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Adoption of CA technologies among Followers of Lead Farmers: How Strong is the Influence from Lead Farmers? [1]

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Abstract

This study investigates how the Farmer-to-Farmer-Extension (F2FE) system with lead farmers and follower farmers influences adoption of Conservation Agriculture (CA) technologies in Malawi. Using data from 180 lead farmers and their 455 followers in central and southern Malawi, we assess the level of influence lead farmers have on their followers' familiarity with and adoption of CA. The main findings are that (a) lead farmers have significant influence on CA familiarity and adoption among followers

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through their motivation, familiarity, and own adoption and (b) F2FE is a complement rather than a substitute for other agricultural extension activities. Policy implications are discussed.

Keywords: Africa; conservation agriculture (CA); farmer-to-farmer extension (F2FE); Malawi; technology adoption; lead farmers; followers of lead farmers.

JEL codes: Q16.

1. Introduction

Farmer-to-farmer extension (F2FE) has become increasingly common in developing countries, in response to the decline of investments in government extension services (Davis, Franzel, and Spielman, 2016). Entrusting in farmers the important task of diffusing new agricultural technologies is consistent with empirical evidence documenting information failures as a key impediment to technology diffusion and the importance of social learning in overcoming such failures (Foster and Rosenzweig, 1995; BenYishay and Mobarak, 2014). F2FE is particularly relevant where public extension is insufficient or ineffective, owing to low budgetary allocation, understaffing, and low staff morale, as in many countries of sub-Saharan Africa (SSA) (Kiptot and Franzel, 2014).

It is only quite recently that F2FE has become common in SSA. For example, a survey across seven regions of Cameroon revealed that 31% of the 151 organizations providing extension services were using F2FE, and 58% of those had only started using the approach in 2005/06 (Tsafack et al., 2014). In Malawi, a survey of 37 of the largest extension organizations found that 78% were using F2FE (Masangano and Mthinda, 2012), while another survey of 25 organizations currently using F2FE indicated that the majority had adopted it only since 2003 (Kundhlande et al., 2014). Information on the impact and sustainability of F2FE programs in SSA is sparse.

This paper presents a case study of the Malawi government's reliance on F2FE to spread conservation agriculture (CA).[2] F2FE offers a potentially low-cost and wide-reach approach to diffusing CA to smallholders. Malawi's Department of Agricultural Extension Services (DAES) currently works with more than 12,000 lead farmers country-wide who train and promote agricultural technologies, including CA, through their networks of follower farmers ("followers") and through demonstration trials.[3]

Using new data collected in 2016 from a survey of lead farmers and their followers in four districts of central and southern Malawi, we examine how much influence lead farmers have on the awareness and uptake of CA among their follower farmers. We test hypotheses that familiarity with and adoption of CA technologies among followers of lead farmers is influenced by the lead farmers' motivation, familiarity with CA, and own adoption of CA technologies. We also test the hypothesis that other extension contacts that followers have are more important for the diffusion of CA technologies than the influence from lead farmers. The study focuses on five specific CA practices: crop rotation, minimum tillage, use of herbicides, soil coverage (mulching), and organic manure. Survey data are available for these practices and they are being promoted by the government of Malawi as key elements of sustainable and climate-smart agricultural development (Asfaw et al., 2014).

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[2] Conservation agriculture (CA) aims to achieve improved and sustained agricultural productivity, increased profits and food security, while preserving and enhancing the resource base, through the application of three linked principles: minimum soil disturbance, permanent soil cover, and crop rotation (FAO, 2013).

[3] We use the term "lead farmer" when referring to such farmer trainers, given its prominence in Malawi the geographic focus of our study, but several other labels are also commonly used (e.g., opinion leader, model farmer, community knowledge worker, contact farmer, volunteer farmer), depending on the specific roles and tasks performed.

This study contributes to the literature on agricultural technology adoption in four main ways. First, we employ a unique dataset on 180 lead farmers linked to their 455 follower farmers, enabling a more direct examination of lead farmer influences on technology diffusion than is otherwise possible. We know of only three other studies on F2FE that used this type of data, and the sample sizes for two such studies were very small (Kiptot, Franzel, and Kirui, 2012; Nakano et al., 2015; Wellard et al., 2013). Second, we offer comparative estimates of the role of learning from lead farmers vs. other sources of agricultural information. In Malawi, information on CA has been spread using a variety of approaches (e.g. lead farmers, extension agent visits, and electronic media). We examine the relative importance of different information sources for the familiarity with and adoption of CA among follower farmers. Empirical studies have explored the role of extension services (Anderson and Feder, 2004), information and communication technologies (ICTs; Aker, 2011), and social learning (Bandiera and Rasul, 2006; Matuschke and Qaim, 2011), but rarely have the various sources of agricultural information been studied together (Krishnan and Patnam, 2013).[4]

A third contribution is evidence on the role of lead farmers in diffusing a range of CA practices. The influence of lead farmers is likely to differ across technologies for several reasons, such as the technology's complexity and stage in the diffusion process, and based on how much the technology's performance varies across farms and therefore the perceived applicability of the lead farmers' advice and experience (Liverpool-Tassie and Winter-Nelson, 2012; Munshi, 2004;

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[4] Exceptions are Beaman et al. (2016), BenYishay and Mobarak (2014), Krishnan and Patnam (2013), and Genius et al. (2013).

Matuschke and Qaim, 2009). The literature is rather thin on this topic, and we add another empirical point towards filling this knowledge gap.

Finally, the study results are highly relevant to agricultural policy making in Malawi. While the suitability of CA for smallholders in SSA has been much debated in recent years, sparked by the paper of Giller et al. (2009), more recently it is argued that the "niche" where CA fits in eastern and southern Africa is large and growing. In particular, CA holds great potential in terms of saving energy (including labor and draft power), controlling soil erosion, and water-use efficiency (Baudron et al., 2015). CA appears highly relevant for Malawi, given high rural population density (for SSA), very small landholdings, water constraints, soil degradation, low livestock densities, and low demand for crop residues for livestock feed (Andersson and D'Souza, 2014; Ellis, Kutengule, and Nyasulu, 2003; Ngwira et al., 2014; Wani et al., 2009). Despite the promise of CA, adoption by farmers in SSA remains low (Andersson and D'Souza, 2014; Giller et al., 2009), and high abandonment of practices has been documented in some areas (Arslan et al., 2014). A recent estimate for six districts of central and southern Malawi in 2009/10 is that 18.5% of farmers were practicing two or three CA principles (i.e. minimum soil disturbance, permanent soil cover with crop residues, and crop rotations) on an average 10% of their agricultural landholding, representing about 2.1% of cultivated area (Ngwira et al., 2014). We ask in this paper whether and how F2FE can help spread CA practices to Malawi smallholders?

2. Background on the public agricultural extension system and the farmer-to-farmer extension approach in Malawi

In Malawi, agricultural extension services are largely the responsibility of the DAES, one of seven technical departments of the Ministry of Agriculture, Irrigation, and Water Development (MoAIWD). Public agricultural extension services are also provided by specific projects of

MoAIWD, such as the Farm Income Diversification Project. In the last few decades, there has been increased involvement of non-state actors in agricultural extension provision, owing to the introduction in 2000 of a policy that promoted pluralistic and demand-driven extension systems, but DAES remains the main extension service provider in the country. Non-state actors involved in agricultural extension include private-sector organizations (e.g. companies that supply farm inputs to farmers), farmer organizations, and non-governmental organizations (NGOs) (Masangano and Mthinda, 2012).

The government extension system in Malawi relies on Agricultural Extension Development Officers (AEDOs) who are employed by the MoAIWD to work with individual farmers and conduct village-wide field days. The AEDOs are in theory responsible for one agricultural extension section each, covering about 15-25 villages. However, in practice AEDOs are responsible for multiple sections, due to field staff shortages (BenYishay and Mobarak, 2014). In 2011, for example, the ratio of AEDOs to farmers was 1/1,848 (Khaila et al., 2015).

The DAES began using the F2FE approach in 2003, which was formally institutionalised within DAES' programs in 2007 (Kundhlande et al., 2014). Under the F2FE approach, each AEDO partners with one lead farmer per village who is responsible for training other farmers in some of the technologies and topics for which the AEDO would otherwise be responsible (BenYishay and Mobarak 2014). The DAES also advocates community awareness raising meetings and participatory rural appraisals to orient communities in the use of F2FE (Khaila et al. 2015).

There are no firm guidelines for lead farmer selection in Malawi (Khaila et al., 2015). Two recent surveys of lead farmers and extension organizations using F2FE reveal that lead farmers are usually selected by the communities they serve with the main selection criteria being literacy, community residence, being a hard worker, having a reputation of good behavior, innovativeness, and availability (Khaila et al., 2015; Kundhlande et al., 2014). The selected lead farmers generally receive an initial training from extension organizations, covering technical topics and communication skills (Khaila et al., 2015). The amount of training received is not extensive – typically covering a single day and limited to an initial training only. While most lead farmers interviewed by Khaila et al. (2015) say they have sufficient knowledge and skills for the job, many perceive their performance could improve with more training.

On average, the lead farmers surveyed by Khaila et al. (2015) had 61 follower farmers (median = 25). Their main activities as lead farmers are training, advising, monitoring their followers, and establishing demonstration plots. The main technologies promoted are CA, maize pit planting, the Sasikawa planting method, compost making, and other land conservation and agroforestry technologies.

Lead farmers' report two main motivations for becoming and remaining lead farmers: to improve their knowledge of farming and to help others (Khaila et al., 2015). They appear to receive minimal monetary compensation and material support. The main challenges as lead farmers are lack of transport, limited budget for activities, and low adoption of technologies by followers.

3. Conceptual framework and hypotheses

The simple conceptual framework in Figure 1 illustrates four hypotheses for how information about the CA technologies flows from lead farmers to their followers, while also considering other information sources that may influence followers' familiarity with and adoption of these technologies. Hypothesis 1 is that lead farmers' motivation (as lead farmers) influences the familiarity with and adoption of CA technologies among their followers. We assume lead farmers who are more motivated are better at convincing followers about the advantages of the CA technologies than less motivated lead farmers. BenYishay and Mobarak (2014) found that offering peer farmers in Malawi a small performance incentive increased their effort to learn about pit planting and, in turn, their effectiveness at convincing other farmers to adopt. And qualitative studies suggest that motivation of lead farmers is important to the success of F2FE in disseminating new technologies (Davis, Franzel, and Spielman, 2016).

Hypothesis 2 is that lead farmers' familiarity with CA technologies increases followers' familiarity with and adoption of CA technologies. This hypothesize is self-evident: familiarity with a CA practice is a necessary condition for a lead farmer to diffuse the technology to other farmers. The third hypothesis proposes that lead farmers' own adoption of CA technologies is positively associated with followers' familiarity with and adoption of CA technologies. That is, we assume that a key way followers learn about new technologies is by observing lead farmers' experimentations. There is some empirical work in support of this contention. Matuschke and

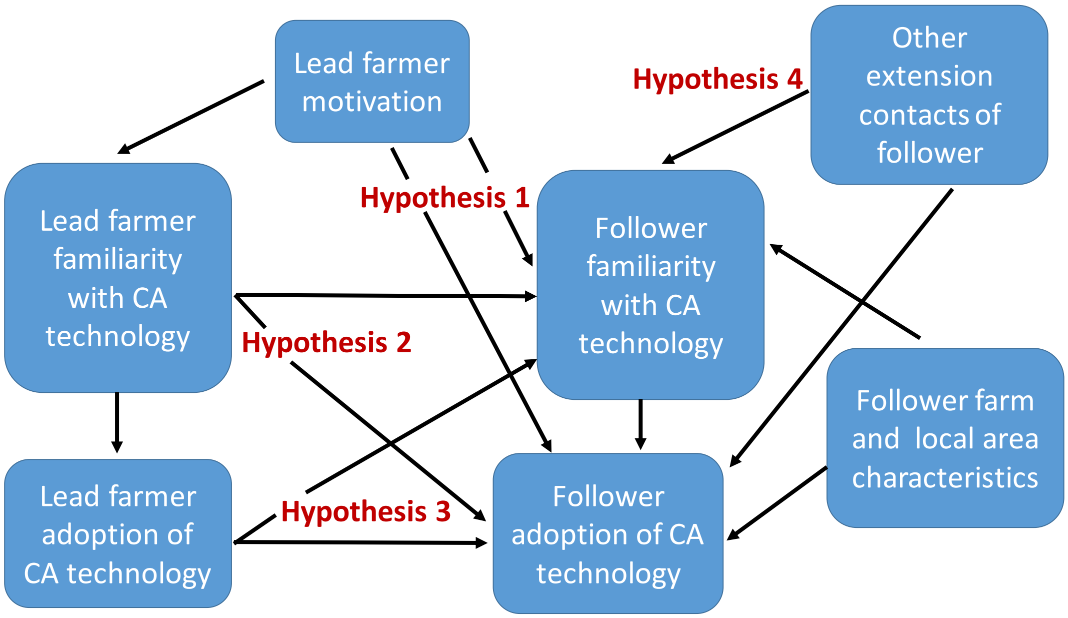

Figure 1. Conceptual framework

Qaim (2009), for example, found in their study of hybrid seed adoption in India that a farmer's decision to adopt a new technology was strongly influenced by the adoption choices of the farmer's social network members. Bandiera and Rasul (2006) examined how Mozambican farmers' decisions to adopt a new crop (sunflower) are influenced by the adoption choices of their social networks. They found a nonlinear (U-shaped) relationship between probability of adoption and the number of adopters among family and friends. In other words, social effects were positive when there were few adopters in the network, and negative when there were many.

Finally, Hypothesis 4 is that other sources of extension information (e.g., agricultural extension officer visits, ICTs) are also very important for the familiarity and adoption of CA technologies by followers, i.e. multiple sources of information can help diffuse new technologies. For example, Beaman et al. (2016) found that farmers in Malawi needed to receive information from multiple sources before they were willing to try out pit planting. Krishnan and Patnam (2013) found for Ethiopia that learning about improved seeds and fertilizer from extension agents was initially high, but wore off after some time, whereas the importance of learning from other farmers was sustained over time. A third related study (Genius et al., 2013) found that irrigation technology adoption in Greece was strongly determined by both extension services and social learning, and the effectiveness of these information channels was enhanced by the presence of the other.

4. Data and methods

4.1. Data

The data used in this study come from a household survey conducted mainly in four districts in Malawi in 2016. These four districts are Lilongwe and Kasungu in the Central Region and Machinga and Zomba in the Southern Region. In addition, we have a smaller sample from Chiradzulu and Thyolo districts in the Southern Region. The selection of the four (six) districts followed earlier surveys where data has been collected on panel households between 2006 and 2015. The first round of the panel surveys took place in 2006 where an initial sample was drawn using a simple random sampling technique following the 2004 Integrated Household Survey (IHS2). The current survey identified the agricultural extension planning areas (EPAs) where the previous surveys have been conducted. A list of lead and follower farmers was provided in each of the EPAs where respondents were randomly sampled. The number of lead farmers was relatively small in our previous survey areas and necessitated expanding the coverage of the survey by adding more EPAs in each district to enlarge the sample of lead farmers and followers[5]. While we included all the lead farmers in each EPA, we randomly chose two to four followers of each lead farmer. A simplified and modified for our purpose version of the IHS4 (LSMS-ISA) survey instrument was used. A set of additional questions related to CA technologies and extension contacts were among the parts added to the survey instrument. It was programmed in in the software Survey Solutions (World Bank) and the data were collected using tablets that also were used to record the GPS locations of respondents and to measure their farm plots. Fifteen enumerators were trained in the use of the tablets for the interviews. In the beginning they managed to interview only one household per day but as they became more skilled they managed to complete two interviews in a day.

The uniqueness of this dataset lies in the sampling of lead farmers with the subsample of followers which allows us to assess the impacts of lead farmer characteristics on their followers' familiarity with and adoption of CA technologies. We got a list of follower farmers for each sampled lead farmer from which the sample of follower farmers was drawn. The lead farmer is directly in contact with his/her followers. Usually these are farmers from the same EPA section and in most cases from the same village as the lead farmer. This implies that both the lead farmer and follower farmers are quite familiar with each other. The follower farmer is able to follow the activities of their lead farmer and is likely to be influenced by his/her familiarity and adoption of the technologies and may be able to witness their performance on the lead farmers' own fields as well as on demonstration field plots.

[5] This added to the survey costs and the survey budget caused a more limited coverage in Chiradzulu and Thyolo districts.

4.2. Estimation strategy

We first assess factors associated with follower farmers' familiarity with the five CA technologies using linear probability models with robust standard errors. We also include simple OLS models with robust standard errors for the aggregate number of CA technologies that the followers are familiar with. We start with parsimonious models for follower farmer familiarity that include only the lead farmer (i.e. motivation, familiarity with CA, and adoption of CA) and other extension contact variables. These models can indicate the relative importance of the various potential sources of information and the extent to which they may explain the systematic difference in familiarity with CA technologies among the sample of followers of lead farmers.

Next, we run a set of familiarity models where we add to the first specification a range of follower household and farm characteristics and district fixed-effects as controls, as these may contribute to the observed variation in followers' familiarity. We assess how inclusion of the control variables affects the significance and size of the parameters on the lead farmer variables as a robustness check of their importance across the five CA technologies. The changes in these parameters across specifications give insights into the issue of potential selection bias related to the different sources of information, and the consistency of the results and significance levels across models indicate the degree of robustness of the results.

The final step of empirical modeling identifies the main factors that explain adoption of the five CA technologies by followers. We use an approach that takes the familiarity into account, as it is endogenous. For this we use bivariate probit models for each CA technology. Similarly to the familiarity models, we start with more parsimonious models and then add controls for household characteristics and district fixed effects. A comparison of the changes in the coefficients across models and technologies provides insights about the mechanisms in the adoption process. The adoption models also include binary variables for follower farmer familiarity with the CA technologies, since adoption is conditional on familiarity.

There are a number of endogeneity issues of concern in this analysis. The number of extension contacts themselves with different sources are potentially endogenous. We assess this by regressing them on the additional follower and farm control variables. These models are presented in Table A2 in the Appendix. We can see that observable follower household and farm characteristics to a small extent are correlated with these extension contact variables. By running models without and with the same set of control variables and inspecting the key variables of interest, we further assess the extent to which there can be endogeneity bias in the results.

5. Descriptive analyses

Table 1 shows the difference in familiarity with the five different CA technologies between followers of lead farmers and lead farmers and similarly for adoption of the CA technologies. Familiarity and adoption levels are higher for the lead farmers than their followers for all the technologies but the differences are not large in most cases. The difference is largest for the adoption of minimum tillage with 24% for lead farmers versus 13.8% for followers and for adoption of herbicides with 7.1% for lead farmers and 1.8% for followers.

Table 2 shows the cumulative adoption of the CA technologies. Hardly any (<1%) of the farmers have adopted all the five CA technologies. 2.6% of the lead farmers and 0.9% of the followers have adopted four out of the five CA technologies, while 7.7 and 4.4% of lead farmers and followers respectively have adopted three of the CA technologies. At the other end, we see that 11 and 22% of the lead farmers and followers have adopted none of the CA technologies, while 48.4 and 49.5% of the lead farmers and followers have adopted one of the CA technologies.

Table 1. Familiarity with and adoption of CA technologies among followers and the lead farmers

	Crop rotation	Minimum tillage	Herbicides	Mulching	Organic manure	CA combined
Followers						
Familiarity with CA technologies	0.735	0.659	0.317	0.427	0.801	2.939
Adopted CA technologies	0.401	0.138	0.018	0.125	0.475	1.158
Lead farmers of followers						
Familiarity with CA technologies	0.760	0.710	0.405	0.501	0.818	3.194
Adopted CA technologies	0.459	0.240	0.071	0.150	0.514	1.434

Source: NMBU Malawi CA survey 2016. The table gives average rates for followers and the lead farmers of the same followers (lead farmers weighted by the number of followers in the sample). CA combined is the within household count for familiarity and adoption of all the five CA technologies.

Table 2. Aggregate adoption levels of CA technology components at farm level by household type

	-----------Followers--------			---------Lead farmers---------		
Number of CA tech adopted	Freq.	Percent	Cum.	Freq.	Percent	Cum.
0	100	21.98	21.98	50	10.99	10.99
1	225	49.45	71.43	220	48.35	59.34
2	105	23.08	94.51	136	29.89	89.23
3	20	4.4	98.9	35	7.69	96.92
4	4	0.88	99.78	12	2.64	99.56
5	1	0.22	100	2	0.44	100
Total	455	100		455	100	

Source: NMBU Malawi CA survey 2016. *Note:* The table gives the distribution of the number of CA technologies adopted by followers and their lead farmers.

Table 3. Number of other extension contacts of followers, by source.

Variable	Obs	Mean	Std. Dev.	Min	Max
Government ag extension contacts	455	1.93	2.24	0	11
Private ag extension contacts	455	0.08	0.45	0	6
NGO contacts	455	0.18	0.63	0	7
Farm field day visits	455	0.23	1.14	0	10
Village extension meetings	455	0.07	0.61	0	7
Other farmer advice contacts	455	0.10	0.41	0	5
Electronic media contacts	455	0.29	0.97	0	8

Source: NMBU Malawi CA survey 2016.

Table 4. Additional control variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Female head, dummy	451	0.191	0.393	0	1
Age of household head	451	47.9	13.7	12	86
Hh size	455	5.297	1.956	1	12
Average education of adults in hh	455	3.037	2.560	0	20
Owned farm size, ha GPS	444	1.064	1.196	0.032	17.098
District FE: Base: Kasungu	455	0.213			
Lilongwe	455	0.220			
Machinga	455	0.149			
Zomba	455	0.347			
Chiradzulu	455	0.066			
Thyolo	455	0.004			

Source: NMBU Malawi CA survey 2016.

Table 3 presents data on the extent of extension contacts, other than lead farmers, that followers reported having. The table shows the number of contacts during the last year with the different sources of potential technology information. We see that government agricultural extension contacts are most frequent. There is substantial variation in the number of contacts for all sources.

Table 4 gives an overview of additional control variables used for assessment of the robustness of the findings. We see that most of the sample was from four districts; Kasungu and Lilongwe in Central Region and Machinga and Zomba in Southern Region, but we also had a small sample from Chiradzulu and Thyolo in Southern Region.

6. Results and discussion

6.1. Followers' familiarity with CA technologies models

Table 5 presents the results for how the familiarity of follower farmers with the CA technologies relate to the lead farmers' familiarity and adoption for each CA technology, the lead farmers' motivation, and other extension contacts of followers. Table 5 shows that lead farmers' familiarity with four of the five CA technologies is significantly (to varying degree) positively associated with followers' familiarity with these technologies. For example, lead farmers' familiarity with minimum tillage is associated with a 16.5% higher likelihood that their followers also are familiar with minimum tillage. Lead farmers' adoption of the CA technologies is significantly and positively associated with followers' awareness of minimum tillage and the overall count of CA technologies they are aware of (CA combined). Lead farmers' adoption of minimum tillage is associated with a 15.7% higher likelihood that the followers were familiar with minimum tillage. Lead farmers' motivation is also positively and significantly associated with followers' awareness of herbicide, mulching, and organic manure technologies and the total number of CA technologies they were aware of.

Table 5 shows that many of the other extension variables are significant. For example, government agricultural extension contacts positively correlates to almost all the CA practices (herbicide and mulching are exceptions), and the marginal effects are particularly large for private agricultural extension and village extension meetings in the CA combined model. These results suggest that multiple sources of information are important for followers' awareness of CA technologies. There are systematic variations across the CA technologies, however. Follower familiarity with crop rotation, minimum tillage, and organic manure is positively associated with several of the other extension contact variables. Surprisingly, however, the coefficients are

Table 5. Followers' familiarity with CA technologies and how it is correlated with their lead farmers' awareness and adoption of the CA technologies, lead farmers' motivation, and other extension contacts of followers.

	Crop rotation	Min. tillage	Herbicide	Mulching	Org. Manure	CA combined
Lead farmer familiar with technology	0.147***	0.165***	0.083*	0.109**	0.003	0.185****
Lead farmer has adopted technology	0.029	0.157***	0.153*	0.111	0.040	0.176**
Lead farmer motivation: 1(low)-4(high)	0.037	-0.004	0.057**	0.074**	0.047*	0.191**
Government ag extension contacts	0.035****	0.019**	-0.005	-0.030***	0.028****	0.047*
Private ag extension contacts	0.091***	0.031	0.108	0.156****	0.014	0.437***
NGO contacts	0.065**	0.061**	0.012	-0.079***	0.014	0.051
Farm field day visits	0.039****	0.002	-0.051****	-0.053***	0.017	-0.059
Village extension meetings	0.056****	0.061****	-0.041***	0.044	0.051****	0.164***
Other farmer advice contacts	0.056	-0.021	0.130*	0.038	-0.017	0.204
Electronic media contacts	0.009	0.033**	0.069***	-0.046**	-0.010	0.059
Constant	0.378****	0.457****	0.067	0.195*	0.538****	1.280****
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.087	0.081	0.077	0.102	0.040	0.098
Number of observations	455	455	455	455	455	455

Source: NMBU Malawi CA survey 2016. *Note*: Results from Linear Probability Models (OLS) with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

negative for several of the extension contact variables in the case of the mulching and herbicide technologies. We have no good explanation for this.

An assessment of the robustness of the results by inclusion of a set of controls for follower characteristics and district dummies is presented in Table A1 in the Appendix. The lead farmer familiarity and adoption variables remained significant in most of the models while the lead farmer motivation variable remained significant only in one of the models, that for mulching.

6.2. Followers' adoption of CA technologies models

Table 6 presents average marginal effects from bivariate probit models for the adoption of each CA technology conditional on farmers being familiar with it, including only the lead farmer and other extension contacts variables. The marginal effects relate to the probability that both the adoption and familiarity variables are equal to one. The full results from the bivariate probit models are presented in Table A3 in the Appendix.

Findings in Table 6 indicate that followers are 11.9% more likely to have adopted crop rotation if their lead farmers are familiar with the practice. Adoption of crop rotation by followers is 7.1% more likely when their lead farmers have adopted crop rotation. Other extension contacts are also important for the adoption of this technology. Lead farmers' familiarity is not significantly related to the adoption of any of the other CA technologies by followers, but lead farmers' adoption of herbicides has a positive influence on followers' adoption of herbicides. Lead farmers' motivation is positively associated with followers' adoption of minimum tillage and mulching. Participation in village extension meetings is significantly positively related to crop rotation and organic manure adoption and negatively related to herbicides and mulching. The coefficients are quite large for this variable, but we should interpret these results cautiously given the low frequency of this variable in the data (see Table 3).

Table 6. Average marginal effects from bivariate probit models for adoption conditional on familiarity with CA technologies

	Crop rotation	Min. tillage	Herbicides	Mulching	Org. Manure
Lead farmer familiar with technology	0.119 **	0.033	-0.007	0.026	0.065
Lead farmer has adopted technology	0.071 *	0.027	0.037 **	0.054	0.052
Lead farmer motivation: 1(low)-4(high)	0.014	0.060 ***	0.007	0.043 **	0.012
Government ag extension contacts	0.036 ****	0.003	0.002	0.000	0.037 ****
Private ag extension contacts	0.059	-0.941 ****	0.010	0.104 ****	0.049
NGO contacts	0.097 ***	0.010	-0.010	-0.030	0.014
Farm field day visits	0.094 ****	0.018 *	0.001	0.004	-0.015
Village extension meetings	0.400 ****	0.048	-0.144 ***	-0.585 ****	0.374 ****
Other farmer advice contacts	0.038	0.049	0.004	-0.135 *	-0.010
Electronic media contacts	-0.025	-0.002	0.002	-0.007	0.001

Source: NMBU Malawi CA survey 2016. *Note*: Results from bivariate probit models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

We assessed the robustness of these results with bivariate probit models with additional controls in form of household characteristics and district fixed effects. The average marginal effects of this model are presented in Table A4 in the Appendix, while the full model results are presented in Table A5. One important difference when the household and district controls are included is that the lead farmer familiarity variable becomes significant for three of the four CA technologies (Table A4). Followers are 12.3, 6.4 and 14.6% more likely to have adopted crop rotation, minimum tillage, and organic manure when their lead farmers are familiar with these technologies. Several of the extension variables are significant and positive in the crop rotation and organic manure models, while their signs and significance levels are mixed for the minimum tillage and mulching technologies. Adoption of crop rotation is much more likely in Kasungu district than in the other districts.

We now summarize the results in relation to the four study hypotheses. The first hypothesis states that lead farmer motivation affects the familiarity with and adoption of CA technologies among their followers. Results show lead farmer motivation is significant and positively associated with follower familiarity of three CA technologies (herbicides, mulching, and organic manure) and follower adoption of two technologies (minimum tillage and mulching). We therefore cannot reject Hypothesis 1.

The second hypothesis is that lead farmer familiarity with the CA technologies affects their followers' familiarity and adoption. Lead farmer familiarity is significant and positive for four of five CA technologies (exception is organic manure) and the CA count variable in the follower familiarity models. Lead farmer familiarity influences follower farmer adoption only for the case of crop rotation, in the parsimonious model (Table 6); but familiarity also influences follower adoption of minimum tillage and organic manure in the extended models Table A4). These results are in support of Hypothesis 2 and suggest that lead farmer familiarity primarily influences followers' familiarity. The results for the followers' adoption decisions are less robust, as could be expected.

The third hypothesis states that lead farmers' adoption of CA technologies affects their followers' familiarity and adoption. Lead farmer adoption is significant with a positive sign in two of the familiarity models and in two of the adoption models. Lead farmers' own adoption decisions therefore seem to influence the decisions of their followers. It is not only what the lead farmers say but also what they do that matters for the followers' learning and doing. This is consistent with Matuschke and Qaim (2009) who found that farmers in India were more likely to adopt new seed technology if their social network members were adopters.

The final hypothesis states that other extension contacts are important for the followers' familiarity and adoption. The empirical findings provide some support for this contention although the results are somewhat mixed across the CA technologies. Other extension contacts are important for the familiarity with crop rotation and minimum tillage; but contrary to expectations, we find negative significant results for herbicide and mulching technologies. We are not sure how to interpret the latter findings. Low adoption rates of herbicides and mulching may partly explain these unexpected results.

Our study reveals variation in lead farmer influences on their followers across CA practices. In terms of follower familiarity, lead farmer influences are greatest for minimum tillage and mulching and weakest for organic manure. For follower adoption of CA practices, lead farmers appear to exert more influence for the case of crop rotation and herbicides and less influence for organic manure. It appears that lead farmers in Malawi are having greater success at diffusing relatively complex technologies (e.g. herbicides and minimum tillage) than simple technologies (organic manure). By contrast, a study in Ethiopia found that social learning was more evident for complex vs. simple technologies (Liverpool-Tassie and Winter-Nelson, 2012).

7. Conclusions

Our paper examines adoption of CA technologies among follower farmers of lead farmers focusing on the strength of the lead farmer-follower farmer link in Malawi. In summary, with reference to the study hypotheses, first we find evidence that lead farmer motivation positively influences familiarity of herbicides use, mulching, and organic manure and adoption of minimum tillage and mulching. Second, the results support the hypothesis that lead farmer familiarity with CA technologies positively and significantly affects their followers' familiarity of four of five CA technologies (exception is organic manure) and enhances adoption of crop rotation and organic manure. Third, lead farmer own adoption is positive and significant in two of the familiarity models and in two of the adoption models, suggesting that it is not just what lead farmers say but also what they do that influences follower farmers. Lastly, other extension contacts are found important for the familiarity with crop rotation and minimum tillage, though with a negative influence on herbicide and mulching technologies. These results suggest that multiple sources of information are important for diffusing CA technologies to follower farmers.

Together the findings of this study indicate some important ways the government agricultural system can support F2FE in Malawi. Lead farmer motivation clearly matters to the spread of CA practices among follower farmers. How can the motivation of lead farmers be supported? One possibility is continuation and standardization of the small performance-based incentives (e.g. boots, bags of seed) that are currently part of F2FE in Malawi, keeping in mind that stronger incentives may create distortions that may not lead to durable adoption (Fisher, Holden, and

Katengeza, 2017). Ben Yishay and Mobarak (2014) found for Malawi that incentives were crucial for encouraging farmer promoters to learn about CA technologies and make efforts to disseminate them to other farmers. But salaries and allowances might not be needed, and extension providers can make their F2FE programs more effective and sustainable by learning what motivates their lead farmers (Davis, Franzel, and Spielman, 2016). Lead farmers in Malawi say their main reasons for becoming and remaining a lead farmer are to gain knowledge and help others (Khaila et al., 2015). Where knowledge is the primary motivation, important incentives are training, brochures, reference materials, and visits with researchers and innovative farmers. For those lead farmers motivated by altruism and social benefits, incentivizing their job could be through means of recognition, such as certificates or public recognition from local leaders (Davis, Franzel, and Spielman, 2016).

A second key finding with policy implications is that lead farmer familiarity is important to the familiarity with and adoption of CA by follower farmers. To help lead farmers gain familiarity with the various CA practices, expansion of the lead farmer training program may be warranted with specific emphasis on training lead farmers in the various CA practices. As mentioned earlier, a survey of lead farmers in Malawi suggests lead farmers do not currently receive sufficient training (Khaila et al., 2015).

Our study shows that lead farmer adoption has a strong influence on familiarity and adoption of CA among their followers. The F2FE approach may be a cost-effective approach for introduction of new technologies given the small incentives used (Fisher, Holden, and Katengeza, 2017). To encourage adoption among the lead farmers it is important to identify motivated and skilled lead farmers that have farm and household characteristics similar to those of the target population. Further research should investigate the importance of the social position of lead farmers for their influence on technology adoption among their followers. Further research is also needed on the trickle down of adoption from followers to other farmers.

Finally, results make clear that F2FE is a complement rather than a substitute for other agricultural extension activities, consistent with some other studies (Genius et al., 2013; Krishnan and Patnam, 2013). Findings also suggest that the effectiveness of different forms of agricultural extension varies across CA practice. For example, we do not find evidence of lead farmers influencing their followers' familiarity and adoption of organic manure; whereas lead farmers appear to influence followers' familiarity with minimum tillage and mulching and followers' adoption of crop rotation and herbicides. Another example of variation in the role of extension by CA practice is that government agricultural extension visits and village extension meetings are found to positively influence followers' familiarity and adoption of crop rotation and organic manure. But village extension meetings negatively correlate to familiarity and adoption of herbicides, and farmer field days have a negative association with familiarity of both herbicides and mulching. Further research is recommended to better understand these results and thereby uncover ways to improve the design and targeting of agricultural extension programs to specific CA practices.

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Appendix

Table A1. Marginal effects from LPM (OLS) Familiarity models with additional household controls and district fixed effects.

	Crop rotation	Min. tillage	Herbicides	Mulching	Org. Manure	All CA technologies
Lead farmer familiar with technology	0.138**	0.203****	0.101**	0.099**	0.018	0.206****
Lead farmer has adopted technology	0.027	0.132**	0.153	0.124*	0.029	0.192**
Lead farmer motivation: 1(low)-4(high)	0.020	-0.003	0.037	0.070**	0.042	0.144
Government ag extension contacts	0.036****	0.015	-0.009	-0.031***	0.027****	0.038
Private ag extension contacts	0.086***	-0.009	0.094	0.134****	-0.006	0.328**
NGO contacts	0.072***	0.059*	0.006	-0.092***	0.009	0.024
Farm field day visits	0.042****	-0.004	-0.046****	-0.053***	0.019	-0.060
Village extension meetings	0.059****	0.054***	-0.036**	0.047*	0.050****	0.170****
Other farmer advice contacts	0.074*	-0.022	0.118	0.049	-0.009	0.225
Electronic media contacts	-0.009	0.031*	0.049**	-0.063***	-0.025	-0.001
Female head, dummy	-0.044	0.032	-0.074	-0.090	0.003	-0.171
Hh head age	-0.002	-0.002	-0.003	-0.001	-0.003**	-0.010**
Household size	-0.007	0.030**	0.002	-0.005	0.000	0.015
Adult education mean years	-0.004	0.020***	-0.004	-0.005	0.001	-0.003
Own farm size, ha GPS	0.010	-0.003	0.037**	0.030	0.018	0.092**
District FE: Kasungu=base	0.000	0.000	0.000	0.000	0.000	0.000
Lilongwe	-0.025	0.150**	0.147*	0.218***	0.145**	0.661***
Machinga	-0.082	0.021	-0.028	-0.002	-0.007	-0.014
Zomba	-0.108*	0.112	-0.051	0.141**	0.074	0.217
Chiradzulu	-0.149	0.376****	-0.051	0.268**	0.128	0.768**
Thyolo	-0.858****	0.018	0.649****	-0.392****	-0.219	-0.681*
Constant	0.665****	0.220	0.234	0.197	0.611****	1.485***
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.127	0.137	0.129	0.149	0.071	0.153
Number of observations	440	440	440	440	440	440

Source: NMBU Malawi CA survey 2016. *Note*: Results from Linear Probability (OLS) models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

Table A2. Assessment of endogeneity of extension contact variables

	Government ag extension contacts	Private ag extension contacts	NGO contacts	Farm field day visits	Village extension meetings	Other farmer advice contacts	Electronic media contacts
Female head, dummy	0.019	0.005	-0.016	-0.083	0.042	-0.034	-0.174**
Hh head age	0.003	0.001	-0.001	-0.002	0.000	0.000	-0.002
Household size	0.099	0.004	-0.004	0.026	0.018	-0.008	-0.013
Adult education mean years	-0.002	0.019**	-0.016	-0.003	0.014	-0.006	0.036
Own farm size, ha GPS	0.081	0.053	0.013	-0.030	-0.009	-0.010	0.020
District FE: Kasungu=base	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lilongwe	1.103***	0.077	-0.048	-0.218	-0.042	-0.107	0.245
Machinga	0.185	0.016	-0.191***	0.012	-0.070	-0.131*	-0.211*
Zomba	0.489*	0.026	0.000	-0.037	0.052	-0.084	-0.169
Chiradzulu	-0.102	0.382*	0.161	0.328	-0.066	0.015	-0.232
Thyolo	1.527**	0.045	-0.224***	-0.355*	-0.079	0.811	-0.338***
Constant	0.723	-0.182	0.320*	0.289	-0.048	0.274***	0.410
Prob > chi2	0.045	0.140	0.000	0.022	0.699	0.329	0.000
R-squared	0.042	0.068	0.021	0.017	0.011	0.038	0.059
Number of obs.	440	440	440	440	440	440	440

Source: NMBU Malawi CA survey 2016. *Note*: Results from OLS models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

Table A3. Bivariate probit models for adoption and familiarity with each of the CA technologies

Adoption models	Crop rotation	Min. tillage	Herbicide	Mulching	Org. Manure
Lead farmer familiar with technology	0.319**	0.129	-0.268	0.123	0.199
Lead farmer has adopted technology	0.224*	0.096	1.143***	0.275	0.132
Lead farmer motivation: 1(low)-4(high)	0.026	0.301***	0.195	0.225**	0.002
Government ag extension contacts	0.097****	0.011	0.080*	0.009	0.089***
Private ag extension contacts	0.126	-4.684****	0.271	0.528****	0.148
NGO contacts	0.275***	0.030	-0.313	-0.146	0.036
Farm field day visits	0.276***	0.088*	0.060	0.041	-0.059
Village extension meetings	0.186*	-0.157	-4.607****	-3.430****	0.074
Other farmer advice contacts	0.096	0.245	0.074	-0.797*	-0.024
Electronic media contacts	-0.093	-0.016	0.023	-0.023	0.011
Constant	-1.024***	-2.296****	-3.109****	-2.039****	-0.576*
Familiarity models	Crop rotation	Min. tillage	Herbicide	Mulching	Org. Manure
Lead farmer familiar with technology	0.403***	0.444***	0.255*	0.251*	0.006
Lead farmer has adopted technology	0.083	0.469***	0.463*	0.336*	0.133
Lead farmer motivation: 1(low)-4(high)	0.108	-0.012	0.174**	0.212**	0.166*
Government ag extension contacts	0.118****	0.055*	-0.017	-0.086***	0.116****
Private ag extension contacts	0.352**	0.099	0.277	0.701****	0.023
NGO contacts	0.260**	0.243**	0.037	-0.232**	0.041
Farm field day visits	0.199***	-0.007	-0.253****	-0.152**	0.058
Village extension meetings	5.512****	5.000****	-0.175**	0.129	5.224****
Other farmer advice contacts	0.156	-0.046	0.351*	0.088	-0.034
Electronic media contacts	0.031	0.095*	0.200***	-0.150**	-0.036
Constant	-0.411	-0.130	-1.252****	-0.840***	-0.074
Athrho Constant	0.595****	0.836****	0.715***	1.110****	0.591****
Rho	0.534****	0.683****	0.614***	0.804****	0.530****
Log pseudolikelihood	-500.101	-431.127	-299.035	-410.902	-507.834
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Number of obs.	455	455	455	455	455

Source: NMBU Malawi CA survey 2016. *Note*: Results from bivariate probit models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

Table A4. Robustness check for marginal effects for adoption in bivariate probit models, with additional follower controls and district FE (full model in Table A5)

Adoption models	Crop rotation	Minimum tillage	Mulching	Organic manure
Lead farmer familiar with technology	0.123 **	0.064 *	0.016	0.146 **
Lead farmer has adopted technology	0.046	0.007	0.067 *	0.031
Lead farmer motivation: 1(low)-4(high)	-0.005	0.071 ****	0.050 **	0.016
Government ag extension contacts	0.042 ****	0.004	0.000	0.032 ****
Private ag extension contacts	0.041	-0.960 ****	0.094 ****	0.059 *
NGO contacts	0.104 ****	0.005	-0.029	0.002
Farm field day visits	0.097 ****	0.013	0.003	-0.020
Village extension meetings	0.397 ****	0.067 *	-0.598 ****	0.349 ****
Other farmer advice contacts	0.036	0.036	-0.144 **	-0.013
Electronic media contacts	-0.033 *	0.007	-0.021	0.009
Female head, dummy	-0.074	0.007	-0.079 **	-0.012
Hh head age	-0.002 *	0.000	0.001	0.000
Household size	-0.010	0.014 *	-0.005	0.019
Adult education mean years	-0.007	0.008	0.003	0.000
Own farm size, ha GPS	0.028	0.006	0.001	-0.006
District FE: Kasungu=base				
Lilongwe	-0.247 ****	-0.051	0.073	0.084
Machinga	-0.178 **	-0.003	0.006	0.049
Zomba	-0.251 ****	0.027	0.058	0.116 *
Chiradzulu	-0.252 ***	0.231 **	0.070	0.221 **
Thyolo	-0.556 ****	0.274	-0.085 ****	-0.012

Source: NMBU Malawi CA survey 2016. *Note*: Results from bivariate probit models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.

Table A5. Bivariate probit models with additional follower controls and district fixed effects (full model with the marginal effects presented in Table A4)

Adoption models	Crop rotation	Min. tillage	Mulching	Org. Manure
Lead farmer familiar with technology	0.369**	0.273	0.072	0.455**
Lead farmer has adopted technology	0.151	-0.002	0.356	0.082
Lead farmer motivation: 1(low)-4(high)	-0.030	0.362***	0.273**	0.017
Government ag extension contacts	0.124****	0.015	0.012	0.076***
Private ag extension contacts	0.072	-4.874****	0.478***	0.188*
NGO contacts	0.310***	-0.005	-0.142	0.001
Farm field day visits	0.311***	0.066	0.037	-0.077
Village extension meetings	0.221*	-0.146	-3.576****	0.061
Other farmer advice contacts	0.068	0.187	-0.871**	-0.040
Electronic media contacts	-0.115*	0.026	-0.104	0.045
Female head, dummy	-0.249	0.025	-0.445**	-0.034
Hh head age	-0.007	0.000	0.005	0.002
Household size	-0.034	0.063	-0.026	0.059*
Adult education mean years	-0.024	0.033	0.020	-0.001
Own farm size, ha GPS	0.079	0.029	-0.003	-0.037
District FE: Kasungu=base	0.000	0.000	0.000	0.000
Lilongwe	-0.812****	-0.337	0.386	0.175
Machinga	-0.543**	-0.025	0.049	0.163
Zomba	-0.777****	0.105	0.323	0.306
Chiradzulu	-0.745**	0.774**	0.355	0.623**
Thyolo	-6.675****	1.183	-5.226****	0.253
Constant	0.254	-3.104****	-2.516****	-1.380***
Familiarity models	**Crop rotation**	**Min. tillage**	**Mulching**	**Org. Manure**
Lead farmer familiar with technology	0.377**	0.607****	0.238*	0.028
Lead farmer has adopted technology	0.092	0.421**	0.392**	0.079
Lead farmer motivation: 1(low)-4(high)	0.048	-0.016	0.229**	0.161*
Government ag extension contacts	0.130****	0.046	-0.092***	0.116****
Private ag extension contacts	0.349**	-0.037	0.741****	-0.011

NGO contacts	0.325**	0.326**	-0.274***	0.033
Farm field day visits	0.218***	-0.030	-0.164**	0.072
Village extension meetings	5.403****	5.543****	0.147	4.966****
Other farmer advice contacts	0.282	-0.065	0.112	0.003
Electronic media contacts	-0.030	0.092	-0.202**	-0.082
Female head, dummy	-0.109	0.097	-0.251	-0.017
Hh head age	-0.008*	-0.005	-0.003	-0.010**
Household size	-0.015	0.112***	-0.013	0.001
Adult education mean years	-0.011	0.078***	-0.006	0.007
Own farm size, ha GPS	0.109	-0.016	0.082	0.083
District FE: Kasungu=base	0.000	0.000	0.000	0.000
Lilongwe	-0.108	0.400*	0.580***	0.536**
Machinga	-0.264	0.051	0.005	0.011
Zomba	-0.404*	0.323*	0.454**	0.304
Chiradzulu	-0.552	1.374****	0.889***	0.369
Thyolo	-8.287****	0.081	-5.096****	-0.631
Constant	0.466	-1.058**	-1.034**	0.086
Athrho constant	0.544****	0.852****	1.179****	0.617****
Rho	0.496****	0.692****	0.827****	0.549****
Log pseudolikelihood	-457.960	-399.981	-380.836	-480.088
Prob > chi2	0.000	.	0.000	.
Number of observations	440	440	440	440

Source: NMBU Malawi CA survey 2016. *Note*: Results from bivariate probit models with robust standard errors. Significance levels: * 0.10 ** 0.05 *** 0.01 **** 0.001.