Effect of social networks on household dietary diversity: Evidence from smallholder farmers in Kisii and Nyamira counties, Kenya

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Abstract

Nutrition knowledge is an important driver of household dietary diversity that can be improved through access to nutrition information. However, in many rural areas, the formal flow of nutrition information is limited, although social networks could play an important role as an informal source of such information. This paper evaluates the effect of nutrition information networks on household dietary diversity in Nyamira and Kisii counties in Kenya. The paper employs a Poisson regression model on a sample of 462 farmers selected using a multi-stage sampling technique. The results show that the average household dietary diversity of an individual's network (a proxy for social networks) had a positive and significant effect on the dietary diversity of the individual, implying that social networks have a positive effect on household dietary diversity. Moreover, the average education of an individual's network, along with household size, wealth status and farm size, had positive significant effects on household dietary diversity. These results imply that farmers' social networks could be used as a complementary tool for the effective delivery of nutrition education targeting the enhancement of nutritional quality.

Key words: dietary diversity; Poisson model; nutrition networks; social learning

1. Introduction

Despite increased food production globally, malnutrition remains a major problem, particularly in Africa and Asia (IFPRI 2014; UNICEF *et al*. 2015). The term 'malnutrition' comprises three aspects, namely undernourishment, micronutrient deficiency and over-nutrition (Gomez & Ricketts 2013). According to Suryanarayana (2013), most policies addressing malnutrition in developing countries are biased toward the 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 the adequacy of diets of people or groups of people (Steyn *et al*. 2006a; Kennedy *et al*. 2007). 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 & Ruel 2002; Arimond *et al*. 2010).

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

Several studies have identified 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), the formal flow of information, including nutrition information, is low in many rural areas. In contexts where formal information institutions often underperform, social networks can play an important role as a source of information (Chuang & Schecheter 2015). Social interactions in such networks often lead to social learning due to peer effect and imitation (Hogset & Barrett 2010).

A few studies have examined the effect of social networks on a variety of outcomes, such as adoption of agricultural technologies (Maertens & Barrett 2013; Muange & Schwarze 2014; Thuo *et al*. 2014), agricultural productivity (Van den Broeck & Dercon 2011; Muange *et al*. 2015; Mekonnen *et al*. 2018), health (Oster & Thornton 2012; Martire & Franks 2014) and financial decisions (Banerjee *et al*. 2013; Murendo *et al*. 2018). However, studies focusing on the effect of social networks on dietary diversity, particularly in the African context, are largely lacking. Moreover, limited research has been conducted on the effect of social networks on nutrition in Kenya, the reported high levels of malnutrition notwithstanding.

Moreover, even though there is an extensive body of literature on the determinants of household dietary diversity (Langat *et al*. 2011; Taruvinga *et al*. 2013; Sibhatu *et al*. 2015), such studies have not evaluated the effect of social networks on household dietary diversity. Hence, while the relationship between dietary diversity and economic resources is well established, the effect of social networks as a potential informal source of nutrition information is not well understood. This paper aims to fill this gap by evaluating the effect of social networks on household dietary diversity and analysing the factors influencing the formation of nutrition information networks among smallholder farmers in Kisii and Nyamira counties, Kenya. The results of this paper provide evidence of the importance of nutrition information networks in influencing household dietary diversity in rural Kenya, unlike earlier studies, which focused on agricultural information networks.

The results illustrate the importance of social networks as an alternative pathway for information dissemination, especially in developing countries, where poor access to formal information sources limits households' decision-making processes on the adoption of new technologies. The reminder of this paper is organised as follows. Section 2 presents the study methods, while the results and discussions are presented in Section 3 and Section four respectively. Finally, the conclusions and policy recommendations are provided in Section 5.

2. Methods

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. The learning is enhanced by social interactions within the network. Such interactions influence the attitudes, behaviour and performance of network members in two ways: social learning and social influence (Young 2009; Hogset & Barrett 2010; Mekonnen *et al*. 2016).

Social learning is enhanced by interactions and links that enable individuals to obtain new information, which in turn may influence their decisions (Bandiera & Rasul 2006). Therefore,

information sharing among network members influences their opinions, attitudes and actions directly or indirectly (Munshi 2008; Conley & Udry 2010). 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 their behaviour (Hedström *et al*. 2000; Easley & Kleinberg 2010).

Based on these arguments, this paper assumes that, as individuals interact through their social networks, they learn, observe and use other people's experiences to improve the quality of their diets, after assessing the consequences and effectiveness of their actions. Hence, nutrition information networks are considered in this paper as one pathway through which people change their behaviour with regard to household dietary diversity.

2.2 Empirical model

To estimate the effects of nutrition information networks on dietary diversity, the paper follows 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. Given that household dietary diversity score is measured as count data, the error term is assumed to follow a Poisson distribution, leading to a Poisson regression. Following Mekonnen *et al*. (2018), the Poisson regression model was specified as:

$$Y_{ikt} = \beta_0 + \beta_1 \bar{Y}_{-ikt} + \beta_2 \bar{X}_{-ikt} + \beta_3 X_{ikt} + \beta_k + \varepsilon_{ikt}, \tag{1}$$

where Y_{ikt} denotes the 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 that 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 the 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 the adoption of new technologies (Mekonnen *et al*. 2016; Murendo *et al*. 2018). An increase in household dietary diversity within the network therefore is hypothesised to increase individual *i*'s household dietary diversity.

Exogenous effects were controlled using the 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. Even though the groups in this study were for both men and women, 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 therefore was hypothesised

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.

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. The first approach is to introduce dynamisms into the model and assume a lag in the diffusion of the endogenous effect, such that the individual's behaviour is related to the lag value of the network's average behaviour. The other approach is to use an instrumental variable that directly affects the outcome of some but not all network members.

Following the first suggestion by Manski (2000), dynamism was introduced into 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 the respondents, which is likely to be correlated with present ones. Therefore, equation (1) is specified as follows:

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

2.3 Data sources

This study used survey data collected from a sample of 426 households in the Kisii and Nyamira counties of Kenya in 2015 and 2016. Stratified by common interest groups encompassing both men and women, the households were selected using a two-stage sampling procedure. A complete list of the 94 existing farmer groups in Kisii (71) and Nyamira (23) was obtained from the Counties Departments of Cooperatives and used as the 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 fewer than 20 households, all the households were interviewed. In total, 824 households (557 in Kisii and 267 in Nyamira) were interviewed.

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

Households were interviewed on farm and dietary practices using questionnaires that were designed and pre-tested in the field before actual data collection and administered in the local language by trained enumerators. The targeted respondent for the diet diversity questionnaire was the person mainly responsible for food preparation in the home. 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, uses pairs of group members who were part of the sample only, since the social network information on those who were not sampled was unavailable.

2.4 Measurement of variables

To capture nutrition information networks, the following question was asked of the 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 Banerjee *et al.* (2013) and Comola and Prina (2017), the paper assumes 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*) whom the individual (*i*) had mentioned to have shared the nutrition information with (Mekonnen *et al.* 2016; 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 categorised into *very often*, *often*, *sometimes* and *rarely*. If a farmer had a link with individuals with 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 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, which included both men and women. This was given by 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 eight years of formal education). All these variables were computed using the second round of the 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 as a proxy for the household's wealth status. Principle components analysis (PCA) was used to compute the wealth index and assign weights to different assets.

Following Langyintuo and Mungoma (2008), the assigned weights were then used to compute the wealth index by applying the following formula:

$$W_j = \sum_{i=1}^{k} b_i \ (a_{ij} - x_i)/s_i, \tag{3}$$

where W_j is the wealth index, b_i are the weights assigned to (k) assets on the PCA, a_{ij} is the value of the *k*th asset for the *i*th household, 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 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 seafoods, 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. The dietary diversity score was then calculated by summing all the food groups consumed within the household in the seven days.

3. Results

Table 1 presents the social-economic characteristics of farmers in the Kisii and Nyamira counties. Most of the farmers were middle aged (48 years) and, on average, had a post-primary school level of education, which corresponds to eight years of school attendance that qualifies one to attain a primary school certificate (Table 1). Farming was the primary occupation for a majority of the farmers, who owned 1.5 acres of land on average. Close to three-quarters of the respondents were female, while 76% of the farmers had at least one nutrition information link within the farmer group (Table 1). On average, the nutrition networks comprised three relative and at least one neighbour (Table 1).

Table 1: Socioeconomic characteristics of farmers in Kisii and Nyamira counties

Variables	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 neighbours 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
Observations	*713*			

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 (see Appendix).

Table 2 presents the descriptive statistics of the sub-sample (of respondents who had a nutrition information link) and the definitions of the 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% of the link being females (Table 2). 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% of network members mentioned by an individual were connected by weak ties.

Table 2: Variable names, definition and descriptive statistics of Poisson regressors

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 to 2016)	0.11	0.06
Network education level	Sum of individuals with post-primary1* 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 with whom an individual shares 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 assets	0.08	0.10
County dummy	County to which the household belongs (1 = Kisii, 0 = otherwise)	0.66	0.22

Notes: * = Completed the first eight years of formal education in the Kenyan education system

The results of the Poisson regression estimates of the effect of social networks on dietary diversity are presented in Table 3. Overall, social networks (as proxied by the social network variables), age, farm size, household size and wealth status had significant effects on household dietary diversity in Kenya at least at the 5% level. While social networks, farm size, household size and the wealth status had positive, significant effects on household dietary diversity at the 5% level, the age of the household head had a negative, significant effect on the household's dietary diversity at the 5% level (Table 3). Among the social network variables, the change in the average network's HDDS, the average education of the network member and the average age of the network member, had positive, significant effects on household dietary diversity, which implies that social networks have a positive influence on household dietary diversity in Kenya.

Table 3: Effect of nutrition information networks on household dietary diversity

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

To test for the robustness of the findings, network size and its square were introduced into the model and the results are presented in Table 4. 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 of the endogenous effects did not change substantially (compared to those shown in Table 3), indicating that the effects were not from network size. The insignificant coefficients of 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 4: Robustness of the effect of network structure on household dietary diversity

Variable	Marginal effects	SE
Change in average 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: ** and *** denote significance at the 5% and 1% levels respectively; SE = standard errors at the mean

4. Discussion

One of the key findings of this study is that, on average, households had a dietary diversity score of 10 out of a possible 12 food groups. These high levels of dietary diversity are plausible for smallholder farms with high levels of diversity in farm production, since they consume much of what they produce. These findings are also consistent with earlier studies in Kenya, such as those of Sibhatu *et*

al. (2015) and Muthini *et al.* (2020), who report dietary diversities in the range of nine to 11 food groups out of the possible 12. With regard to the number of social networks, farmers had about three nutrition information links, which compare favourably with previous findings that report between one and four networks for agricultural information networks (Muange *et al.* 2015; Mekonnen *et al.* 2016). As would be expected in any African setting, close to two thirds of the social network members were female.

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 the average household dietary diversity score of an individual's network members leads 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, in which members gain nutrition information from their peers. 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 the eating habits of network members, which may lead to the consumption of improved diets. This finding is supported by earlier studies that reported positive endogenous network effects on technology adoption (Van den Broeck & Dercon 2011; Mekonnen *et al.* 2016; Murendo *et al.* 2018) and agricultural productivity (Van den Broeck & Dercon 2011; Mekonnen *et al.* 2016).

The average education level of the members of the nutrition network had a positive effect on the household in terms of the dietary diversity of the individual farmer, which was significant at 5%. A unit increase in the number of network members with post-primary education increased the household dietary diversity score by 7.6%. Educated network members are likely to have more nutrition information, and when this is shared, it would lead to the consumption of quality foods. The results are comparable with 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 influence on the productivity of individual network members in Tanzania.

The effect of the average network age was positive, but weakly significant. In addition, the rest of the social network 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 an absence of correlated effects 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% level) effect on the household dietary diversity score. Households with bigger farm sizes consumed more food groups. 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 increases. This finding is supported by the work of Jones *et al.* (2014), who reported that farm size has a positive influence on household dietary diversity.

Larger families consumed more food groups than smaller ones. This could be attributed to the fact that the former have a larger labour force that can be invested in agricultural production and, in turn, improve their dietary diversity through the 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 a greater 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 the household dietary diversity score at the 10% level. 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, namely that age had a negative effect on household dietary diversity.

5. Conclusions and recommendations

This study evaluated the effect of social networks on household dietary diversity using a Poisson model. The results indicate that nutrition information networks have a positive influence on household dietary diversity and have an endogenous effect. 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 that indicated that 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 finding indicates that the dietary diversity of a household is influenced by the personal characteristics of the household head.

In conclusion, it is clear from the study that the more educated the network members are, the higher an individual household's dietary diversity score. Taking education as a proxy for knowledge, nutrition education therefore would increase farmers' nutrition knowledge. 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 can be channelled to enhance household nutrition quality.

The study recommends that governments and development partners should consider the use of nutrition information networks as a tool for the effective delivery of information in 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 at improving the 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.

References

Aberman N-L, Meerman J & Benson T, 2015. Mapping the linkages between agriculture, food security and nutrition in Malawi. Malawi Strategy Support Program Working Paper, International Food Policy Research Institute (IFPRI), Washington DC.

Arimond M & Ruel M, 2002. Summary indicators for infant and child feeding practices: An example from the Ethiopia Demographic and Health Survey 2000. Food Consumption and Nutrition Division Discussion Paper, International Food Policy Research Institute (IFPRI), Washington DC.

Arimond M, Wiesmann D, Becquey E, Carriquiry A, Daniels MC, Deitchler M, Fanou-Fogny N & Torheim EL, 2010. Developing simple measures of women's diet quality in developing countries: Methods and findings. Journal of Nutrition 140: 2059–69.

Bandiera O & Rasul I, 2006. Social networks and technology adoption in northern Mozambique. The Economic Journal 116(514): 869–902.

Bandura A, 1977. Social learning theory. Englewood Cliffs NJ: Prentice-Hall Inc.

Banerjee A, Chandrasekhar AG, Duflo E & Jackson MO, 2013. The diffusion of microfinance. Science 341(6144): 1236498. doi:10.1126/science.1236498

Basu K & Foster JE, 1998. On measuring literacy. Economic Journal 108: 1733–49.

Chuang Y & Schechter L, 2015. Social networks in developing countries. Annual Review of Resource Economics 7:451–72.

Comola M & Prina S, 2017. Treatment effects accounting for network changes. Mimeo, Case Western Reserve University.

Conley TG & Udry CR, 2010. Learning about a new technology: Pineapple in Ghana. The American Economic Review 100(1): 35–69.

Darapheak C, Takano T, Kizuki M, Nakamura K & Seino K, 2013. Consumption of animal source foods and dietary diversity reduce stunting in children in Cambodia. International Archives of Medicine 6: 29.

Easley D & Kleinberg J, 2010. Networks, crowds, and markets: Reasoning about a highly connected world. New York NY: Cambridge University Press.

FAO, 2007. Guidelines for measuring household and dietary diversity. Rome: FAO, Nutrition and Consumer Protection Division.

Fu Y-C, Ho H-C & Chen HM, 2013. Weak ties and contact initiation in everyday life: Exploring contextual variations from contact diaries. Social Networks 35(3): 279–87.

Gómez M & Ricketts K, 2013. Food value chain transformations in developing countries: Selected hypotheses on nutritional implications. Food Policy 42: 139–50

Hedström P, Sandell R & Stern C, 2000. Mesolevel networks and the diffusion of social movements: The case of the Swedish social democratic party. American Journal of Sociology 106(1): 145–72.

Hogset H & Barrett CB, 2010. Social learning, social influence, and projection bias: A caution on inferences based on proxy reporting of peer behavior. Economic Development and Cultural Change 58(3): 563–89.

Ibnouf F, 2009. The role of women in providing and improving household food security in Sudan: Implications for reducing hunger and malnutrition. Journal of International Women's Studies 10(4): 144–67.

IFPRI, 2014. Global nutrition report: Actions and accountability to accelerate the world's progress on nutrition. Washington DC: International Food Policy Research Institute (IFPRI).

Jones AD, Shrinivas A & Bezner-Kerr R, 2014. Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. Food Policy 46: 1–12.

Kennedy GL, Pedro MR, Seghieri C, Nantel G & Brouwer I, 2007. Dietary diversity score is a useful indicator of micronutrient intake in non-breast-feeding Filipino children. The Journal of Nutrition 137(2): 472–7.

Kennedy G, Fanou-Fogny N, Seghieri C, Arimond M, Koreissi Y, Dossa R, Kok F & Brouwer ID, 2010. Food groups associated with composite measure of probability of adequate intake of 11 micronutrients in the diets of women in urban Mali. Journal of Nutrition 140(11): 2070–8.

Langat BK, Ngeno VK, Sulo TK, Nyangweso PM, Korir MK, Kipsat MJ & Kebenei JS, 2011. Household food security in a commercialized subsistence economy: A case of smallholder tea famers in Nandi south district, Kenya. Journal of Development and Agricultural Economics 3(5): 201–9.

Langyintuo AS & Mungoma C, 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. Food Policy 33(6): 550–9.

Maertens A & Barrett CB, 2013. Measuring social networks' effects on agricultural technology adoption. American Journal of Agricultural Economics 95: 353–9.

Manski CF, 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60(3): 531–42.

Manski CF, 2000. Economic analysis of social interactions. The Journal of Economic Perspectives 14(3): 115–36.

Martire LM & Franks MM, 2014. The role of social networks in adult health: Introduction to the special issue. Health Psychology 33(6): 501–4.

Mbogori T, 2013. Dietary diversity and child malnutrition in Kenya. Discussion Paper No. 151, Kenya Institute for Public Policy Research and Analysis, Nairobi, Kenya.

Mekonnen DA, Gerber N & Matz JA, 2016. Social networks, agricultural innovations, and farm productivity in Ethiopia. Working Paper Series No. 235, African Development Group, Cape Town, South Africa.

Mekonnen D, Gerber N & Matz J, 2018. Gendered social networks, agricultural innovations, and farm productivity in Ethiopia. World Development 105: 321–35.

Muange E & Schwarze S, 2014. Social networks and the adoption of agricultural innovations: The case of improved cereal cultivars in Central Tanzania. Socioeconomics Discussion Paper Series Number 18, International Crops Research Institute for the Semi-Arid Tropics, Patancheruvu, India.

Muange EN, Godecke T & Schwarze S, 2015. Effects of social networks on technical efficiency in smallholder agriculture: The case of cereal producers Tanzania. Paper presented at the 2015 Conference of the International Association of Agricultural Economists, 9–14 August, Milan, Italy.

Munshi K, 2008. Social learning. In Durlauf SN & Blume LE (eds.), The new Palgrave dictionary of economics. Second Edition. London: Palgrave Macmillan.

Murendo C, Wollni M, De Brauw A & Mugabi N, 2018. Social network effects on mobile money adoption in Uganda. The Journal of Development Studies 54(2): 327–42.

Muthini D, Nzuma J & Nyikal R, 2020. Farm production diversity and its association with dietary diversity in Kenya. Food Security 12: 1107–20. https://doi.org/10.1007/s12571-020-01030-1

Odini S, 2014. Access to and use of agricultural information by small scale women farmers in support of efforts to attain food security in Vihiga County, Kenya. Journal of Emerging Trends in Economics and Management Sciences 5(2): 80–6.

Ogle BM, Hung PH & Tuyet HT, 2001. Significance of wild vegetables in micronutrient intakes of women in Vietnam: An analysis of food variety. Asia Pacific Journal of Clinical Nutrition 10: 21–30.

Oster E & Thornton R, 2012. Determinants of peer effects in menstrual cup take-up. Journal of the European Economic Association 10:1263–93.

Ragasa C, Aberman N & Mingote C, 2017. Does providing agricultural and nutrition information to both men and women improve household food security? Evidence from Malawi. IFPRI Discussion Paper No. 01653, International Food Policy Institute, Washington DC.

Rah JH, Akhter N, Semba RD, De Pee S, Bloem MW, Campbell AA, Moench-Pfanner R, Sun K, Badham J & Kraemer K, 2010. Low dietary diversity is a predictor of child stunting in rural Bangladesh. European Journal of Clinical Nutrition 64: 1393–8.

Röper A, Völker B & Flap H, 2009. Social networks and getting a home: Do contacts matter? Social Networks 31(1): 40–51.

Ruel MT, 2003a. Is dietary diversity an indicator of food security or dietary quality? A review of measurement issues and research needs. Food Nutrition Bulletin 24(2): 231–2.

Ruel MT, 2003b. Operationalizing dietary diversity: A review of measurement issues and research priorities. Journal of Nutrition 133(11): 3911S–26S.

Sibhatu KT, Krishna VV & Qaim M, 2015. Production diversity and dietary diversity in smallholder farm households. Proceedings of the National Academy of Sciences 112(34): 10657–62.

Smith LC, Alderman H & Aduayom D, 2006. Food insecurity in Sub-Saharan Africa. New estimates from household expenditure surveys. Washington DC: IFPRI.

Song L & Chang T, 2012. Do resources of network members help in help seeking? Social capital and health information search. Social Networks 34(4): 658–69.

Sraboni E, Malapit MJ, Quisumbing AR & Ahmed A, 2014. Women's empowerment in agriculture: What role for food security in Bangladesh? World Development 61: 11–52.

Steyn NP, Maunder EMW, Labadarios D & Nel JH, 2006b. Foods and beverages that make significant contributions to macro and micronutrient intakes of children in South Africa – Do they meet the food-based dietary guidelines? *South African Journal of Clinical Nutrition* 18(2): 66–76.

Steyn NP, Nel JH, Nantel JH, Kennedy G & Labadarios D, 2006a. Food variety and dietary diversity scores in children: Are they good indicators of adequacy? Public Health Nutrition 9: 644–50.

Suryanarayana MH, 2013. The pursuit of food security in India: Policies sans concept and commitment? The International Policy Centre for Inclusive Growth, One Pager No. 207, Poverty Practice, Bureau for Development Policy, UNDP, Brazil. Available at http://www.ipc-undp.org/pub/IPCOnePager207.pdf

Taruvinga A, Muchenje V & Mushunje A, 2013. Determinants of rural household dietary diversity: The case of Amatole and Nyandeni districts, South Africa. International Journal of Development and Sustainability 2(4): 2233–47.

Thuo M, Bell AA, Bravo-Ureta BE, Lachaud MA, Okello DK, Okoko EN & Puppala N, 2014. Effects of social network factors on information acquisition and adoption of improved groundnut varieties: The case of Uganda and Kenya. Agriculture and Human Values 31(3): 339–53.

UNICEF, WHO and World Bank, 2015. Levels and trends in child malnutrition: Key findings of the 2015 edition. Washington DC: WHO. Available at www.who.int/nutgrowthdb/jme_brochure2017.pdf

Van den Broeck K & Dercon S, 2011. Information flows and social externalities in a Tanzanian banana growing village. Journal of Development Studies 47: 231–52.

Workicho A, Belachew T, Feyissa GT, Wondafrash B, Lachat C, Verstraeten R & Kolsteren P, 2016. Household dietary diversity and animal source food consumption in Ethiopia: Evidence from the 2011 Welfare Monitoring Survey. BMC Public Health 16(1): Article no. 1192.

Young HP, 2009. Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. American Economic Review 99(5): 1899–924.

Zhang Y, Lin N & Li T, 2012. Markets or networks: Households' choice of financial intermediary in Western China. Social Networks 34(4): 670–81.

Appendix

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
$chi^2(7) = 2.78$			
$Prob > chi^2 = 0.9044$			

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