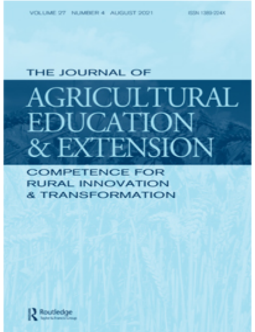

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Diffusion of agricultural knowledge in Southern Ethiopia: finding the real opinion leaders through network analysis

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ABSTRACT

Purpose: Agricultural extension services in poor countries often identify opinion leaders based on criteria such as wealth and social status. We explore the effectiveness of this top-down approach by analysing the role of so-called model and nodal farmers in the diffusion of malt barley in a highland community in Ethiopia.

Research approach: We use a retrospective case study design where we combine quantitative network analysis with qualitative data.

Findings: Nodal farmers played a more central role in knowledge diffusion of the technology than model farmers. While model farmers were wealthier and better connected to the local authorities, nodal farmers were socio-economically more similar to their fellow farmers. Nodal and model farmers, as well as farmers closely connected to them, had a significantly higher adoption index than the rest.

Practical implications: The diffusion of knowledge is an important condition for the adoption of modern agricultural technologies, but it is not enough, particularly when access to external inputs is limited. Moreover, relying on assumed opinion leaders has its limitations and may even reinforce existing inequalities.

Theoretical implications: This paper has shown the complementarity of network approaches. We propose network approaches such as social network analysis to identify community brokers who emerge from bottom-up or clan-based, political, knowledge networks that mediate access to agricultural technologies.

Originality: Our combined research approach differs from the mainstream of studies in this field that employ either ethnographic fieldwork or (spatial-)econometric methods. We aim to create a bridge between the often separated worlds of (technical) agronomic research, (qualitative) rural sociology, and (quantitative) econometric analysis.

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Introduction

The process of innovation is often thought to be initiated or supported by opinion leaders, who have the ability to influence others' attitudes and knowledges (Feder and Savastano 2006). Agriculture extension methods are heavily influenced by the seminal work of Rogers, who states that opinion leaders have the following characteristics in common: greater exposure to media; more cosmopolitan; more contact with change agents; greater social participation; higher socio-economic status; more innovative and moral authority (Rogers 2003, 316–319). Many agricultural research for development (AR4D) initiatives in Low and Middle Income Countries (LMICs) work with the so-called model farmers approach, reasoning that when appointed opinion leaders are satisfied with a new technology, others will follow them sooner or later. While there has been much research done on the effectiveness of the model approach in health care (Valente and Davis 1999; Griensven and Kalichman 2007), there is limited empirical research on the effectiveness of this approach in disseminating agricultural technologies in LMICs.

Opinion leaders can emerge in diverse ways (Valente and Davis 1999; Bamakan et al. 2019), for instance through a built up reputation based on expertise or legitimacy, or by being appointed/assigned by peers or influential figures. Opinion leaders can also emerge from within rural communities, without being formally appointed by any authority or organisation (Valente and Davis 1999). A study on the diffusion of microfinance in India found that the centrality of local actors such as shop keepers, input suppliers and village heads constituted a strong predictor of eventual village-level participation in microfinance (Banerjee et al. 2013).

The lion's share of literature uses the individual characteristics of opinion leaders as a proxy for the ability of opinion leaders to influence others. However, there has been limited field research done to explore whether people with the individual characteristics of opinion leaders (as identified by Rogers) do indeed (1) have a wide social network and (2) share their knowledge with others. Social network theory provides a useful perspective for studying this. For instance, a network analysis on the diffusion of integrated pest management practices in an Indian village found that a small group of brokers was able to bridge between homogeneous caste groups and other actors such as the NGO that introduced the practices (Arora 2012, chapter 8). Thus, next to individual characteristics, the effectiveness of opinion leadership may also depend on the composition of and pre-existing social relations in the community in question.

Problem statement

This research explores the role of opinion leaders in the diffusion of the malt barley technology in a highland community in South Ethiopia that is characterised by constraints in information availability (Leta et al. 2018; de Roo et al. 2019) and imperfect input and output markets. The two research questions are: (1) to what extent are appointed model farmers better than non-model farmers in sharing knowledge about improved agricultural technologies? And, (2) to what extent does connectedness among different categories of farmers to knowledge sources result in a higher uptake of improved technologies? Both questions will be addressed in the specific context of information asymmetry and imperfect input and output markets.

Many smallholder farmers in LMICs countries have limited access to information about technologies and how they perform on-farm (Conley and Udry 2001), partly because governments in these countries have limited resources for public extension services (Swanson 2008). In addition, low mobility and lack of media exposure limit farmers' options to identify new technologies, implying that farmers heavily rely on their social networks for information. Little empirical research has been undertaken to explore the role of opinion leaders under conditions of information asymmetry. It could be argued that, when information is harder to come by, they may act as 'gatekeepers' and disseminate information to certain people and not to others. This would imply that their role is quite important, and that information may not reach all people.

Imperfect input and output markets refers to the scarcity of inputs and limited market access for individual smallholders and is a common phenomenon in many LMICs (Jack 2011; Katungi et al. 2011), Ethiopia included (Byerlee et al. 2007; Asfaw et al. 2011; Yu et al. 2011). Earlier research in our study area indicates that having a strong social network facilitates access to inputs, although it is not clear how opinion leadership affects access to inputs in such conditions.

In the following section, we describe our materials and methods. Thereafter we present the empirical findings, followed by a discussion and conclusions.

Methods

We use a retrospective case study design (Yin 2009), in which we combine quantitative network analysis with qualitative data to understand the role of opinion leaders during the introduction of the malt barley technology (MBT) in the study site. Our approach differs from the mainstream of studies in this field, which employ either ethnographic fieldwork or (spatial-) econometric methods. We aim to bridge the often separated worlds of (technical) agronomic research for development, (qualitative) rural sociology, and (quantitative) econometric and network analysis by using a combined approach.

We employ a social network approach to identify who shares knowledge with who in the study area. Applying social network theory, we consider farmers as nodes, and the talks (knowledge exchange) between farmers as the connections between them. We follow the approach developed by Borgatti, (2005) on network measures and take eigenvector centrality (Bonacich 1987) as measure for the importance of nodes in the social network. Eigenvector centrality is not simply the total degree (sum of all connections, this is called 'centrality'), but the *weighted* sum of connections of a node: each connection's weight is determined by its own eigenvector centrality (Beaman et al. 2018). The idea behind eigenvector centrality is as follows. Even if node 'A' connects with just one other node 'B' in a network, if node 'B' subsequently connects with many other nodes (who themselves connect again with more others), then node 'A' can be regarded as highly influential in that community (Borgatti, 2005, 61). In our case, we use a direct network approach, whereby we identify knowledge flows between farmers. To shed a light on the influence of being connected to a model or nodal farmer, we also explored whether first-tier and second-tier connections of model and nodal farmers had a significantly a higher uptake of improved technologies.

Potential opinion leadership: model farmers and nodal farmers

In this paper, we compare two categories of potential opinion leaders: model farmers and nodal farmers. The Ethiopian extension programme employs the model farmer approach whereby certain farmers are appointed to try out new technologies and best practices first (MoA and ATA 2014). In policy documents, model farmers are often described as vanguards and innovative farmers who have to show the way to other farmers. Model farmers are expected to transfer their knowledge to their fellow farmers (five 'followers' for each model farmer). Model farmers are often (but not always) appointed as host farmers for demonstration trials. We contrast this group with 'nodal farmers'; farmers from within the community who play an important role in knowledge exchange, as expressed in their high eigenvector centrality (see Table 1).

Study site and the technology

The malt barley technology package (MBT) consists of seed of an improved variety from a trustworthy source, fertiliser recommendation, and improved agronomic practices such as ploughing (a minimum of three times before planting), row planting, and hand weeding (three times). The MBT was introduced in 2012 in Guguma, a highland kebele[1] in Melga woreda, in Sidama Zone, in the South of Ethiopia (Figure 1). The livelihoods of the majority of inhabitants in Guguma are based on a mixture of agricultural activities such as the production of cereals, enset, pulses and livestock (Abebe et al. 2015). For more background on the introduction of the MBT in Guguma we draw on our earlier research (de Roo et al. 2019).

For pragmatic reasons, we define adoption of the MBT as the extent to which respondents apply elements of the MBT on their farm at a given time. We realise that this is a limited view, and that the wider uptake of the MBT requires a reconfiguration of socio-technical and institutional elements in the system, such as making seed and fertiliser available on time, ensuring market access, and removing bottlenecks such as the scarcity of labour and oxen (de Roo et al. 2019). Based on earlier research in Ethiopia (Croppenstedt, Demeke, and Meschi 2003; Asfaw et al. 2011; de Roo et al. 2019), we argue that inputs are a critical constraint for the wide-scale uptake of modern agricultural technologies. Given this constraint, we will assess whether farmers who are appointed by the extension system as model farmers are significantly more likely than nodal farmers or other farmers to apply external inputs on their farm. In Annex I we define the variables used in this analysis.

Table 1. Categories of farmers used in this paper.

Category	Definition	Size
Model farmer	The respondent was identified as a model farmer in 2016 by the extension system*.	n=31
Nodal farmer	The 33.3% respondents with the highest eigenvector centrality*.	n=31
The rest category	When we compare nodal farmers with the rest, the rest consist of model farmers and ordinary farmers. When we compare model farmers with the rest, the rest consist of nodal farmers and ordinary farmers.	n=77
	* Due to overlap in the samples, this category also consists of 9 nodal farmers. * Due to overlap in the samples, this category also consists of 9 model farmers.	

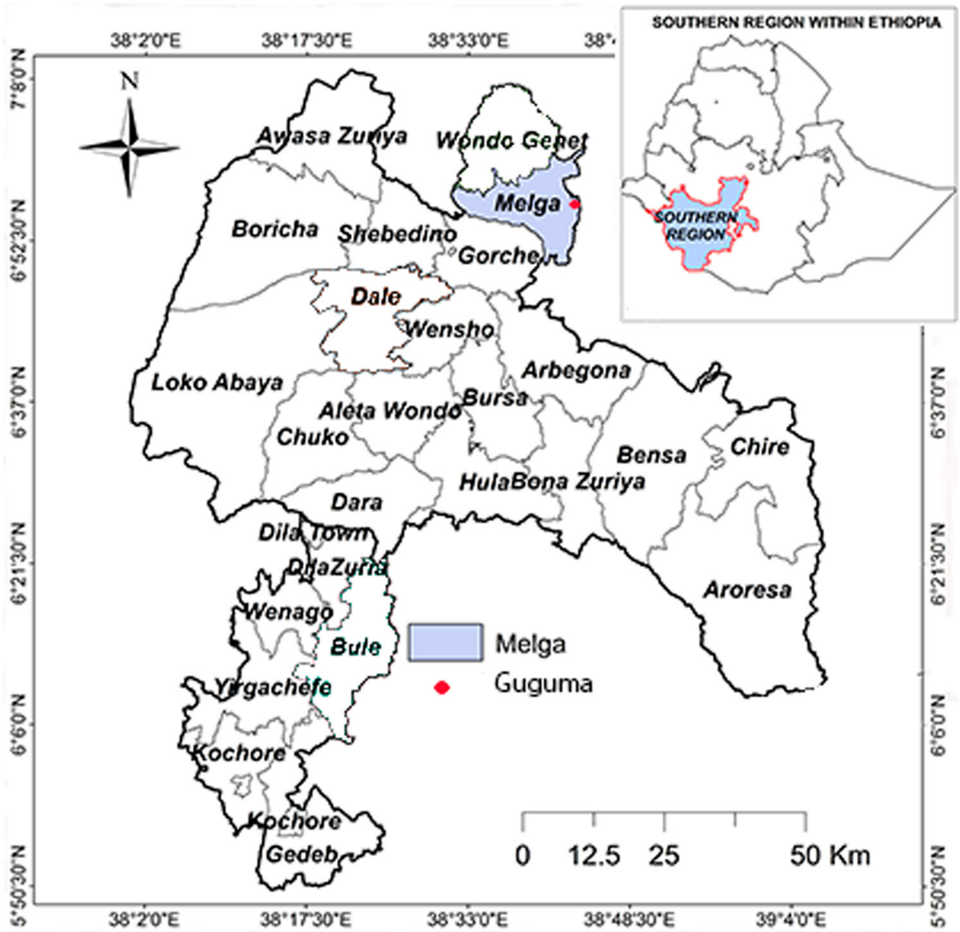

Figure 1. Map of the study area (Source: adapted from (Mellisse et al. 2017)).

Data collection and analysis techniques

We first present the network data, collected in 2017. Given the network character of our research, we used a snowball strategy to sample respondents. We started by asking the Head of Extension in Guguma to identify five farmers he considered to be most influential in sharing knowledge of new agricultural technologies (these are the descriptions that are locally used to refer to model farmers). We interviewed the persons mentioned by the extension head ($n = 5$), and asked them 'since the introduction of malt barley in this community, to whom in this community did you provide knowledge about malt barley?'. Conversely, 'From who in this community did you receive knowledge about the malt barley technology?' From the total number of persons that the farmer referred to, we followed up on the first five reported names. Next, we visited these five farmers and asked the same questions. We continued this exercise until we had a sample of 65 farmers. We also collected details about the farmers' socio-economic characteristics, membership of formal and informal groups and political and religious organisations, and their uptake of the MBT. Because this research was part of the Dutch funded CASCAPE programme,[2] we also had access to quantitative data of another 65 farmers in the same kebele. This second sample was randomly selected from a list of the households obtained from the kebele administration office. We also collected network data from this sample. The two samples (snowball and random) are biased towards male heads of households. This is the inevitable result of the dominant culture in Ethiopian rural society which considers the man as the head of the household. When asked for influential farmers, respondents automatically mention men. This implies that spouses and non-farm owners are underrepresented in this study.

Due to data entering errors and overlap in the two samples, we only used the data of 115 of the 130 farmers for our analysis, approximately 10 percent of the total population of Guguma. We only use one social network to answer the research question. This implies that our study has limited external validity.

Since we found no statistically significant difference between the snowball and random sample for key variables such as land size, uptake of the malt barley package, education level, social status and asset base,[3] we combined the two samples for further analysis.

We established a category of model farmers ($n = 38$) based on those farmers in the sample who were appointed by the kebele administration. Every year, the Kebele administration evaluates farmers and decides whether they are a model farmer or a follower. Criteria are not always clear, but in general they include: exemplary farmers who are expected to transfer their knowledge to their fellow farmers; often (but not always) appointed as host farmers for demonstration trials. Next, we selected the 38 farmers with the highest eigenvector centrality; our nodal farmers. Sixteen farmers fell into both categories. This overlap needed to be reduced because otherwise, we would be comparing two groups with similar respondents. To reduce this overlap, we randomly selected seven respondents who were both model and nodal farmers and deleted them from the sample; removing more farmers from the analysis would have resulted in too few farmers in each category to conduct statistical tests. The total sample for further analysis thus consisted of 108 farmers: 31 model farmers and 31 nodal farmers, with nine farmers belonging to both categories. We compared model farmers with the rest and we compared nodal farmers with the rest; in both cases the rest was a sample of 77 farmers (see Table 1).

Besides quantitative network data, we also collected qualitative data from participant observation and semi-structured interviews among key informants during two periods of fieldwork in July-August 2016 and August-September 2017. From the sample of 65 farmers, we selected 3 representative model farmers and conducted in-depth interviews with them.

Data analysis

For the quantitative analysis of the data, we used both parametric and non-parametric tests, depending on the normality test of the variables. For all ordinal variables (education level, frequency of contact with DA, frequency of participation in training and demo-trial in the past five years) we simply compared means. For continuous variables (adoption index, eigenvector centrality, land size, experience in malt barley cultivation, land size, tropical livestock unit, distance of the household to the nearby town market) we conducted an independent samples t-test (Field 2013). We used SPSS version 25 (for the statistical tests), Gephi 9.2 (for the visualisation of network data and calculation of eigenvector values). We analysed the qualitative data by making use of inductive coding. For this we used Atlas.ti.

Results

Knowledge networks in guguma

In a situation of perfect information symmetry, the model farmer approach would ensure that knowledge reaches all farmers in the network via a hierarchical structure (Figure 2a): each model farmer (M) would share his or her knowledge with five other farmers (F1), who in turn share this knowledge with five other farmers (F2), who also share their knowledge with five other farmers (F3). Figure 2(b) shows the empirical data of our network analysis ($n = 108$) whereby the size of the nodes indicates the eigenvector centrality. Our presentation of the network places farmers with many connections in common close to each other, rather than representing physical distance. Knowledge flows well within clusters, but less easily between clusters. Figure 2(b) shows the presence of structural holes: the white spaces next to, and between, clusters of nodes close to each other. The smallest nodes represent farmers who shared knowledge on malt barley with no-one or just one other farmer; they can be assumed to play an insignificant role in terms of knowledge dissemination. Figure 2(b) also shows that the knowledge did not diffuse exactly according to the 1–5 model-follower system, although most model farmers do share knowledge with a few others. The presence of quite a few big sized black nodes, suggests some other farmers share knowledge with more farmers than model farmers do. We analyse this further in the next section.

Characteristics of model farmers

We analysed whether model farmers shared knowledge about malt barley with significantly more people than other farmers and also compared model farmers with the rest

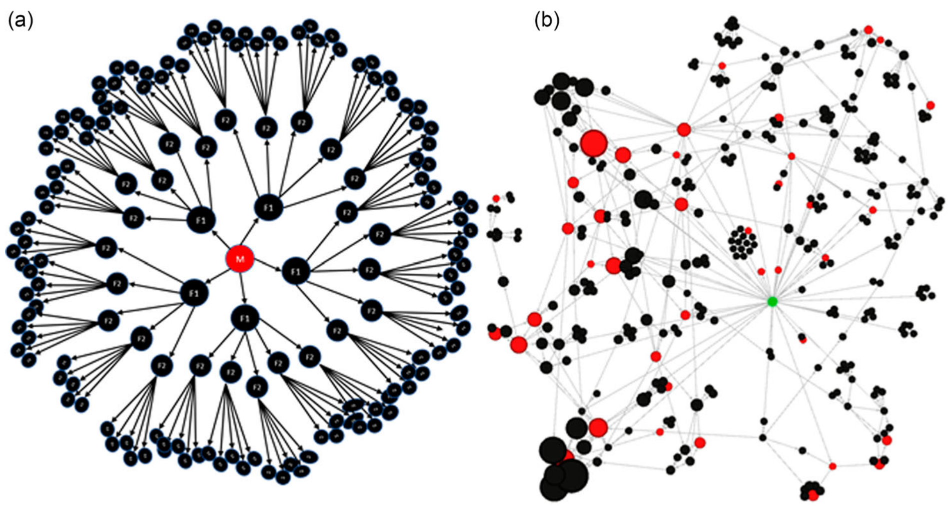

Figure 2. A and B Perfect information symmetry (a = left) and actual empirical knowledge network in Guguma (b = right)*. * Left: M = DA, F1 is model farmer and first-tier, F2 is second-tier and F3 is third tier connection to DA. Right: Green is the DA, Red nodes are model farmers, black nodes are the rest of the farmers. The biggest nodes are nodal farmers.

of the farmers in terms of their socio-economic and socio-political position. The results of the statistical tests are presented in Table 2 and Figure 3.

We found that model farmers were more experienced in malt barley cultivation, had a higher land size, more livestock (TLU – Tropical Livestock Units), and lived closer to the market.. Only land size and TLU was significant (at $p < 0.05$ and $p < 0.01$ significance level, respectively). Model farmers were also more frequently in contact with DAs and participated more often in training and demo-trials than other farmers. This was to be expected, since DAs appointed the model farmers as examples for the community. Most of the findings, except the education level, are typical for the characteristics of opinion leaders (Rogers 2003).

Moreover, model farmers were much more likely to belong to a royal family, had family members in the political party and in the kebele management, and occupied an influential position in church. This shows that model farmers were institutionally and politically better connected than the rest. Lastly, 77% of the model farmers were member of the malt barley cooperative, compared to only 36% of the rest. The primary cooperative was set-up to support farmers in accessing inputs and marketing (de Roo et al. 2019). It seems logical that those farmers who tried out the new technologies introduced by the extension service, the model farmers, were also among the first members of a cooperative that facilitates access to inputs and markets for this technology package. The findings of Figure 3 are in line with the dominant literature on opinion leadership which states that opinion leaders often have a high social status (Rogers 2003). However, the network findings show that model farmers were not more inclined than other farmers to share their knowledge about the MBT: their average eigenvector centrality was not significantly different from the rest (Table 2). In short, model farmers fitted most of the characteristics often ascribed to opinion leaders, but their role in diffusing knowledge was lower than expected.

Characteristics of nodal farmers

A similar comparison of the characteristics of nodal farmers with the rest of the farmers showed little differences: they did not have more land or livestock and neither were they

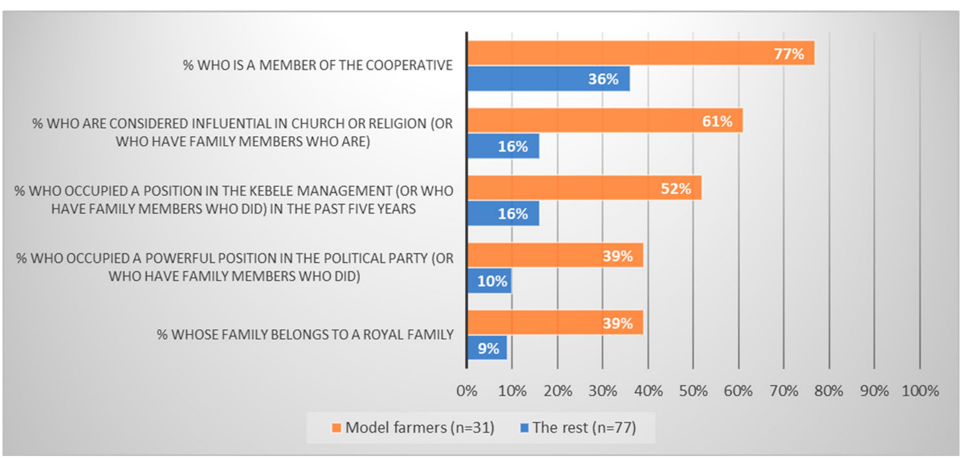

Figure 3. Socio-political characteristics of model and The rest of the farmers.

Table 2. Characterisation of model farmers and the rest.

	Model famers ($n = 31$)		The rest ($n = 77$)			Levene's Test for Equality of Variances		t-test for Equality of Means			
Ordinal variables	Mean	St.dev	Mean	St.dev							
Education level (0-3)	1.68	0.75	1.57	0.95							
Frequency of contact with DA (0-4)	2.16	0.90	1.17	1.01							
Frequency of participation in training in the past five years (0-5)	2.32	1.60	0.96	1.7							
Frequency of participation in demo-trial in the past five years (0-5)	1.06	1.66	0.57	1.27							
Continuous variables	Mean	St.dev	Mean	St.dev		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference
Eigenvector centrality	0.07	0.10	0.08	0.15	Equal variances assumed	0.253	<0.616	0.389	106	<0.698	0.011
Number of years the individual household head has been engaged in barley cultivation	16.58	8.19	14.71	10.47	Equal variances assumed	1.513	<0.221	−0.889	106	<0.376	−1.866
Total land size of household in hectares	2.18	1.52	1.43	0.9	Equal variances not assumed			−2.557	39	**<0.015**	−0.748
Tropical Livestock Units* that the household owned in 2016 production season	7.57	3.45	4.5	2.99	Equal variances assumed	1.045	<0.309	−4.623	106	**<0.000**	−3.074
Distance of the household to the nearby town market in km	1.09	0.62	1.15	0.83	Equal variances not assumed			0.449	74	<0.655	0.066

* Tropical Livestock Unit: see Annex 1

more often selected as host of demo-trials or did they participate in malt barley trainings than the rest (Table 3). Lastly they did not have a higher socio-political status (Figure 4). They were not more often in contact with DAs and not significantly more likely to be a member of the malt barley cooperative than other farmers (Figure 4). Nodal farmers lived further away from the town centre (significant at $p<0.05$ significant level). Lastly, they obviously shared knowledge with others (since eigenvector centrality was the variable determining this category of farmers).

Adoption of the malt barley technology

Both model farmers and nodal farmers had a higher adoption index[4] (0.84 and 0.79 respectively) than ordinary farmers[5] (0.68), indicating that they applied more elements of the MBT (Table 4). Those farmers who had a direct knowledge connection to model farmers and nodal farmers (we call them first-tier connections) also had a significant higher adoption index than farmers who were not so closely connected to model or nodal farmers (Table 4). First-tier connections of nodal farmers had a similar adoption index as nodal farmers (0.78), while farmers with only an indirect connection with nodal or model farmers had an adoption index of 0.70. In the case of model farmers, first-tier, second-tier and third-tier connections all had an adoption index of 0.78, indicating that they adopted 78% of the malt barley package.

We further explored the uptake of different input elements of the MBT separately. We found that model farmers apply more input related elements, and they do this more often as well, as compared to the rest of the farmers (significant at $p < 0.01$ confidence level, data not presented). By contrast, nodal famers used a similar level of inputs as the other farmers (data not presented).

Why are some farmers better connected than others?

The quantitative data shows that nodal farmers were quite similar to other farmers, except that they occupied a central position in the knowledge network. To try to explain this, we analysed the profiles of three nodal farmers, which we obtained through the participant observation and in-depth interviews (Table 5). These profiles are representative for the other nodal farmers.

The qualitative data indicates that nodal farmers often have a combination of formal/political and informal/social positions in the community. In addition, they seem to have a long standing credibility among the community, mostly in trade. Business men who are well known in the community are also important sources of new information and knowledge, particularly if they travel to other places and come back with new knowledge about agricultural practices or seeds of new varieties of crops. The participant observation and key informant interviews furthermore suggest that clan-based relationships play an important role in the exchange of knowledge and other goods or inputs, which corroborates the findings of earlier qualitative research in the same community (de Roo et al. 2019). The following testimony also highlights how the social clan-based structure influences knowledge and resource distribution in the community:

Table 3. Characteristics of nodal farmers and the rest.

	Nodal famers (n=31)		The rest (n=77)			Levene's Test for Equality of Variances		t-test for Equality of Means			
Ordinal variables	Mean	St.dev	Mean	St.dev							
Education level (0-3)	1.74	0.73	1.55	0.95							
Frequency of contact with DA (0-5)	1.26	1.03	1.53	1.08							
Frequency of participation in training in the past five years (0-5)	1.29	1.32	1.38	1.94							
Frequency of participation in demo-trial in the past five years (0-5)	0.07	1.38	0.74	1.42							
Continuous variables (Independent t-test)	Mean	St.dev	Mean	St.dev		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference
Eigenvector centrality	0.23	0.18	0.02	0.02	Equal variances not assumed			−6.377	30	**<4.592**	−0.208
number of years the individual household head has been engaged in barley cultivation	16.52	10.6	14.74	9.58	Equal variances assumed	0.996	<0.321	−0.845	106	<0.400	−1.776
total land size of household in hectare	1.53	1.11	1.69	1.18	Equal variances assumed	0.083	<0.774	0.659	106	<0.511	0.163
total livestock unit that the farmers owned in 2008 production season	4.7	3.1	5.65	3.51	Equal variances assumed	1.189	0.278	1.314	106	<0.192	0.951
the distance of the household to the nearby town market in km	1.39	0.74	1.03	0.77	Equal variances assumed	0.316	<0.575	−2.233	106	**<0.028**	−0.362

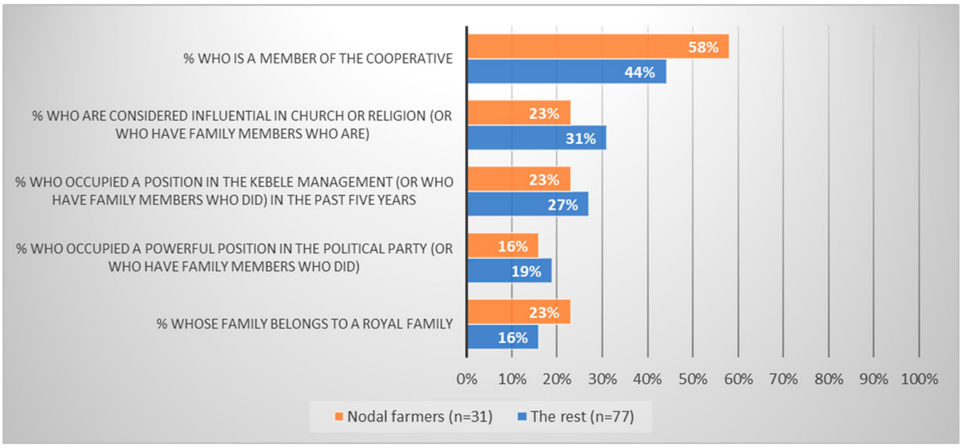

Figure 4. Socio-political characteristics of nodal farmers and the rest.

Table 4. Adoption of the MBT by farmer category.

	Average adoption index[1]	St.dev
Model farmers (n=31)	0.84	0.23
First-tier connection to model farmers (n=29)	0.78	0.21
Second-tier or third-tier connection to model farmers (n=48)	0.78	0.25
Nodal farmers (n=31)	0.79	0.19
First-tier connection to nodal farmers (n=10)	0.78	0.17
Second-tier or third-tier connection to nodal farmers (n=67)	0.7	0.32
'Ordinary' farmers (n=54)	0.68	0.31

[1]The adoption index measures the intensity of adoption of a farmer. See Annex 1 for a more elaborated definition.

Table 5. Description of selected nodal farmers'.

Socio-economics	Description of the person
Land size 1.5ha, No oxen, non-model farmer	ID3, trader, is part of a family of which two other brothers are also nodal farmers and traders. He trades in several commodities and travels a lot to nearby towns. The three brothers are not appointed as model farmer and they do not occupy political functions in the kebele. They all live in the same sub-kebele. The largest nodes in Figure 2 correspond with this family.
Land size: 1.25ha, 1 ox, model farmer	ID7, chair of sub-kebele, is from the dominant clan and appointed as a model farmer. He is also the chairman of one of the sub-kebeles of Guguma and has been an influential person in the kebele for a long time. Given his position he is invited to meetings where new technologies are being discussed. He explains how good performance in the community is rewarded: *Once you perform well in the system, you get other responsibilities as well. It is nice to do something for the community. (interview with ID7)*
Land size: 3,5 ha, 2 oxen, non-model farmer	ID142, farmer/trader is a wealthy farmer with many connections in the village and in surrounding towns. He used to be a trader (he still trades commodities and fertiliser on the black market). He was asked to become a member of the cooperative but refused. He prefers not to depend on the government. He thinks that the government is unreliable and does not like the hard life in Guguma: *I used to live in Addis Adaba, I travelled a lot. Back then I was a merchant. I met a lot of different people. I only came back because my father asked me to as he was dying. I am the oldest son and my brothers could not come back. [he starts to cry] I am so said he died. He was strong. I have the responsibility to take over his land and farm. But I don't want to be a farmer! I don't want to have this harsh life and depend on the government for everything. I feel trapped. But I can't let my father down now, he is dead. (interview with ID 142, July 2016)*

> Last year the government provided 1100 KG of improved malt barley seed to incentivise the entire kebele to grow malt barley. This ended up in a few hands, namely the few families who were among the first to benefit from the technology. The chairman of the fertiliser union distributed seeds to 11 families; I know this was in exchange for protection. Those families who receive gifts will never openly badmouth the chairman, because they realise that doing so means the end of the gifts. I don't want to be part of it. I have never been interested in politics. (interview with ID56, August, 2017).

Discussion

We have compared two categories of farmers with the rest: model farmers who are appointed 'top-down' by the extension system and farmers with a high eigenvector centrality, who we called nodal farmers.

We first discuss our first research question 'what extent are appointed model farmers better than non-model farmers in sharing knowledge about improved agricultural technologies?'

Despite the fact that the characteristics of model farmers largely match with the characteristics sketched in earlier research on opinion leaders (Rogers 2003; Feder and Savastano 2006), model farmers seem to play only a limited role in knowledge dissemination. This raises the question of the effectiveness of the model farmer approach, or more broadly: whether model farmers are opinion leaders at all, as the Ethiopian extension model assumes. On the other hand, farmers referred to nodal farmers more often than to other farmers as a source of knowledge on malt barley. The high eigenvector centrality (0.23 versus 0.07) indicates that they were more effective than the model farmers in disseminating knowledge about malt barley to the entire community. Because their eigenvector centrality was high, we know they are either gatekeepers or closely connected to gatekeepers, who are the link between different sub-communities in the village. One of the explanations for the centrality of nodal farmers may be their socio-economic similarity to their peers, which may make them more easily accessible to others. Because model farmers were significantly wealthier and tended to have important political functions in the community, there may be socio-political barriers that affect their capacity to act as an example for others. Other farmers may think that their lower level of resource endowment makes them different to model farmers and that the technologies that model farmers adopt are not suitable for them. In a study on the diffusion of integrated pest management in farming communities in Indonesia, Feder and Savastano (2006) similarly found that when the social status of opinion leaders was markedly different from others in the community, this reduced their effectiveness in disseminating knowledge.

With respect to the effectiveness of the government appointed model farmers approach, our findings suggest that solely relying on government structures for knowledge diffusion runs the risk that knowledge remains within a small elite and many people are not reached. The empirical evidence on this topic is ambiguous. Some scholars have pointed to the risk of elite capture (Platteau 2004), referring to rural elites who have the capacity to capture resources allocated for rural development projects. However, in a seed network analysis, Tadesse et al. (2017) found that model farmers were the most effective sharers of seed of new potato varieties in their community and thus the most effective collaborators for development projects to achieve their goals. In an experimental study (using randomised control trials) on the local management of development projects in Sierra Leone, Voors et al. (2018) found that local elites were powerful players who could block or hamper development projects. Based on our study we argue that a social network analysis (combined with qualitative socio-political analysis) may be an effective alternative to relying on government structures and for identifying bottom-up opinion leaders. Making use of those members of the community with bridging capital (Burt 2000), i.e. those who are able to connect different horizontal and vertical social groups, increases the likelihood that knowledge about agricultural technologies reaches more people and more sub-communities.

Our second research question was 'to what extent does connectedness among different categories of farmers to knowledge sources result in a higher uptake of improved technologies?'

The higher adoption index for first-tier and second-tier farmers under the model farmer model, confirms that peer-to-peer learning was a powerful force for adopting new technologies. This has also been found by others (such as Krishnan and Patnam 2014). However, the study also shows that knowing about a technology is not the only factor of importance, access to inputs is also critical. In Guguma, cooperative membership is a good proxy for access since membership enables privileged access to scarce inputs such as seed and fertiliser (on a credit basis).

An important complementary insight that emerged from the qualitative data was that clan-based relationships, sometimes dating back generations, play an important role in the exchange of knowledge and goods. The relevance of ethnicity and clan-based relations was also found in a study on agricultural extension in Oromia communities in Ethiopia (Matouš, Todo, and Mojo 2013). It was not possible to quantify the influence of clan-based relations on knowledge dissemination.

Conclusions

Our findings suggest that the effectiveness of the model farmer approach in the Ethiopian extension approach is limited by two main factors: firstly, model farmers are not very effective in disseminating knowledge and secondly, they may be too different from the rest of the community – socially, politically and economically – to be regarded as effective examples.

Our study suggests that knowledge and technologies do not travel in neutral or free-from-bias ways to the wider community, but tend to remain within certain cliques. The complexity of social relations in the community shows how difficult it is for development projects to identify 'the right' people who can help to introduce and scale-up agricultural technologies in a community.

Our findings have two important implications for organisations promoting the diffusion of improved technologies in LMICs.

Given the findings of this study, it is recommended for governments and organisations promoting the uptake of agricultural technologies to use network approaches to identify appropriate entry-points for the diffusion of knowledge about agricultural technologies.

Secondly, this study shows that – albeit an important pre-condition for the uptake of agricultural technologies – knowledge is not enough. Demonstrating new technologies should always be accompanied by efforts to remove barriers to access to seed and inorganic fertiliser (and output markets). Our case shows that when inputs are scarce, pre-existing social relations in the community may perpetuate inclusion and exclusion, with model farmers, who are well connected to the local political system, having better access to inputs than other categories of farmers.

Notes

1. Kebele is the lowest administrative unit in the Ethiopian government structure.
2. CASCAPE stand for Capacity building for scaling up of evidence based best practices in Ethiopia
3. The output is available on a server hosted by WUR. Request for access to the raw data and analysis output will be given upon request; please contact the corresponding author at nina.deroo@wur.nl.
4. See Annex I for the definition of adoption index.
5. Respondents who were neither model farmer nor nodal farmer are referred to as 'ordinary' farmers ($n = 54$).

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