Selective Attention and Information Loss in the Lab-to-Farm Knowledge Chain: The Case of Malawian Agricultural Extension Programs

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Abstract:

A multitude of approaches and modalities are available for delivering useful information to rural communities. However, evidence regarding the information efficiency of these modalities is limited, as is evidence identifying the mechanisms of potential information loss in the agricultural extension system. In this paper, we assess information efficiency along the knowledge transmission chain from researchers to agricultural extension agents (EAs) to lead farmers (LFs) to other farmers. By asking the same set of questions about a fairly well known technology, pit planting, we construct a measure of knowledge at each node of the knowledge transmission chain. Evidence shows that the majority of information loss happens at the researcher-to-EA link and the EA-to-LF link, and that the loss is potentially caused by teaching failures or by selective attention and learning among both the EAs and the LFs concerning all important details of the technology. Results highlight the need for greater emphasis during training and learning on key dimensions of technology packages that are commonly ignored.

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Keywords: extension service, information efficiency; knowledge chain; selective attention; technology adoption

1. Introduction

Agricultural extension can play a crucial role in promoting agricultural productivity, increasing food security, and improving rural livelihoods. As one of their major functions, extension services are critical for moving research and technologies from the lab to the field, thereby translating new knowledge into innovative practices. Several changes and shifts in thinking and practice in agricultural extension occurred over recent decades. One shift has been from a system of solely public extension to a pluralistic system with greater roles for private and nongovernmental organizations. Another shift has been in moving the focus from agricultural production alone to a broader set of services targeting income, market linkage, food and nutrition security, and improved well-being. A third shift has stemmed from increased criticism of the transfer-of-technologies approach, shifting it toward a promotion of methods based on facilitation, learning processes, and increased capacity to innovate. However, in many countries, the linear approaches still dominate, as does the focus on agricultural production. Therefore, much of the research on this theme is heavily linked to technology adoption and farm productivity (Birner et al. 2006; Faure et al. 2016).

Given these shifts and the broadening of definitions, rigorous evaluation of the quality, effectiveness, and development impacts of agricultural extension service approaches and models is scanty, owing to various measurement challenges, attribution issues, and data limitations (Birner et al. 2006; Faure et al. 2016; Ragasa and Mazunda 2018). First, measuring the quality of services or information has proven to be challenging. Various studies have used innovate ways to ask farmers about their satisfaction with, and their feedback on, the extension services or advice they have received, and in almost all settings the ratings have been overwhelmingly high (Berhane et al. 2017; Buadi, Anaman, and Kwarteng 2013; MIHS dataset 2010, 2013; Ragasa et al. 2013; Ragasa and Niu 2017a; World Bank and IFPRI 2010). On the one hand, this response is credible and so is the possibility that the extension information is useful and is acted upon by the farmers. On the other hand, other studies have highlighted caution in interpreting responses to questions that ask farmers about satisfaction, as there may be problems of overreporting and a serious social desirability bias in the responses in some settings and country contexts. Moreover, satisfaction with extension services is also highly correlated with the promotion and provision of inputs, as has already been highlighted by Elias et al. (2015) and Ragasa and Mazunda (2018). Therefore, one may need to exercise caution in interpreting responses on satisfaction, but at the same time one may be able to learn from the insights such surveys provide into *why* there is satisfaction or dissatisfaction.

Second, measuring the effectiveness or impact of extension services on technology adoption, productivity, or income is extremely challenging, given that information access is only one of the factors that contribute to these outcomes and attribution is difficult. Existing research has focused on measuring the marginal product or direct effect of access to extension services on farm productivity by using production models in which production output is expressed as a function of land, capital, inputs, and other factors (see review by Birkhaeuser, Evenson, and Feder [1991], and more recent studies by Owens, Hoddinott, and Kinsey [2003] and Ragasa et al. [2013]); or by using frontier models, in which extension services are used as a factor to explain differences in technical efficiency levels rather than as an input in the production function (for example, Seyoum, Battese, and Fleming 1998; Young and Deng 1999); or by using a combination of these models (Dinar et al., 2007).

Some have measured the impact of access to extension services on welfare outcomes using time-series data (Dercon et al. 2009; Krishnan and Patnam 2014). Others have attempted to evaluate the impact of a particular approach or modality, such as farmer field school, using variants of matching, double-differencing, or instrumental variable techniques, depending on the nature of the datasets available (Benin et al., 2012; Davis et al., 2009; Feder, Murgai, and Quizon 2004). Nonetheless, these evaluative models are challenging given the inherent interlinkages among extension services, technology, and input use and their confounding effects on production and welfare outcomes. Even rates of return to extension services are difficult to measure, since they are often interlinked with investments, breeding, research, and other factors affecting technology adoption.

Another approach is to focus on the information provided itself and trace the flow of that information from its source to the intended recipients, while also tracing feedback mechanisms. This paper takes this last approach by examining a particular technology package and analyzing the flow of information along the knowledge chain and measuring the loss of this information in each node along the chain. The research attempts to evaluate the efficiency of information transmission along the knowledge chain from lab to farm and assess the types of information failure, whether teaching or learning failures. By tracking knowledge scores of geographically linked extension agents (EAs), lead farmers (LFs), and other farmers (OFs), we provide an objective measure of information loss for the current extension modality in Malawi, while at the same time focusing on the quality of information provision, avoiding challenges in attribution. This paper answers the following questions:

- How efficient is the information transmission from scientist to extension agent (EA) to lead farmer (LF) to other farmer (OF)?
- If there is information loss along the chain, where does it happen?

- Which extension delivery approaches are linked to greater or less information loss?
- How does this information inefficiency affect technology adoption?

2. Background

We focus our analysis on Malawi, which is among the poorest and most food-insecure countries in Africa (Malawi, MoAIWD 2016), because in recent years the Malawian government has pioneered several modalities in disseminating knowledge from research to farmers. These include the pluralistic and demand-driven extension systems, promoted in 2000; and the LF (or farmer-to-farmer) approach, begun in 2003 and formally institutionalized in the Malawi Department of Agricultural Extension Services programs in 2007 (Kundhlande et al. 2014), which has been commonly used by donors, farmer associations, and nongovernmental organizations (NGOs). These policies make Malawi an ideal country in which to assess the information efficiency of different information transmission modalities. The results of our analysis in Malawi also have the potential to exert a major influence on many other developing countries.

Lack of information has long been recognized as one explanation for low adoption of agricultural technology that promotes productivity (Conley and Udry 2010; Foster and Rosenzweig 1995; Levitt, List, and Syverson 2013; Micheels and Nolan 2016), along with other explanations such as credit constraints, differences in preferences, differences in agroecological conditions, and spatially heterogeneous costs and benefits (Duflo, Kremer, and Robinson 2011; Suri, 2011). The research on information failure has usually focused on diffusion through a social network, and the policy recommendation that has emerged from such research is to target the most socially connected people in the networks to reduce cost and increase information efficiency (Conley and Udry 2010; Foster and Rosenzweig 1995).

The modality of lead farmers (or contact farmers) aligns with this line of research (Beaman et al., 2017; Kondylis, Mueller, and Zhu 2017). In Malawi, as in many other countries, both governmental and nongovernmental agencies have adopted the LF concept. An LF is supposed to learn from the EA and then diffuse the information to other farmers in his or her community. However, recent studies on this modality provide mixed evidence regarding its efficacy. Fisher, Holden, and Katengeza (2017) link 180 LFs and 455 followers in four districts in Malawi and find that LFs' motivation, awareness, and adoption of conservation agriculture techniques are positively associated with OFs' awareness and adoption. However, their study does not address the information efficiency problem among LFs and OFs. Nationally representative surveys in Malawi show that 1 to 3 percent of households report getting some agricultural advice from an LF (Ragasa and Mazunda 2018; Ragasa and Niu 2017a). Some analyses find that training LFs might not increase the information efficiency or technology adoption by farmers in the community in the context of Mozambique (Beaman et al. 2015; Kondylis, Mueller, and Zhu 2017) and raise questions about the effectiveness of this modality of information transmission. Using field experiments, Kondylis, Mueller, and Zhu (2017) find that while LFs increase their adoption rates after training, their knowledge about the technologies does not increase significantly. Additionally, they find that the training of EAs and LFs does not affect adoption by OFs.

Agricultural technologies do exist that potentially can improve Malawi's agricultural productivity, food security, and nutrition, including conservation agriculture, pit planting, and proper planting and spacing heavily promoted during the Sasakawa Global 2000 (see Ragasa and

Niu 2017a); however, there are constraints to their adoption. Among the potential constraints is information failure due to poor understanding of a multidimensional technology, which means that several important parameters or details are attached to the successful implementation of a particular technique.

To understand the information failure, we borrow the selective attention and learning theory from psychology. Schwartzstein (2014) and Hanna (2014) present a general model of belief formation when an agent is selectively attentive. The theory suggests that there are mental costs attached to each additional dimension of knowledge in the learning process, and thus individuals must also decide which dimensions to attend to, where attending is costly. An individual who believes that a particular dimension does not matter may not focus on it; and as such, he or she may never process freely available data that could contradict his false belief. This theory explains that a failure to learn comes from a failure to notice; and suggests that learning failures could be concentrated on dimensions where individuals report ignorance.

In order to best test the selective attention theory of information failure, we use *pit planting*—a technology proven to promote yields (Haggblade and Tembo 2003)—as our focus in this analysis. Pit planting is among the improved agricultural technologies widely promoted by governmental and nongovernmental service providers in Malawi to boost productivity and at the same time adapt to extreme weather. It is ranked at the top of all technologies on which Malawian farmers have received advice from extension agents (Ragasa and Niu 2017a). The technique is also relatively well known among Malawian farmers: 26 percent of farmers in Malawi are aware of or have heard of pit planting as an improved technology being promoted, according to a recent national survey (Ragasa and Niu 2017a). However, its adoption is low: 10

percent of farmers have adopted pit planting, and only 4 percent of crop area has been put under this planting method (mostly in maize and legume plots).

Another reason for choosing pit planting as our focus is that the costs of the technique are mostly for labor—monetary costs are low—and therefore we can isolate the information failure hypothesis from alternatives such as credit constraints. Most important, pit planting is rather complicated and multidimensional.

3. Theoretical Background

We base our analysis on a theoretical model of technological learning under which people learn through noticing: they choose which technical dimensions to attend to when learning to apply a technology from EAs or OFs. Hanna, Mullainathan, and Schwartzstein (2014) point out that learning is about not only the availability of data but also what people notice in those data. In the context of dissemination of agricultural technology, learning usually takes place at demonstrations, visits, or meetings organized by EAs or LFs. Even though the essential details of a technology are demonstrated and mentioned during the teaching sessions, farmers might not pay attention to every one of those details. And when the farmers experiment with the technology by themselves, they tend to consistently ignore the dimensions that they did not pay attention to at the beginning. A vicious feedback loop arises: even with readily available data generated from initial teaching and from their own experimentations, farmers who initially ignore an important dimension of a technology may continue to pay no attention to it and consequently will not learn whether it matters or not.

The selective attention and learning model builds on Schwartzstein's (2014) study in psychology. Three major assumptions are used to set up the model. First, there are N parameters associated with a technology. Those parameters are unknown to the farmers and need to be learned through training, demonstrations, and experiences or some combination of these. In addition, farmers attach prior weights of importance to the various parameters; farmers might not think all parameters are equally important. Second, attention is costly in the sense that there is a shadow cost of mental energy and time associated with paying attention to each dimension of the *N* parameters. The more dimensions farmers attend to, the greater the cost they will incur. Third, farmers maximize the expected net payoff, which is the yield minus attentional costs.

The model produces four predictions that are relevant to our analysis. *First*, farmers may fail to attend to some dimensions. This naturally arises from considerations of the cost of attention, so that farmers tend to be selective about what they pay attention to. *Second*, farmers may persistently choose only suboptimal parameter levels along dimensions that they do not attend to. *Third*, farmers may fail to optimize parameter levels of neglected dimensions even if they are generating data during experiments that would allow them to optimize. This last prediction points out the possibility that farmers might not be able to learn a technology fully by themselves if no one reminds them of the dimensions that they have neglected from the beginning. A failure to learn can be explained by a failure to notice, and therefore learning failures should be concentrated on dimensions where agents report ignorance, that is, where they cannot answer key questions about what they themselves do (or have done) along that dimension. *Fourth*, summaries of data or reminders of key dimensions or knowledge that are often ignored can change farmers' behaviors (see Hanna, Mullainathan, and Schwartzstein 2014).

We apply this theory to explain why the pit planting technology package that is heavily promoted in Malawi is not well-adopted. We show the extent of information loss along the knowledge chain, the dimensions often ignored, and extension approaches that are linked to greater or less information efficiency.

4. Data and Analytical Methods

This research is based on data from multiple sources, which include a household survey, a community survey, a survey of service providers, interviews with scientists, and in-depth interviews with LFs and EAs. The surveys and interviews were conducted by the International Food Policy Research Institute (IFPRI) between August 2016 and March 2017. The surveys cover a nationally representative sample of 3,001 households and 299 sections (communities) in all 29 districts in Malawi (excluding Likoma). In selected modules (on extension services and technology adoption), a main female adult and a main male adult of the same household were interviewed separately, providing a total of 5,065 interviewed individuals. Among them, 544 individuals were LFs, who were interviewed in detail. The service provider surveys cover 151 state and nonstate providers of extension services. The in-depth interviews cover 72 extension agents from both governmental and nongovernmental organizations. For a more comprehensive summary of the data collection and sample characteristics, please refer to the IFPRI reports (Ragasa and Niu 2017a; Ragasa et al. 2017).

In this research, we focus on the portion of the sample population who were aware of or had heard of pit planting, and we regard the rest of the sample as having zero knowledge of this technology. To measure farmers' knowledge vis-à-vis the dimensions of pit planting being promoted, we asked the farmers who were aware of pit planting the following six questions about the technology:

1. How long should the diameter of the pit be (centimeters)?

2. How deep should the pit be (centimeters)?

3. What is the distance between the pits (centimeters)?

4. Do you use fertilizer in the pits?

5. What type of fertilizer is used?

6. How are your pits distributed on the ground?

Farmers' answers to these questions were recorded and compared to the suggested range of correct answers provided by the agronomic researchers. Using that information, we construct six binary variables to identify whether the farmer's answer falls in the suggested range, and the summation of those six binary variables is called the knowledge dimension variable, which measures the farmers' overall knowledge of pit planting.

We are fully aware that these questions will not exhaust all the knowledge about pit planting. However, these questions have been suggested by the local experts who train the EAs to insure a relatively successful implementation of the technology. It is also possible that farmers are learning from others, and this may not be consistent with the messages of EAs and/or LFs. There is also the possibility of different messages being promoted by EAs, especially in a context such as Malawi where there is a multitude of service providers and extension agents and certification and quality control are absent.

Nonetheless, the focus in this paper is measuring the information along the knowledge chain based on the published results of research on the key dimensions of pit planting to maximize yield gains and based on interviews with scientists and technical officers in Malawi. We measure the gap between farmers' actual knowledge and the research-based "ideal" dimensions of the technology package, which constitutes the information loss (Tables 5.1–5.4 and Figure 5.1). Then we identify which farmers have greater and lower gaps and the factors explaining these gaps, with a focus on the source of information or the extension service modality (Tables 5.5-5.6). Additionally, we test the localization of knowledge to make sure our answers to these questions are not biased toward farmers who farm on a certain type of land or raise certain crops. In other words, we check whether technology knowledge is clustered locally to see if this knowledge is adjusted for local conditions (Figures 5.2 and 5.3). Lastly, we show whether knowledge intensity is associated with technology adoption (Table 5.7).

5. Results

5.1. Knowledge Chain Analysis

Before examining the geographically linked knowledge chains, we use all the available knowledge information we have for EAs, LFs, and OFs and plot that distribution in Figure 5.1. We can see that the EAs are more likely to achieve higher scores than farmers; however, none of them achieves a perfect score on all six dimensions, which reflects the potential inefficiency in the EA trainings. The distributions of LFs and OFs are not obviously different, which means that in general, LFs' knowledge is not superior to that of the other farmers.

To determine whether any information loss occurs along the lab-to-field knowledge transmission chain, we link EAs, LFs, and OFs by the agents' operational and farmers' residential areas. This geographical information is covered in both the extension provider surveys and the household surveys, where EAs and LFs are asked about their respective operational areas. Using this information, we construct one complete knowledge chain (EA-LF-OF) with 253 OFs, 89 LFs, and 47 EAs. To fully utilize the data, we also construct two partial chains: an EA-LF chain with 37 EAs and 123 LFs, and an LF-OF chain with 240 LFs and 1,063 other farmers.

With the EA-LF partial chain, we use a paired t-test to see whether the knowledge scores or overall knowledge dimensions of the EAs are the same as those of the LFs. Table 5.1 shows the test results. Within this partial chain, the EAs score an average of 4.35 dimensions of pit planting correctly, which is significantly higher than the LFs' average score. The difference is 0.56 and is statistically significant at the 1 percent level, which reveals information loss in this part of the knowledge chain.

We look at the LF-OF partial chain in Table 5.2. The paired t-test results show that the average knowledge of LFs is slightly better than that of the OFs; however, the difference is not statistically different from zero. This means that there is not much difference between the LFs' knowledge of pit planting and the ordinary farmers' knowledge. The results show that information loss is minimal at the link between LFs and OFs. However, both types of farmers know only slightly more than half of the dimensions that are required to maximize the benefits of the technology. These observations are consistent with the literature that looks at learning from neighbors, which finds that the impact of EAs is significant at the beginning but in the long term learning from neighbors (or LFs) plays a more critical role (Conley and Udry 2010; Krishnan and Patnam 2014).

5.2. Selective Attention Model as a Potential Cause of Information Loss

Table 5.5 presents the regression results of overall knowledge dimension variables on extension service variables and a set of control variables, using all farmers who are aware of pit planting. Specification (1) is the simple model that shows the correlation between overall knowledge and receiving advice about pit planting from any EAs, regardless of the type of the EA. This extension variable is positive and significant in explaining farmers' overall knowledge, which means that extension services are effective at increasing farmers' overall knowledge, so this does not support the teaching failure hypothesis.

Specification (2) includes the control variables that represent other forms of access to information, financial and land capital, human capital, geospatial variables, and social capital. The coefficient on the extension service variable remains positive and significant after adding the control variables into the regression. Specifications (3) and (4) are similar to (1) and (2) but replace the extension service variable with variables that differentiate the types of EA. We observe that only advice from government EAs has a significant impact on farmers' overall knowledge about pit planting. Potentially, this could indicate that government EAs are more efficient than nongovernment EAs in teaching farmers about this technology.

To investigate possible learning failures, we further look at the impact of extension services on each dimension of pit planting knowledge. Table 5.6 shows the results of these regressions with controls. We see that the extension service variable has significant impact only on the third dimension (distance between pits) and not on the other dimensions. This means that even though in Table 5.5 we find EAs to be effective in teaching, farmers can improve only on limited dimensions of knowledge. The limited attention model of learning (Hanna, Mullainathan, and Schwartzstein 2014) can be applied to understand this result—that is, students can attend to only selective dimensions of a new technology, especially when learning a multidimensional technology such as pit planting. As an implication of this selective attention, technologies with multiple dimensions are often adopted in stages or steps, as is found in the literature on sequential learning or stepwise adoption and learning (Aldana et al. 2011; Byerlee and de

Polanco 1986; Khanna 2001). Since the dependent variables here are binary, we use probit models as robustness checks; the results are consistent with those in Table 5.6.

5.3. Cluster Analysis of Knowledge

We now turn to the question of whether there is localization of knowledge. That is, are the knowledge scores clustered within geographical areas? If localization of knowledge is present, we would need to reconsider the way we define the correct answers to our knowledge questions. Since the smallest geographical unit that we use to sample is the *section* (which is composed of various villages), it is natural to test whether the knowledge variables are clustered at the section level.

We employ dendrogram clustering analysis, which is a type of hierarchical clustering analysis, to understand the localization of knowledge. A dendrogram is a visual representation of the compound correlation data in the form of a tree graph. The individual compounds are arranged along the bottom of the graph and referred to as leaf nodes. The vertical lines in the graph show the dissimilarity of the compound compared to the others, and are calculated with a distance measure. Compound clusters are formed by joining/connecting individual compounds according to their dissimilarities with the join point, referred to as a node.

Figure 5.2 shows the dendrogram for cluster analysis of the overall knowledge dimension variable with average linkage. The height of the graph represents the dissimilarity of knowledge within a section as compared to the other sections. From the dendrogram, only seven out of 268 sections are statistically different from the other 261 sections, which means that the majority of the sections, with a dissimilarity measure of zero, do not form any clusters. As a result, 97 percent (261/268) of the sample is not clustered or localized, so that we do not need to worry about localizing the correct solutions to knowledge questions.

We further analyze single-dimension knowledge with dendrograms. Figure 5.3 shows that for each dimension, there are at most two sections that are different from the other sections, whose section IDs are labeled on the horizontal axis in each dendrogram.

5.4. Knowledge and Adoption

We have analyzed information transmission along the knowledge chain, looking at the types of failures that result in the loss of information, as well as considering the localization of knowledge. Now we would like to show whether our measure of knowledge is important in explaining adoption behavior. The regression model we used in the analysis uses as dependent variable binary adoption variable, which takes value one if the farmer has adopted the pit planting technology. If the knowledge variable has no significant impact on adoption behavior, then efforts to improve information transmission might not result in satisfactory behavioral change. Table 5.7 shows the regressions of the binary pit planting adoption variable. Specification (1) includes only the extension variables and the same set of controls that we used in Section 5.1. We find that receiving advice during an extension provider's visit does not affect adoption behavior. Attending a farmer cluster or visiting an agricultural training center significantly increases the likelihood of adopting the technology.

Specification (2) includes our measure of knowledge, that is, the knowledge dimension variable. We see that the knowledge variable is positive and significant in explaining adoption behavior, and the magnitude tends to be larger than those of the extension service variables. There could be two explanations for this observation. First, receiving extension services is important in determining the farmers' adoption behavior, but the effect operates only through the knowledge variable. In other words, after controlling for farmers' knowledge, the extension service variables do not provide additional information in explaining adoption. Second, it is possible that extension services have effects other than teaching farming techniques, such as urging and persuading farmers to adopt the technologies, but these other effects are not as important as farmers' knowledge in contributing to adopt a technology. Although we cannot determine the causal impact of extension services on adoption, the observation here suggests that the knowledge variable could serve as an important subjective measure of knowledge, one that explains adoption behavior well.

6. Conclusions

There are multitude of approaches and modalities for delivering useful information to rural communities. However, there is limited evidence regarding the information efficiency of these modalities or the mechanisms through which potential information loss operates in the agricultural extension system. In this research, we assess the efficiency of information transmission along the lab-to-field knowledge chain. Because LFs have become an important modality of transmitting knowledge to farmers in the Malawi context, we link the EAs, LFs, and OFs within their respective geographical sections. Using the complete knowledge chain, we find that most information loss occurs at the EA-LF link. We further unpack information loss, asking whether it is likely due to teaching failure (on the EA side) or learning failure (on the LF and OF side).

Further regression analyses of the impact of extension services on overall and single-dimension knowledge show that the information failure between EAs and LFs is potentially caused by the teaching failures of EAs, who might not emphasize all of the important details for a successful implementation of pit planting. Some EAs even have a negative effect on farmers' knowledge. However, when we consider the OFs, the analysis reveals the selective attention of farmers when learning a multidimensional technology. Farmers seem to focus on some dimensions but ignore the rest, resulting in their limited knowledge of the latter. The most common dimensions ignored are the diameter and distribution of the pits.

Because we find that the knowledge variable better explains adoption behavior than extension service variables, we argue that receiving advice, in itself, might not be enough to induce adoption, and that a better understanding of the technology and more intensive training and learning are more important in altering behavior. Most of the results in this analysis are correlations and lack a standard causal inference, but the results are consistent across estimation methods and they raise questions about the efficiency of the LF modality in transmitting information and about the teaching methods employed by the extension services.

This research has some straightforward policy implications. Governmental and nongovernmental extension providers should focus on modifying the LFs' training programs. We suggest that during demonstrations, visits, group meetings, and other training sessions, EAs explicitly point out the importance of fully understanding a complicated technology. A low-cost, one-page handout or a short video for farmers with a checklist of important details of the technology might be useful in reducing the loss of information. The most common dimensions ignored are the diameter and distribution of the pits, so reminders and illustrations focusing on these dimensions may be useful.

In terms of the extension method or approach, our evidence suggests that more intensive and more face-to-face interactions (face-to-face visits and group/village meetings) improve knowledge scores and reduce information loss. In the case of complex technologies, follow-ups and continued mentoring by EAs of both LFs and OFs are necessary. EAs report that on average it will take two to three years of continuous teaching and follow-up by EAs and intensive learning by farmers for farmers to master and adopt the technology. As more and more technology comes in the form of packages of multiple techniques, the adoption of a package might not only depend on the complementarity of the techniques (Ward et al. 2016) but could also be limited by farmers' knowledge. This makes addressing information inefficiencies along the knowledge chain a priority among the tasks of promoting agricultural technologies.

Further analysis is necessary to better purge the other behavioral alternatives in the information transmission process. Because this research is embedded in the early phase of the more comprehensive extension service research project led by IFPRI, we would be able to revisit the question when more data become available, such as a panel dataset where time-invariant fixed effects could be used to control for individual heterogeneity.

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Table 5.1 T-test of EA and LF knowledge

	Mean	Std. Err.	95% CI	
Knowledge dimension of EA	4.35	0.07	4.21	4.49
Knowledge dimension of LF	3.79	0.09	3.59	3.98
Difference	0.56***	0.12	0.33	0.79

Source: Data are extracted from Malawi household survey (IFPRI 2016), and extension service provider survey (IFPRI 2017).
Note: The partial information chain is constructed by merging EAs and LFs by their operational area. The knowledge dimension variable is the number of questions answered correctly about pit planting. CI = confidence interval; EA = extension agent; LF = lead farmer.

Table 5.2 T-test of LF and OF knowledge

	Mean	Std. Err.	95% CI	
Knowledge dimension of LF	3.79	0.07	3.65	3.93
Knowledge dimension of OF	3.69	0.08	3.53	3.84
Difference	0.11	0.09	-0.07	0.28

Source: Data are extracted from Malawi household survey (IFPRI 2016), and extension service provider survey (IFPRI 2017).
Note: The partial information chain is constructed by merging LFs and other farmers by their operational area. The knowledge dimension variable is the number of questions answered correctly about pit planting. CI = confidence interval; LF = lead farmer; OF = other farmer.

Table 5.3 T-test of EA-LF info loss and LF-farmer info loss

	Mean	Std. Err.	95% CI	
Difference EA-LF	0.56	0.12	0.33	0.79
Difference LF-farmer	0.05	0.13	-0.2	0.3
Difference	0.52***	0.2	0.11	0.92

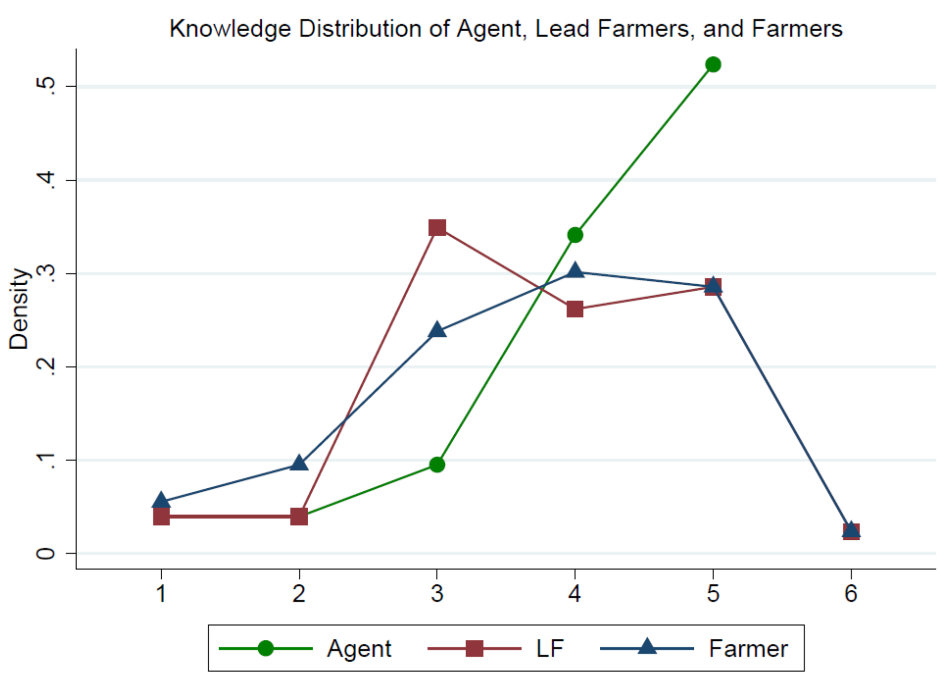
Source: Data are extracted from Malawi household survey (IFPRI 2016), and extension service provider survey (IFPRI 2017).
Note: Partial information chain is constructed by merging EA and LF by their operational area. The knowledge dimension variable is the number of questions answered correctly about pit planting. CI = confidence interval; EA = extension agent; LF = lead farmer.

Table 5.4 T-test of OFs' knowledge with and without direct EA contact

Knowledge dimension of OF	Mean	Std. Err.	95% CI	
with direct contact of EA	3.62	0.08	3.46	3.78
without direct contact of EA	4.53	0.23	4.03	5.02
Difference	-0.91***	0.3	-1.49	-0.33

Source: Data are extracted from Malawi household survey (IFPRI 2016), and extension service provider survey (IFPRI 2017).
Note: Partial information chain is constructed by merging EA and LF by their operational area. The knowledge dimension variable is the number of questions answered correctly about pit planting. CI = confidence interval; OF = other farmer; EA = extension agent.

Figure 5.1 Knowledge distribution of extension agents, lead farmers, and other farmers



Source: Data are extracted from Malawi household survey (IFPRI 2016), and extension service provider survey (IFPRI 2017).
Note: The knowledge dimension variable is defined as the number of questions answered correctly about pit planting.

Table 5.5 Impact of extension services on knowledge dimension of all farmers

	Specifications							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Ordinary least squares				**Poisson**			
Variables	**Knowledge dimension**				**Knowledge dimension**			
Receive advice about pit planting from …								
Any EA	0.389***	0.233**			0.099**	0.058		
	(0.108)	(0.110)			(0.047)	(0.050)		
Government EA			0.484***	0.304***			0.122***	0.075
			(0.108)	(0.114)			(0.047)	(0.051)
Private EA			-0.117	0.038			-0.028	0.014
			(0.344)	(0.343)			(0.151)	(0.154)
NGO EA			-0.023	-0.029			-0.005	-0.007
			(0.158)	(0.159)			(0.070)	(0.072)
Farmer organization EA			0.349	0.432			0.083	0.109
			(0.409)	(0.410)			(0.175)	(0.181)
Number of months with abnormal rainfall		-0.105*		-0.100*		-0.028		-0.027
		(0.059)		(0.059)		(0.027)		(0.028)
Attend farmer cluster		-0.109		-0.105		-0.029		-0.028
		(0.129)		(0.130)		(0.059)		(0.060)
Attend farm demonstrations		-0.066		-0.072		-0.017		-0.019
		(0.089)		(0.089)		(0.041)		(0.041)
Use print materials on agriculture		-0.208		-0.214		-0.054		-0.055
		(0.192)		(0.192)		(0.089)		(0.089)
Use library or resource centers		0.543		0.619		0.133		0.153
		(0.579)		(0.579)		(0.250)		(0.251)
Attend agricultural training centers		-0.418**		-0.459**		-0.110		-0.121
		(0.178)		(0.179)		(0.084)		(0.085)
Use radio		0.127*		0.133*		0.033		0.035
		(0.075)		(0.075)		(0.035)		(0.035)
Attend listening clubs		-0.281		-0.231		-0.074		-0.061
		(0.262)		(0.262)		(0.121)		(0.121)
Use TV		-0.167		-0.167		-0.045		-0.045
		(0.306)		(0.306)		(0.147)		(0.147)
Use phone/SMS		0.019		0.017		0.004		0.003
		(0.165)		(0.165)		(0.075)		(0.075)
Attend VAC		0.112		0.082		0.029		0.021
		(0.118)		(0.119)		(0.054)		(0.055)
Attend GAC		0.228		0.205		0.057		0.052
		(0.141)		(0.142)		(0.064)		(0.065)
Attend meetings in the community		0.308***		0.297***		0.081**		0.078**
		(0.077)		(0.077)		(0.035)		(0.036)
Receive information from mobile vans		-0.038		-0.038		-0.009		-0.009
		(0.196)		(0.196)		(0.092)		(0.092)
Total livestock units		-0.001		-0.001		-0.000		-0.000
		(0.002)		(0.002)		(0.001)		(0.001)
Household asset value (1,000 MWK)		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Landholding		-0.025**		-0.026**		-0.007		-0.007

		(0.012)		(0.012)		(0.006)		(0.006)
Household head education in years		0.011		0.011		0.003		0.003
		(0.009)		(0.009)		(0.004)		(0.004)
Number of adults in the household		0.050		0.051		0.013		0.013
		(0.036)		(0.036)		(0.016)		(0.016)
North		-0.174		-0.176		0.042		0.040
		(0.150)		(0.150)		(0.056)		(0.056)
South		-0.331***		-0.325***		0.089		0.088
		(0.119)		(0.119)		(0.056)		(0.056)
Quintile of distance to roads		0.018		0.022		0.005		0.006
		(0.022)		(0.022)		(0.010)		(0.010)
Connectivity index		-0.019		-0.017		-0.006		-0.005
		(0.040)		(0.040)		(0.019)		(0.019)
Number of people in network		-0.048**		-0.050**		-0.014		-0.015
		(0.021)		(0.021)		(0.011)		(0.011)
Number of associations attended		0.169***		0.161***		0.043**		0.042**
		(0.041)		(0.041)		(0.018)		(0.019)
Constant	3.752***	3.903***	3.729***	3.874***	1.322***	1.276***	1.316***	1.270***
	(0.034)	(0.257)	(0.034)	(0.257)	(0.015)	(0.086)	(0.016)	(0.087)
Observations	1,243	1,240	1,243	1,240	1,243	1,240	1,243	1,240

Source: Data are extracted from Malawi household survey (IFPRI 2016).

Note: The knowledge dimension variable is the number of questions answered correctly about pit planting. Standard errors in parentheses. EA = extension agent; NGO = nongovernmental organization; SMS = short message service; VAC = village agricultural committee; GAC = group agricultural committee; MWK = Malawian kwacha.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Table 5.6 Impact of extension services on each dimension of pit planting knowledge

	Specifications					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**1st dimension**	**2nd dimension**	**3rd dimension**	**4th dimension**	**5th dimension**	**6th dimension**
Receive advice about pit planting from …						
Government EA	0.007	-0.006	0.120**	0.044	0.037	-0.030
	(0.037)	(0.043)	(0.050)	(0.036)	(0.025)	(0.040)
Private EA	0.112	0.243*	-0.162	-0.093	-0.084	0.106
	(0.111)	(0.128)	(0.149)	(0.109)	(0.079)	(0.122)
NGO EA	0.036	-0.043	-0.006	0.007	-0.002	-0.021
	(0.052)	(0.060)	(0.070)	(0.051)	(0.035)	(0.057)
Farmer organization EA	0.123	-0.033	-0.117	0.136	0.065	0.085
	(0.133)	(0.153)	(0.178)	(0.131)	(0.087)	(0.146)
Number of months with abnormal rainfall	-0.036*	-0.029	-0.012	0.013	-0.006	-0.100***
	(0.020)	(0.023)	(0.026)	(0.019)	(0.014)	(0.021)
Attend farmer cluster	-0.060	0.007	-0.103*	-0.023	-0.028	0.084*
	(0.043)	(0.050)	(0.057)	(0.041)	(0.028)	(0.046)
Attend farm demonstrations	0.002	-0.032	-0.003	0.008	0.012	-0.076**
	(0.030)	(0.034)	(0.040)	(0.029)	(0.020)	(0.032)
Use print materials on agriculture	-0.072	0.027	-0.008	-0.069	0.000	0.164**
	(0.067)	(0.079)	(0.090)	(0.061)	(0.044)	(0.068)
Use library or resource centers	0.141	0.587***	-0.150	0.125	-0.248**	-0.078
	(0.188)	(0.217)	(0.252)	(0.185)	(0.122)	(0.206)
Attend agricultural training centers	-0.074	-0.131*	-0.056	-0.058	0.008	-0.080
	(0.059)	(0.068)	(0.079)	(0.057)	(0.040)	(0.064)
Use radio	0.002	0.034	0.022	0.027	-0.049***	0.076***
	(0.025)	(0.029)	(0.034)	(0.024)	(0.017)	(0.027)
Attend listening clubs	0.023	0.017	-0.090	-0.145*	-0.003	-0.013
	(0.085)	(0.098)	(0.114)	(0.084)	(0.059)	(0.093)
Use TV	-0.056	-0.120	-0.087	0.030	-0.085	0.035
	(0.103)	(0.123)	(0.138)	(0.098)	(0.070)	(0.109)
Use phone/SMS	-0.007	0.103	0.060	-0.063	0.075**	-0.013
	(0.056)	(0.065)	(0.075)	(0.053)	(0.037)	(0.058)
Attend VAC	0.001	-0.034	-0.031	0.024	-0.030	0.037
	(0.039)	(0.045)	(0.053)	(0.038)	(0.026)	(0.042)
Attend GAC	0.059	-0.018	0.045	0.044	0.020	0.028
	(0.047)	(0.054)	(0.063)	(0.045)	(0.032)	(0.051)
Attend meetings in the community	0.096***	-0.014	0.084**	0.082***	0.032*	-0.006
	(0.026)	(0.030)	(0.035)	(0.025)	(0.017)	(0.027)
Receive information from mobile vans	-0.222***	0.191**	-0.102	0.037	-0.003	0.084
	(0.067)	(0.079)	(0.093)	(0.063)	(0.044)	(0.070)
Total livestock units	-0.001*	-0.001	0.001	0.000	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Household asset value (1,000 MWK)	0.000	-0.000	-0.000	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Landholding	-0.002	0.004	-0.000	-0.013***	-0.005	0.000
	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)
Household head education in years	0.006**	0.002	-0.002	0.005*	0.003	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)
Number of adults in the household	0.027**	-0.019	-0.002	0.012	-0.012	0.021*
	(0.012)	(0.014)	(0.016)	(0.011)	(0.008)	(0.013)

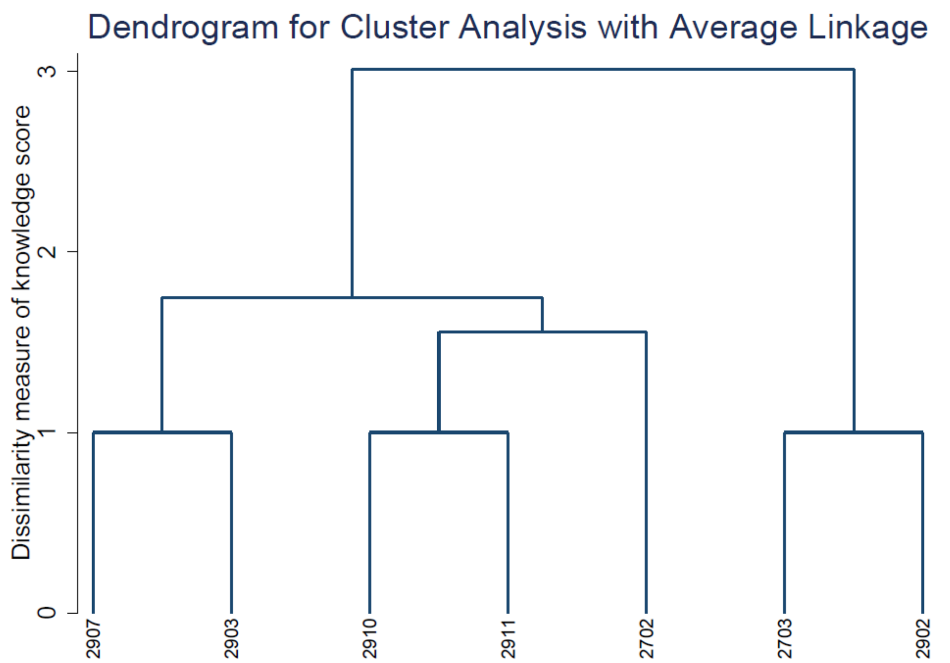
North	0.005		0.139**	-0.068	-0.001	-0.225***
	(0.050)		(0.068)	(0.048)	(0.035)	(0.053)
South	-0.105***	0.081*	0.041	-0.111***	-0.068**	-0.096**
	(0.040)	(0.046)	(0.054)	(0.038)	(0.028)	(0.042)
Quintile of distance to roads	0.010	0.007	-0.014	0.007	0.011**	-0.005
	(0.008)	(0.009)	(0.010)	(0.007)	(0.005)	(0.008)
Connectivity index	-0.028**	0.022	-0.010	-0.010	0.008	0.004
	(0.014)	(0.016)	(0.018)	(0.013)	(0.009)	(0.014)
Number of people in network	0.003	-0.008	-0.002	-0.007	-0.005	-0.023***
	(0.007)	(0.008)	(0.009)	(0.007)	(0.005)	(0.007)
Number of associations attended	0.011	0.001	0.070***	0.028**	0.015	-0.013
	(0.014)	(0.016)	(0.018)	(0.013)	(0.009)	(0.015)
Constant	0.836***	0.291***	0.353***	0.769***	0.963***	1.182***
	(0.087)	(0.082)	(0.116)	(0.082)	(0.060)	(0.091)
Observations	1,150	1,147	1,149	1,240	1,055	1,240
R-squared	0.066	0.045	0.058	0.061	0.067	0.070

Source: Data are extracted from Malawi household survey (IFPRI 2016)

Note: Knowledge dimension variable is the number of questions answered correctly about pit planting. Standard errors in parentheses. EA = extension agent; NGO = nongovernmental organization; SMS = short message service; VAC = village agricultural committee; GAC = group agricultural committee; MWK = Malawian kwacha.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Figure 5.2 Dendrogram for cluster analysis of overall knowledge dimension variable with average linkage



Source: Data are extracted from Malawi household survey (IFPRI 2016).

Note: Analysis is based on the knowledge dimension variable, which is defined as the number of questions answered correctly about pit planting. Horizontal axis provides section ID numbers. The rest of the sections have a zero dissimilarity measure.

Figure 5.3 Dendrograms for cluster analysis for each knowledge dimension

Source: Data are extracted from Malawi household survey (IFPRI 2016).

Note: Analysis is based on the binary knowledge variable for each knowledge dimension, and each graph shows cluster analysis on one of six dimensions of knowledge. Horizontal axis provides section ID numbers. The rest of the sections have a dissimilarity measure of zero and are omitted from the graphs.

Table 5.8 Impact of knowledge dimension on adoption of pit planting

Variables	(1)	(2)	(3)	(4)
	Adoption of pit planting			
	All farmers		Lead farmers	
Knowledge dimension		0.029**		0.091***
Receive advice about pit planting from …		(0.012)		(0.031)
Government EA	0.058	0.051	0.128	0.123
	(0.057)	(0.057)	(0.100)	(0.099)
Private EA	-0.001	0.018	0.225	0.318
	(0.187)	(0.187)	(0.333)	(0.330)
NGO EA	0.100	0.096	-0.023	-0.010
	(0.084)	(0.084)	(0.152)	(0.150)
Farmer organization EA	0.089	0.073	0.106	-0.029
	(0.233)	(0.233)	(0.397)	(0.394)
Number of months with abnormal rainfall	-0.028	-0.025	0.022	0.036
	(0.025)	(0.025)	(0.051)	(0.051)
Attend farmer cluster	0.254***	0.257***	0.171**	0.175**
	(0.056)	(0.056)	(0.084)	(0.083)
Attend farm demonstrations	0.052	0.053	0.090	0.091
	(0.039)	(0.039)	(0.072)	(0.071)
Use print materials on agriculture	-0.033	-0.027	0.011	0.045
	(0.084)	(0.083)	(0.118)	(0.117)
Use library or resource centers	0.132	0.115	0.085	0.032
	(0.251)	(0.251)	(0.308)	(0.304)
Attend agricultural training centers	0.224***	0.237***	0.173*	0.198**
	(0.077)	(0.077)	(0.093)	(0.092)
Use radio	0.008	0.005	0.018	0.014
	(0.032)	(0.032)	(0.064)	(0.063)
Attend listening clubs	-0.141	-0.133	-0.007	0.022
	(0.113)	(0.113)	(0.146)	(0.144)
Use TV	-0.037	-0.033	0.322	0.267
	(0.133)	(0.133)	(0.384)	(0.379)
Use phone/SMS	-0.083	-0.084	-0.071	-0.065
	(0.071)	(0.071)	(0.101)	(0.100)
Attend VAC	-0.034	-0.037	-0.052	-0.053
	(0.051)	(0.051)	(0.091)	(0.089)
Attend GAC	-0.032	-0.038	-0.028	-0.051
	(0.062)	(0.062)	(0.098)	(0.097)
Attend meetings in the community	-0.028	-0.037	-0.065	-0.088
	(0.033)	(0.033)	(0.066)	(0.065)
Receive information from mobile vans	0.112	0.113	0.040	0.033
	(0.085)	(0.085)	(0.155)	(0.153)
Total livestock units	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Household asset value (1,000 MWK)	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Landholding	0.008	0.008	0.001	0.005
	(0.005)	(0.005)	(0.009)	(0.009)
Household head education in years	0.002	0.002	0.007	0.006
	(0.004)	(0.004)	(0.010)	(0.010)
Number of adults in the household	0.044***	0.043***	0.028	0.026

	(0.015)	(0.015)	(0.025)	(0.025)
North	0.061	0.066	-0.185	-0.190
	(0.065)	(0.065)	(0.127)	(0.125)
South	0.104**	0.114**	-0.127	-0.078
	(0.051)	(0.051)	(0.104)	(0.104)
Quintile of distance to roads	-0.006	-0.006	-0.045**	-0.044**
	(0.010)	(0.010)	(0.021)	(0.020)
Connectivity index	-0.018	-0.018	0.016	0.006
	(0.017)	(0.017)	(0.046)	(0.045)
Number of people in network	0.009	0.011	-0.002	0.004
	(0.009)	(0.009)	(0.015)	(0.015)
Number of associations attended	0.054***	0.049***	-0.032	-0.045
	(0.018)	(0.018)	(0.031)	(0.031)
Constant	0.269**	0.155	0.657***	0.242
	(0.112)	(0.121)	(0.211)	(0.251)
Observations	1,240	1,240	283	283
R-squared	0.101	0.105	0.104	0.134

Source: Data are extracted from Malawi household survey (IFPRI 2016)
Note: Knowledge dimension variable is the number of questions answered correctly about pit planting. Standard errors in parentheses. EA = extension agent; NGO = nongovernmental organization; SMS = short message service; VAC = village agricultural committee; GAC = group agricultural committee; MWK = Malawian kwacha.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.