops and keep different livestock species as their farm size increased. This finding was supported by Jones *et al.* (2014) who reported that farm size influences household dietary diversity positively.

Larger families consumed more food groups than smaller ones (Table 5.4). This could be attributed to the fact that the former have more labour-force which can be invested into agricultural production and in return improve their dietary diversity through production of diverse agricultural products or increased income through hired labour relative to the latter (Workicho *et al.*, 2016). Wealthier households were also found to have higher dietary diversity scores than poorer ones. This is perhaps because wealthier households have higher ability to buy more diversified foods from the markets compared to their poorer counterparts. This corroborates the results of Sibhatu *et al*. (2015) who found an association between higher income and higher household dietary diversity scores in Kenya, Ethiopia and Malawi.

The age of the household head had a negative and significant effect on household dietary diversity score at the 10 percent level (Table 5.2). Younger farmers had higher household dietary diversity scores than older ones probably because younger farmers are more informed through print and electronic media and thus have more nutrition knowledge. Jones *et al.* (2014) reported similar findings, that age influenced household dietary diversity negatively.

To test for robustness of the findings, network size and its square were introduced into the model and the results presented in Table 5.5. The squaring of network size was undertaken to clarify whether the reported network endogenous effects were driven by the average behaviour of the network or by the endogenous network size in conformity with Mekonnen *et al.* (2018). The results on the endogenous effects did not change qualitatively (compared to those shown in Table 5.4), indicating that the effects were not from network size. The insignificant coefficients on network size and the network size squared further confirmed that the network effect is not driven by network size but rather by social externality (i.e., a benefit emanating from the overall behaviour of the group) Mekonnen *et al.* (2018).

Table 5.4 Robustness of the effect of network structure on household dietary diversity in Kisii and Nyamira

Variable	Marginal Effects	SE
Change in Ave. HDDS	0.075^{**}	0.038
Network size	-0.047	0.078
(Network size)^2	-0.002	0.003
Sum post primary	0.174^{**}	0.070
Average age	0.013^{**}	0.006
Share of females	0.300	0.188
Share of weak ties	-0.244	0.173
Gender	0.168	0.126
Age	-0.011^{**}	0.005
Occupation	-0.212	0.129
Education	-0.128	0.112
Household size	0.078^{**}	0.032
Wealth index	0.067^{**}	0.032
Farm size	0.149^{***}	0.050
County dummy	-0.112	0.131
Observations	*461*	

Notes: **, *** denote significance at t 5% and 1% levels, respectively. SE= standard errors at the mean.

5.4 Conclusions and recommendations

This study evaluated the factors influencing the formation of nutrition information networks among smallholder farmers in Kisii and Nyamira counties of Kenya using a Probit model. The study found that the household head's level of education increased the probability of sourcing nutrition information from the network. Further, an increase in the number of neighbours within the farmer group increased the probability of sourcing nutrition information from the network.

The study also assessed the effect of social networks on household dietary diversity using a Poisson model. The study found that the dietary diversity of an individual's nutrition network positively influences the individual's dietary diversity hence endogenous effects of social network. Having more network members with more than primary education increased an individual's household dietary diversity score. This suggests the positive spill-over effects of education not only to the individual but also to his/her entire network (exogenous effects).

The study found no correlated effect such that, the dietary diversity was not influenced by network members having similar individual characteristics or facing similar institutional environments. Finally, household size, wealth index and the farm size had a positive and significant influence on household dietary diversity while age had a negative effect. This indicate that dietary diversity of a household is influenced by personal characteristics of the household head.

In conclusion, it is clear from the study that higher education level increases the probability of forming nutrition information networks. Additionally, the more educated the network members are the higher is an individual household's dietary diversity score. Nutritional education would therefore increase farmers' nutrition knowledge, which would further widen their nutrition information networks. Moreover, improved nutrition knowledge of an individual's network members would also improve his/her own dietary diversity through social learning. Therefore nutrition information networks are important pathways through which nutrition information could be channelled to enhance household nutrition quality.

The study recommends use of nutrition information networks as a tool for effective delivery of information within nutrition education programmes. Most importantly, nutrition education programmes could benefit from the social multiplier effect generated by the endogenous network effects such that an individual's nutrition quality improves with an improvement in the average nutrition quality of the network. In such a case, an effective programme targeting to improve nutrition quality of network members does not have to target everyone in the network. Hence, investment in educating some members (instead of all members) of a network could eventually improve the nutrition quality of everyone in the network through social learning. Such a strategy would be cost saving.

CHAPTER SIX

GENERAL CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study examined the effect of social networks as an informal strategy to mitigate the adverse effects of malnutrition among smallholder farmers in Kisii and Nyamira counties of Kenya. The study used a panel data of 815 households collected in two rounds in the two study areas. Round one was collected October and December 2015 while round two was collected between October and December 2016. A multistage sampling procedure was used to select the households that were interviewed.

The study focused on how social networks affect different aspects of household food consumption. The first objective evaluated the effect of income and health shocks on the formation of financial and non-financial networks. The main aim was to understand whether social networks are formed to respond to shocks. Objective one reported that smallholder farmers form financial networks to respond to health shocks. The second objective then sought to understand, despite farmers forming networks to respond to shock, do social networks really insure household food consumption? The objective reported this to be the case.

The first two objective showed that social networks can be used to curb malnutrition by enhancing availability of food quantities in presence of shocks. The third objective focused on whether and how social networks would enhance food quality since literature suggests enhancing both quantities and quality of food as a way of curbing malnutrition. Third objective therefore, focused on effects of social networks on dietary diversity (proxy for dietary qualities). The objective reported positive effects of social networks on dietary diversity.

The study addressed three objectives as mentioned earlier, objective one used using a dyadic LPM to evaluate the effect of income and health shocks on the formation of financial and non-financial networks as informal *ex post* risk sharing strategy. The study found that kinship, geographical proximity, education and age were important determinants of both credit and food-sharing links. Further, health shocks were found to positively influence the formation of financial but not non-financial networks while income shocks did not have any effect on both financial and non-financial networks.

It was therefore concluded that the formation of both financial and non-financial networks is determined by geographical and social proximity probably because of the need to enhance monitoring and enforcement within social networks. Informal financial links play a risk-sharing role when farmers are faced with health shocks; however, while smallholders form informal financial networks as insurance against idiosyncratic health shocks, they may not need them to cope with idiosyncratic income shocks. Additionally, income shocks affecting smallholder farmers are not insured within informal (financial and non-financial) networks.

Objective two assessed the effect of social networks on household food consumption smoothing in the presence of health shocks using a fixed effects model. The results showed that health shocks had a negative and significant effect on purchased food among the smallholder farmers in Kisii and Nyamira Counties. Further, the study found that credit networks had a positive effect on purchased food consumption in the presence of health shocks while food-sharing networks did not have any effect. Therefore, financial networks play an insurance role against health shocks in purchased food consumption.

The results further indicated that social networks did not have any significant effect on insurance of total food consumption against health shocks. The study however could not reject the hypothesis that networks play an insurance role against health shocks in total food consumption. This is because food gifts that are likely to reduce the effects of health on total food consumption were also most likely exchanged through food-sharing or other networks such as friendship and kinship ties.

Objective three evaluated the factors influencing the formation of nutrition information networks and the effects of those networks on household dietary diversity using a Probit and a Poisson regression model respectively. The study found that education and the number of neighbours within the farmer group increased the probability of sharing nutrition information among smallholder farmers. Further, the endogenous effects of nutrition information networks had a positive effect on household dietary diversity score. In addition, having more network members with higher education than primary level increased an individual's household dietary diversity score. The size of the household, wealth index and farm size had a positive influence on household dietary diversity while age had a negative effect.

The study lays emphasis on the importance of social networks as a tool for improving the quantity and quality of household food consumption. The study indicates that smallholder farmers form specific social network as an insurance against household shocks. The social networks act as safety nets in time of hardships through risk-sharing by mitigating effects of such shocks on household food consumption. Lastly the study demonstrates the importance of social interactions within networks, as a critical nutrition information channel, through which nutrition knowledge is acquired which in turn influences dietary diversity positively. Social networks are therefore key in any policy that targets to improve food and nutrition security.

6.2 Recommendations

The findings of objective one suggests that informal financial networks are formed to serve a risk sharing role when farmers are faced with health shocks and therefore they could be harnessed as an informal way to insure farmers against health shocks. Thus, any program aiming at helping farmers in dealing with idiosyncratic health shocks can benefit from such networks. However, any investment in the formation of farmer groups should consider the geographical and social proximity of the members which influences formation of the networks positively.

Objective two finds social networks to act as an indispensable food safety net in times of adversity. Smallholder communities seem to be efficient in providing food safety nets amongst themselves through use of social networks. However in some cases, these safety nets do not provide full risk-sharing opportunities. It would be advisable, therefore that policymakers provide food safety nets that complement community-driven initiatives in order to enhance the effectiveness of indigenous risk-hedging strategies. They should also provide the safety nets through utilizing the most efficient networks that offer full risk sharing against shocks.

Based on the findings of objective three, education is an important precursor in the formation of nutrition information networks and also positively influences an individual households' dietary diversity. There is therefore need for nutrition education programs targeting to improve quality of diets. Such programs should use information networks as pathways through which nutrition information could be channelled. Most importantly, the programs can take advantage of the social multiplier effect generated by the endogenous network effects. That is, the program does not need to target everyone in the network, rather it could educate a few members who would then influence the whole network through social learning as a cost-saving strategy.

The last recommendation is on area for further research. While this study evaluated how idiosyncratic shocks affect food consumption and the role of social networks in insuring smallholder farmers against such shocks, it is well known that smallholder farmers in Kenya are often affected by both covariate and idiosyncratic risks. There is therefore need for further studies to address the effect of covariate shocks such as droughts and the role of social networks in their mitigation. This would give a wider understanding of the insurance role of social networks in the presence of both idiosyncratic and covariate shocks. Another study focusing on the effect of social networks on other nutrition outcomes such as anthropometric measures (BMI, waist-to-hip ratio, etc.**)** would complement this study. In addition, there is need for a further study to identify influential people in nutrition networks and how such influence affects the effectiveness of such networks.

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APPENDICES

Appendix 3A: Instrumenting for income

	Instrument for income differences		Instrument for income sum	
	Coefficient	SE	Coefficient	SE
Differences of:				
Working household size	**0.071*****	0.012	0.000	0.015
Age	0.003	0.002	0.000	0.003
Education	0.066***	0.008	0.000	0.009
Gender	-0.001	0.043	0.081	0.051
Occupation	-0.002	0.062	0.072	0.068
Sum of:				
Working household size	0.000	0.012	**0.088*****	0.014
Age	0.000	0.002	-0.003	0.002
Education	0.000	0.008	0.088***	0.009
Gender	0.001	0.053	0.290***	0.064
Occupation	0.001	0.076	-0.048	0.096
Relationships;				
Neighbour	0.062	0.060	0.098	0.062
Kinship	-0.081	0.057	0.010	0.067
Constant	0.019	0.325	20.511***	0.372
Observations	*13318*			
Anderson-Rubin (AR) *test*	$X^2=0.39$			
	P-value=0.8214			

Notes: Dependent variable; Income differences/sum);*, **, *** denote significance at, 10%, 5%, and 1% levels, respectively; SE = clustered standard errors at two dimensions (I and j).

Appendix 5A: Chow test in a linear regression; individuals with nutrition information networks and those without.

	Coefficient	Std. Err.	P>z
Age	-0.009**	0.004	0.048
Education	0.022	0.015	0.138
Gender	0.132	0.105	0.206
Household size	0.064***	0.024	0.006
Wealth index	0.046	0.036	0.203
Farm size	0.118***	0.037	0.001
Occupation	-0.121	0.117	0.303
chi2(7) = 2.78			
Prob > chi2 = 0.9044			

Notes: **, *** denote significance at the 5% and 1% levels respectively. The dependent variable is household dietary diversity score.

Appendix 8A: Household Survey Questionnaire

Goettingen University-Germany, University of Nairobi-Kenya and Africa Harvest Biotech Foundation International (Africa Harvest) are carrying out a research on different aspects of agricultural development. We are currently doing a survey which aims to provide more understanding about farmers' production and marketing decisions, and nutrition and health status. Your participation in answering these questions is very much appreciated. Your responses will be **COMPLETELY CONFIDENTIAL** and will only be used for research purpose.
Do you have any questions that we need to clarify? [Make clarifications in case there are questions]If *No*, do you agree to take part in this survey, including the interviews?
If *Yes*, let the potential respondent write name and sign below

Name___________________________________

Signature________________________________

MODULE 0 Household ID

1	Household ID		8	County		13	**First visit date**	
2	Group ID		9	Sub-County			Result: 1=Interview completed 2= Interview partly completed 3= Specify	
3	Date of interview		9	Division		14	**Enumerator Name**	
4	Start Time (24 Hr)		10	Village		15	**Second visit date**	
5	End time (24 Hr)		12				Result: 1=Interview completed 2= Interview partly completed 3= Specify	
6	HH head Full Name					16	**Enumerator Name**	
7	Cell phone number							

MODULE 1: HOUSEHOLD DEMOGRAPHIC INFORMATION (reference period between 1st Oct 2015 and 30th Sep 2016)

Household composition**:** *Please list all household members (All those who are under the care of household head in terms of food and shelter provision, and those who normally live and eat their meals together), starting with the household head.*

1	2	3	4	5	6	7	10	11	12
MEMID	**Name of the HH member**	**Gender** ***M = 1 F= 0***	**R/ship with HH head (C*odes A)***	**Age in yrs**	**Years of formal education (*Highest level attained*)**	**Marital Status *(Codes B)***	**# of months in the last 12 months [NAME] has been away from home**	**Main Occupation based on time spent *(Codes D)***	**Household farm labour contribution *(for those above 16 years of age in the upper category) (Codes E)***
			1						

Code A
1= Head
2=Spouse
3=Son/daughter
4=Father/mother
5=Sister/brother
6=Grandchildren
7=Grandparents
8=Step children
9=Step parents
10 = Father/mother-in-law
11 =Sister/brother-in-law
12 = House girl
13 =Farm labourer
14 = Other relative
15= Other Unrelated

Code B
1= Married-monogamous
2= Married polygamous
3= Single
4= Divorced/separated
5= Widow/widower

Code D
0= None
1= Farming (crop + livestock)
2= Casual labour on-other farm
3= Casual labour off-farm
4= Self-employed off-farm
5= Salaried employment (civil servant etc)
6=Student/school
77= Other (Specify)______

Code E
1= Part time
2= Fulltime
3=Does not work on farm

MODULE 2: LAND HOLDING IN ACRES (period between 1st Oct 2015 and 30th Sep 2016)

2.1 How much land do you own in acres? ________________
2.2. How much of your total land is under homestead? _______________
2.3. Do you have a title deed for your land? ___________Yes=1 (all land), No=0 (no land), 3=partly

Land category	Short rain season (Oct-Nov 2015)		Long rain season (Mar-Apr 2016)	
	Cultivated	Fallow	Cultivated	Fallow
1. Own land (A)				
2. Rented in (B)				
3. Rented out (C)				

CODES FOR MODULE 3

Codes A
Maize
Rice
Sorghum
Millet
Cassava
KK 15 Beans
Other Field beans
Bananas
Cabbage
Cowpea
Groundnut
Soybean
Sweet potatoes
Orange Fleshed Sweet Potatoes (OFSP)
Black night shade
Sugarcane
Pineapple
Jute Mallow (Omutere)
Amaranthas leaves (Emboga)
Pumpkin leaves
Sukuma wiki (Kales)
Carrots
Passion Fruit
Irish potato
Bean leaves
Tea
Onion
Kales
Coffee
Napier grass
Avocado
Spider Plant
Vine Spinache
Pumpkin
Trees
Mangoes
Guava
Wheat
Paw Paw
Tomatoes
Loquat
Green grams
Tree Tomato
Strawberry
Spring Onion
Desmodium
Spinach
Arrow Roots
Green Peas
Pysallis
Corriander
Capsicum
Pepper
Grass
Butternut
Lemon
Beetroot
Cumcumber
Water melon
Tree Seedlings
Raspberry
Gooseberry
Pyrethrum

Other______________
Other______________
Other______________

Codes B
1. Improved
0. Local

Codes C
Kilogram
Litre
90 Kg bag
50 Kg bag
25 Kg bag
Gorogoro
Debe
Wheelbarrow
Ox-cart
Bunch (bananas)
Piece/number
Not yet harvested (for perennials only)
Stools
Glas"
Suckers
Bucket
Ml
Spoonful
5 kg bag
10 kg Bag
250 Ml
Yellow paper bag
Grams
Pick up
Trees
Green paper bag
Lines
Packet (250g)
Crates
Bundle
Handful
Cuttings
Vines
Head load
Lorry
Seeds
Bushes
45kg bag
Bottle top
Seedlings
Tonne
500 Ml glass
25 grams

Cobs
Poles
Crop failure/ (MLND)
Black paper bag

77Other (specify)________

MODULE 3: NON-LABOUR PURCHASED INPUT USE (1st Oct 2015 and 30th Sep 2016 planting seasons, record separately by plots)

1	2	3	12	4	5	6			7			8	9		10			11		
Plot Code (*Use alphabets in Cap*)	Crop Grown ***A***	Land under crop	Intercrop (1= Yes; 0= No)	Number of trees	Crop variety **B**	Seed **C**			Fertiliser(planting) (Fill once for intercrops) **C**			Oxen/ tractor hire Cost	Farm manure (Fill once for intercrops ***C***		Pesticides/herbicides ***C***			Crop output ***C***		
						Qty	units	Price /Unit	Qty	Units	Price /Unit	Ksh	Qty	unit	Price /unit	Qty	units	Price /unit	Qty	Unit
Short Rains																				
Long Rains																				
Perennial Crops																				

MODULE 9: HOUSEHOLD ASSETS (Prompt for each item as listed below)

9.1 **As at September 2016**, how many of the following items did the household own that are in **usable/repairable** condition?
To estimate the value ask the respondent how much they would be willing to buy the item in its current state if it were being sold to them

	ASSET	Total Quantity	Estimate total current value of the asset(s) if you were to buy it in its current state		ASSET	Total Quantity	Estimate total current value of the asset(s) if you were to buy it in its current state
1	Tractor			**2**	Slasher		
3	Car/Van			**4**	Axe		
5	Pickup			**6**	Panga		
7	Motorcycle			**8**	Hoes/Jembes		
9	Bicycle			**10**	Spades/shovel		
11	Television			**12**	Chemical spray pump		
13	Radio			**14**	Treadle pump		
15	Mobile Phone			**16**	Powered water pump		
17	Refrigerator			**18**	Mosquito net		
19	Solar panels			**20**	Greenhouse		
21	Generator			**22**	Water tank		
23	Chaff cutter			**24**	Store for farm produce		
25	Ploughs for tractor			**26**	Lanterns		

27	Reaper			**28**	Main house		
29	ox-plough			**30**	Wheelbarrow		
31	Cart			**32**	Computer/laptop		
33	Livestock Kraal			**34**	Biogas digesters		

MODULE 11: OTHER SOURCES OF INCOME AND TRANSFER

11.1 Do you have off-farm employment? _______________ (*1=Yes; 0=No*)*If NO, skip to 11.2.*

Please prompt the codes to make sure nothing is forgotten					
1	2	3	4	5a	5b
MEM ID	Type of Occupation **A**	Average Number of days worked per month 10/15 – 9/16	Average Number of months worked per year 10/15 – 9/16	Earning per unit	
				Ksh	**B**

Code A*: 1: Agricultural labour (casual+permanent)2Casual labour (non-agricultural) 3 Salary (Permanent non-agricultural employment)*

Code B*: 1=Day, 2=Month, 3=Year, 4=Lump sum, payment, 77=other specify*

11.2 Do you have any other sources of income? ___________ (*1=Yes; 0=No*)

	Please prompt the codes to make sure nothing is forgotte)			
	1	2	3	4
	Categories	Code	Type of occupation	Amount /value received between Oct15/ Sept 16/ *for small businesses ask for profit (+) losses (-)*
1	Remittances/gifts/transfers/food aid	1		
2	Pension	2		
3	Small business	1	Brick making	
		2	Carpentry	
		3	Construction	
		4	Grain mill	
		5	Handicrafts	
		6	Beverage, local brew	
		7	Sales in shop, petty trade	
		8	Transport	
		77	Other, specify______	
4	Sales of forest products	9	Sale of wood and charcoal,	
		10	Sale of wild nuts/fruits	
5	Other agric. Income	11	Sale of crop residues	
		12	Leasing out land	
		13	Renting out oxen for ploughing	
		14	Hiring out machinery services to other farmers	
		15	Dividends (T-bills, bonds, shares)	
		16	Tea bonus	

MODULE 12: NON-FOOD EXPENDITURE

Consider the **last year (Oct 15 - Sept 16)** generally how much has your HH spent on the items listed in a typical year (see specification indicated for each item)?

		1	2
		Read out: Please exclude Business Expenditures *Enter 88if respondent does not know.*	How much did your household spend on [ITEM/SERVICE] during the last year (Oct. 15 – Sept 16)?
			Value in Khs
Non-food	1	Rent (housing)	
	2	Personal care supplies	
	3	Clothes, shoes and bags, accessories	
	4	Detergent/washing powder	
	5	Electricity	
	6	Other non-food	
Transportation + communication	7	Fuel, maintenance, insurance, and tax for motorbike/car	
	8	Public transport	
	9	Airtime (incl. MPESA)	
	10	Other transportation, communication	
	11		
	12		
Education	13	School fees, books, Student's dress/uniform, Tuition and rental fee	
	14	Other cost of schooling	
	15		
	16		
Health	17	Medicine, doctor fees	
	18	Other health cost	
	19		
	20		
Social	21	Celebration and funeral cost	
	22	Recreation and entertainment	
	23	Contributions (eg. Church, groups)	
	24	Tobacco (incl. snuff and miraa)	
	25	Insurance (eg. Car, life, health)	
	26	Remittances transferred to other HH	
	27	Other social cost	

MODULE 17: SHOCKS EXPERIENCENCED BY THE HOUSEHOLD

	1	2	3	4
	Please answer the following questions accordingly	Did you experience[NAME OF SHOCK] in the last 12 month? *1=Yes, 0=No* *If No Skip to the next shock*	If yes, how many times has it occurred.	What was the intensity of the last shock to this household? 1=Severe 2= Moderate 3=Mild
	Climatic shocks			
1	Drought			
2	Floods			
3	Frosts			
4	Hailstorm			
	Biological shocks			

5	Pests or diseases that affected crops before harvest			
6	Pests or diseases that led to storage losses			
	Economic shocks			
7	Large increase in agricultural input prices			
8	Large decrease in agricultural output prices			
9	Large increase in food prices			
	Other shocks			
10	Loss of family member			
11	Job loss			
12	Acute illness			
77	Other (specify______________________________)			

MODULE 19: SOCIAL NETWORKS

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
GRP MEM ID	Name of the group member	Do you know NAME? *(1=Yes; 0=No), if no: cross out name and skip to next person*	Please specify your relationship to NAME **A**	Is NAME's plot bordering yours? *(1=Yes; 0=No)*	Do you share food with NAME? (1=Yes; 0=No)	Did you lend or borrow any agricultural produce from NAME between Oct15 and Sept16? 0=no 1=lend 2=borrow 3=lend and borrow	If you suddenly needed money, would you ask NAME to lend it to you? *(1=Yes; 0=No),*	Have you talked to NAME between Oct15/Sep16? *(1=Yes; 0=No), if no cross name out and skip to next person*	How often did you talk with NAME between Oct15/ Sep16? **B**	Did you share information on nutrition with NAME? *(1=Yes;0= No) If no skip to 23*
		1								
		2								
		3								
		4								
		5								
		6								
		7								
		8								
		9								
		10								
		11								
		12								
		13								
		14								

Code A

1 Parent
2 Spouse
3 Child
4 Brother/sister
5 Grandparent
6 Grandchild
7 Nephew/Nice
8 Uncle/Aunt
9 Cousin
Mother/father in low
11 Brother/Sister-in law
12 Other relative
13 Neighbour
14 Friend
15 Fellow villager
16 Attend same church/mosque
17 Business colleague
77 Other, specify___

Code B

1 Very often
2 Often
3 Sometimes
4 Rarely

TARGET PERSON: PERSON RESPONSIBLE FOR FOOD PREPARATION

MODULE 20: HOUSEHOLD FOOD CONSUMPTION

Respondent MEMID:____________________

	14	15	16	17	17a	17 b	17c	18
				Source (*record quantities*)				
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	*Own production*	*Purchased*	*Gift*	*Other, specify*	**Average price per purchased unit Ksh…**
1	**Staple foods**							
2	Maize green							
3	Maize grain							
4	Maize flour							
5	Yam Tuber							
6	Yam flour							
7	Cassava Tuber							
8	Cassava flour							
9	Orange fleshed sweet potato							
10	Other sweet potato							
11	Irish potato							
12	Irish potato chips							
13	Arrowroots							
14	Sorghum grain							
15	Sorghum Flour							
16	Millet grain							
17	Millet flour							
18	Brown rice							
19	White rice							
20	Wheat grain							
21	Wheat flour brown							
22	Wheat flour white							
23	Cooking banana							
24	**Other staple foods**							
25								
26								
27								
28	**Vegetables**							
29	Amaranth leaves (Emboga)							
30	Black night shade (Rinagu)							

	14	15	16	17	17a	17b	17c	18
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	**Source (*record quantities*)**				**Average price per purchased unit Ksh…**
				Own production	*Purchased*	*Gift*	*Other, specify*	
31	Butternut							
32	Cabbage							
33	Carrot							
34	Cow pea leaves							
35	Cucumber							
36	Eggplant							
37	Jute mallow (Omotere)							
38	Kales							
39	Mushrooms							
40	Okra							
41	Onion							
42	Pepper							
43	Pumpkin							
44	Pumpkin leaves (Risosa)							
45	Spider plant (Chinsaga)							
46	Spinach							
47	Stinging nettle (rise)							

	14	15	16	17	17a	17b	17c	18
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	**Source (*record quantities*)**				**Average price per purchased unit Ksh…**
				Own production	*Purchased*	*Gift*	*Other, specify*	
48	Sweet potato leaves							
49	Tomato							
50	Vine spinache (Enerema)							
51	**Other vegetables**							
52								
55	**Nuts and Pulses**							
56	Beans dry							
57	Beans fresh							
58	Black beans							
59	Cashew nut							
60	Green grams							
61	Groundnut (boild)							
62	Groundnut (roasted)							
63	Lentils							
64	Peas (incl cowpea (Egesare), pigeon peas, green peas)							
65	Sesame seeds							

	14	15	16	17	17a	17 b	17c	18
				Source (*record quantities*)				
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	*Own production*	*Purchased*	*Gift*	*Other, specify*	**Average price per purchased unit Ksh…**
66	Soya meat							
67	Soybean							
68	Soybean flour							
69	**Other pulses and nuts**							
70								
71								
72								
73	**Fruits**							
74	Apple							
75	Avocado							
76	Coconut							
77	Guava							
78	Melon							
79	Orange							
80	Passion fruit							
81	Physalis/goose berry							
82	Pineapple							
83	Ripe bananas							
84	Ripe mango							
85	Ripe pawpaw							
86	Sugar cane							
87	**Other fruits**							

	14	15	16	17	17a	17 b	17c	18
				Source (*record quantities*)				
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	*Own production*	*Purchased*	*Gift*	*Other, specify*	**Average price per purchased unit Ksh…**
88								
89								
90								
91	**Meat and animal Products**							
92	Beef sausage							
93	Bush meat (Game meat)							
94	Chicken							
95	Chicken							
98	Fish							
99	Goat/ Sheep meat							
100	Liver (from any animal)							
101	Offal's (matumbo)							
102	Pork							
103	Sardine (dagaa)							
104	Termites							

	14	15	16	17	17a	17b	17c	18
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	**Source (*record quantities*)**				**Average price per purchased unit Ksh…**
				Own production	*Purchased*	*Gift*	*Other, specify*	
105	Turkey (batamzinga)							
106	**Other meats**							
107								
108								
109								
110	**Dairy products**							
111	Cheese							
112	Ice cream							
113	Milk (cow/goat milk)							
114	Powdered milk							
115	Sour milk (mala)							
116	Yoghurt							
117	**Other dairy product**							
118								
119								
120								
121	**Beverages**							
122	Cocoa powder							

	14	15	16	17	17a	17b	17c	18
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	**Source (*record quantities*)**				**Average price per purchased unit Ksh…**
				Own production	*Purchased*	*Gift*	*Other, specify*	
123	Coffee (powder)							
124	Drinking chocolate							
125	Milo powder							
126	Soya powder							
127	Tea (leaves)							
128	**Other beverages**							
129								
130								
131	**Drinks**							
132	Apple juice							
133	Bottled beer							
134	Local beer							
135	Orange juice							
136	Pineapple juice							
137	Other juice (concentrates)							
138	Soft drinks (coke/fanta/etc)							
139	Wine							
140	**Other drinks**							

	14	15	16	17	17a	17b	17c	18
				Source (*record quantities*)				
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	*Own production*	*Purchased*	*Gift*	*Other, specify*	**Average price per purchased unit Ksh…**
141	Water							
142								
143	**Condiments and spices**							
144	Salt							
145	Curry							
146	Ginger (tangawizi)							
147	Ketchup, Tomato sauce							
148	Pepper							
149	**Other Condiments and spices**							
150								
151								
152								
153	**Snacks**							
154	Bread							
155	Biscuit/cookies							
156	Popcorn							
157	Cakes							
158	Mandazi							
159	**Other snacks**							
160								

	14	15	16	17	17a	17b	17c	18
				Source (*record quantities*)				
	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 7 days?**	**Unit of quantities consumed** *(Use codes above A)*	*Own production*	*Purchased*	*Gift*	*Other, specify*	**Average price per purchased unit Ksh…**
161								
162	**Sugar and sweets**							
163	Sugar							
164	Chocolate							
165	Honey							
166	Sweets							
167	**Other sugar and sweets**							
168								
169								
170	**Fat and Oil**							
171	Animal fat							
172	Butter							
173	Corn oil							
174	Groundnut oil							
175	Margarine							
176	Sunflower Oil							
177	Vegetable oil							
178	Vegetables Fat							
179	**Other oil**							
180								
181								