Social Networks and Household Dietary Diversity, Evidence from Smallholder Farmers in Kenya.

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Abstract:

An important driver of household dietary diversity is nutrition knowledge which can be improved through access to nutrition information. However, in many rural areas, formal flow of nutrition information is limited, and social networks could play an important role as an informal source of such information. This paper evaluates effects of social network on household dietary diversity in Kenya. Cross sectional data collected from 198 farmers using multi stage sampling technique, was analysed using a Poisson regression model. The results show that the average household dietary diversity of an individual's network members has a positive effect on the dietary diversity of the individual. The effects are more when the network includes at least a strong tie. Household size and farm size also have a positive effect on household dietary diversity. These results imply that farmers' social networks could be used as a complementary tool for effective delivery of nutrition education which targets to enhance nutritional quality.

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1. Background Information

Malnutrition is a major problem worldwide, but more pronounced in Africa and Asia (IFPRI, 2014; UNICEF, WHO and World Bank, 2015). Malnutrition incorporates three aspects of undernourishment, micronutrients deficiency and over-nutrition (Gomez *et al*., 2013). According to Suryanarayana (2013), most policies tackling malnutrition in developing countries are biased towards consumption of sufficient calories only. However according to Ruel (2003a), nutrition policies should not only consider sufficient calorie intake but also diversified diets. This is because research has shown that an increase in diet diversity leads to a decrease in the proportion of malnourished population (Darapheak *et al*., 2013; Frempong and Annim, 2017)

Dietary diversity, defined as the number of different food groups eaten by an individual or household over a given reference period, has been used as a proxy for dietary quality (Ruel, 2003b). It has also been used as a measure of the degree to which the nutritional requirements of an individual/household have been achieved (Ruel 2003a). 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).

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, niacin, vitamin C, and zinc than women with lower food group diversity. A high dietary diversity has also been associated with better nutritional status of children (Arimond and Ruel, 2004; Arimond *et al.*, 2010) and improved anthropometric status (Onyango *et al.*, 1998; Arimond and Ruel, 2002). Therefore, improving dietary diversity is key in achieving household food and nutrition security (Steyn *et al*., 2006b; Kennedy *et al.*, 2007b; Kennedy *et al.*, 2009).

Twenty five percent of households in Kenya have poor 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. Such low dietary diversity could be caused a number of factors.

Several studies identify nutrition knowledge as one of the important 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 scarce. In such contexts where formal institutions often underperform, social networks are an important source of information (Chuang and Schecheter, 2015). Social interactions in such networks lead to social learning due to peer effects (Hogset and Barrett, 2010).

Several studies have analysed the effects 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.,* 2016), health, (Oster and Thornton 2012; Martire and Frank, 2014) and financial decisions (Banerjee *et al.,* 2013; Murendo *et al.,* 2017). However, information on the effects of social networks on dietary diversity, nutrition decisions and outcomes is largely lacking.

Moreover, although there is extensive literature on the determinants of household dietary diversity (Langat *et al.*, 2013; Taruvinga *et al.*, 2013; Sibhatu *et al*., 2015), such studies have not investigated the role of social networks in dietary diversification. Hence, while the relationship between dietary diversity and economic resources has been well established, the effect of social networks as potential informal sources of nutrition information on dietary diversity is not well understood. This study aims to fill this gap by evaluating the effects of nutrition information networks on household dietary diversity.

2. Determinants of social learning within networks

The effectiveness of learning within social networks depend 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), and network transitivity (Jackson, 2011). Moreover, strength of the networks (Granovetter, 1973), homophily (Jackson, 2011), network behaviour (Manski 1993) and social resources entrenched in one's network (Murendo *et al.,* 2017) are also important network characteristics that enhance social learning.

Network size, defined as the number of links an individual has in a network, have been found to affect the quality and quantity of information within networks (Zhang *et al.*, 2012). Therefore individuals who have 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.

Another important structure of networks that influence social learning is transitivity. According to Jackson (2011), transitivity is the extent to which if actor *i* is linked to actor *j*, and *j* is linked to *k*, then *i* is linked to k such that the relation that relates two actors (*i* and *j*) in a network are connected by an edge (k). The frequency of the occurrence of the transitivity in a network is referred to as clustering. Transitivity improves information flow because it influences the extent to which connections create new actors. It also enhance the capability of a network to follow up and enforce behaviours (Jackson, 2011).

The quality and process of information diffusion within networks depend with the strength of social ties (Granovetter, 2005). Strong ties are referred to as relations among individuals who are emotionally connected within a network (kinship relations, friends, and neighbours) while weak ties are acquaintance relations that link a network to the society at large (Granovetter 2005). 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.,* 2017).

There have been different findings on how the effects of social networks are impacted by the strength of the ties. Fu *et al.* (2013) argue that both strong and weak ties are important because, network members with strong ties have regular meetings and discussions while those with weak ties rarely meet but exchange diverse information when they meet. Moreover, Ruef (2002) highlights that social learning can be heightened by making use of strong ties to confirm information that people are already aware of, while weak ties can be used to acquire new information. However, Granovetter (1983) argues that strong ties limit people to only gathering information that they already know therefore affecting social learning negatively.

Homophily, which is based on characteristics of actors in the network, is another important determinant of social learning. It is the tendency of individuals forming networks with others who are similar to them (McPherson *et al.,* 2006). Jackson (2011) argues that in some instances, these factors affecting the formation of network (homophily) also influences individuals' behaviour or decisions. This could be because, homophily minimizes possible areas of disagreement in the networks (Sheriff, 1958), which enhances information flow and learning within the network.

Another important characteristics of the social networks that influence 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), argues that this is caused by social externalities. For example, if the average productivity of a network increases as a result of adoption of a new technology 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. The knowledge leads to adoption of new technologies and products (Zhang *et al.,* 2012; Murendo 2017) and improved productivity (Van den Broeck and Dercon, 2011; Mekonnen *et al.,* 2016).

3. Study Methods

3.1 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 also through other peoples' experiences. Based on these arguments the paper assumes that as individuals interact through nutrition information sharing within their networks, they learn, observe and use other people's experience to improve the quality of their diets, after assessing the consequence and effectiveness of their actions.

Interactions within social networks influences the attitudes, behaviour and performance of network members through social learning or social influence (Young, 2009; Hogset and Barrett, 2010; Mekkonen, 2017). The learning is enhanced by social interactions and links which enable individuals to obtain new information which may in turn influence their decisions (Bandiera and Rasul 2006). On the other hand social influence is an outcome of imitation through observation. In this case, the individuals change their behaviour to conform to the observed behaviour of other individuals in their networks without necessarily having accurate information about the behaviour (Hedström *et al.*, 2000; Easley and Kleinberg, 2010).

3.2 Empirical model

To estimate the effects of social networks on dietary diversity, this paper follows Manski (1993) who argues that individual in the same group behave similarly due to endogenous effects, exogenous effects and correlated effects. Endogenous effects refer to the tendency of an individual's behaviour to vary with the overall behaviour of the network. On the other hand exogenous effects are 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 face similar institutional environments

Following Mekonnen *et al.* (2016) the empirical model was specified as follows;

$$Y_{ikt} = \beta_0 + \beta_1 \bar{Y}_{-ikt} + \beta_2 \bar{X}_{-ikt} + \beta_3 X_{ikt} + \varepsilon_{ikt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where Y_{ikt} denotes household dietary diversity score for individual *i*'s household belonging to network *k* at time *t*. $\bar{Y}_{ikt}$ capture the endogenous effects, measured by average behaviour of the network members of network *k* excluding *i* in time *t*. $\bar{X}_{ikt}$ denotes the exogenous effects which are measured by the average observable characteristic of the network (*k*) members excluding *i* in time. X_{ikt}, denotes personal characteristic of individual i (such as age, gender, education, occupation, wealth status, farm size, household size) while ε_{ikt} is the error term. Therefore $\beta_1 \neq 0$ and $\beta_2 \neq 0$ suggest presence of endogenous and exogenous effects respectively while $\beta_3 \neq 0$ denotes direct effects

Following Manski (1993), this paper used average household dietary diversity of the network members as the measure of endogenous network effects. Endogenous effects have been found to have appositive effect on outcomes such as adoption of new technologies (Mekonnen *et al.*, 2016; Murendo, 2017).Therefore, an increase in household dietary diversity within the network is hypothesized to increase of an individual *i*'s household dietary diversity.

Exogenous effects were controlled for using three variables namely, share of weak ties, average education of the network members and sum of females in an individual's network. Zhang *et al.* (2012) and Thuo *et al.* (2014) shows that weak ties are important since they influence the quality and diversity of information within networks. Furthermore, given the important role that women play in a household's dietary diversity (Ibnouf, 2009; Sraboni *et al.*, 2014), gender, represented by the number of females in an individual's network is of interest in this paper. Lastly, according to Röper *et al.* (2009) and Song and Chang (2012), education of the network members influences the ability of an individual to acquire information. This paper hypothesizes that the three variables have a positive effect on household's dietary diversity.

The paper controls for correlated effects by including farmer group fixed effects. According to Murendo *et al.* (2017), if correlated effects are present, the endogenous effect (β_1) should decrease in the model where group effects have been controlled compared to the model where correlated effects have not been controlled for. Since household dietary diversity score is a count data, the error term is assumed to follow a poison distribution leading to a Poisson regression.

A key challenge in estimating endogenous effect is the refection problem also referred as simultaneity. This problem arises when the network behaviour influences an individual's behaviour and in turn the individual's behaviour also influences the behaviour of the network (Manski, 1993). Manski (2000) suggests two ways of solving the problem, one of the solutions 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 solution is introducing an instrument variable that directly affects the outcome of some but not all network members.

Following the first suggestion by Manski, dynamism is introduced in the model. $\bar{Y}_{ikt}$ was therefore replaced with its lag, $\bar{Y}_{ikt-1}$ capturing the network mean household dietary diversity by a one year lag. Equation (1) was then specified as follows;

$$Y_{ikt} = \beta_0 + \beta_1 \bar{Y}_{-ikt-1} + \beta_2 \bar{X}_{-ikt} + \beta_3 X_{ikt} + \varepsilon_{ikt} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Additionally, the paper estimated equation 2 with the farmers disaggregated into those that had mentioned strong ties and those that did not. The aim was to measure the heterogeneous effects of social networks on household dietary diversity with regard to the strength of the ties.

3.3 Data sources

The study used primary data, collected in Kisii and Nyamira counties of Kenya, using a household survey. Despite high agriculture productivity in the two counties, there are high levels of malnutrition. For example 25.5 percent of all the children in both Nyamira and Kisii are stunted; 4.1 and 1.7 percent of all children in Nyamira and Kisii respectively are wasted, while; 9.6 and 8.4 percent of all children in Nyamira and kisii respectively are under weight (KHDS, 2014). There was therefore, a need to understand other ways, beside agricultural productivity, of improving the 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 obtained from Africa Harvest Biotech Foundation International, a non-profit organization that was implementing projects in the region, was used as a sampling framework. 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 then 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.

Data was collected in two rounds: the first between October and December 2015, and the second between October and December 2016. In the first round, 824 farmers were interviewed while in the second round, 745 farmers were interviewed. This paper used only farmers who had nutrition networks in both survey rounds, since a lagged household dietary diversity score from the first round was used. In the second round, only 338 farmers reported nutrition networks, and out of those only 198 had mentioned nutrition networks during the first round. Hence, our analysis is based on the latter sample.

3.4 Measuring social network indicators

To collect social networks data, the sampled farmers were matched with all the members of their farmer group. However the analysis in this paper used matches 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 which are the focus of this study, the following question was asked to farmer *i*; "*Did you share nutrition information with farmer j* (the match)*?"* If the answer was yes then farmer *j* was considered to be a member of farmer *i'*s network.

Several network variables were computed and used to capture different networks effects. Following, Van den Broeck and Dercon (2011) and Mekonnen *et al.* (2016), the average network behaviour was measured by the average household dietary diversity score of the network members in each individual's network. Network size was computed by summing the total number of the individuals (*j*) who were mentioned to have shared the nutrition information with farmer *i* (Mekonnen *et al.*, 2016; Murendo *et al.*, 2017).

Share of weak ties, was measured by a proportion of weak ties in a household's social network. Following Granoveter (1993), relationship type was used to measure the strength of the network. Kinship relations, were used to categorize those farmers whose links were considered as weak ties and those considered as strong ties. If a farmer had a link with individuals whom they had blood relations, the link was defined as a strong tie while if the link did not have any blood relation, it was considered as a weak tie.

Sum of females was measured by summing all the female members of an individual's network. Lastly, network education was measured by the average education of the network members. All these variables were computed using the second round of data which was except for the average household dietary diversity score of the network members. This was computed using the networks mentioned in the first round of data.

3.5 *Measuring household dietary diversity score*

Household dietary diversity score was computed using a household 7 day recall food consumption data. The score was computed based on the FAO's guidelines 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 7 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 7 days.

4. Results and discussions

4.1 Social economic characteristics of the sample.

Table 1 presents social-economic characteristic of farmers in Kisii and Nyamira counties and definition of variables used in the Poisson regression model. Most of the farmers were middle aged (46 years) and on average had post primary school education. Farming was the primary occupation for a majority of the farmers who on average owned 1.5 acres of land (Table 1). On average the famers had a positive wealth index (appendix) which could be interpreted as not poor and on average consumed 10 out of 12 food groups (Table 1).

Table 1 Definition and descriptive statistic of variables used in regressions

Variable	Definition	Mean (n=198)	SE
Dependent variable			
Household dietary diversity	Household dietary diversity score (count of food groups consumed)	9.85	0.10
Independent variables;			
Social network			
Lagged network household dietary diversity	Average lagged household dietary diversity score of the households in the house hold's social networks	9.51	0.11
Network education	Average years of formal education of heads in the household's social network	8.83	0.21
Sum of females	Number of females in the household's social network	1.86	0.17
Share of weak ties	Proportion of weak ties in household's social network	0.69	0.03
Network size	Number of group members an individual communicated to about nutrition	2.86	0.22
Household characteristics			
Gender	Gender of the household head(1=Male, 0=female)	0.4	0.34
Age	Age of household head (years)	45.7	0.84
Occupation	Occupation of household head (1=farming, 0=otherwise)	0.81	0.03
Education	Education of household head (years)	9.3	0.24
Household size	Size of the household (number)	5.46	0.14
Farm size	Size of farm (acres)	1.48	0.08
Wealth index	Index constructed using household's asset using PCA	0.08	0.10

The social network variables descriptive (Table 1) shows that an individual's network had an average household dietary diversity score of 10 food groups, while the mean level of formal education of heads in an individual's network was nine years. The average network size was three people, of which, on average two were females. Moreover, on average more than half of network members mentioned by an individual, were connected by weak ties.

4.2 Effects of social network on household dietary diversity

The results of the social network factors affecting dietary diversity are presented in Table 2. In the estimation, endogenous effects were estimated separately from exogenous and correlated effects. Two models were estimated, where model 1 presents the results of Poisson regression without controlling for the farmer group fixed effects while model 2 shows the results after controlling for group fixed effects by clustering the standard errors. The results indicate that there are no exogenous social effects of network education, share of weak ties and number of females on an individual's network on household dietary diversity.

Table 2. Poisson regression estimates of the effects of network characteristics on household dietary diversity

	Model 1		Model 2	
	Coefficient	SE	Coefficient	SE[1]
Lagged network household dietary diversity score	0.014**	0.007	0.014**	0.006
Network education	0.001	0.004	0.001	0.004
Sum of females	-0.004	0.006	-0.004	0.006
Share of weak ties	0.026	0.024	-0.026	0.025
Gender	0.004	0.022	0.004	0.025
Age	-0.001	0.001	-0.001	0.001
Occupation	-0.024	0.022	-0.024	0.021
Education	0.002	0.003	0.002	0.003
Household size	0.010**	0.005	0.010**	0.005
Wealth index	0.002	0.004	0.002	0.005
Farm size	0.019***	0.008	0.019**	0.008
Constant	2.104***	0.097	2.104***	0.096
Observations	198		198	
Pseudo R^2	0.005		0.005	

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

The lagged household dietary diversity score of the network members in both models has a positive and significant effect (at 5 percent level) on the household dietary diversity (Table 2). This implies that nutrition information networks have an endogenous effect on household dietary diversity and confirms the hypothesis that household dietary diversity of the network members has a positive effect on dietary diversity of an individual. This finding is validated by Van den Broeck and Dercon (2011), Mekonnen *et al.* (2016) and Murendo *et al.* (2017) who reported positive endogenous network effects on adoption of technologies and agricultural productivity.

A one unit increase in the lagged household dietary diversity score of the network members, will lead to a 1.4 percent increase in the household dietary diversity, significant at 5 percent level in both models (Table 2). The magnitude of the endogenous effects does not change after controlling for fixed effects, which suggest absence of correlated effects on the household dietary diversity. Thus, having individuals who have similar individual characteristics or face similar institutional environments in a network do not necessarily have the same dietary diversity scores.

Observable characteristics of the household such as household size and farm size had a positive effect on household dietary diversity. Households with bigger farm sizes are shown to consume more food groups. This could be explained by the fact that farmers mostly consume what they grow in their farms which implies that they are likely to grow more diverse crops and keep more livestock as their farm size increases. This finding is supported by the findings of Jones *et al.* (2014).

Households with more household members consumed more food groups (Table 2). This could be explained by the fact that, households with more members have more labour force which can be invested into agriculture production and in return improve their dietary diversity through increased production diversity or increased income through hired labour (Workicho *et al.*, 2016).

Robustness check

To test for robustness of the findings, network size and its square are introduced into the model (Table 3). This is to clarify whether the reported network endogenous effects were driven by the average behaviour of the network or by the endogenous network size (Mekonnen *et al.*, 2016). The results on the endogenous effects do not change qualitatively (as shown by comparing Table 2 and 3) indicating that the effects are not from network size. The insignificant network size and the network size squared (Table 3) further confirms that the network effects are not driven by network size but rather from social externality.

Table 3. Robustness of Poisson regression estimates of the effects of network structure on household dietary diversity

	Model 1		**Model 2**	
	Coefficient	SE	Coefficient	SE
Lagged Household dietary diversity score	0.014	0.007^{**}	0.014^{**}	0.006
Network size	0.002	0.012	0.002	0.011
$(\text{Network size})^2$	0.000	0.001	0.000	0.001
Network Education	0.001	0.004	0.001	0.004
Sum of females	-0.009	0.010	-0.009	0.010
Share of weak ties	0.024	0.025	0.024	0.026
Gender	-0.002	0.024	-0.002	0.026
Age	-0.001	0.001	-0.001	0.001
Occupation	-0.025	0.023	-0.025	0.022
Education	0.002	0.003	0.002	0.004
Household size	0.010	0.005^{**}	0.010^{**}	0.005
Wealth index	0.002	0.004	0.002	0.005
Farm size	0.019	0.008^{**}	0.019^{**}	0.008
Constant	2.088	0.094^{***}	2.088^{***}	0.094
Observations	198		198	
Pseudo R^2	0.005		0.005	

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

4.3 Social network effects by the strength of nutrition information ties

To test for the heterogeneous effects, a Poisson regression was estimated separately for households whose network was composed of purely weak ties and those that had at least a strong tie in their networks. The findings indicate that the endogenous network effects are positive and significant (at 5 percent level) for the households that had at least a strong tie within their network (Table 4). However, for the household whose network was composed of weak ties only, the endogenous effects did not have a significant effect (Table 4).

Table 4. Social network effects differentiated by the strength of nutrition information ties

	Strong ties		**Weak ties**	
	Coefficient	SE[1]	Coefficient	SE[1]
Lagged Household dietary diversity score	0.026**	0.013	0.009	0.007
Ave education	0.002	0.005	0.002	0.005
Sum of females	-0.004	0.008	0.001	0.010
Gender	0.017	0.025	-0.015	0.039
Age	-0.001	0.002	0.000	0.001
Occupation	0.022	0.038	-0.059*	0.031
Education	0.002	0.006	0.003	0.004
Household size	0.007	0.008	0.013**	0.006
Wealth index	0.005	0.010	0.001	0.004
Farm size	0.027*	0.015	0.013	0.009
Constant	1.974	0.193	2.116	0.117
Observations	82		116	
Pseudo R^2	0.008		0.004	

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

This implies that social interaction and information sharing in nutrition networks enhance learning more, when people use their strong ties to affirm the nutrition information that they might already know as highlighted by Ruef (2002), in addition to the new information they gain through their weak ties. Todo *et al.* (2016) found similar results where strong ties with clients improved the productivity of firms in Japan. Van den Broeck and Dercon (2011) also highlighted that social learning through agricultural information networks happens better when there are strong network ties.

5. Conclusions and recommendations

This paper analyses the effects of social networks on household dietary diversity of households in Kisii and Nyamira counties in Kenya. It controls for correlated effects (as farmer group fixed level effects), endogenous effects, exogenous effects and also observable household characteristics. The results indicated that endogenous network effects were positive and significantly influenced household dietary diversity. The behaviour of an individual's network in terms of nutrition quality positively influences the individual's nutrition quality. The results further indicated that the endogenous effects are more evident in households which have at least a strong network tie than those with weak network ties

In contrast, average observable characteristics of the network members (exogenous effects) did not have any significant effect on the household dietary diversity. The findings also suggested absence of correlated effects. Finally, household size and the farm size had a positive and significant influence on household dietary diversity. The paper therefore concludes that social networks are important pathways through which nutrition information flows to enhance households' nutrition quality through endogenous effects.

Social networks could therefore be used as a tool for effective delivery of nutrition education which targets to enhance nutrition quality. Such programmes should however focus on social networks that exclusively involve exchange of nutrition information. The policy makers should also note that the endogenous effects are more evident when the networks have at least a strong network tie. In cases where only weak ties constitute a network, then they should consider reconstructing the networks first and include at least a strong tie in each network.

Additionally, such 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. Therefore, an effective programme targeting to improve nutrition quality of network members doesn't have to target everyone in the network. Hence, investments in educating only a few members (instead of all members) of a network which would eventually improve the nutrition quality of everyone in the network through social learning. Such a strategy would be cost saving.

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Appendix

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

$$W_j = \sum_{i=1}^{k} b_i \ (a_{ij} - x_i)/s_i \qquad (5)$$

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 the standard deviation

A negative index was interpreted as, relative to the community's measure of wealth, the household is poorly endowed and hence worse-off while a positive index means that the household is well-off. A zero figure, suggests that the household is neither well-off nor worse-off (Langyintuo and Mungoma, 2008).