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# Social networks and *ex post* risk management among smallholder farmers in Kenya

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## ABSTRACT

Smallholder farmers in developing countries are vulnerable to idiosyncratic and covariate risks. The risks affect their welfare through the shocks they impose on income, assets, health and food supply. To cope with these shocks, smallholder farmers have extensively relied on informal risk management strategies such as social networks, due to the poorly developed or missing formal insurance markets. Social networks play a risk-sharing role through transfers (loans and gifts) within the networks. This paper 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. Results show that kinship, geographical proximity, education and age are important determinants of both financial and non-financial links. Health shock is also 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 paper concludes that financial networks act as insurance against idiosyncratic health shocks.

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## KEYWORDS

Social networks; risk-sharing; shocks; dyadic regression; idiosyncratic

## 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, Kimura, and Antón 2013). The two types of risks affect the welfare of the farmers through the shocks they impose on incomes, assets, health and food supply (Pinstrip-Anderson, Pandya-Lorch, and Rosegrant 2001; Fafchamps 2010; Murendo, Keil, and Zeller 2011).


To cope with the shocks, the smallholder farmers can reduce risk *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, Kimura, and Antón (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, Kimura, and Antón 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, Kimura, and Antón 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

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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 (Berman 2007; Lauber, Decker, and Knuth 2008; Maertens and Barrett 2012).

In the absence of formal insurance, smallholders mitigate effects of shocks by developing informal mutual insurance arrangements among themselves (Fafchamps and Lund 2003; Bramoullé and Kranton 2007). Through the informal insurance, the needy are assured of survival and are aware that reciprocity is expected from them in future (Ligon, Thomas, and Worrall 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 paper. 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, Todo, and Mojo (2013) studied social and geographical determinants of financial and non-financial networks, their study did not capture risk-sharing aspects of the networks studied.

This paper 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. Findings in this study addresses a fundamental questions 'does the formation of non-financial networks, in fact, overlap with the formation of non-financial networks' and are they formed as an insurance to health and income shocks?

The rest of this paper is organized as follows; study methods which explain data sources and the study's theoretical and empirical approaches are discussed in Section 2. The results are discussed in Section 3 while the conclusions and policy implications of the study are discussed in Section 4.

## 2. Material and methods

### 2.1 Data sources and sampling

The study used primary data, collected in Kisii and Nyamira counties, using a household survey. 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, Ondimu, and Mirona 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 in this paper uses 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 this analysis because the respective 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.

### 2.2 Key variables and their measurement

The dependent variables in this study are 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, farmers were asked, 'If you suddenly needed money, would you ask [NAME of farmer  $j$ ] to lend it to you?' Just to note, 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 the questions was yes, then farmer  $i$  was considered to have a link with farmer  $j$ , otherwise, they did not.

Formation of risk-sharing networks is influenced by information flow across the agents, trust, norms and the capacity to enforce the network institution (De Weerdt 2002). One of the crucial variable 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 Weerd 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 network. In this study, kinship is defined as blood relationship between the dyad members while being neighbours was used as a proxy for geographical distance. The two were measured as binary variables where, 1 indicated kinship or neighbours and 0 indicated otherwise.

Social distance between agents also influences formation of risk-sharing networks (Fafchamps and Gubert 2007). For example, correlation of income flow within a dyad affects 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 (De Weerd 2002). Income was therefore included as an explanatory variable of network formation. It was measured by summing both off-farm 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 and Schwarze 2014; Mekonnen, Gerber, and Matz 2016). The expectation is that such networks are formed by households that are similar to each other with regard to education and age 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 purposefully as a way to deal with shocks (Bramoullé and Kranton 2007), particularly idiosyncratic shocks since they don't affect an entire network. 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.

## 2.2 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, Peters, and Janssen 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 paper assumes that the preferences for the outcome (risk sharing) are already known. Therefore, decision to form food sharing links in the case of this paper 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:

$$L_{ij} = 1 \text{ if } B(d_{ij}, 1) - B(d_{ij}, 0) - C(d_{ij}) + e_{ij} > 0, \text{ and } 0 \text{ otherwise,} \quad (1)$$

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 paper uses geographical distance and socio-economic factors such as blood relations, age, education income, farm size and gender to measure the social distance between farmer  $i$  and  $j$  (Van den Broeck and Dercon 2011; Muange and Schwarze 2014; Mekonnen, Gerber, and Matz 2016).

The cost of maintaining the link is expected to increase with social and geographical distance. This is because, the cost of enforcement, overcoming information asymmetry and moral hazards as well as conflicts, would increase as the distance increases (Sherif 1958; Fafchamps and Gubert 2007). Consequently, it is expected that individuals would mostly form links with people who are similar to them (McPherson, Smith-Lovin, and Brashears 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. The benefits would, therefore, be more if the risk between individual  $i$  and  $j$  is uncorrelated (Fafchamps and Gubert 2007). In such cases, individuals mostly form links with others who are different or geographically far from them to maximize the benefits of the networks.

### 2.3. 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 that 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

$$Y_{ij} = \alpha + \beta_1 |x_i - x_j| + \beta_2 (x_i + x_j) + |w_{ij}| + u_{ij}. \quad (2)$$

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 (Fafchamps and Gubert 2007) as specified:

$$Y_{ij} = \alpha + \beta_1 (x_i - x_j) + \beta_2 (x_i + x_j) + w_{ij} + u_{ij}. \quad (3)$$

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 ( $\beta_2$ ) cannot be identified due to the dyadic nature of the observations, meaning only the effects of the differences between the observations ( $\beta_1$ ) can be estimated.

The challenge of statistical inference is with regard to the standard errors of dyadic regressions. In dyad analysis, it is expected that  $i$  and  $j$  may have similar attributes, which lead to a problem of non-independence of residuals. 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  $j$  (Cameron, Gelbach, and Miller 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 paper follows the first approach which besides adjusting the standard errors, also corrects for heteroscedasticity.

### 2.4. Empirical model

The data collected on both food sharing and credit network 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 also observed in other studies (De Weerd and Fafchamps 2011; Liu, Slotine, and Barabasi 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) that desire to link is the most appropriate model to interpret self-reported risk-sharing network formation process. The relationship studied in this paper 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 1 was then specified further as follows

$$Y_{ij} = \alpha + \beta(x_i - x_j) + \vartheta(x_i + x_j) + \gamma w_{ij} + u_{ij}, \quad (4)$$

where  $Y_{ij}$  is the link between  $i$  and  $j$ .  $x_i$  and  $x_j$  are the attributes of  $i$  and  $j$ .  $\beta$  is a vector of coefficients that measure the effects of the differences in attributes of  $i$  and  $j$  while  $\vartheta$  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 (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, one of the advantages of LPM is that the estimates are easily interpreted as they are close to the probit and logit estimates (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, Gelbach, and Miller 2011; Petersen 2009).

One challenge of this study is a causal reference in the case of our dependent variable of interest, health shock. The cause of the challenge is reverse causality between health shock and social networks. While we hypothesize that, risk-sharing networks are formed to respond to health shocks (Fafchamps and Lund 2003; De Weerd and Fafchamps 2011), several studies have reported the effect of social networks on health outcomes. For example, according to Nagayoshi et al. (2014) and Chang et al. (2017), social networks reduces the incident of stroke and coronary heart disease.

Given that our health shocks variable includes acute sickness whose incidence is influenced by social networks, the study cannot infer causality. Literature suggests the use of an instrument variable or lag of the endogenous variable to deal with the possible endogeneity. However, given the challenge in availability of panel data and lack of a strong instrument for health shocks, this study cannot infer causality in the model that includes health shock as a dependent variable. The study, therefore, discusses 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. Results and discussion

Table 1 presents the characteristics of the sampled farmers. On average, the farmers were middle-aged, with a primary level of education. Women formed the majority (62%) of the farmers involved in farmer groups and farming was the main occupation for 86%

**Table 1.** Descriptive statistics of the sampled farmers.

Variables	Mean	SD	min	max
Age (years)	46.51	12.52	18	79
Education (years)	8.67	3.68	0	17
Farm size (acres)	1.62	1.26	0.06	9.74
Income (Kshs)	133,074	90,606	600	376,459
	<b>Number</b>	<b>Percent</b>		
Gender (1 = male 0 = otherwise)	321	38		
Occupation (1 = farmer 0 = otherwise)	706	86		
Marital status (1 = married 0 = otherwise)	619	75		
Relationship with head (1-head 0 = otherwise)	502	60		
<b>Idiosyncratic health shock</b>				
Acute illness (1 = Yes 0 = No)	491	60		
Observations	815			

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 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 2 provides a comparison of the average differences and sums of social 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% of all the dyads respectively.

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 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% 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 as opposed to between more educated and high-income farmers. 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. 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.

**Table 2.** Definition and descriptive statistic of variables used in dyadic regressions.

Variable	Food networks			Credit networks		
	Yes n = 1068 Mean	No n = 12256 Mean	Diff. Mean	Yes n = 2030 Mean	No n = 11288 Mean	Diff. Mean
Difference in:						
Age (years)	-1.56 (0.46)	0.14 (0.15)	-1.70***	-0.39 (0.34)	0.07 (0.15)	-0.46
Education (years)	-0.10 (0.15)	0.01 (0.05)	-1.11	-0.44 (0.10)	0.08 (0.05)	-0.52***
Income (000' Ksh)	-3.95 (3.639)	0.32 (1.07)	4.27	-11.29 (2.59)	2.00 (1.12)	13.29***
Health shock	0.00 (0.02)	-0.00 (0.01)	-0.00	0.04 (0.01)	-0.01 (0.01)	-0.04***
Sum of:						
Age (years)	91.99 (0.58)	93.27 (0.18)	-1.28**	94.06 (0.44)	93.01 (0.44)	1.06**
Education (years)	16.81 (0.17)	17.37 (0.05)	-0.60***	17.3 (0.13)	17.3 (0.05)	-0.04
Income (Ksh)	253.08 (4.27)	266.89 (1.23)	13.82***	274.78 (3.16)	264.17 (1.28)	-10.61***
Health shock	0.81 (0.02)	0.79 (0.01)	-0.02	0.84 (0.02)	0.78 (0.01)	-0.05***
Gender (1 = male 0 = otherwise)	0.64 (0.02)	0.76 (0.01)	-0.12***	0.81 (0.01)	0.74 (0.02)	0.07***
Occupation (1 = farmer 0 = otherwise)	1.77 (0.02)	1.72 (0.01)	0.05***	1.72 (0.01)	1.73 (0.01)	-0.01
	<b>Percent</b>	<b>Percent</b>	<b>Chi<sup>2</sup></b>	<b>Percent</b>	<b>Percent</b>	<b>Chi<sup>2</sup></b>
Kinship (1 = blood relation between <i>i</i> and <i>j</i> 0 = otherwise)	30	20	60.94***	33	19	196***
Neighbor (1 = <i>i</i> and <i>j</i> fields border each other 0 = otherwise)	24	4	804***	16	4	535***
Differences in:						
Gender (1 = <i>i</i> and <i>j</i> have different gender 0 = otherwise)	29	37	29.01***	30	38	42.38***
Occupation (1 = both <i>i</i> and <i>j</i> are not farmers 0 = otherwise)	20	24	11.64***	24	24	0.03

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

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 5% level. Those who did not mention the link had a higher average sum, suggesting that matches with more males are 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% 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. This suggests 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 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 with an intention to share income risk, we included the variable income and also occupation as part of the regressors. Income alongside other dependent variables is endogenous hence an instrument, number of working adults in a household, was used, (results in online appendix 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, our 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 findings of Fafchamps and Gubert (2007).

**Table 3.** LPM results of the factors influencing formation of financial and non-financial networks.

Variables	Credit networks		Food sharing networks	
	Coefficients	SE	Coefficients	SE
Differences of:				
Income diff (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	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*).

Age differences had a negative and significant effect on both food sharing and credit links at the 1% level (Table 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), Fafchamps and Gubert (2007) and Mekonnen, Gerber, and Matz (2016) found similar results on the effect of age difference but the result is at odds with De Weerd 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 financial networks.

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 the findings of Van den Broeck and Dercon (2011) and Mekonnen, Gerber, and Matz (2016), but contradict the findings of De Weerd and Fafchamps (2011). 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 relations (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 and Schwarze (2014) and Mekonnen, Gerber, and Matz (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 Barrett (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, we broaden our definition of risk and include health shock (defined by presence of a family member with acute illness). We then re-estimated Equation (4), replacing the predicted income with health shock (Table 4). In this analysis, we report the correlations given the reverse causation between social network and health outcomes. The finding shows that farmers' health shock differences are positive and significantly correlated with the formation of credit networks, but do influence the formation of food sharing networks. This suggests that farmers who have household members with 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 findings of Fafchamps and Gubert (2007).

**Table 4.** LPM results of the factors influencing 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	0.000***	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
_cons	0.110***	0.036	0.124***	0.023
Observations	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*).



Health shock sum is also positive and significantly correlated with the formation of credit links at the 5% level. Increasing the sum of the health shocks increases the probability of reporting a credit link (Table 4). 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 found 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% 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 Barrett (2012) and Muange and Schwarze (2014).

The sum of male dummy has a negative correlation with food sharing links and apposite 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, Gerber, and Matz (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 is important. 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.

#### 4. Conclusions and policy implications

This paper evaluates 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 was analysed using a dyadic LPM. Results show that age, gender and education are 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 when in the formation of food sharing networks.

We conclude 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 of the 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.

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