Learning for adopting: Technology adoption in developing country agriculture

Edited by Alain de Janvry, Karen Macours
and Elisabeth Sadoulet

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Introduction

Alain de Janvry, Karen Macours and Elisabeth Sadoulet

Productivity growth in agriculture is expected to be the main source of successful structural transformation and industrialization for pre-industrial developing countries with an un-captured potential in agriculture. Indeed, history tells us that agricultural revolutions have preceded industrial revolutions in most countries with rural populations. Recent experiences with industrialization in countries such as China, India, and Brazil support this proposition. Productivity growth in agriculture requires the availability of technological innovations for agriculture and adoption of these innovations by the farm community. In recent years, emphasis has been given to the lag between the presumed availability of promising innovations and their adoption. Many factors can be associated with lack of adoption, such as credit constraints, lack of insurance coverage, high transaction costs on markets, or behavioral inadequacies. In addition, as information about new technologies is a necessary, if not sufficient, condition for adoption, a good understanding of potential information failures that limit farmers adoption of available technologies is considered key. This puts the focus on the performance of extension services and the transfer of information through social networks, agro-dealers, or farmer's commercial partners upstream in the value chain.

Motivated by this observation FERDI (Fondation pour les études et recherches sur le développement international) and SPIA (Standing Panel on Impact Assessment of the Consultative Group for International Agricultural Research) organized a workshop to explore the current knowledge on how farmers learn and decide on adoption. We present here a summary of the main conclusions reached in the workshop and a brief outline of the presentations made. The presentations are summarized in the eleven policy briefs that follow this introduction.

Learning for adopting in agriculture is a complex process. This is due to the fact that (1) decisions that farmers must take are multidimensional as there is a wide range of options in input use, (2) the underlying production function in agriculture is only partially understood (as with the human body for health decisions) with much unknown in the relation, many non-observable phenomena, and a high degree of heterogeneity of conditions, (3) the relation is subject to random shocks, principally under the form of weather events with incompletely known probability distribution due to limited records or to climate change, (4) production takes a long time, typically limiting the updating of information to an annual exercise, (5) data for learning by doing or learning from others are incomplete and poorly recorded, and (6) there are externalities in learning, with incomplete internalization of benefits and strategic delays in adoption. Several years of repeated observations may be needed to assess the value of a technology that is not beneficial in all states of nature.

As a result of this complexity, we should expect slow diffusion to be the norm for most innovations. Extension interventions should hence aim at accelerating learning for adopting, and their optimal design likely differs depending on the nature and complexity of the innovation itself.

The optimal design of extension services should start from a good understanding of the farmers' learning process. Yet there are many open questions and competing models of farmers' decision-making about innovations. Simple diffusion models based on the threshold concept--whereby a farmer decides on adoption when there is a sufficient fraction of neighbors using the innovation--may be insufficient. Indeed, complexity of decision-making, heterogeneity of conditions, and changing circumstances imply that farmers often cannot be expected to decide based on simple imitation, but must learn for themselves what works best for their own particular circumstances. Assisting learning in a cost-effective fashion thus creates a major challenge for the design of extension services. To address this challenge, the design of current extension approaches may need to be deeply modified.

The approach pioneered by the Training and Visit (T&V) system, with Agricultural Extension Officers (AEO) connecting to contact farmers for the diffusion of innovations in social networks, is still the main organizational principle to extension directed at smallholder farmers in developing countries. In contrast, in more advanced countries private agents in value chains play increasing roles in providing information to farmers. This latter model cannot yet operate in many developing countries due to weak connection of smallholder farmers to value chains either because they are producing largely for home consumption or because the value chain for what they produce and sell is hardly developed. In recent years, various improvements have been suggested to the T&V approach, in particular by experimenting with which contact farmers can be considered optimal entry points into social networks.

The choice of contact farmers as injection points into social networks should depend on the barrier to be overcome for securing diffusion in those networks. Contact farmers could be lead farmers (that can be self-selected in response to willingness to pay to access the technology) because of their capacity to demonstrate, they could be farmers designated or voted in by the community for maximum social benefit as perceived by others, they could be peer farmers because they maximize similarity with a particular subset of farmers in an heterogeneous population, they could be opinion leaders if others rely on trusted figures when there is much hidden information about the innovation, they could be members of a producer organization or social group (such as women Self Help Groups) for their ability to communicate information, they could be central to a particular social network for their maximum connection with others in a simple or complex contagion perspective, or they could even be random farmers to cover the whole range of heterogeneous conditions in a community.

It has long been recognized that lack of proper incentives for agricultural extension agents is often a key weakness in extension models. When the AEO-contact farmer-social network approach is used, provision of high-powered incentives to contact farmers may also be crucial for them to pro-actively engage in seeking contacts with other farmers that will help diffuse the innovation. Incentives may further be necessary to overcome the risk of liabilities in providing advice to others as it can lead to an adverse outcome. Much less recognized, but possibly even more effective, is that a mechanism could be put into place to induce farmers in the network to actively seek information from the contact farmers. This may simply involve informing the social network that an innovation is available through mass media. Such an approach could transform the basic T&V model from a supply-driven approach to one that is demand-driven. The demand-driven approach may be more effective in handling heterogeneity of circumstances across farmers in the social network due to asymmetrical information on production conditions.

Heterogeneity of circumstances under which smallholder farmers operate implies that lessons learned regarding the application of an innovation by one farmer may not transfer to others and makes learning from others particularly difficult. Under these conditions, identifying to whom the innovation applies requires targeting and customization. Learning from others requires identification of peer farmers operating under similar circumstances. Because there are many non-observables affecting outcomes, revealing who are the relevant peers may require a specific extension design. One option for this is to let contact farmers choose the counterfactuals against which innovations are evaluated in their fields, thus revealing their peer value to others through the choice of counterfactual.

To improve the quality of signals, Head-to-Head (H2H) demonstration trials at the farm level should also be reorganized away from demonstrations where farmers produce under extension agent's directives and with provided inputs, to trials under the farmer's control, and as much as possible with self-provided complementary inputs. In this way, the technology is demonstrated under the farmer's own circumstances, increasing the likelihood of sustained adoption in subsequent years. Choice of control plots helps other farmers in the community identify peer farmers relevant to them. These farmer-led H2H trials can be used to organize farmer field days, with good documentation to reveal procedures, events (weather), and outcomes for each trial. Visits to multiple trials can improve learning if there is heterogeneity of circumstances in a community.

Coordination for experimentation in producer organizations helps internalize a greater share of learning externalities, and reduce strategic delays in adopting. Regional Consortia for Agricultural Experimentation (CREA) in France and Argentina give examples of how farmer groups can privately invest in experimentation to learn for adoption.

When value chains are well developed, specific private agents can play important roles in inducing farmers to learn and adopt. This includes agro-dealers (especially for fertilizers, seeds, and agro-chemicals), commercial partners (agro-industry, agro-exporters, and supermarkets) with interlinked contracts with farmers or farmer groups, private for profit or NGO service providers, and social organizations such as producer organizations and cooperatives. Because these agents behave strategically in providing information to farmers, there are issues of agendas (incentive compatibility) and trust that affect the use of information. This requires careful use of industrial organization principles for the design and regulation of contracts. Certification, reputation building, rating, and third-party audits typically become necessary to establish credibility and trust. Active role of these multiple agents in the information-adoption nexus redefines the role of the state in extension from that of a core service provider to that of a regulator, coordinator, and provider of targeted services to smallholder farmers and marginal populations to complement what the private sector does.

These issues were addressed in policy briefs prepared by workshop participants.

• **Elisabeth Sadoulet** reviews a large number of theoretical learning models addressing the questions of what do farmers have to learn to decide on adoption, how do they learn it, and from whom can they learn it? Models include simple and complex contagion, social influence and conformity, Bayesian updating based on one's own experience or the experience of others, aggregating information received from numerous others, strategic decisions about whether or not to experiment when there are benefits from learning from others, giving selective attention to available information, and the role of various injection points in social networks in influencing subsequent diffusion. She concludes with a number of unresolved issues in learning for adopting: How to interpret signals received from others when there is heterogeneity of benefits, and whether signals can be transmitted along with information on the specific circumstances of the farmer emitting the signal? How does information circulate in social networks and how is this information aggregated into a useful message? And what are the best injection points to maximize diffusion, especially when quality of signal matters in addition to quantity?

• **Stefano Caria** asks whether social networks, which are important for the diffusion of information in agrarian communities, are formed efficiently to maximize the extent and speed of diffusion. He and co-author use a game-in-the-field approach with Indian farmers. They find that networks tend in fact to be formed inefficiently, in particular because some members include the "most popular" farmers in their network as opposed to farmers that will maximize the flow of information in a most efficient cycle network. Rawlsian inclusion (the benevolent inclusion of least favored farmers) also has an efficiency cost. By contrast a social planner strategy always reaches efficiency. This implies that there can be a role for policy interventions that change the structure of social networks and create incentives to create connection with less popular nodes.

• **Jeremy Magruder** asks the question of how to design extension services when there is social learning. With a simple decision-making model, $Y = \Omega X$, farmers adoption decisions (Y) are based on existing information, beliefs, or practice that farmers are learning from actions X, and on network characteristics Ω such as social connections and aggregation decisions. Interventions could then aim at changing Ω or at manipulating X, for instance by strategically choosing entry points that take into account information regarding Ω. Using a randomized control trial approach for pit farming in Malawi, he and colleagues choose entry points based on diffusion theory and knowledge about the pre-existing network and hypothesize that farmers learn better when they have access to information from more than one lead farmer. Implication for the design of extension services would be that it is better to train multiple contact farmers within a same village rather than spreading demonstrations thin across a larger number of villages.

• **Sylvain Chassang** asks the question of how to best target adoption subsidies for maximum diffusion in social networks when there are heterogeneous externalities across farmers. Heterogeneity implies that some farmers are better demonstrators than others and have more impact on the decisions made by others. Difficulty is that information about entry points is largely private. This information needs to be extracted through self-targeting or through community targeting. The first can be done by having farmers bid for willingness to pay or willingness to work for the advantage of receiving the adoption subsidy. The second can be done by community voting in selecting the subsidized contact farmer with maximum expected benefit to others. Self- and community-selection of entry points introduce a powerful way of increasing the effectiveness of social learning. It raises the interesting issue of external validity when entry points are endogenous to self-selection or to community selection.

• **Alain Desdoigts** analyzes the diffusion of technological innovations in cocoa farming in Ivory Coast. The observation he and co-author make is that adoption is low, with yields achieving only a fraction of potential. They use cross-sectional survey data to identify correlates of adoption and find that behavior is the main apparent determinant of low yields. According to them, farmers are subject to a conservative status quo bias, and do not pursue profit maximization behavior. Social networks are however important in influencing behavior. Farmers with more social capital are likely to be more prone to acquiring knowledge from others and using it to achieve higher yields. Social networks convey information across members of producer organizations, rather than simply through kinship relations.

• **Alain de Janvry** reviews the different approaches to the provision of extension services, noting that they have generally performed below expectations and appear to be strong limiting factors to adoption. In developing countries where value chains and private agents in these value chains are yet weakly present, the general approach has been for public extension agents to train contact farmers who are in turn expected to diffuse information and promote adoption in their social networks. To improve this approach, recommendations made by him and co-authors are to select contact farmers according to the main constraint to diffusion, for instance focusing on peer farmers (most analogous to others) when there is heterogeneity, and on lead farmers (that can serve as role models in decision-making) when there is much hidden information. Also recommended is to organize farmer field days run by farmers themselves using head-to-head trials that they manage under their own objective functions and specific constraints. Choice of counterfactual plots by these farmers helps reveal their type to others and identify them as peer farmers for specific others when there is heterogeneity of circumstances. When value chains are more developed, private agents become important self-motivated sources of information, in particular agro-dealers with their clienteles and commercial partners (agro-industries, agro-exporters, and supermarkets) through interlinked transactions where contracts include information and technology.

• **Kyle Emerick** reports on research in Eastern India and Bangladesh that tests alternative approaches to extension. In Bangladesh, he and co-authors use an RCT approach to test the role of social networks in the diffusion of information about a new drought tolerant rice variety, BD56. They show that the most effective entry point for the diffusion of knowledge about BD56 is large farmers, compared to average farmers, farmers with the highest willingness to pay, farmers voted best by the community, and randomly selected farmers. They calculate that this is due to the greater centrality of large farmers in social networks. These results suggest that large farmers should be the ones selected to carry out demonstrations and to hold farmer field days in this context. His policy brief additionally proposes new research that explores the relative effectiveness of farmer-based versus dealer-based agricultural extension in promoting the adoption of new seed varieties.

• **Emilia Tjernström** puts emphasis on how heterogeneity of circumstances across farmers affects learning in social networks. Heterogeneity is characterized by soil conditions as observed through soil testing in Kenya and learning is about new seeds. Building on the randomized rollout of these seeds across villages, she finds that social networks do affect adoption, and that farmers respond to the evaluation of new seeds made by others in their network, rather than merely imitating the actions of others. She further finds that greater soil heterogeneity reduces learning from others, suggesting that farmers are aware of the importance of this heterogeneity and that it affects how much they know they can learn from their social contacts. This has strong implications for the design of extension services and reliance on social networks for the diffusion of information from contact farmers. With greater heterogeneity, direct learning may become relatively more relevant than social learning.

• **Karen Macours** stresses the complexity of decision-making in agriculture, with numerous combinations of inputs such as seeds and fertilizers under heterogeneous conditions. She and co-author use an RCT approach in Kenya for the cultivation of maize, soybeans, and intercropping. They find that, due to complexity, learning is slow, but knowledge tests reveal that it gradually converges toward what agronomists know from experimental plot trials. Results show that farmers who participate in trials learn and communicate with each other. Yet increases in knowledge and in expressed willingness to pay for inputs are only partially reflected into actual higher fertilizer use, revealing the existence of other constraints to accessing inputs. They also find that there are few knowledge spillovers to non-participating farmers, questioning the effectiveness of social networks as a vehicle for the diffusion of complex information.

• **Xavier Giné** looks at the adoption of technological innovations by maize farmers in Tlaxcala, Mexico, and its impact on yields achieved. He and co-authors focus on the role of heterogeneity in soil conditions as informed by soil testing. Using an RCT approach, they offer extension services to all farmers, complemented by soil testing at the individual or community level, and subsidies that can be under the form of fertilizer in kind, flexible cash grants, or no grant. Results suggest that farmers interpret the recommendations based on soil testing as useful signals of the quality of their land as it leads to a decline in the expected volatility of yields. They further show that there is no gain from (more costly) individualized soil testing compared to an area average test, making it potentially more feasible to include such recommendations in extension interventions at scale. Yet recommendations alone may not be enough, and farmers respond most by adopting when they are provided with a package of interventions that includes extension services, in kind grants, and agro-dealer provision of the right fertilizer mix. Conclusion is thus that adoption decisions are complex and multidimensional, requiring a comprehensive approach as opposed to piecemeal interventions.

• **Kelsey Jack** raises the issue of using adoption subsidies when there are subsequent maintenance investments that will need to be made if the technology proves to be profitable. When time comes to pay these costs, adopters may decide to follow-through with the technology or not. She and co-authors study the adoption of nitrogen-fixing trees by smallholder farmers in Zambia. She finds that uncertainty about the cost of follow-through increases take-up as farmers want to have the option of following-through should the technology prove to be profitable. As a consequence, initial take-up subsidies are both less cost effective and less necessary. With high uncertainty, increasing the price of the technology does not increase the rate of follow-through, but reducing uncertainty would, as would rewarding follow-through directly. Subsidies to follow through may thus be more effective than subsidies to take-up.

Chapter 1

Review of Theories of Learning for Adopting

Elisabeth Sadoulet

1. Overview

The diffusion of a new agricultural technology requires farmers to learn about the existence and the benefits of the technology. What do they have to learn, how do they learn it, and from whom, is the subject of a large literature, both theoretical and empirical. The purpose of this brief is to review the most prominent learning models, briefly assess recent empirical results derived from these theories, and raise a few important remaining issues not explicitly addressed by the theories. We will focus on the literature that refers to learning from experience, either own or that of others, giving prominence to the network of connections that farmers have. This review is purposefully very selective, with the objective of illustrating concepts and categories of models, rather than providing a genuine literature review.

Models differ along four main dimensions: (i) what is to be learned, (ii) what is observed or transmitted by the social network, (iii) how do farmers aggregate the information that they receive from different sources, and (iv) what is the assumed network structure.

What is to be learned: In some models, farmers learn from others the simple facts of the existence or the adoption by others of a technology. This factual knowledge is simple: the information is either transmitted or not, and if transmitted, it contains no error or noise. This is the essence of a class of models called 'diffusion models' (reviewed in section 2). Being informed is a binary variable. Adoption is then a function of simply knowing about the technology or knowing people that have adopted it.

In other models, what farmers need to learn before deciding to adopt a technology is an expected profit or yield, or a (stochastic) optimal input to be used. This is substantially more difficult, as one never observes expected values, but only specific realizations of the stochastic variable. These realizations provide 'signals' on the underlying outcome of interest. We refer to these models as 'learning models' in section 3 below. A key assumption of most models is that there is no fundamental heterogeneity among farmers. Expected profit/optimal input are the same for all and the signal is unbiased.

A more realistic view of the world of heterogeneity in agricultural production suggests that what farmers should be learning is a more complex multivariate relationship, $\pi^*(x,z)$ between input and characteristics x, z, respectively, and outcome, here expected profit or yield, π^*. Only such models allow learning from cross-sectional (land quahty, input use, farmer ability) or over time (function of weather realizations) heterogeneity. We will review one such model by Schwartzstein in section 3.4 below. The paper focuses on a specific aspect of the challenge facing farmers, called 'selective attention', which is to properly assess the set of covariates that matter in the relationship.

What is transmitted by the social network: In diffusion models, the information that is transmitted is without ambiguity. In more complex learning models, farmers can transmit to each other either the information they have about the technology or their own action regarding adoption (resulting from their net assessment of the information they have). The full information (including where it comes from beyond one's own experience) is more informative, but not as easily transmissible. A recent literature (described in section 5) addresses this question in the context of fully controlled experimental games. Throughout the empirical literature, authors have pointed out cases where farmers resist transmitting their decisions or all the information they have, which of course is only possible when it is not directly observable by others (Conley and Udry, 2010; Cai *et al.* 2015).

How do people aggregate the information they receive: Let's say that a few farmers have the information on or have adopted the new technology, and that the information starts diffusing in the network. Uninformed people receive the information or signals on the variable of interest, possibly from different sources. A key question is how do they aggregate these different sources of information.

In diffusion models, the information is simple, and once acquired is not reversible: once you are informed or have adopted, this is it. Different models however specify different rules by which information from others translate into being informed or adopting., e.g., a non-adopter will adopt as soon as he is in contact with a threshold number of adopters, or a fraction of his friends have adopted, either with certainty or with a certain probability.

In learning models, people receive signals on the outcome of interest, and use them to update their prior. Key issue is whether people aggregate following the sophisticated Bayesian rule, where different signals are weighted according to their probability of occurrence and precision, or whether people use more heuristic formulae, with some ad'hoc weighting schemes, as suggested by DeGroot. Another issue is whether people can recognize the origin of the information, and for example whether they can properly correct for a unique information that reached them through two different channels (e.g., a signal originating from person A, and transmitted to D by both B and C). While early models simply stated either a Bayesian or a DeGroot rule, recent empirical work described in section 5 use experimental games to study the issue.

What is the structure of the network: Most of the early literature assumed that networks are 'complete' in the sense that all links between the different members of the networks exist, and the network itself is defined by a large population, most often the village. When network are complete no one has any particular position. In contrast, the recent literature has paid attention to the structure of the network, i.e. the links that exist between any two members of the population. In such incomplete networks, different people have different ability to facilitate the diffusion of information, some people are more 'central' than others. Recent work described in section 4 show how the centrality concept is related to the diffusion model.

With learning models, where the information or signal (such as a realized profit) needs to be generated by each member of the network, the nodes of the network acquire some other important characteristics, such as their ability as demonstrators to develop useful information. In addition, links themselves may be of different strength, if for example information provided by more trusted members of the network is more persuasive. There is not much theoretical development on these aspects, but this is an important question with strong policy implications regarding the choice of whom to select as injection points for diffusing a new technology.

The paper proceeds as follows. We first review early models that assume full netwroks (section 2 and 3 for the diffusion and learning models, respectively) and then review models and empirical studies that are anchored in the specific structure of the network (in section 4 and 5 for the diffusion and learning models, respectively). In section 6, we ask the question of how to select the injection points in a network in order to maximize the diffusion of a technology, a policy relevant question addressed in many current empirical works.

2. Diffusion models

In diffusion models, people adopt when they come in contact with others who have already adopted. There is no explicit theory of learning, but a dynamic model of transmission of behavior. We follow Young (2009) in presenting the models in the context of a large population with random encounters.

Contagion models: In the simple contagion model, a non-adopter will adopt as soon as he encounters an adopter. Let $\lambda > 0$ be the instantaneous rate at which a current non-adopter 'hears about' the innovation from a previous adopter within the group, and let $\gamma > 0$ be the instantaneous rate at which he hears about it from sources outside of the group. In the absence of heterogeneity, the proportion of adopters in period t, pit), follows the differential equation:

$$p'(t) = (\lambda p(t) + \gamma)(1 - p(t)),$$

and the solution is

$$p(t) = [1 - e^{-(\lambda+\gamma)t}]/[1 + \frac{\lambda}{\gamma} e^{-(\lambda+\gamma)t}].$$

Individual are characterized by their individual values (λ,γ), λ is a sort of rate of social interaction with the rest of the population, and 7 with the external world.

In complex contagion models individuals adopt if they are connected to at least a threshold number of adopters. A recent test of these models in the context of incomplete networks is proposed by Beaman *et al.* (2014) and discussed in section 4.

Social influence models: In these models, non-adopters are persuaded to adopt when a certain fraction of the population has already adopted, what has been called a 'conformity' motive. Each agent i is characterized by the minimum proportion $r_i \geq 0$ that needs to have adopted before he adopts. The parameter measures a degree of responsiveness to social influence. A key feature of such a model is that adoption depends on the innovation's current popularity rather than on how good or desirable the innovation has proven to be.

You need a group of people that are willing to adopt on their own, even without anyone else having adopted before them. After that, those with the lower level of adopts first, and then on. Let $\lambda > 0$ be the instantaneous rate at which these people convert. Then the adoption process is described by the differential equation:

$$p'(t) = \lambda[F(pt)) - p(t)]$$

where $F(.)$ is the cumulative distribution function of thresholds r in the population.

Susceptible infected models: In these models, being informed does not automatically translate into adoption, but only makes you 'susceptible' to adopt. Informed non-adopters only adopt with a certain probability, that possibly depends on their own characteristics.

For example, Banerjee *et al.* (2013) develop a model of information diffusion through a social network that discriminates between information passing (individuals must be aware of the product before they can adopt it, and they can learn from their friends) and endorsement (the decisions of informed individuals to adopt the product might be influenced by their friends' decisions). They apply it to the diffusion of microfinance loans, in a setting where the set of potentially first-informed individuals is known. The underlying model is as follows:

– An informed person transmits the information with probability q^P if he participates in the MFI, and q^N if he does not.

– An informed individual i decides to participate in the MFI with probability p_{it} at time t:

$$log\left(\frac{p_{it}}{1-p_{it}}\right) = X_i'\beta + \lambda F_{it}$$

where F_{it} is the fraction of his informed network links that participate.

The model allows to estimate separately the information channels (q^P and q^N) and the endorsement ('action') channel (λ). They find no evidence of endorsement effect. And the estimates for the information transmission are $q^P = 0.35$ *to* 0.50 and $q^N = 0.05$. This suggests that in this context non-adopters have little influence, and transmission of adoption is quite partial.

3. Learning models

In this section we present examples of learning models. Each is built as a specific combination of the outcome to be learned, the information that is transmitted, and the aggregation rule used by the receiving agent to update his prior information. The first two models are the widely used targeted input model with Bayesian updating, and a model that illustrates a DeGroot aggregation mechanism. We then present three models that each focus on an additional aspect of the learning process: (i) a dynamic learning model, in which farmers can strategically adopt the new technology to increase learning, (ii) a model in which what is to be learned is a complex production function, and (iii) a model that points to the difference between the time series information collected by self experience over time and cross sectional information collected from experiences by others.

3.1. The Target Input Model: Bayesian learning based on unbiased signals reduces uncertainty and hence increases Eπ

This model is presented in Bardhan and Udry (1999) and used by BenYishay and Mobarak (2015). The production function is known to the producer with certainty, except for one parameter, usually conceptualized as the optimal input:

$$q_{it} = 1 - (k_{it} - h^*_{it})^2 \tag{1}$$

where q_{it} is output or profit, k_{it} is input used, and h^*_{it} is the optimal ('target') input.

The optimal input level is subject to idiosyncratic variation μ_{it} around a mean value h^*, i.e., $h^*_{it} = h^* + \mu_{it}$, with $\mu_{it} \sim N(0, \sigma^2_{\mu i})$.

If h^* is known, maximization of expected profit leads to choosing $k_{it} = E_t(h^*_{it}) = h^*$ and expected profit is $\pi_{it} = 1 - \sigma^2_{\mu i}$. This variance $\sigma^2_{\mu i}$, is due to the inherent variation in conditions that implies that the optimal input cannot be known at the onset of period t. It can be specific to producer i. There is thus fundamental heterogeneity in expected profitability.

If, however, h^* is unknown, producers rely on beliefs about h^*, further reducing expected profit. Beliefs are modeled as a distribution of potential level for h^*. Say that producer i's belief at the beginning of year t is normally distributed $N(h_{it}, \sigma^2_{uit})$. Maximization of expected profit leads to choosing $k_{it} = E_t(h^*_{it}) = h_{it}$ and expected profit is $\pi_{it} = 1 - \sigma^2_{\mu i} - \sigma^2_{uit}$.

Updating from own experience. At the end of year t, producers can observe q_{it} and hence infer what should have been h^*_{it} . The useful information from that observation is what it tells him about h^*, since μ_{it} is structural. h^*_{it} is thus an unbiased signal of variance $\sigma^2_{\mu i}$ about h^*. Beliefs are updated in year $t+1$ as the posterior distribution of h^*, a normal distribution with mean and variance as follows:

$$h_{it+1} = \frac{(1/\sigma^2_{uit})h_{it} + (1/\sigma^2_{\mu i})h^*_{it}}{(1/\sigma^2_{uit})h + (1/\sigma^2_{\mu i})}$$
$$\frac{1}{\sigma^2_{uit+1}} = \frac{1}{\sigma^2_{uit}} + \frac{1}{\sigma^2_{\mu i}} \tag{2}$$

Producers choose to apply $k_{it+1} = h_{it+1}$ and expected profit is $\pi_{it} = 1 - \sigma^2_{\mu i} - \sigma^2_{uit+1}$. Hence as information accumulates, the uncertainty about h^* decreases and expected profit increases until it converges to the expected profit under perfect information about h^*.

Updating from others' experience. Suppose all farmers in the village have the same production technology, and that the optimal inputs are drawn from the same distribution, i.e., $h^*_{it} \sim N(h^*, \sigma^2_\mu)$. When producer i observes the production of N_t farmers, he receives a signal h^*_t, with variance σ^2_μ / N_t. The updating equations for his beliefs are thus:

$$h_{it+1} = \frac{(1/\sigma^2_{ut})h_{it} + (N_t/\sigma^2_\mu)\bar{h}^*_{it}}{(1/\sigma^2_{ut}) + (N_t/\sigma^2_\mu)}$$
$$\frac{1}{\sigma^2_{ut+1}} = \frac{1}{\sigma^2_{ut}} + \frac{N_t}{\sigma^2_\mu} \tag{3}$$

Adoption. Suppose producers had access to a perfectly known traditional technology with constant profit, and choose to cultivate with either the traditional or the modern technology. First note that once a producer switches to the new technology, he never returns to the older one. This is because in this model expected profit can only improve with more experience. If farmers are myopic, then they will switch to the new technology whenever they have learned enough (from the others) so that the expected profit of the new technology is higher than the profit of the traditional technology. If however they are forward looking, they will include the benefits of experimenting to acquire information and may adopt even when there is expected current loss, if it is lower than the discounted gain in future profitability (see a dynamic learning model in section 3.3 below). If producers are learning from each others, then who decides to experiment and who decides to wait for the others to experiment depends on the structure of their interactions. This model is formalized in Bandiera and Rasul (2006).

Adaptation in BenYishay and Mobarak (2015). Assume that the production function is the same for all farmers, $q_i = 1 - (k_i - h^*)^2$. There is a common prior belief regarding the optimal input for the new technology which is distributed $N(0, \sigma^2)$. If a farmer uses the technology with $k = 0$, the corresponding expected profit is then $q = 1 - \sigma^2$.

Farmers are selected by the experiment to try the new technology. [If h^* was not stochastic, the experimenter would immediately learn about the true value h^*.] These selected farmers x then choose whether to communicate or not the information gained from their experience to others. Since all farmers have the same production function, the signal is unbiased. However, the precision of the signal received by another farmer θ has two components: (i) one, ρ is related to the cost $c(\rho)$ incurred by the sender, and (ii) a second related to the distance $|x-\theta|$ between the two farmers. Using the same notation as above, the signal received by θ on h^* is:

$$s_{x\theta} = h^* + \frac{|x-\theta|}{\rho}\varepsilon_\theta$$

where $\varepsilon_\theta \sim N(0, 1)$. Farmer θ then updates his prior about h^* as follows:

$$\begin{aligned} E[h^*|s_{x\theta}, \rho] &= \frac{(\rho^2/(x-\theta)^2)s_{x\theta}}{1/\sigma^2 + \rho^2/(x-\theta)^2} \\ \frac{1}{var[h^*|s_{x\theta}, \rho]} &= \frac{1}{\sigma^2} + \frac{\rho^2}{(x-\theta)^2} \end{aligned} \tag{4}$$

With this model, the distance between farmers produces an increase in noise (not in bias) of the signal. This noise, in turn, induces a reduction in expected profitability. Note that the precision on the prior σ could be farmer specific σ_θ, indicating farmer θ's own 'ability' for example.

3.2. Munshi (2004): DeGroot updating from observation of the network's average decision and outcome

Farmers have the choice between two technologies, a traditional technology, with a certain yield y_{TV} identical for all farmers, and a modern technology with higher but risky return. The risky yield y_{it} is written:

$$y_{it} = y(Z_i) + \eta_{it} \tag{5}$$

where the expected yield $y(Z_i)$ is function of the farmer's characteristic Z_i, and the stochastic term η_{it} is of mean 0 and variance λ_i^2. Note that both expected value and variance of yield are farmer specific.

If the farmer had perfect information, he would choose to allocate its land between the two crops, maximizing utility over the return. Under standard hypotheses, this would lead to land allocated to the new crop to be increasing in expected return and decreasing in the variance of return, i.e.:

$$A_i^* = A(y(Z_i) - y_{TV}, \lambda_i) \tag{6}$$

If the farmer does not know $y(Z_i)$, he uses an estimate $\hat{y}_{it}$ with variance σ_{it}^2, and the land allocation is:

$$A_{it} = A(\hat{y}_{it} - y_{TV}, \lambda_i, \sigma_{it}) \tag{7}$$

At the end of the season, the farmer obtains a realized yield y_{it}.

Timing of decisions and information flows are as follows: Farmers receive private signals. Based on these they update their own yield expectation ($\hat{y}_{it}$) and decide how much to plant, A_{it} Yields are then realized.

How are these yield estimates $\hat{y}_{it}$ formed?

Social learning when conditions are identical across farmers

Expected yield is the same for all farmers, and information from neighbors are just as good as information from one's own field. Each farmer transmits two pieces of information: Planting decision, which reveals the private signal he received, and realized yield which provides another signal on expected yield. We assume that farmers share a common knowledge $\hat{y}_t$ which they each combine with the personal signal u_{it}. The updating of the common knowledge is based on the new information received by the village, i.e., the average of all signals received by individuals and their realized yields. This gives:

$$\hat{y}_{it} = \alpha\hat{y}_t + (1 - \alpha)u_{it} \tag{8}$$
$$\hat{y}_t = (1 - \beta - \gamma)\hat{y}_{t-1} + \beta\bar{u}_{t-1} + \gamma\bar{y}_{t-1} \tag{9}$$

Using a linear function for (7), the law of motion of land allocation thus becomes:

$$A_{it} = \pi_0 + \pi_1\hat{y}_{it} + g(X_i, \sigma_{it}) \tag{10}$$
$$= \pi_0 + \pi_1\alpha(1 - \beta - \gamma)\hat{y}_{t-1} + \pi_1\alpha\beta\bar{u}_{t-1} + \pi_1\alpha\gamma\bar{y}_{t-1} + \pi_1(1-\alpha)u_{it} + g(X_i, \sigma_{it}) \tag{11}$$

$\bar{u}_{t-1}$ and $\hat{y}_{t-1}$ are not observable to the farmer, but can be shown to be function of $\bar{A}_{t-1}$ and A_{it-1}, so that :

$$A_{it} = \eta_0 + \eta_1 A_{it-1} + \eta_2\bar{A}_{t-1} + \eta_3\bar{y}_{t-1} + \varepsilon_{it} \tag{12}$$

A_{it-1} contains all the information about the expected yield that was available at the beginning of period $t-1$. Conditional on A_{it-1}, $\bar{A}_{t-1}$ represents the new information that was received by the village in period $t-1$ through the exogenous signals. Similarly, $\bar{y}_{t-1}$ represents the information that was obtained from the yield realizations in that period.

In the language of the current network theory (section 5), this model is about the aggregation function. The network is implicitly defined as being the whole village sufficiently connected that everyone knows what everyone else does. There is transmission of both the action (area planted based on the signal received) and the information (the obtained yield).

Social learning when conditions vary across farmers

Without a formal analysis, Munshi's assessment of how the model applies when there is heterogeneity is as follows: "The grower could condition for differences between his own and his neighbors' observed characteristics when fearning from them. But the prospects for social learning decline immediately once we allow for the possibility that some of these characteristics may be unobserved, or imperfectly observed. Mistakes that arise because he is unable to control for differences between his own and his neighbors' characteristics when learning from their yields are persistent, and therefore more serious. Take the case where all the neighbors' characteristics are unobserved by the grower. He now has two choices. He could rely on his own information signals and yield realizations, ignoring information from his neighbors. Consistent but inefficient estimates of the expected yiefd woufd be obtained with such individual learning. Alternatively, he could continue to utilize information from his neighbors, measured by the mean acreage and the mean yield, as before. The efficiency of his estimates increases with social learning since more information is being utilized, but some bias will inevitably be introduced since the grower cannot control for variation in the underlying determinants of the yield when learning from his neighbors. The grower will ultimately choose between individual learning and social learning on the basis of the trade-off between bias and efficiency."

3.3. Dynamic learning model, with strategic adoption to increase learning

This model is presented in Besley *et al.* (1994). The authors develop a dynamic model of learning, where individuals are forward looking and Bayesian. The returns to technology adoption are twofold: it could affect current profits; and it could also induce learning about the value of this technology (information), which is a public good and will pay off when future decisions are made.

In this framework, uncertainty about a new technology can be represented by a state variable a, which can be perceived as the increased profitability from adoption. There are M farmers indexed by i. Each farmer has N_i fields, and he has to choose how many to sow to the new variety (the new technology) at each date t. His current expected payoff from sowing n_{it} fields to the new technology is $f^i(n_{it}, \alpha_t)$, where α_t is the the belief about α at time t. $f^i(n_{it}, \alpha_t)$ is assumed to be increasing, twice differentiable with $\partial^2 f/\partial n_{it}\partial\alpha_t > 0$. Uncertainty in this model comes from the fact that people could not precisely estimate the effect of the technology, but instead only evolve a behef based on past experience, which is represented by a conditional distribution function $H^t(\alpha_{t+1} \,|\, \alpha_t, \Sigma_i n_{it})$.

Given the setup, a farmer's sowing decision can be described by:

$$W_t^i(\alpha_t, \sum_{j\neq i} n_{jt}) \equiv \max_{n_{it}} \{f^i(n_{it}, \alpha_t) + \beta \int V_{t+1}^i(\alpha_{t+1}) dH^t(\alpha_{t+1} \mid \alpha_t, \sum_{j=1}^{M} n_{jt}) \mid n_{jt} \leq N_i\} \quad (13)$$

where β is the discount factor and $V_t^i(x)$ is the value function, defined as the value of entering period t with state variable x:

$$V_t^i(x) \equiv W_t^i(x, \sum_{j\neq i} n_{jt}(x)) \quad (14)$$

Farmers are assumed to be risk-neutral, and there exists a trade-off between current profitability and the value of learning that arises through the dependence of future beliefs on sowing decisions. Information is a pubhc good and there exists externahties of technology adoption (every farmer's decision affects the conditional distribution function of behefs about technology), so every farmer's sowing decision should be conditioned on that of all other farmers. The Nash equilibrium is a vector of sowing decisions: $\{n_{1t}^*(\alpha), \ldots, n_{Mt}^*(\alpha)\}$.
As the state variable α_t evolves over time, the farmers reach a succession of Nash equilibria conditioned on the value of α_t in each period t. Therefore, this sequence gives us a Markov Perfect Equilibrium.

For comparison, the authors also consider two further cases: when learning is undertaken cooperatively by the farmers and when farmers are myopic. In the first case, farmers maximize joint profit, so the problem is no longer M farmers choosing M variables, now only one decision is made, in which the total number of fields sown to the new technology, n_t is chosen. The model could be further extended such that the planner in this cooperative case may also choose how to allocate the sowing decisions across farmers, making use of side payments to bring about the planning allocation. In the second case, the farmers are assumed to be myopic, so their decisions are based solely on current profitability. This corresponds to $\beta = 0$ in the model. If this is the case, then whether farmers are cooperative or non-cooperative no longer makes a difference, since coordination behavior affects only expected future payoffs.

Bandiera and Rasul (2006) also present a version of this strategic dynamic model. It is based on the targeted input model. Their empirical analysis studies the adoption of sunflower by farmers in the Zambezia region of Northern Mozambique. It is based on cross-sectional data on 198 household heads from 9 villages. Each farmer was asked how many of the people they know have adopted, and how many of those are family or friend. They find the relationship between farmers' decisions to adopt and the adoption choices of their network of family and friends to be inverse-U shaped, suggesting social effects are positive when there are few adopters in the network, and negative when there are many. They also find that (i) adoption decisions of farmers who have better information about the new crop are less sensitive to the adoption choices of others., and (ii) adoption decisions are more correlated within groups of family and friends than in religion-based networks, and uncorrelated among individuals of different religions. Note however that all these results are correlations as there is no identification strategy. Their argument is that contextual effects and mimicry would create positive correlation. So finding an inverse U-shape suggests this is not all.

3.4. Learning a complex relationship: the problem with selective attention

Schwartzstein (2014) explicitly considers the case where what is to be learned is a multivariate relationship between inputs and output. The angle that the author considers is the issue of the bias and distortion that occur in the learning process if the farmer fails to recognize all the necessary dimensions of the production function. The paper presents a model of selective attention: an agent learns to make forecasts based on past information, but is selective as to which information he pays attention to.

Specifically, the agent wants to accurately forecast y given (x, z), where y is a binary variable and x and z are finite random variables. In each period t, the agent observes a random draw of (x, z), (x_t, z_t), from a fixed distribution $g(x, z)$; then he gives his prediction of y, $\hat{y}_t$ to maximize $-(\hat{y}_t - y_t)^2$; then he learns the true y_t. The agent knows that given (x, z), y is independently drawn from a Bernoulli distribution with fixed but unknown success probability $\theta_0(x, z)$ in each period: $p\theta_0(y = 1|x, z) = \theta_0(x, z)$. He also knows the joint distribution $g(x, z)$, which is positive for all (x, z).

The author assumes that z is important to predicting y, while x is important to predicting y in the absence of conditioning on z (there could be cases where x is no longer predictive once we control for z). The agent does not know the functional form of the success probability θ_0. To estimate this function, he needs to (i) choose the model (i.e., decide whether x and/or z are important) and (ii) estimate the parameters that he thinks are important using a standard Bayesian approach. Let $M_{i,j}$ where $i \in \{X,\neg X\}$, $j \in \{Z,\neg Z\}$ designate the four potential models. And let $\pi_x(\pi_z) \in (0,1]$, be the subjective prior probability that $x(z)$ is important to predicting y. The learning process is a standard Bayesian one. The history through period t is denoted by:

$$h^t = ((y_{t-1},x_{t-1},z_{t-1}), (y_{t-2},x_{t-2},z_{t-2}),\ldots,(y_1,x_1,z_1)) \tag{15}$$

So the agent updates his beliefs about the model and about the parameters based on history, and uses the updated belief to forecast. In period t, his forecast of y given x and z can be written as:

$$E[y|x,z,h^t] = E[\theta(x,z)|h^t] = \sum \pi^t_{i,j} E[\theta(x, z)|h^t, M_{i,j}] \tag{16}$$

where $\pi^t_{i,j} \equiv Pr(M_{i,j} \,|\, h^t)$ equals the posterior probability placed on model $M_{i,j}$.

It follows that if the agent is Bayesian and has access to full history h^t at each date, then he should make asymptotically accurate forecasts, and he should learn the true model. Therefore, in this setting, any deviations from such perfect learning must stem from selective attention (the agent fails to pay attention to a variable in certain periods, so could not recall it later).

Standard Bayesian approaches assume that the agent perfectly encodes (y_k, x_k, z_k) for all $k < t$. But if the individual is "cognitively busy" in a given period k, he may not attend to and encode all components of (y_k, x_k, z_k) due to selective attention. Intuitively, this can be thought of as the agent sorting into his memory, and only remembering the elements that were perceived to be important. Therefore, at date t, the agent may only have access to an incomplete mental representation of true history h^t, which is denoted by $\hat{h}^t$.

The author makes several assumptions to put structure on $\hat{h}^t$. Basically, the agent always encodes x and y, so selective attention only applies to z. And the likelihood that the agent attends to z is increasing in the current probability that he thinks z is predictive for y. In addition, the author assumes that the agents are naive: when they cannot recall the z in the past history, they recall such missing information as a fixed but distinct non-missing value. This assumption is important in generating the main results of the paper.

One of the main proposition derived from the model is that if the agent settles on encoding z, he learns the true model almost surely; if the agent settles on not encoding z, he does not learn the true model. The intuition is that when he encodes z, this is identical to standard Bayesian process, so he learns the true model. But if he does not encode, he believes that x is important to predicting y (by assumption, x predicts y when not conditioning on z), and fails to realize that this is driven by his ignorance of z due to the naivete assumption (the agent treats missing values of z as non-missing distinct values). This result means that in some cases, the agent interprets correlative relationships as causal, and he makes such errors persistently because he has selective attention and could not recall the complete history.

Using this framework, Hanna *et al.* (2014) suggest that failing to notice a gap between knowledge and actual practice, and not the information set itself, may be a key barrier to learning. They show that seaweed farmers in Kenya acted on the information received only when it included descriptions of the relationship between yield and pod size from their own plot.

The strong effect of *field visits* in inducing demand for the new rice variety shown in Emerick *et al.* (2016) may be interpreted as an opportunity to point to some of the benefits of the new technology and/or how to use it. In which case it would help counteract these failure to notice by making them salient.

3.5. Private learning from time series vs. social learning from cross sectional observations

An interesting point made by Wang *et al.* (2013) is that private learning proceed from the observation of time series of realized events, while learning from others is based on cross-sectional observations of stochastic events. The authors build a model where farmers consider an investment project, whose value function follows a geometric Brownian motion (a continuous-time stochastic process widely used in finance). Departing from the standard learning framework, the authors assume that a key parameter (the drift rate) of the Brownian motion is unobservable to the farmer (parameter uncertainty). Therefore, the farmer is imperfectly informed about the expected rate of return, which he has to figure out in order to decide the optimal timing of investment. Learning then happens in two ways: (1) private learning, by extracting information on the true drift from a continuous observation of past realized returns on the project value. (2) Social learning, by obtaining discrete noisy signals of the true drift (learning from early adopters in the farmer's social network).

Unfortunately, the authors do not further elaborate on the distinction between the two types of variability. Thinking of agricultural production, it is quite clear that the cross sectional variability of yield across farmers is not at all the same concept as the variability over time. This issue is common to all the models that compare or combine learning from one self and learning from others.

The empirical analysis seems to have lost the interesting distinction between the two learning processes. It is a simple censored tobit model for the time it takes to adopt. They conclude that social learning has a significant positive impact on greenhouse adoption: 10 more adopters in the farmer's social network increase the probability of adoption by 32%, which is an economically significant effect. Moreover, results from the duration analysis confirm this finding with social learning reducing the waiting time significantly in greenhouse adoption.

4. Diffusion models in incomplete networks: The key role of injection points

While the basic diffusion and network models reviewed in section 2 refer to the social network as an important source of information, these networks are relatively unspecified: They are generically referred to as the village population, and assumption is that everyone is equally connected to everyone in the network. In the real world however, networks have structure (or topology). They consist in the set of links that exist between the members of a given population. In these 'incomplete' webs of relationships, the diffusion process depends on where the entry points for the information/adoption are in the network.

With diffusion depending on the diffusion model, the definition of links in the network, and the entry points in a non-separable way, testing for the diffusion model becomes intrinsically linked to the choice of injection points. Beaman *et al.* (2014) addresses exactly this issue. The different diffusion models of agricultural technology they consider are: 1) simple contagion model with network links defined from a survey; 2) complex contagion model with network links defined from a survey; and 3) complex contagion model with network links define by geographical proximity. For each of these three cases, optimal injection points are selected based on network simulation. The control arm is defined by the *status quo*, i.e., entry points are the extension workers' choice. The authors then compare rates of diffusion, and find: a) farmers chosen by network theory yield greater adoption rates over three years; b) the learning environment is more consistent with the complex contagion model where farmers need to know more than one person with the new technology to decide to adopt. That is, "the complex contagion model with optimal entry points" performs better than any other model with its associated optimal injection points.

Banerjee *et al.* (2013) start from a different diffusion model, the susceptible infected model described in section 2, where information is transmitted though active finks, one leg per period of time, and informed people decide whether to adopt based on their own characteristics and the adoption rate among their informed network neighbors. After having estimated the model parameters, they can compute a measure of communication centrality for each leader (injection points). This is defined as the fraction of households who would eventually participate if this leader were the only one initially informed. To compute this fraction, they simulate the model with information passing and participation decisions being governed by the estimated values of q^N, q^P, β. Finally, they develop an easily computed proxy for communication centrality, which they call diffusion centrality.

5. Learning models in incomplete networks: Diffusion and aggregation of information

Learning includes three elements: what information is transmitted from one person to the next (either the belief, typically a probability, or the action taken based on that belief), the diffusion of information within the network, and the aggregation of received signals.

As seen above, diffusion models assume that what is transmitted is the action ('adoption'), and that it is passed along one fink. The diffusion models then specify different aggregation functions: The contagion models specify that adoption will take place if at least a threshold number of network neighbors have adopted; the social influence model is a certain fraction of the network neighbors that have adopted.

In a series of recent articles (Chandrasekhar *et al.* ,2012; Grimm and Mengel, 2014; Mobius *et al.*, 2015), researchers have resorted to lab experiments to better understand the diffusion and aggregation of information in networks. These experiments are about the discovery of one truth (among several options), and whether the learning process converges to the truth. So for example in Chandrasekhar *et al.* (2012), the world (a bag containing 7 balls) is either blue or yellow. In the blue bag there are 5 blue balls and 2 yellow balls, with the reverse in the yellow bag. There are 7 participants. Each participant receives a signal (blue or yellow), with a 5/7 probability that the signal is correct. Each participant only receives one signal and then relies on additional information from its limited network. Each individual's initial best guess of the color of the world is 1/2 (since the bag was randomly selected). After receiving the signal and collecting information from his network, each individual provides a new assessment of the color of the world. These second round guesses are transmitted through the networks, leading to a third round set of assessments and guesses, etc.

5.1. Bayesian vs. DeGroot aggregation of information

In Chandrasekhar *et al.* (2012), the network transmits the best guess of each individual (and not the information that served to establish it, nor the mechanism by which the person aggregated this information): This is an "action" model. The diffusion along the network is perfect, as it is done by the experiment itself. What varies is the structure of the network. What the paper is trying to uncover is the aggregation rule used by the subjects in the experiment. Specifically, are they Bayesian (the aggregation rule is a Bayesian updating of their belief) or DeGroot (aggregation is some weighted average of their own and their network's past actions, with ad'hoc weights). The way this is done is by simulating the outcomes that we should observe under a number of scenarios: all are Bayesian, all are DeGroot, a certain fraction are Bayesian and this is common knowledge, all are Bayesian but they don't know what others are, etc. The authors find that it is the "all DeGroot" model that comes closest to what is observed.

Why is this important? Any model but a correct Bayesian model can lead to some cluster of participants being stuck in error (because they initially received some wrong signals, which are never properly reassessed with correct (Bayesian) weights).

Grimm and Mengel (2014) present a horserace between the Bayesian and naive DeGroot models of learning in an experimental game similar to Chandrasekhar *et al.* (2012). All games are with 7 players, with 3 different network structures (circle, star, and kite), 2 different initial signal distributions (more or less clustered), and 3 degrees of information given to participants on the network structure. They ask whether agents reach a consensus, and if so whether they agree on the correct truth, and how long it takes them. They can predict the outcome under perfect information with each of these two rules, and find that the naive model is a better predictor of *individual* decisions than the Bayesian model. However this model fails to predict the overall network performance (in terms of convergence, convergence to the correct answer, and speed of convergence), so it seems that the equal weights of the pure naive model do not represent what people use.

An interesting part of the paper estimates the empirical aggregation rule, i.e., the weights $\lambda_{i,j}(t)$ given by each participant i to each of his network member j over time in the following model:

$$g_i^t = 0 \quad \text{if and only if} \quad \lambda_{ii}(t) g_i^{t-1} + \sum_{j \in N_i} \lambda_{ij}(t) g_j^{t-1} < \frac{1}{2} \tag{17}$$

where $g_i^t \in \{0,1\}$ is the guess by player j at time t about the correct urn.

This of course requires observing interactions between the same players in multiple games. Further, they analyze the estimated weights λ_{ii} that players give themselves as function of their network position, etc. They find that people put more weight on themselves than the pure naive model. This leads them to define some alternative model for the weights that depends on the position in the network and the degree of clustering in the network, etc., and that nests the naive rule and can approximate the Bayesian rule. The model is then estimated in more complex networks (rectangle and pentagon). Note that the paper offers a good literature review on experimental papers testing these network learning models.

5.2. Diffusion of information

In Mobius *et al.* (2015), participants again have to discover a truth (the answer to three binary-choice questions). The pool of players is a group of 800 students from which the network of up to 10 best Facebook friends was elicited. The game is played on fine. Participants receive an initial signal with three suggested answers, and are told that all participants received independent signals, correct in 60% of the case. They make a first choice. They are then encouraged and incentivized to talk to as many people as they want from the group of people playing the game (they can search for participants). They can update their choice as often as they want. Whenever they submit a choice, they also have to record the name of all the people they talked to since the last submission. The experiment thus provides the full endogenous network of conversation links with a time stamp. The paper addresses the two questions of diffusion and aggregation. On diffusion, the authors show that the information does not travel beyond two nodes. In terms of aggregation, they examine whether people are aware that there is some double counting in the signal received. This is for example the case if you get information from two people (A and B) who both had talked to a common third (C) person. This is done by estimating the weight given to information that itself contains different information. For example they find that the weight given to a direct contact is not influenced by the number of paths to it (either several conversations with the same person or an indirect link in addition to the direct link), but that weights given to an indirect partner (C in the example above) does depend on how many paths you have to this partner (two in the case described). This is very plausible if your direct contacts did not tell you whom they themselves were influenced by. Similarly, in Cai *et al.* (2015), people who had a direct experience of insurance (either receiving or not a payout) are not influenced by the others.

The paper discusses the 'tagged' model which is when there is transmission not only of the signals but also of where it comes from, which allows the recipient to properly avoid double counting, for example if the same information reaches you through two channels.

5.3. What do networks transmit? Information vs. action

In Tjernström (2015), the author conducts a RCT in rural Kenya which explicitly elicits farmers' experiences with the technology to examine the influence of social networks on knowledge about and adoption of a new agricultural technology. Specifically, they randomly select treated villages, in which some farmers (directly treated) receive small packs of a new maize variety and conduct on-farm trials with the seeds; their fellow villagers (indirectly treated) only have access to information about the seeds through their social networks. No intervention is conducted in the control villages. In the treated villages, the author obtains the directly treated farmers' evaluation of how well the on-farm experiment went, and assumes that the signal that a given farmer receives about the new technology is a function of the distribution of these evaluations in his information network. This design could help separate two competing theories in the network and adoption literature: if social pressure is the main reason for adoption, then the number of treated links should largely explain the adoption decisions; if learning actually causes adoption, then farmers should respond to the actual evaluation of the new seeds by their network.

The author finds that networks transmit information (as opposed to 'action') and affect respondents' willingness to pay for the variety: the indirectly treated farmers respond strongly to the signals available in the network, above and beyond the impact of the number of treated links in their network. She also finds that the observed social network effects are weaker in villagers where soil quality is more varied (greater heterogeneity), which illustrates how heterogeneity in returns can handicap network effects. This further confirms that the observed network effects come from learning rather than imitation.

In Miller and Mobarak (forthcoming), the authors design a two-stage RCT to study the adoption of non-traditional stoves in Bangladesh. They promote two types of stoves: "efficiency" stoves whose effects are less observable ex-ante; and "chimney" stoves whose effects are more observable ex-ante. Based on ex-post feedback, "efficiency" stoves are not useful, while "chimney" stoves are useful. These two types of stoves therefore also allow them to study the heterogeneous learning effects caused by positive and negative information.

In the first period, the authors randomly publicize whether or not the local "opinion leaders" choose to order the non-traditional stoves, and look at the effects of this information on the adoption decisions of other households. They find that villagers' adoption decisions are affected by the decisions of opinion leaders, and the effects are stronger for the less observable "efficiency" stoves. Also, the results are more salient for negative information as compared to positive information.

In the second period, the authors study how the first period adoption decisions would affect the decisions of other households in the same network. The difficulty of studying this questions is that it is hard to distinguish social learning from common unobservable shocks faced by network members. To address this issue, the authors randomly assign subsidies to induce stove adoption in the first period, which creates exogenous variation in stove adoption and allows them to study whether the presence of network members who are stove owners (causally) affects other households' subsequent propensity to purchase stoves. They find that for both stove types, social ties to first-round participants reduce the likelihood that second-round participants purchase any stoves, suggesting that all villagers were overly optimistic about the effect initially. This negative social network effect is much larger for the "efficiency" stoves, which have been proved to be not useful.

5.4. The difference between lab experiment and real world network diffusion

While the lab experiments provide rigorous tests on how networks function in their own context, it is unclear how much their insights can be extended to a real world situation. This is because there are at least two fundamental differences between lab experiments and the real world that are more than a question of degree or simplification.

– In experimental games, players seek the information (they know that they need it and know where it is available). In the real world of agricultural extension, agricultural officers or selected experimentators know that the information exists but have no incentive to push it onto others (BenYishay and Mobarak, 2015), while farmers know their problems, but they don't know whether a solution exists for any particular one, and as a consequence are not likely to be seeking it.

Do we expect the info on agricultural technology to be pulled or pushed?

Can/should we facilitate this communication, e.g., through farmer field days as in Emerick *et al.* (2016))?

– In real world settings, the value of the information may depend on the person that transmits it (quality of signal, trustworthiness). Hence weights correspond to some underlying relationship between people.

5.5. Network learning when there are heterogeneous benefits

In Magnan *et al.* (2015), the authors study how social learning influences demand for a resource-conserving technology (Laser Land Leveling or LLL) in India. They design a RCT with two components: (1) a pair of binding experimental auctions for LLL custom service hire held one year apart, and (2) a lottery to determine who among the winners of the first auction would actually adopt the technology. The auctions capture demand for LLL before and after its introduction, allowing the authors to compare the benefits of LLL that farmers perceive to the actual benefits before and after any social learning takes place. The lottery generates exogenous variation in the number of adopters in each farmer's network, allowing them to estimate network effects. This randomization also allows them to estimate the benefits of the technology within the sample. The main point of the paper is to show the effect of heterogeneity in benefits in the diffusion of the technology. Their results demonstrate some important nuances in how social networks drive technology adoption. On average, LLL reduced water use by 25% within the sample and appears to be profitable for 43 to 59% of farmers at the likely market price. However, in the first auction only two percent of farmers bid at or above this price, indicating that although the technology would benefit many farmers, potential benefits were initially not widely-appreciated by farmers. The authors find strong evidence that farmers learned about LLL benefits over the course of the study, and their demand in the second auction reflects this. Having a benefiting in-network adopter increased WTP by over 50%, equivalent to a 32% subsidy of the likely market price. Adjusting initial demand for LLL by this mean network effect indicates that for 39% of farmers network effects could incite adoption. However, not all farmers receive this network effect because networks are sparse and the technology is not profitable for all farmers. Consequently, the authors calculate that in a village where 12% of farming households initially adopt LLL at a discounted price, network effects would increase adoption by 9% the following year.

6. Learning models in incomplete networks: What are the optimal injection points?

The choice of injection points must depend on two factors: what information is to be transmitted and what the diffusion process is.

1. If what is being transmitted is simple information (such as the existence of a product), all that matters is the injection point's network position in terms of the diffusion model. For example Beaman *et al.* (2014) defined by simulation the optimal entry points for either a simple or complex contagion model, based on a complete map of network links.
2. If we are interested in the transmission of adoption decisions rather than information, it is likely to be quite imperfect, in that an informed person may only adopt with a certain probability. If the probability is constant (as in the standard Susceptible-Infected model), then transmission is lower but the choice of entry points is unaffected. If however different people have different propensities to convert information into adoption, then the choice of entry points would need to take into account the network structure in terms of both links and adoption propensities.
3. More generally, if what needs to be transmitted is information about the net benefit of a technology, the entry points need to be both good "demonstrators" and good "communicators" for the first round of information transmission to begin. The proper balance between these qualities obviously depends on the product.
4. Finally, the benefits may be heterogeneous in the population. One would need a characterization of the source of heterogeneity to model the diffusion process and the corresponding optimal choice of entry points.

Beaman *et al.* (2014) and Banerjee *et al.* (2013) simulated models give example on how to deal with cases 1 and 2 above. The selection of best demonstrators could be addressed with the use of 'selective trials', as proposed by Chassang *et al.* (2012) and Jack (2013). It consists in using a bidding mechanism (uniform price, sealed bid procurement auction), to select the recipients with the highest expected return to what is offered.

In term of empirical work, several papers report on RCTs, where the new technology was introduced in a village through varying entry points. BenYishay and Mobarak (2015) test the influence of three different communicators: 1) extension agents, 2) lead farmers who are more educated and can afford the new technology; and 3) peer farmers who represent the general population of target farmers. They find that peer farmers with small performance-based incentives are most effective in promoting new agricultural technology. Without incentives, peer farmers do not learn about the new technology or put effort in dissemination. This is a point made in Kondylis *et al.* (2014) where they implemented a randomized training of the "contact" farmers (CF) to study the impact on diffusion of the new technology. They find that directly training CFs leads to a large, significant increase in CF adoption, with no immediate increase in knowledge. Higher levels of CF adoption have limited impact on the behavior of other farmers.

Emerick *et al.* (2016) study the diffusion of new rice varieties, attempting to contrast injection points selected in three different ways: (i) by the village ofhcial/elite, (ii) in a village meeting, and (iii) by the women Self-Help Group. While these different injection points are notably different in their observable characteristics, they find no difference in diffusion one year later.

There are a number of less well identified analyses that address the same issue:
– Maertens (2015) looks at the diffusion of Bt cotton in India, based on recall data on when each farmer started to use Bt cotton. She finds that farmers appear to be exclusively learning from, and free-riding on the experimentation of, a small set of "progressive" farmers in the village.
– Genius *et al.* (2014) find that extension services and learning from peers are complement.
– Feder and Savastano (2006) review the literature on the characteristics and impact of opinion leaders on the diffusion of new knowledge, concluding that there is no clear evidence on whether opinion leaders are more effective if they are similar in socioeconomic attributes to the other farmers rather than superior to would-be followers. A multivariate analysis of the changes in integrated pest management knowledge in Indonesia among follower farmers over the period 1991-98 indicates that opinion leaders who are superior to followers, but not excessively so, are more effective in transmitting knowledge. Excessive socio-economic distance is shown to reduce the effectiveness of diffusion.

7. Conclusion

We conclude with mention of a few salient unresolved issues.

What is to be learned may vary from simple information on the existence of a technology or its adoption by others, to more complex information such as the expected benefit of the technology, or even the relationship between key characteristics and inputs and expected profits. In the more complex cases, the information that is transmitted in the network is only a signal on the outcome of interest, which is then used to update priors. A key unresolved issue is how to deal with heterogeneity in benefits. What value does a signal have if it is biased, and the extent of the bias is unknown? Are some outcomes less heterogeneous than others, and hence more amenable to be usefully transmitted in networks? Are there ways by which the heterogeneity of outcomes can be made more transparent and transmissible? Can the transmission of a relationship characterize this heterogeneity?

How does the information circulate and is aggregated through the network? We have seen the first couple of tests and estimations of diffusion models. We are still far from specifying and testing models of diffusion and aggregation of more complex information, such as signals on expected benefits or the distribution of benefits, or on conditional expected benefits.

Who should generate the information/signals on what is to be learned? This is the key question of the choice of optimal injection points in social networks that would maximize the diffusion of the new technology. In diffusion models, people are solely characterized by their position in the network, and the objective is to define the most 'central' person in relation to the specific diffusion model. However, when signals have to be generated, like in most learning models, the quality of the person as experimenter also matters. The best experimenters are those that generate the most useful information for the others. Are they the best farmers, the median farmers, etc.? There is also potential tension between who are the best "diffusers" (in terms of centrality for the diffusion) and who are the best "demonstrators".

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Chapter 2

Can Indian Farmers Form Efficient Information-Sharing Networks in the Lab? *

Stefano Caria
Marcel Fafchamps

Abstract
A large literature in development economics argues that information about agricultural innovations diffuses through farmers' social networks. The structure of these network influences the extent and speed of information diffusion. In an artefactual field experiment in rural India we find that subjects form inefficient information-sharing networks and lose 35 percent of payoffs as a result. The game is designed so that the efficient network can be reached if all players choose strategies consistent with self-interest. These strategies are played frequently, but not often enough. Participants also often target the 'most popular' player in the network and this causes large efficiency losses in this experiment. Further, in randomly chosen sessions we disclose information about group membership. The networks formed in these sessions have more connections between subjects of the same group, but are not significantly less efficient. The networks formed in these sessions have more connections between subjects of the same group, but are not significantly less efficient. Networks play an important role in the diffusion of information. If they are inefficiently structured, policies that affect how individuals interact with each other have the potential to increase welfare.

* This chapter reports preliminary results, which are also discussed in Caria and Fafchamps (2015).

Policy context

Imperfect knowledge about new technologies is a commonly cited cause for the low levels of adoption of many profitable agricultural innovations in developing countries. In many cases, the perceived returns of these innovations may not be aligned with the actual returns and incorrect beliefs about their optimal use may be widespread. Further, imperfect knowledge increases the perception of risk associated with technology adoption.

To help farmers learn about new technologies, governments in many developing countries subsidize a variety of agricultural information services. According to some estimates, there are nearly 1 million workers employed in the dissemination of agricultural information services worldwide and development agencies have spent in the region of 10 billions US$ to support these activities (Feder 2005).

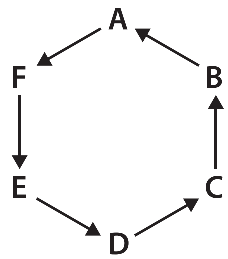
Experiment design

Our experimental game is played by groups of six male, adult farmers, selected through random door-to-door sampling. We select farmers from randomly selected villages in four "talukas" (provinces) in the vicinity of Pune, in the Indian state of Maharashtra.

In the experiment, each farmer can create one link to another farmer in the group. Players identities are anonymous and players are identified by simple IDs. At the beginning of the experiment, there are no links in the network. Farmers create links sequentially, after observing the choices of those who have already played. At the end of the game, one player in the group is randomly selected to receive a monetary prize. Farmers who are connected directly or indirectly to the winner of the random draw receive a monetary prize of the same value. The prize is thus non-rival.

In this simple game, a farmer maximizes his chances of winning the prize by securing the highest possible number of indirect connections. He achieves this if he links to the player with the highest number of indirect connections at that point in the game. If farmers follow this simple link formation rule, the network structure converges to the cycle within two turns of the game. In the cycle, as Figure 1 illustrates, every farmer is connected to every other farmer and hence all farmers win the monetary prize with certainty. In our experiment, the cycle is the efficient network structure, which maximizes social welfare.

Figure 1. The cycle network



To investigate whether social identity affects network structure and efficiency, we assign players to arbitrary groups at the beginning of each experimental session. Then, in randomly selected sessions, we disclose information about the group membership of players at the beginning of the network formation experiment.

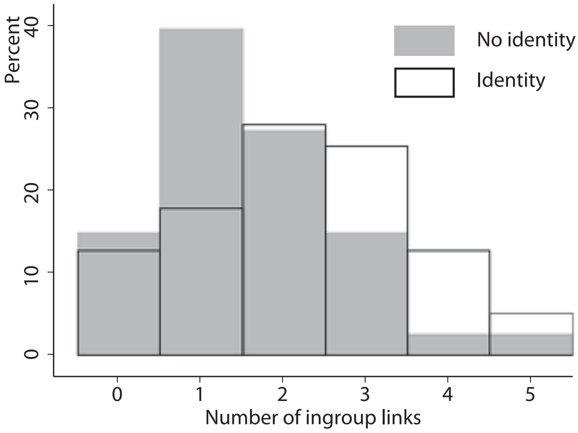
Findings

We find that players systematically form inefficient networks. On average, a player is connected with only 3.2 of the 5 other players in the game and payoffs are about 35 percent lower than those in the efficient network.

Pooling all decisions together, we find that players choose links consistent with payoff maximisation about half of the times. They also often connect to the least well-off player in the network. Lastly, in about two thirds of the remaining cases, links target the 'most popular' player – the player with the largest number of direct connections at that point in the game. Simulation analysis shows that this strategy is responsible for the largest efficiency losses. The efficiency loss would be reduced to 5 percent if links to the most popular player were re-wired according to the strategy that maximises payoffs.

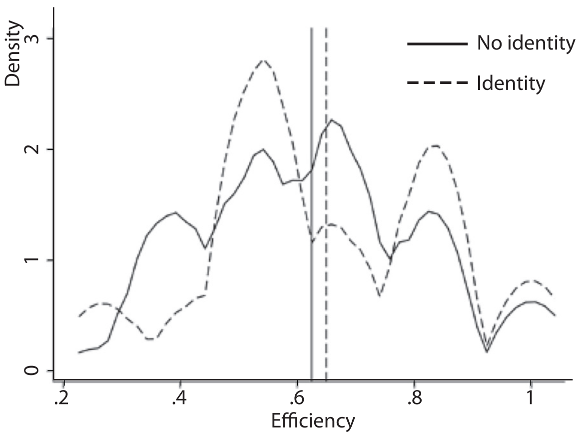
We find some evidence that players are more likely to target the most popular player when it is more cognitively demanding to identify the efficient. Also, we find that links to the most popular player are more common in the second round of the experiment, when complexity is higher and mental resources are depleted. These findings are consistent with models of thinking in complex environments where individuals minimize cognitive costs.

Figure 2. In-group links in sessions with and without disclosure of group identity



Finally, we have two main results on the effect of disclosing information about group identity. First, the frequency of in-group links increases. Figure 2 shows a histogram of the number of in-group links in the final network for sessions where group identity is disclosed and session where it is not. The distribution clearly shifts to the right. A Wilcoxon rank-sum test confirms this difference is significant at the 5 percent level ($Z= 2.23$, $p= .02$).

Figure 3. Network efficiency in sessions with and without disclosure of group identity



Second, we cannot detect a systematic effect of disclosing players' group identity on network efficiency. This is documented graphically in figure 3, which shows kernel density estimates of the distribution of network efficiency in sessions where group membership is disclosed and sessions where it is not.

Policy implications

Our findings on network inefficiency lend support for interventions that change the structure of social networks (Feigenberg et al., 2013; Vasilaky and Leonard, 2013; Fafchamps and Quinn, 2015; Cai and Szeidl, 2016). In these studies, researchers have often focused on creating more connections. Our results suggest that creating incentives for individuals to create different connections – in particular, connections with less popular nodes – may be particularly effective at improving information diffusion.

Our results are also consistent with the existence of deeply held social norms restricting social interaction across groups. This suggests that diffusion of information among farmers in communities with diverse social identities will be challenging. In such communities, programs that promote the adoption of innovations can choose to bypass social structures altogether and rely instead on modern technologies. Recent trials show that agronomic information transmitted via SMS, phone lines, and voice messages can be effective at increasing yields, and discouraging the use of inefficient pesticides (Cole and Fernando, 2012, Casaburi et al., 2014). Alternatively, interventions should ensure that information is disseminated across social groups.

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Chapter 3

Models to Action: Proactive Integration of Social Learning Theory

Jeremy Magruder

1. Social Learning for Technology Adoption

Suppose our primary motivation for the study of social learning is to understand the problem of technology adoption. We accept as given that (a) social learning takes place, so that farmers learn from other farmers about productive characteristics of new technologies; (b) farmers are maximizing expected profits, potentially risk adjusted; (c) farmers do not (at baseline) have perfect information about a new technology. The focus of this brief is to understand not if social learning happens, but rather can we manipulate social learning effectively?
One of the challenges in developing actionable implications of social learning theory is that social learning itself is more of an ambient process: individuals learn from a network which is hard to observe, and most learning opportunities probably take place at hard to predict points in time. Broadly, we can collect a number of social learning models into a relatively simple framework, particularly if we are willing to abstract a bit from learning dynamics. More specifically, suppose we have a network of n members and we want to examine learning on technology k. Let us summarize social learning models similarly to more general social interaction models:

$$Y\,k_{t+1} = \Omega_k\, X_t^k$$

Where Ω_k is an nXn weighting matrix for technology k; and Y^k_{t+1} and X^k_t will be nX1 vectors, often of the same variable at different points in time. For example, with De Groot learning, Y^k_{t+1} and X^k_t would both be beliefs on the new technology, where the Y^k_{t+1} represent the updated beliefs after learning according to the weighting matrix on others' beliefs, Ω_k 1. This formulation also makes clear that the learning structure may depend on the technology, *k*. This may be particularly relevant in agriculture, as heterogeneity in land characteristics may make some individuals' experiences and beliefs more or less relevant to ones' own agricultural decisions, and the learning weighting matrix may be very different for different technologies which interact with different land characteristics.

While simple, and too broad for specific learning predictions, this formulation makes clear that there are essentially two points for intervention that would be consistent with a formal framework. One could attempt to influence Ω_k, the learning weighting matrix; or one could attempt to influence X^k_t, the input vector of information.

2. Efforts to influence model parameters

A number of recent empirical studies have attempted to influence both manipulable parts on the social interaction model of social learning. First, one could attempt

1. This approach is not rich enough, however, to effectively contrast De Groot from Bayes learning, as much of the differences depend on the source of the information and will be realized primarily in dynamic differences.

to influence the social structure of learning. In fact, it seems likely that virtually any extension or training-type intervention would change social learning patterns in some ways: if nothing else, raising awareness of the existence of a new technology may generate an increase in conversations about the technology and the sensitivity to others' beliefs and experiences (particularly if limited attention, as in Hanna *et al.* 2014, is an important constraint to adoption). That said, effective manipulation of social learning patterns would require policies which move the structure of Ω_k in a predictable way, for example by generating new learning relationships. There are some strong *prima facia* challenges with influencing the social structure of learning. As learning relationships are fundamentally contextual and developed over potentially long time horizons, it is unclear to what extent a short-run program suitable for trial can move these relationships. In agriculture, this hurdle seems particularly high, because of the interaction between technological growth and hard-to-observe land characteristics. That said, there is some reason for optimism: three recent studies have focused on proactively changing Ω_k, with promising results. Outside of agriculture, Cai and Szeidl (2016) try to change elements of Ω_k from zero to non-zero, by forging introductions and conducting trainings between business managers of small and medium enterprises in China. Fafchamps and Quinn (2014) similarly form random connections between entrepreneurs in Africa by forming training groups of these entrepreneurs. More closely related to this report, Vasilaky and Leonard (2016) generate connections between female cotton farmers in Uganda for a joint training and find increased yields for those paired (as opposed to trainings which did not emphasize social capital). While none of these studies can directly isolate changes in learning patterns as the mechanism for these results, and the large broader literature on social interactions suggest the importance of a variety of channels, they do suggest that systematic manipulation of learning networks may be feasible. One may even interpret these estimated effects as lower bounds of what could be achieved as all interventions reviewed here generate random connections rather than building connections that theory suggests may be particularly useful.

The second potential parameter for manipulation is X_t^k, the vector of existing information, beliefs, or practice that farmers are learning from. Of course, any extension program involves a manipulation of X_t^k; as new information is provided the learning environment changes. In many ways, this manipulation may be attractive to researchers as the outcomes of the trainings – new knowledge or practices – may be much easier to measure than a change in the existence or intensity of a social tie. Efforts to incorporate social learning theory into the manipulation of knowledge or practices, then, should be based around a systematic element on the manipulation of X_t^k, for example, by changing the identity, number, or knowledge set of new trainings.

A number of recent studies have explored practical means of manipulating X_t^k. For example, Kremer *et al.* (2011) paid local community members to serve as marketing agents to promote water chlorination in rural Kenya; Miller and Mobarak

(2014) identified "opinion leaders" through guided focus groups, promoted improved cookstoves to those leaders, and shared information about those leaders' adoption decisions with other villagers; and BenYishay and Mobarak (2015), promoted Pit Planting in Malawi (similar to the main evaluation results presented here) cross randomized villages to receive a single lead farmer chosen through the usual extension process against villages which would receive 5 "peer farmers" elected by disparate focus groups[2]. These interventions are heterogeneous in a number of dimensions, even beside the technological and geographic contexts: first, the selection rule for the injection point is different between interventions. Second, the presence of incentives in Kremer *et al.* (2011) and for some groups in BenYishay and Mobarak (2015) alter the interpretation of social learning models, as most social learning in agriculture (and elsewhere) takes place in the absence of direct financial incentives. Perhaps unsurprisingly, these interventions have been heterogeneously effective – Kremer *et al.* (2011) and Miller and Mobarak (2014) find significant adoption effects, while BenYishay and Mobarak (2014) find larger adoption for unincentivized lead farmers than a group of unincentivized peer farmers, which reverses in the presence of incentives.

Taking these results together, we can conclude that there is at least some evidence that injection points for new ideas affect ultimate take-up. Immediately, this suggests that Ω_k is not a simple, complete network graph: if the identity of information sources affects take-up rates than everyone does not learn equally from everyone else. This is also a necessary condition for the effective integration of social learning theory into policy: if it were the case that social learning happened equally and efficiently regardless of the injection point, then there would be little need for the consideration of social learning in the design of implementation plans. Moreover, in some contexts, local institutions were identified which could practically exploit heterogeneity in learning potential. However, we have little to guide our thoughts on how the heterogeneous selection rules used in these studies map into the network graph: if one institution is effective in one context, but we do not understand how it targeted the network, it will be difficult to guess whether it would be similarly effective for a different technology, geographic context, or time period.

One study helps bridge the gap between theory and selection mechanisms based on local institutions. Banerjee *et al.* (2012) examine the diffusion of microfinance in India. Just as in the previous studies, partners were chosen to disseminate and market the microfinance product using local institutions. More specifically, local leaders were identified, who had key roles in the community such as shopkeepers or schoolteachers. Banerjee *et al.* demonstrate that in villages where these leaders occupied positions in the network which theory suggests should be particularly useful for dissemination, overall take-up was higher. This provides support for a broad class of diffusion models, though specific guidance on the design of

2. This study also cross-randomized incentives to promote the technology as marketers.

particular implementation policies remains somewhat elusive as any variation in the implementation policy was measured and assessed ex post and is based on natural, rather than explicitly exogenous, variation.

Taken together, this body of literature suggests that entry points matter, which indicates that there is a role for incorporating learning theory to manipulate social diffusions. What remains is to demonstrate that a specific theory can generate useful predictions on partner selection. In the remainder of this brief, I discuss work-in-progress by Beaman, BenYishay, Magruder, and Mobarak (2015) which explicitly chooses entry points based on a diffusion theory and lessons which derive for future work.

3. Proactive implementation from Diffusion Theory

There are a number of sophisticated theories of social learning which could be integrated into the choice of entry points. However, a few practical concerns may mute the differences between some models. Returning to Equation 1, many of the precise predictions for different models are based on the formation of beliefs, and the beliefs of network members. These are difficult to reliably estimate. Moreover, measurement of learning weights (Ω_k) are likely to generically have a great deal of error as well, particularly for learning processes which depend on technological characteristics.

What is needed for a systematic study of entry points is a class of theories under which the choice of entry point may have important implications for adoption. Beaman *et al.* (2015) propose using threshold models (e.g. Granovetter 1978; Centola and Macy 2007; Acemoglu *et al.* (2011)) as a starting point. More specifically, suppose each individual has a threshold λ, and they adopt pit planting if they are connected to at least λ adopters. If $\lambda = 1$, described by Centola and Macy 2007 as a "Simple Contagion", then being connected to a single adopter generates adoption. In equation 1, this is approximately the case where Y, X are vectors representing adoption decisions, and $\Omega_k (i,i)$ is small relative to $\Omega_k (i,j)$ for some j's[3]. Under simple contagion, the choice of entry points is relatively unimportant: people will generically be connected somehow to the village network, and so getting the idea started with almost anyone is likely to bring about a high adoption rate. To the extent that one may train multiple partners, one may as well spread them out in the network to avoid redundancy in information.

An alternate possibility is that $\lambda > 1$. This case, termed by Centola and Macy (2007) as a complex contagion, is very different in terms of its predictions for entry points. In our above model, it would be a case where $\Omega_k (i,i)$ is large relative to the $\Omega_k (i,j)$ elements. If $\lambda > 1$, and there is only one farmer trained in the new technology, then no one will ever be persuaded to adopt. Moreover, even if multiple

3. Abusing notation due to the binary nature of adoption decisions, and assuming that the process is memory-less (i.e. you don't accumulate adoption "potential").

farmers are trained in a new technology, the choice of entry points becomes extremely important: many potential pairs of partners will share no connections. If a pair of partners is trained and they do not share connections, there would again be no adoption.

In work-in-progress, Beaman *et al.* choose farmers as entry points *ex ante*, depending on which farmers would be ideal under different values of λ. More specifically, they first map networks, and then select partners for training by determining which partners would be optimal given the network map and different distributions of λ. Treatment villages, then, are assigned a pair of partners by choosing a pair who would be optimal under either simple or complex contagion. These partners are trained in a new agricultural technology being promoted by the extension service. They will compare these results to a benchmark group of villages where the extension agent chooses 2 partners according to their typical methods, and also test whether geographic data is sufficient for choosing these optimal partners in another group of villages. The primary outcome of interest is adoption of a new technology.

As results become available from Beaman *et al.* (2015), we will learn more about whether there are potential gains from attempting to manipulate X using threshold theory. Moreover, an advantage of this theoretical framing is that it suggests a clear guidance for extension practitioners who would interpret these results with a knowledge of local context. This advantage may be very large and very practical compared to the informal approaches which document that an institution is effective at finding entry points in some context: implementers may be very effective at identifying local institutions to generate a particular outcome. For example, if Beaman *et al.* determine that farmers need multiple data points to be persuaded to adopt, then a sensible extension strategy would work to guarantee multiple demonstration plots or partner farmers in the same village, and take steps to ensure that those trained are in similar parts of the village network. For example, one would want to engineer the opposite of the focus groups in BenYishay and Mobarak (2015), which solicited 5 different focus groups to each select 1 farmer: instead, if one knew that focus groups were an effective means of finding partners in the local context, one would want to find the main group in the village, and train multiple farmers within that group.

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Chapter 4

Evaluating Targeted Subsidies

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Abstract
This note dicusses the value of targeting in the context of technology adoption subsidies. Whenever agents are heterogeneous in their impact on others, targeting subsidies to those who have the greatest externality will improve the impact of subsidies. However, the relevant information needed for efficient targeting may sometimes be private. We describe incentive compatible methods to target subsidies on such private information. Drawing on the existing literature, we clarify what type of private information may be extracted, and how it may be useful for targeting.

1. Heterogeneity of externalities and targeted subsidies

Interventions beyond simple marketing are often necessary for the adoption of a new technology. The most common intervention is a subsidy, or discount, for the new technology. These may be provided by the inventor of a technology, or some other group interested in the technology's adoption. Subsidies for technology adoption are generally motivated by one of three rationales: differing beliefs, information externalities, or direct externalities.

- In the first case, a subsidy is motivated by different beliefs, or preferences over outcomes, between the (potentially) adopting population and the subsidy provider. This may even occur if the subsidy recipient(s) can afford the technology, and the benefits of the technology accrue entirely to the adopter.
- However, in many cases, the benefits of the technology may accrue, in part, to others. This benefit may be due to the information generated by early adopters on the costs of operating the technology and its returns. For many technologies, the rate of return depends on local conditions. For example, in agriculture, climate, soil conditions, prices, and so on, matter for the returns to fertilizer, seeds, and irrigation. Therefore, local experimentation is needed for farmers to make technology adoption decisions (Besley and Case, 1993; Conley and Udry, 2010). However, as the information arising from a local experiment is a public good—farmers in similar conditions benefit from an experimenter's labors—it will be under-provided (Foster and Rosenzweig, 1995; ATAI, 2011). As such, many programs subsidize experimentation: directly through discounting new technologies, or indirectly through extension workers whose demonstrations can effectively substitute for some local experimentation.
- The above information externalities are a special case of more direct externalities. That is, the subsidy provider may also want to promote a technology, for instance, pest and disease control innovations can help both adopters and their neighbors.

This note is interested in the targeting of subsidies driven by a technology with heterogeneous externalities. For example, the externality of information generated by an early adopter of a new varietal will depend on the density of her social network, and the externality due to pest control will depend on the number of neighbors. In these situations, the cost-efficiency of technology subsidy programs can be enhanced by targeting recipients with the greatest externalities.

There are many potential sources of heterogeneity in externalities. There can be variation in

- the subsidy recipients' position within the local social network;
- her willingness to use the technology;
- her skill in doing so;
- her willingness to share information with, or help others;
- how representative she is of the community;

- the specific use she has for the technology.

If there is a lot of heterogeneity across individuals, then targeting subsidies to those who have the greatest externalities promotes information creation and diffusion, as well as increasing the social returns to technology adoption.

2. Targeting based on private information

In many cases, it may be interesting to target subsidy recipients based on their private information. For instance, one may want to target a recipient based on how eager he or she is to experiment, or what is his or her position in the social network.

As Chassang, Padro i Miquel, and Snowberg (2012) highlight, such private information must be elicited in an *incentive compatible way*. For example, when thinking about subsidies that depend on an individual's position in a social network, community members may exaggerate their own centrality, and downplay that of rivals, in order to gain a subsidy.

Incentive compatibility disciplines the range of targeting mechanisms that can be implemented. Broadly, the following principles must be respected:

1. participants must be aware of the rules of the mechanism they are participating in; i.e., be aware of how their response affects targeting;
2. deciding which information to elicit from participants is equivalent to deciding on a choice problem to offer them;
3. targeting schemes must 'respect participants' preferences', that is, although allocations may be random, allocations that participants prefer must be more likely.

We illustrate the above principles through three examples of information elicitation, and targeting based on that information.

Private cash value for the technology. By giving potential recipients a choice between obtaining the subsidy at no cost for a relatively low probability, or obtaining the subsidy at some cost with a higher probability, it is possible to elicit the participant's cash value for the technology. At one extreme, take-it-or-leave-it prices deliver a 0-1 assignment as a function of willingness to pay in cash.

Private effort value for the technology. Instead of offering participants a trade-off between a higher probability of getting a subsidy and cash, one can offer the participant trade-offs between obtaining the subsidy and physical effort—for example, performing basic tasks such as plowing a field—or even between obtaining the technology and time/attention—by attending additional information sessions on the relevant technology.

Preferences over other recipients. Basing subsidy assignment on private information that relevant stakeholders have on potential recipients may be particularly attractive. Voting schemes provide one way to do so. Importantly, the outcome of a vote need not by deterministic, that is, plurality candidates need not be given a subsidy. It is sufficient for the likelihood of receiving the subsidy to be monotonically increasing in the number of votes.

3. Existing findings

The existing literature provides useful guidance on what private information may be usefully elicited from participants.

Willingness to pay cash. The fear that subsidized technologies will be left unused and poorly maintained is widespread. If people who are willing to pay for a technology are more eager to use it, higher willingness to pay may signal a greater externality on others.

As a result, many groups are opposed to heavy subsidization of new technologies—including NGOs that focus on technology adoption. With only small subsidies, a new technology is assigned only on the basis of willingness to pay cash.

Recent evidence from the health sector shows that technologies that are easy to use, such as insecticidal bednets, are well used even if they are heavily subsidized (Cohen and Dupas, 2011; Dupas, 2009; Tarozzi *et al.* 2013). For such technologies, targeting based on willingness to pay cash may not be very useful. For complicated agricultural technologies that require significant experimentation effort, selection of who to target may be much more important in terms of information generation and learning.

Willingness to pay with effort. As argued in Cohen and Dupas (2011), willingness to pay cash may be a very noisy signal of intended usage when participants are credit constrained, or face large liquidity risks. If this is the case, non-monetary choice problems may reveal more useful information. Findings from Atalas *et al.* (2013) and Dupas *et al.* (2016), who study the effectiveness of mechanisms that depend on physical effort or time for targeting cash transfer programs and health subsidies, respectively, suggest that time and effort may be useful in targeting participants with liquidity constraints. These mechanisms serve to target poor recipients. It is unclear whether they can be used to select different types of subsidy targets.

Social information. Several studies show that targeting based on social information may be useful. Beaman *et al.* (2015) show how allocating technologies to more central participants may affect adoption. Banerjee *et al.* (2014) show how both network information and direct elicitation may generate useful information about community members best able to diffuse new information.

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Chapter 5

Learning versus status quo bias and the role of social capital in technology adoption: The case of cocoa farmers in Côte d'Ivoire

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Abstract
In this study, we allege that the hypothesis in favour of a status quo bias is a plausible explanation when it comes to better understanding the lack or the absence of adoption of the best farming practices in small rural communities in sub-Saharan Africa. Our results also suggest that the greater a farmer's social capital, the more likely he is to exchange information, learn and eventually revise his farming practices. Such information about farming techniques disseminates through weak ties (bridges) built within agricultural organisations more than across family or diaspora members (i.e., via their stronger ties).

1. Introduction

In this study, we investigate why Ivorian cocoa farmers have a yield per hectare which is far below what they could "relatively easily" obtain (i.e., from 1500 up to 3000 kg/ha in pilot farms vs. less than 500 kg/ha on average in real life). More generally, how to account for family farming's failure to improve their crop yields in sub-Saharan Africa? The first answer that springs to mind is that they usually do not implement/invest into the most efficient agronomic practices. Less obvious is why? More specifically, what attitude (e.g., status quo or routine versus proactive behaviour) does the farmer adopt about uncertainty, risk and investment? What drives the adoption/diffusion of new agricultural technologies? Firstly, one may want to consider the smallholder's awareness of the need to adopt new technologies or to change his farming practices in order to reach higher yields. This implies that the smallholder shows some intellectual curiosity and interest in developing his agricultural skills and acquiring new knowledge in terms of agronomic practices. Secondly, one must take into account the farmer's capability to weigh up the pros and the cons (i.e., the benefits to be gained against the costs) of adopting them. Eventually, this implies that the farmer shows capability to adopt and effectively use the new agricultural technology, should he so decide.

Barriers to agricultural technology adoption in the economic development literature mostly include external constraints like credit, inputs and output, land and labour market imperfections as well as informational inefficiencies [1]. In this study, we focus instead on internal constraints in order to better understand agronomic decision-making. We take seriously what the Nobel Laureate Herbert Simon (1955, 1957) called "bounded rationality," which refers to situations where actors face alternatives for which they lack information about the problem in question and/or the cognitive capacity to weigh the pros and the cons in order to make a decision, even such a basic decision as learning (see also Kahneman 2003).

To some extent, we expect learning to occur only if the farmer expresses some dissatisfaction, which is a corollary of his awareness about an anomalous state of knowledge. In fact, the farmer may not even be aware of his needs or willing to make an effort to satisfy his needs for information. Eventually, this prevents him from getting out of a habitual behaviour or any mental/cultural trap that limits *in fine* his decision-making freedom (Haushofer and Fehr 2014).

It is also recognized that the need for information may become apparent to the farmer during interactions with peers who may be perceived as more or less trustworthy depending on both their individual and aggregate (i.e., at the community/village level) stocks of social capital. In other words, what about social learning through more or less active participation in social networks (Conley and Udry 2001; Munshi 2004, 2008)? How important is an individual's social capital in shaping agricultural technology adoption, where social capital refers to one's

1. See, for instance, the literature review by Jack (2013).

perception about community members' solidarity, fairness and trust and each member's willingness to live by the norms of community as well as more or less active participation into community activities (Bowles and Gintis 2002).

2. Preliminary evidence for a status quo bias in decision-making

Both a farmer's need for information and his social capital are difficult to pin down. For instance, the need for information cannot be observed directly but only through the farmer's actions. What is observable and measurable is the action or, on the contrary, maintaining the status quo with respect to agronomic practices (i.e., "business as usual", habits, automaticity bias, etc.), where we usually call status quo bias the resistance to change. Because a smallholder's need for information is not directly observable, we explicitly asked them in September 2014: "Have you changed your farming practices over the last two years?" That was about three years after the Ivorian post-election crisis.

Our social capital and agronomic practices survey covers five villages/communities located in the so-called "last cocoa belt" (i.e., South-West Nawa region) of Côte d'Ivoire [2], and concerns more than twelve hundred smallholder cocoa producers. Only 30% (i.e., less than four hundreds) had revised their agronomic practices. Thus, smallholders disproportionately stick to the status quo, which corroborates results from a lot of decision-making experiments (see, for example, Samuelson and Zeckhauser 1988).

What are the possible explanations for this bias? We asked them what is the main reason why they have (not) made any change via an open-ended question. Among those farmers who did not modify their agricultural practices over the last two years, 40% declared that this was because they were "satisfied". Only 20% claimed to "lack resources" whereas 19% referred to "habits" thus suggesting routine behaviour. This is preliminary evidence, which suggests that a smallholder may not be a rational "maximiser" (i.e., striving to get the best out of every decision and any action that follows). Rather, he may be closer to a "satisficer" in accordance with Simon's neologism for "satisfying-sufficing". Interestingly, farmers who did not change their farming practices over the last two years do perform worse on average today in only two villages over the total of five villages surveyed [3]. The null hypothesis of independence between "having changed farming practices over the last two years" and "productivity change over the last three years" is rejected at the 5% significance level. Among those farmers who did (not) modify their practices, two-thirds (three-quarters) experienced no productivity change whereas one-fourth (one-fifth) experienced an increase in productivity.

2. The average yield is 442,7 kg/ha, ranging from 354,5 kg/ha in the least productive village up to 583,9 kg/ha in the most productive village.

3. At least, farmers who did revise their practices over the last two years do not, on average, perform worse whatever the village we consider…

It is also worth noting that, among those farmers who changed their practices, three-quarters report agricultural organisations and cooperatives as their main source of agricultural information and learning. Other sources of learning or information like media (TV, radio) or business relationships (input suppliers, output buyers) are very few in number, 4% and 16%, respectively.

Next, what about the difference in behaviour between internal (mostly Baoulé) and external (mostly coming from Burkina Faso and Mali) migrants? Do they have a particular propensity for having changed their farming practices relative to natives? Are we able to infer that natives are more conservative and thus less inclined to take risks? Interestingly, natives are more inclined to favour the status quo compared to migrants. The null hypothesis of independence is here rejected at the 1% significance level. The opposite is true for those farmers who claim to have administration rights for their plantation. Finally, farmers working a relatively small plantation exhibit a stronger status quo bias, while farmers among the highest performers show a proactive behaviour. Thus, a native farmer working a small plantation and who does not have administration rights over it tends to exhibit a stronger status quo bias [4].

3. Social capital, information exchange, and new technology adoption

How to explain the status quo? In this study, we explore the role of both structural and cognitive social capital. To this end, we first build using a multiple correspondence analysis, a two-dimensional civic capital space within which each farmer is located through coordinates relative to the others (see Bourdieu 1979, for a well-known application of this data analysis technique). Our civic capital space reflects (classified in decreasing order): i) solidarity (e.g., "most of the time, people try to help."); ii) reciprocity (e.g., "people try to take advantage."); iii) trustworthiness (e.g., "most people can be trusted."); and iv) cooperation (e.g., "how often did you take part in a collective action with others over the past three years?") [5]. Thus, we end up with a distribution of civic capital in each surveyed village/community (see Figure 1.a-b). These individual coordinates provide a much less noisy measure of individual trust than usual discrete variables such as "in general, one can trust people."

Firstly, farmers are located in the 2D (two dimensional) civic capital space as depicted in Figure 1.a where those located in the Northeast quadrant tend to see people in their community as trustworthy, fair, and caring. They are also more actively involved in community actions. In contrast, farmers located in the Southwest quadrant are distrustful and suspicious of other people in their community. Note that, similarly to results obtained across countries or for regions belonging to the

4. The null hypothesis of independence between "having changed practices over the last two years" and age on the one hand, and education on the other hand, cannot be rejected.

5. See, among others, the literature reviews by Durlauf and Fafchamps (2005) and Fehr (2009). Guiso et al. (2011) is our reference text to civic capital.

same country (e.g., Italy), there is a wide degree of diversity across villages, even though they do not lie very far apart from each other geographically. Thus, Villages 4 and 5 are characterised by the highest mean civic capital. Incidentally, they are also the most productive ones, which suggests that it may be useful to look at their characteristics (e.g., ethnic, religious, and political balances, history, infrastructures).

Figure 1.a. Cloud of farmers across communities and representative farmers for each village (mean level and 95% confidence ellipse) in the 2D civic capital space.

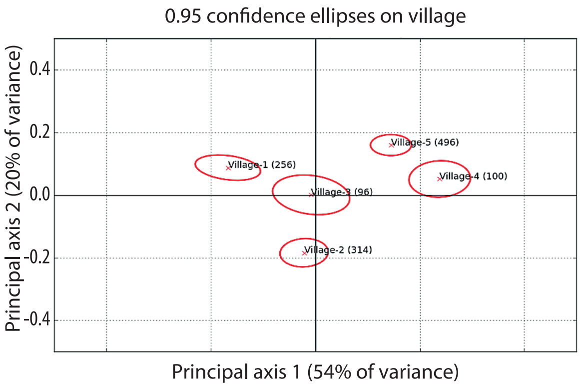
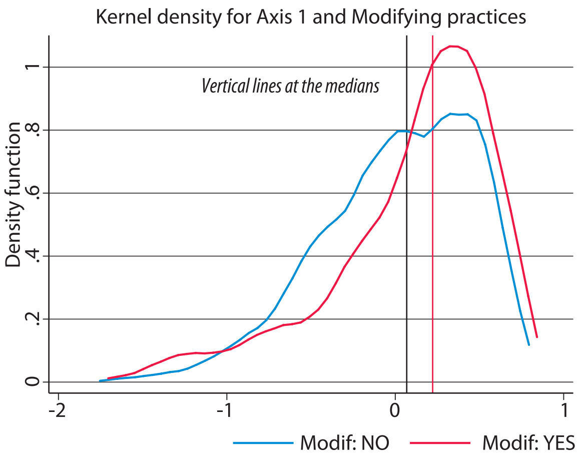


Figure 1.b. Distributions of civic capital along the 1st axis and modification of agronomic practices ('yes' = red, 'no' = blue).



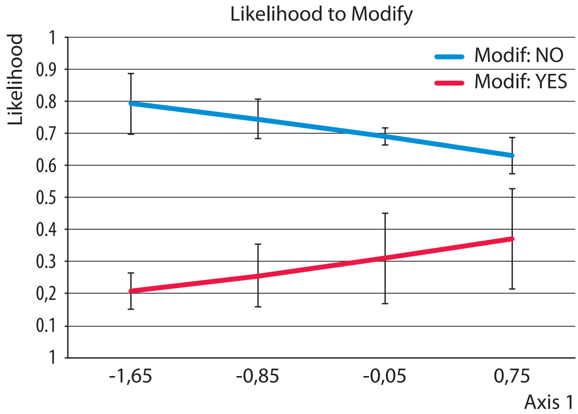
Secondly, the distributions along the first (x-) axis 6 of the civic capital space of farmers who did (red line), and respectively did not (blue line), change their farming practices over the last two years, are depicted in Figure 1.b, where vertical lines indicate median levels of civic capital for each group of farmers. The message here is clear: Most farmers who did modify their practices are concentrated on the right of the distribution of civic capital, while the distribution of farmers who did not adjust their practices is skewed to the left.

Our study aims at testing the following null hypothesis: Individual social capital has no impact on a farmer's decision to have revised his agronomic practices over the last two years. Indeed, a rather optimistic belief about community members' trustworthiness (compared to rather pessimistic beliefs) should lead a farmer to be more proactive in seeking information and trusting those in possession of it like, for instance, representatives and/or members of agricultural organisations, family or diaspora members, neighbours, and friends, eventually leading him to revise his current farming practices.

The determinants of civic capital are examined as a preliminary step to testing the above null hypothesis. To this end, we perform a (OLS) regression where the dependent variable is the first axis of the above MCA 7. Firstly, following Granovetter (1973, 1985), our model corroborates the strength of weak ties in exchanging agricultural information, learning, and technology adoption, which influence a farmer's civic capital. We also find that relational (i.e., outside the family/diaspora networks) in contrast to structural (e.g. family network) embeddedness is positively, respectively negatively, related to civic capital 8. More specifically, in contrast to agricultural information exchange and learning, the exchange of personal information between members (as a declared benefit of group membership) is not significantly related to an individual's civic capital. Secondly, the smallholder who has the administrative rights on his plantation is endowed with more civic capital while migrants are more inclined to mistrust and suspicion than natives. Thirdly, civic capital is related neither to the age nor to the education of the farmer. Fourthly, civic capital does not depend on the size of the plantation. And last, but not least, there is an inverted-U shaped relationship between the crop life cycle and civic capital. A farmer's civic capital increases during the early stage of growth of the plantation. It then reaches a maximum when the plantation reaches maturity (i.e., highest yield) and, eventually, decreases.

6. That is, the most important dimension in terms of the amount of variance accounted for: 54%. (The first and second axes account together for 74% of the variance.)
7. All models are estimated with and without dummies for villages: A check about the relative importance of inter- versus intra-variability.
8. Most farmers (90%) belong to at least one group and less than one hundred farmers are members from more than two groups. For two-thirds of them, the group that they would consider the most important is an agricultural organization (e.g., cooperative, "groupe d'intérêt économique"). Finally, as to whether they found something back in belonging to a group, this is an almost unanimous 'yes'.

Figure 2. Marginal effects of civic capital (x-axis) on having changed or not farming practices (y-axis).



We now perform a Logit regression where the dependent variable is the answer ('Yes' or 'No') to our key question: "Have you changed your farming practices over the last two years?" The farmer's civic capital is a robust determinant of agricultural technology adoption even after controlling for group memberships, smallholder's characteristics 9, plantation size (quartiles), and the crop life cycle, which, interestingly, exhibits now a significant U-shaped relationship with fine-tuning processes and technology adopted by the farmer. More precisely, the probability that a farmer has changed his farming practices over the last two years increases monotonically from 20% up to almost 40% with civic capital as measured by the first axis obtained from the MCA. In Figure 2, we depict the marginal effects of civic capital on having changed (red line) or not (blue line) farming practices for different levels of individual civic capital. In addition, it should be noted that both internal and external migrants on the one hand, and farmers with the administration rights on their plantations on the other hand, are more likely to have changed their farming practices.

These relationships between a farmer's civic capital and the decision to make changes in his farming practices with the crop life cycle intrigue us. In our view, it should lead us to wonder about the different spheres of knowledge, in this case, the traditional agricultural knowledge (i.e., technical-practical) and the more technical-scientific knowledge, which requires to be effectively relayed through experts and scientists who most often come from international organisations or Northern academic institutions (Olivier de Sardan 1995). Is it relevant to address the natural and social environments separately? In our view, such a question is

9. Control variables here include migrant versus native, age (entered in quadratic form), education (binary), administration rights (binary), household size (continuous), and the number of males older than 18 years who work in farming (continuous).

important and should be addressed in future research.

The next challenge now is to better understand the attachment of such a large share of farmers to the status quo. At this stage, it is interesting, based on our research, to emphasize that Ivorian cocoa farmers already make use of inputs (fertilisers, pesticides, and fungicides) as well as give special attention to shade. Indeed, they are more than 80% to report having made use of pesticides and fungicides during the year preceding the survey, and nearly all of them took care of the trees by removing suckers. Maybe, the only downside is that they are only slightly more than half to have applied fertiliser. Thus, most farmers seem to apply a mixture of practical and scientific rules of thumb year after year, whereas those who fine-tune their choices from one year to the next independently from the tree life cycle are the exception rather than the rule.

4. Conclusion

If a status quo bias in terms of technology adoption emerges from our survey of cocoa farmers whereas they only get an average yield three to four times below what they could quite easily obtain, it also appears that the individual social capital of a community member is positively associated with the benefits he derives from interacting with peers within farming organizations. This eventually leads him to revise and fine-tune his farming practices over time. Thus, weak ties built up across members of farming organisations (e.g., cooperatives) appear to be more conducive to both information exchange and new technology adoption than are stronger ties developed among family or diaspora members.

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Chapter 6

Adjusting extension models to the way farmers learn

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Abstract
Extension services play a key role in helping developing countries modernize their agriculture and grow. Yet, these services have almost universally performed below expectation. The hypothesis proposed here is that extension systems could perform better if they delivered services structured on the way farmers learn. To inform this hypothesis, we review critically existing extension systems, extract from learning models and empirical studies of adoption regularities about how farmers learn, and propose a set of reforms to existing extension services that match learning channels. Major reforms to extension would select contact farmers as entry points for diffusion according to the specific constraint to be addressed, organize head-to-head trials in farmers' fields under the jurisdiction of farmers themselves, use private agents in value chains as sources of information, and inform social networks about the existence of innovations using mass media to induce a demand-driven search for information from contact farmers.

The role of agricultural extension services for development

As was learned from the Solow growth accounting model, Total Factor Productivity (TFP) growth is an important source of aggregate economic growth. This is particularly true for agriculture. For that sector in all developing countries in 2000-07, 2/3 of agricultural growth is explained by productivity growth and 1/3 by factor deepening (Evenson and Fuglie, 2010; Gollin, 2010). Improving agricultural productivity is for that reason one of the key objectives for governments in most developing countries, not only from the perspective of growth, but also to achieve food security and improve the welfare of a large share of their populations that is engaged in agriculture.

Public investment in productivity enhancing public goods and technologies continues to be large (World Bank, 2006), even if there is a chronic under-investment in agricultural research (Alston, 2000). However, adoption of technological innovations is constrained by many factors (Jack, 2011). Prominent among them are the following that we address here:

– Low profitability of the innovation in a risk-return framework
– Lack of information about the availability of innovations
– Lack of information about how to use available innovations given heterogeneity of farmer circumstances

Agricultural extension services have a fundamental role to play in disseminating information about the availability of new technologies and the fit of innovations to individual conditions of use. This is particularly the case in developing countries where value chains are yet poorly developed, with missing agents such as agro-dealers and commercial agents that could be sources of information about new technologies.

Agricultural extension is one of the largest public institutions in developing countries, employing and training more than a million extension workers at a world scale (Anderson and Feder, 2007). According to the Neuchatel Initiative (Swanson and Davis, 2014), there are some 618,000 extension agents in China, 90,000 in India, 54,000 in Indonesia, 46,000 in Ethiopia, 35,000 in Vietnam, and 24,000 in Brazil.

The general observation, however, is that current extension systems have not lived up to expectations. Available technological innovations are often only scantly adopted. Large segments of the farming population do not know about the existence of these innovations, or do not know how to use them for maximum efficiency. There is, consequently, a large literature critical of current extension services. Dispersed attempts have been made to experiment with alternative designs to improve on current extension systems. The proposition behind this note is that the redesign of extension services must correspond to the way farmers learn in order to effectively induce adoption and productivity gains.

Traditional approaches to extension

Traditional approaches to extension include the Training and Visit and the Farmer Field School systems. They are based on Everett Rogers' (2003) model of diffusion of innovations where farmers will adopt an innovation once they are surrounded by a threshold of adopters. Both systems have been widely used and also widely criticized.

Training and Visit (T&V)

The World Bank promoted the "Training and Visit" system in over 40 developing countries in the 1970s and 1980s. This system introduces a cadre of trained agriculture extension workers operating under a single line of command, replacing (in India) the previous system of multipurpose village-level workers. At the lowest level of the T&V system are village extension workers who cover each about 800 farm families, 10% of which are chosen as "**contact farmers**" -- mostly larger, well-to-do farmers, who receive intensive training in communication from the agriculture extension workers and are expected to adopt the improved practices and disseminate them among other farmers in the community (Feder, 1986).

What has been the impact of the T&V extension system? This question is yet to be answered with rigorous impact evaluation techniques although there has been growing evidence accumulating over the years. Some of the early evaluations have been in the form of structural economic analyses of investment projects that estimate benefits to farmers and rates of return using an economic surplus approach (Anderson and Feder, 2007). Feder (1986) estimated no significant impact of T&V-type extension on rice production in India, while the return for wheat producing areas was estimated at 15% using simple differences between districts with and without the T&V system a few years after introduction of the extension system. While it is hard to attribute causality, as the author acknowledges citing lack of disaggregated panel data and identification options, these are the only early estimates available.

More recently, Gautam (2000) studied the impact of a revised extension system in Kenya based on T&V called the NEP-I and NEP-II projects. He found that the extension system was mis-targeted away from smallholder farmers. In addition, the system was not effective for beneficiaries. First, the content of services was not demand-driven: it was mainly focused on modern methods of maize production while many smallholder farmers require services on diversified cropping systems and less costly technology. Second, there was no notable change in quality and quantity of extension services from before the program. Third, adoption followed awareness that was limited to maize-related messaging and technology, which already had a high baseline level implying limited impact of the new program. Fourth, the system was targeted at districts that already had high baseline productivity, again, with limited potential for impact. Finally, productivity increased substantially in districts with low baseline productivity but since most of the program was targeted towards high productivity districts, data do not reveal a significant overall impact of extension services.

Anderson and Feder (2007) concluded their review of evidence on T&V by claiming that the system introduced a top-down hierarchical structure with no adjustment to farmers' demands for services, no accountability to farmers, no effective feedback mechanisms, a strict schedule of visits (with no flexibility and no adjustment to heterogeneity of farmer circumstances), and that it was too costly and excessively dependent on external funding, consequently failing to achieve financial sustainability. While the system was largely abandoned in its original form, it still forms the basis of most current existing extension services.

Farmer Field School (FFS)

Under the FFS approach, trained facilitators bring student-farmers to training schools to build skills using a discovery-based approach to learning, i.e., using experimental methods, typically with treatment and control plots managed by the student-farmers themselves under guidance of the trained facilitators. FFS is a participatory approach intended at developing a farmer's own understanding and decision-making capacity, rather than a top-down approach of transfer of information on what to do as in T&V. Student-farmers are trained to not only learn and decide, but also to communicate with others in the community. Results show that the approach can be effective in teaching farmers and helping them decide for themselves under their own circumstances, especially for such issues as the implementation of Integrated Pest Management practices and seed selection (Waddington and White, 2014). The problem with the approach is that it is not cost-effective, and as a consequence is not scalable and sustainable. In addition, trained student-farmers have difficulty communicating to others what they have learned as it is too complex to be transmitted to un-trained farmers. Additionally, they are not equipped with demonstration tools (such as treatment and control plots as used at the FFS) in attempting to provide the information to others.

Agricultural extension system and National Food Security Mission (NFSM) in India

Dedicated agricultural extension services in India, like most around the world, started with the top-down public T&V approach promoted by the World Bank during the Green Revolution period. Over time, this system has evolved to address some of the criticisms of limited reach and inadequacy of adaptation of content to local context. The current public extension system involves the Department of Agriculture at the national and state levels, with district and block level officers in charge of implementation. In recent years, under the current 12th five-year plan (2012-17), a decentralized agency known as the Agricultural Technology Management Agency (ATMA) has become the main coordinating body in charge of implementation. ATMA is a multi-stakeholder agency involving farmer interest groups, NGOs, the private sector, and public officials from different line departments within the agricultural sector. The link between research and extension is mainly overseen at the national level by the Indian Council of Agricultural Research (ICAR) and at the state level by State Agricultural Universities (SAUs). Krishi Vigyan Kendras (KVK), established at the district level, are experimental stations of SAUs where new technologies are tested on experimental plots and extension officers are trained for dissemination.

Recent years have seen a rise in private sector involvement in agricultural extension on a modest scale, including public-private partnerships (PPP), following liberalization and changes in agricultural policies in favor of increasing private sector roles. Some of the PPP initiatives are under the form of agri-clinics and agri-business centers covering parts of the country. These initiatives focus on providing agricultural advisory services and sale of inputs through a cadre of trained agricultural graduates. Private sector players such as ITC Limited, the Tata Group, and the Godrej Group among others have engaged in contract farming as part of vertical integration of their agro-based industries. They have provided extension services by establishing a network of agri-business centers and information kiosks (such as e-choupal by ITC and Tata Kisan Sansar by Tata Chemicals) that provide marketing and price information to farmers.

In addition, many NGOs provide the last mile connectivity between the extension system and farmers through self-help groups (SHGs) and farmer-based organizations (FBOs). BASIX, PRADAN, and BAIF are large national level NGOs engaged in farmer welfare and increasing agricultural productivity, concentrated in the southern Indian states.

Mass media have always been used both by public extension system and more recently by NGOs. Specialized programs on TV, Radio (Krishi channels), and newspapers are among important avenues through which farmers get information. More recently, the government has set up "Kisan call centers" to address demand-driven information requests. Non-profit technology firms like Digital Green provide video-based extension services that have been shown to have better impact than traditional systems.

Glendenning *et al.* (2010) and Ferroni and Zhou (2012) evaluated the Indian extension system, finding many inefficiencies and they call for greater synergies between private and public sectors. The public extension system continues to focus on wealthier progressive farmers and few other farmers report having accessed the extension service. Most small and marginal farmers get information and advice from input dealers and broadcast media; this is particularly salient for fertilizer and animal feed. The authors criticize weak links between extension and research, saying that only few farmers attend demonstrations at SAUs and KVKs. While PPP and private sectors models have been able to address some of the gaps, credit constraints and licensing requirements have prevented them from reaching scale. The private sector provides more context specific services on both production and post-harvest management; however, they tend to service larger contract farmers who are part of their vertical supply chains.

Under the 12th Five-Year Plan, the Government of India introduced the National Food Security Mission (NFSM) in 2007 with a focus on increasing productivity of core cereal crops (NFSM-Rice and NFSM-Wheat) and pulses (NFSM-Pulses). The policy specifies that small, marginal, and women farmers should comprise at least 33 % of contact farmers in the extension system. NFSM provides detailed guidelines on the expected intensity of demonstrations, stating that demonstrations should be held on 0.4 ha of land for every 100 cultivated ha, by dividing contiguous plots into experimental plots for new techniques and other plots for existing practices in order to visually show the impact to farmers by difference between treatment and controls. Extension officers are required to provide sufficient advance information before demonstrations and display boards on demonstration plots. Additional field days are required during the reproductive phase to ensure follow-up and address concerns during the entire farming cycle.

The International Rice Research Institute (IRRI) has held cluster demonstrations under NFSM-Rice for stress tolerant rice varieties (STRV) on 9,700 ha of land across 51 districts. Apart from disseminating information on modern STRV rice among farmers, the demonstrations have helped multiply seeds to meet increasing demand from farmers. A critique of this cluster approach is that it demonstrates the new technology under the cultivation conditions advocated by the extension agent and not as practiced by the farmer. The farmer may not be able to replicate the treatment the year after when he has to buy inputs and pursues his own objective function. What is being demonstrated to other farmers similarly does not correspond to what a peer farmer would be doing. For this reason, this approach has been criticized as broadly ineffective in helping farmers learning and deciding to adopt.

The Neuchatel Initiative on Agricultural Extension and Advisory Services (EAS)

The Global Forum for Rural Advisory Services (Swanson and Davis, 2014) is a platform for member organizations (especially producer organizations) where information is exchanged about best approaches and methods for the provision of rural advisory services in different country situations. It is also referred to as the Neuchatel Initiative and is supported by a coalition of donors including the Bill and Melinda Gates Foundation, the European Commission, and USAID. Based on the comparative analysis of extension services, it has evolved a set of recommendations about the desirable features of extension and advisory services (EAS) that include the following:

- It should be **demand-driven**, responding to farmers' demands for advice, in part through producer organizations (POs)
- It should recognize **diversity** and **heterogeneity** of conditions and needs across farmers
- It should be **participatory** of farmers, in particular through POs

- It should **diversify advice** beyond technology adoption to such issues of concern to farmers as household income, gender roles, empowerment, access to credit and insurance, marketing of produce, risk management, environmental protection, and links to the agricultural innovation systems
- EAS should include farmer **training**, with capacity development at the individual and organizational levels
- It should be **pluralistic**, with roles for the public, private, NGO, and PO sectors in the corresponding value chain. This requires the partial privatization, decentralization, and coordination of advisory services
- It should link extension to **research** as part of an Agricultural Innovation System, with feedbacks between the two
- It should be **financially sustainable**, with co-financing of services

These broad principles derived from comparative experiences are useful in identifying desirable features for the design of extension services.

Figure 1. Sources of information for learning in value chains

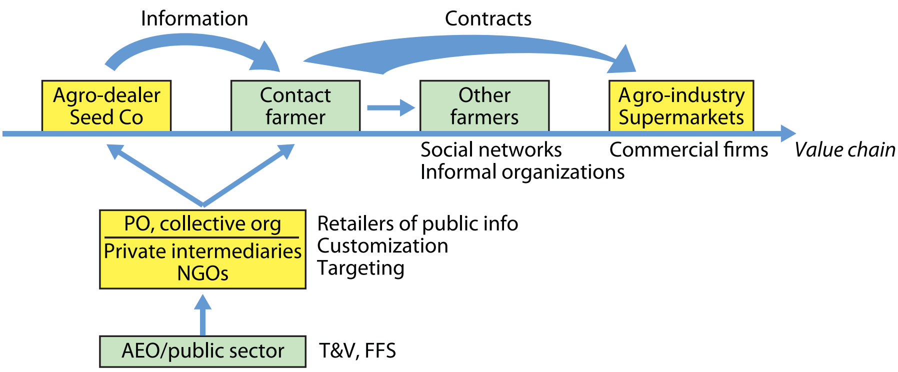

Figure 1 shows the variety of potential sources of information in a value chain framework. The traditional approach (T&V, FFS) involves the Agricultural Extension Officer in the public sector connecting to contact farmers who in turn diffuse information to other farmers in social networks and through informal organizations. The more pluralistic approach recognizes roles for agro-dealers and seed companies, agroindustry and supermarkets, POs and collective organizations, and private intermediaries and NGOs. The latter two categories of organizations act as retailers of public information, with an important role in recognizing heterogeneity of conditions and customizing and targeting information to relevant clienteles.

Advanced extension systems: Lessons from the US Agricultural Information System (Wolf, Just, and Zilberman, 2001)

In the context of agriculture extension in the United States, value chains as well as private and social provision of information are well developed. Issues of contracts and incentives become key to performance. Lessons learned from analyzing these emerging forms of extension services are the following:

- **Agents in value chains** are important sources of information. This includes agro-dealers, private service providers, and commercial partners (agro-industry, supermarkets). These private agents may not compensate for the decline in public extension services, especially for smallholder farmers
- **Private providers** deal with heterogeneity: they can customize public information to the demands of specific subsets of the farmer population.
- There is chronic private under-investment in information due to externalities and public goods effects, leaving a role for government intervention. This includes subsidies to adoption and direct provision of public services to targeted segments of the farmer population.
- **Less educated** farmers, and hence typically smallholder farmers, tend to use:
  – More processed information and less raw data for own analysis and use
  – More commercial intermediaries and NGOs as providers of information
  – More informal sources of information such as social networks and local organizations
  – Adoption can be motivated by the need to adapt, for example to climate shocks. Adoption then occurs in a discontinuous fashion. It is induced by crisis response and triggers, creating lags and recency bias

How farmers learn: Alternative channels

We use here the review paper prepared by Sadoulet (2016) 1 for this workshop that presents a number of models conceptualizing the channels through which farmers learn about innovations. We use them to identify the corresponding dimensions that extension services should have if they are to correspond to the way farmers learn. These dimensions are the following:

- **Private learning (learning-by-doing) by Bayesian updating.** This channel consists of direct learning from own individual actions over time. Prior knowledge about a stochastic phenomenon is updated based on information generated in the latest period (Besley and Case; Bardhan and Udry; Wang).
- **Social learning (learning from others) with Bayesian updating and aggregation of observations** collected from others according to a chosen pattern of weights. Learning from social networks is thus an important complement to direct learning from extension services (Chandrasekhar; Mobius; Ben Yishay and Mobarak).

1. See references in this section in the Sadoulet (2016) paper.

- **Learning by acquiring knowledge from others.** Learning from others in deciding for oneself could be through the transmission of knowledge or of information about the behavior of others that can be imitated. Empirical results show that the transmission of knowledge may be more prevalent in social networks than the transmission of information on actions. This may be because information on actions is not willingly transmitted for reasons of liability and reputational risk, when transmission of knowledge has no implications for eventual adverse outcomes (Tjernström; Cai el al.; Udry and Goldstein).
- **Learning from others under heterogeneity of circumstances.** Heterogeneity of conditions (e.g., soil types, farmer skills) reduces learning from others in social networks (Tjernström). In India, there is less learning from others in rice (with more heterogeneous production conditions) than in wheat farming (more homogenous conditions) (Munshi). More unobserved differential characteristics of others decreases learning from others and induces more private learning. With heterogeneity, farmers learn more from peer farmers (people more similar to them) than from lead (best) farmers. They perhaps require more complex contagion to decide on adoption (information from more than one peer farmer) (Beaman, Magruder, *et al.*).
- **Learning by trusting.** If trust is important in deciding to imitate or use transmitted knowledge, farmers will learn more from large/lead farmers with a well-established social reputation. Farmers will also rely on individuals in social networks where trust prevails, such as women Self-Help Groups (SHG), members of the same caste, community members, and members of a voluntary organization (Ben Yishak and Mobarak).
- **Learning by comparing and differencing.** This is the central learning approach in impact analysis, where fixed effects (farmer and plot characteristics, weather events) are subtracted away by measuring impact as the difference between observed outcomes in treatment and control plots. At the individual level, with only one plot, this is done with zero degrees of freedom in a particular year, requiring Bayesian updating of prior knowledge. At the social level, with large samples, this is done by differencing average outcomes between treatment and control plots. In this case, learning can happen through statistical inference without relying on priors (Banerjee, Chassang, and Snowberg, 2016).
- **Learning by communicating and deliberating.** Farmer field days serve for demonstrating, training, and confirming/interpreting information received. They can be very influential on adoption (Emerick *et al.*, 2016).
- **Learning through noticing.** Farmers can fail to notice important features in the information available to them. By failing to notice some of the determinants of outcomes, omitted variable biases are created in learning. Helping notice can reduce biases in making use of available information (Schwartzstein; Hanna *et al.*).
- **Learning from incomplete and noisy evidence.** Decision-making in agriculture is complex as it concerns use of many inputs under variable conditions and with unobservable returns. If evidence is incomplete about the value of an innovation,

farmers will rely more on opinion leaders. Under these conditions, best users (serving as opinion leaders) give more precise signals about an underlying causal relation than what farmers can obtain for themselves. Self-selection through bidding or willingness-to-pay (WTP) may help reveal who are the best (most eager) and hence potentially most informative users (Chassang; Dupas; Miller and Mobarak).

- **Learning strategically.** Experimenting by early adopters (people with lower discount rates) creates positive externalities on others. Farmers with higher discount rates may delay adoption to learn more from others (Besley).

Adapt new approaches to extension to the way farmers learn

Each of these learning mechanisms has implications for the design of extension services if these services are to be adapted to the way farmers learn for adopting. Specifically:

- **Private learning by Bayesian updating.** A longer time series of data on one's own plot increases expected returns from adoption as it makes input decisions more precise. Keeping formal records (IT based) on past practices (actions), weather (events), and outcomes would help farmers make the updating process more precise.
- **Social learning (learning from others) with updating and aggregation.** Panel data with a larger cross-sectional base of identical farmers allow more precise updating in social learning. Exchange of information across farmers – perhaps at PO/local cooperative/village level - with information on actions and weather events enhances social learning. Incentives can be given to peer farmers to induce adoption by themselves and for them to communicate lessons learned to others. Information on others (household and plot characteristics) would help determine who are your own peers. Demonstrations can be organized for clusters of peer farmers. Keeping formal records (IT based) on others will help updating and aggregation in social learning.
- **Learning by comparing and differencing.** As opposed to cluster head-to-head (H2H) demonstrations, H2H plots can be managed by farmers under their own farming conditions. Farmer field days and visits for training are organized using the farmer-managed H2H plots.
- **Learning by acquiring knowledge from others.** If social networks do not convey information on decisions to adopt, information can be provided separately on decisions made by others. Public postings of names of adopters can be made in the name of transparency when subsidies to adoption have been used.
- **Learning from others under heterogeneity of circumstances.** Peer farmers can be used as injection points and communicators. Demonstrating farmers can be let to choose their control practices to reveal their type to other farmers. Dimensions of heterogeneity can be revealed to help others identify their own peer farmers from among demonstrators. Demonstrations can be run with clusters of similar farmers.

- **Learning by trusting.** Survey questions can be used to find out who are the most trusted farmers in the community. They may be larger/lead farmers. Voluntary organizations can be used for self-selection into trusted groups, such as women SHG, producer organizations, and castes. Mutual insurance networks help reveal relations of trust.
- **Learning by communicating and deliberating.** Farmer field days can be organized with multiple visits to allow heterogeneity and peer farmer recognition. Organizations where psychological security exists (e.g., SHG) facilitate communication. Dealer demonstrations can achieve financial sustainability and scalability, but may need local monopoly to create incentives to invest in the generation of public knowledge. Dealer demonstrations may also be distorted by incentives to sell innovations that may not be the best fit for farmers.
- **Learning through noticing.** Information can be provided on relationships in the data to reduce omitted variable effects. Summaries of relevant relationships in the data can be made available to farmers to help them notice what matters.
- **Learning from incomplete and noisy evidence.** Lead farmers can be used as entry points when information is very incomplete. Self-selection of best users can be induced through auctions and WTP. This will create a trade-off between relevance (peer farmer) and completeness (lead farmer) of information.
- **Learning strategically.** In poor populations with high discount rates, subsidies can be given to induce the emergence of early adopters. Cooperation in experimentation can help internalize learning externalities. This gives a role to producer organizations in managing experimentation for collective learning, as done by the Regional Consortia for Agricultural Experimentation (CREA) in France and Argentina.

Suggestions for the design of new approaches to extension in a changing context

This critical review of existing approaches to agricultural extension, together with lessons from theory as to how farmers learn and empirical results from recent experiments, suggest ideas for the design of new approaches to extension. Some key results are the following:

- Critical reviews of the **T&V system** suggest that contact (lead) farmers are not always the most effective disseminators of new technologies. Peer farmers may be more convincing, because they use the technology in a more relevant fashion for learning. When there is heterogeneity, selection of peer farmers from whom to learn may become essential.
- Reviews of the **Farmer Field School** approach tell us that student-farmers benefit from the training received, but are not in a position to in turn transmit their knowledge to other farmers in helping them decide. When decisions are complex, deciding by imitating may dominate over deciding by acquiring knowledge. Selection (incl. self-selection) of best farmers as demonstrators may then be the most effective source of information for social learning.

- Choice of contact farmers (entry points) as intermediaries between extension agents and social networks depends on the problem to be addressed. In particular, one would want to select as entry points into social networks: (1) **peer** farmers for similarity to others in a context of heterogeneity and for a concern with equity (such as gender), (2) **lead** farmers as role models when information is incomplete, (3) **best** farmers (self-selected for example on the basis of bids in auctions or WTP to acquire the technology) as demonstrators of the inherent value of an innovation, (4) most **central** farmers for the diffusion of information following a contagion model, (5) farmers with most **social capital** (members of PO and SHG; farmers designated by community voting) for trust in adopting or to provide assistance to others, (6) **largest** farmers for seed multiplication and biggest market effects on others (for example employment effect on landless farm workers), and (7) **cooperating** farmers (e.g., members of CREA groups) for internalization of learning externalities.
- **Head-to-head** cluster demonstration plots as practiced by ATMA and NFSM may not be effective because they do not demonstrate the technology according to farmers' objective functions and under farmers' own circumstances. Delegating to farmers the management of these H-to-H trials may be a better option.
- Choice of **control practices** by farmers in H2H trials is important to reveal their type and conditions, especially under heterogeneity. This helps other farmers in the community identify who among demonstrators approximates most for them the status of peer farmer. A multiplicity of trials serves to document the performance of the innovation under heterogeneity.
- **Farmer field days** are useful for training and deliberating. If trust is important in deciding, managing demonstrations through farmer organizations (such as SHG) is important, as recommended by the Neuchatel Initiative.
- Because **updating** is an essential approach to learning, giving information to others on farmer type, conditions of plot, actions taken, and weather events is important. This allows both better private and social learning from the information available. Multiple visits to demonstration plots allow better updating by helping give more weight to peer farmers.
- The **Neuchatel** recommendation of seeking financial sustainability calls on making use of the private sector for the provision of information at the same time as it captures market share for the sale of inputs. Competition among dealers may create disincentives to experiment with public goods information. Interlinked transactions with commercial partners can logically contain information on innovations that the partner would like to see the contracted farmers adopt.
- Increasing privatization of sources of information for learning in value chains redefines the **role of the state** in extension from a direct provider of information to a coordinator and regulator, with in particular targeted services to the social categories and the types of innovations not attended to by the private sector.
- If **strategic learning** under conditions of high discount rates postpones adoption and individual experimentation, use of producer organizations to organize

experimentation helps internalize externalities and reduce under-investment in learning.

- Social networks may act more effectively for diffusion on the demand-side of **knowledge** than on the supply-side of **information** (contagion). Yet, traditional use of social networks for diffusion has been on the supply side, with contact-farmers under T&V and student-farmers under FFS serving as contagion points. These contact and student farmers can be made more pro-active with performance-based incentives rewarding diffusion efforts. Yet, a **demand-driven** approach to social learning may be more effective, especially if contact farmers do not have incentives to pro-actively seek to promote adoption. For this, **demand** for knowledge about innovations must be created in social networks, using in particular mass media, to induce the farmer population to actively search for knowledge from contact- and student-farmers.

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Chapter 7

Optimizing social learning about agricultural technology: Experiments in India and Bangladesh

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Manzoor Dar

Overview

There is a broad view that agricultural extension services in developing countries have under-performed. This signals a need for research into how extension can be improved – or overhauled – in order to improve learning and ultimately increase adoption of proven technologies. Ongoing research outlined here seeks to test innovations to the extension system that are meant to drive adoption. Broadly, the main questions being addressed are who should carry out demonstrations, how should they be carried out, and to what extent should private sector seed dealers be engaged as recipients of extension services.

There are some possible modifications to the extension system that are hypothesized to drive faster adoption of improved technology

- Improved selection of the farmers that cultivate demonstration plots. The importance of social network data for finding demonstrators has been established (Beamen et al, 2015). The outstanding question for policy is whether there are easily measurable proxies that can be used to identify the most suitable demonstrators?
- The returns to new technology are often heterogeneous and this influences learning (Munshi, 2004; Tjernström 2015). Can conducting demonstration plots with explicit counterfactuals increase adoption in this environment? Are counterfactual plots more impactful when demonstrators are influential in a network sense, but perhaps harder to learn from?
- Will adoption proceed faster when extension services are delivered to the private sector via seed dealers?

Figure 1. Demonstration plot w/out counter factual

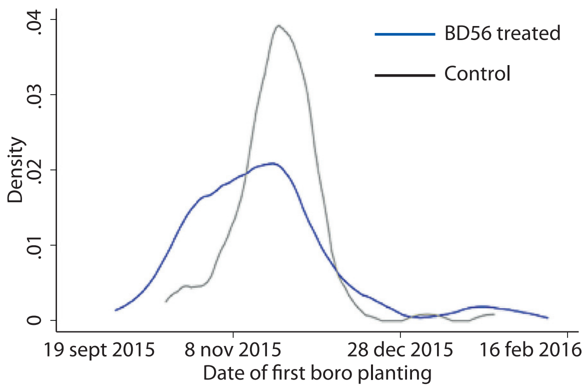
In Bangladesh the study considers BD56, an improved rice variety with three key features:

1. Requires less water, allowing farmers to save on supplemental irrigation fees and preserving groundwater resources. Evidence from a small-scale pilot randomized control trial in 2015 found that BD56 farmers relied significantly less on irrigation during the wet season.

2. By maturing in only 110 days, BD56 allows farmers to take part in early sowing of dry season crops (Figure 2), potentially increasing revenue by allowing early harvesting.

3. As a consequence of its early maturity, yields of BD56 are lower than longer duration seed varieties.

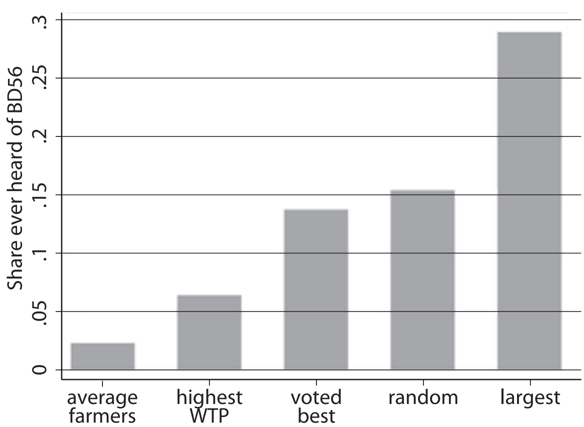
Figure 2. Density of first dry season planting dates. Data are from a pilot RCT in 35 villages of Rajshahi division in Bangladesh



Early piloting suggests that farm size is a useful proxy for how impactful a demonstrator is for spreading information

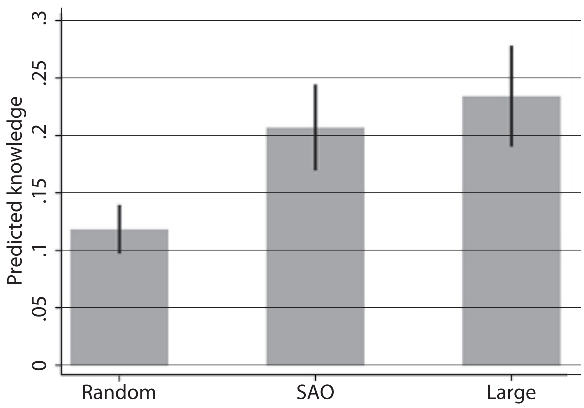
We found in the pilot RCT that almost 30 percent of villagers had knowledge of BD56 in villages where the five largest farmers were chosen as demonstrators. This contrasts with only 15 percent of farmers having knowledge in villages where demonstrators were chosen randomly (Figure 3).

Figure 3. Share of farmers with knowledge of BD56 as a function of how demonstrators chosen. Data are from a pilot RCT in 35 villages of Rajshahi division in Bangladesh



As part of the full study, social network information was collected for 256 villages during April-May 2016. These network data point to large farmers as being better connected to other villagers – rationalizing the pilot finding that information flow was improved with large-farmer demonstrators. A simulation exercise where demonstrators pass information to their social contacts with some probability shows the importance of large-farmer demonstrators. Interestingly, local extension officers (SAO's) also have private knowledge of more influential farmers (Figure 4).

Figure 4. Simulated rates of knowledge on BD56. Simulation based on network data collected for 192 BD56 treatment villages in April-May 2016. Model assumes that each demonstrator passes information to each of their social contacts with probability of 0.5.



The ongoing larger scale RCT will:

- Measure impact of using large-farmer demonstrators more rigorously in a larger number of villages and during a different season.
- Test whether farmers only pay attention to outcomes of demonstrators that are similar to them in terms of observable characteristics.
- Establish whether counterfactual plots are an effective new extension technique, particularly when farmers have a harder time extrapolating outcomes to their own plots.

Ongoing research in India will address the second question on the importance of dealers in the extension process

A randomized trial is being carried out across 10 districts of coastal Odisha India starting in the summer of 2016. The experiment will compare business-as-usual extension with an entirely new approach where information and seeds for testing are delivered to seed dealers rather than farmers. The current business-as-usual model in Odisha involves on-farm demonstrations in "clusters" where the new seed variety is given to many farmers and other farmers are expected to observe and more importantly, spread information. This will be taken as a benchmark in the experiment.

This benchmark will be compared with a new approach where an equal amount of seed is provided to dealers for testing and learning. In addition, dealers will be linked to private seed companies for obtaining seeds. The objective of this new approach is to deliver information directly to a population that has their own private incentive to spread that information. The study will also consider the relative targeting effectiveness of farmer-based versus dealer-based agricultural extension.

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Chapter 8

Signals, Similarity and Seeds: Social Learning in the Presence of Imperfect Information and Heterogeneity

Emilia Tjernström

Abstract

Social networks can help institutions spread information about agricultural innovations and are increasingly thought of as a viable complement to traditional extension services. Taking advantage of experimental variation in the information available to farmers through their social networks, this paper examines the influence of social networks on knowledge about and adoption of a new agricultural technology in rural Kenya. The results suggest that networks affect several aspects of farmer knowledge and their adoption process, but that village-level variability in soil quality makes individuals less likely to respond to their peers' experiences. This finding indicates that policy-makers ought to take the variability of the environment into account when deciding whether to allocate resources towards leveraging social learning for information diffusion, or instead focus on encouraging learning-by-doing.

Context

Approximately three-quarters of poor people in developing countries live in rural areas and depend at least in part on agriculture for their livelihoods (World Bank, 2008). Further, studies show that GDP growth originating in agriculture benefits the poor substantially more than growth originating in other sectors (Ligon and Sadoulet, 2008). Yet, despite many advances in agricultural technology, smallholder farmers still suffer from low productivity, which often leads to chronic poverty and food insecurity. These improved technologies could raise agricultural productivity to both lift poor households out of poverty and grow the economies in which they live, but adoption has been slow in poor countries, especially sub-Saharan Africa.

Understanding how farmers make their production choices is essential to designing effective interventions to promote new agricultural technologies to close yield gaps and reduce poverty. In particular, why don't smallholder farmers adopt technologies that have the potential to boost farm productivity and improve their household's welfare? One reason is that the market in which farmers make their choices is plagued by imperfections. The challenges faced by farmers include credit constraints, imperfect insurance markets, and incomplete information about the availability and profitability of new technologies. This research focuses on the last of these challenges, and examines under which circumstances social learning can play a role in diffusing information about a new agricultural technology. In particular, the study examines whether heterogeneity in underlying conditions affects farmers ability to learn from each other.

The study is built around a randomized roll-out of information about and samples of a private seed company's high-yielding maize hybrids. Until recently, the company faced production capacity constraints and therefore had a limited geographic reach. As a result, prior to this study, farmers in the study areas had neither been exposed to information about these new hybrid seeds nor had a chance to use them. Many blame Kenya's stagnating maize production on how slowly older hybrids are being replaced with newer releases. The relevant decision for farmers is therefore not simply whether to plant a hybrid, but what type of hybrid to choose. In contemporary Kenya, an average of over fourteen new maize varieties have been released on the market each year since 2000, making this a very complex choice. The choice is made even more difficult by the fact that the region being studied is characterized by significant differences in soil quality both within and between villages.

Study design

The study of social learning has grown in popularity over the past few decades, but can be difficult to identify. The primary challenge (detailed by Manski, 1993) is identifying whether members of a social network influence each other or whether they simply behave alike because they are already similar and face similar stochastic shocks (perhaps because of a shared environment or because the network was formed precisely based on the shared characteristics of its members). The key, then, is to identify whether members of a social network influence each other or whether they behave alike simply because they are alike, or are exposed to similar situations and environments. A growing set of papers vary experimentally the information available through social networks to cleanly pick up the effects of social networks (see, for example, Babcock and Hartman, 2010; Carter et al., 2014; Cai et al., 2015 and Magnan et al., 2015). They can then base their social network analysis on the number of members of an individual's network that were treated/received a piece of information, using this number as a proxy for the number of different sources of information to which a farmer has access.

I complement these prior methods with an additional measure of the information available through farmers' social networks. As part of my experiment, villages were randomly designated as either control or treatment villages. In treatment villages, only those farmers randomly selected for inclusion in the study were actually treated. Before the main planting season of 2013, the farmers selected for treatment were invited to an information session and given a 250-gram sample pack of the new seeds. In early 2014 I conducted a phone survey with treated farmers to learn more about their experience with the sample seeds. I then explicitly elicit farmers' experiences with the technology, obtaining the treated farmers' evaluation of how well the on-farm experiment went. Using this information, I construct a more precise measure of the information flowing through the network. Specifically, I calculate the percentage increase of the WSC hybrid harvest over the expected harvest with seeds the farmer would have normally used. The signal that a given farmer receives about the new technology is then defined as a function of the distribution of these evaluations in her information network.

Observing peer effects may reflect mimicry or social pressure rather than actual learning, but these more precise measures of information enable us to more carefully discern between social influence and social learning. We can do this by contrasting individuals' behavioral responses to the number of people who have experience with the new technology with their responses to the actual information transmitted through the network (the signal described above): If people respond to the number of people in their network who adopt a new technology, but not to information about the returns to this technology, then observed effects from the social network are likely to be a sign that mimicry, rather than social learning, is at work.

Findings

I find that social networks do impact farmers' adoption behavior, and that the signal appears to provide additional information – above and beyond the number of treated in one's network. The number of treated farmers in a respondent's network affects their willingness to pay (WTP) for the seeds and their probability of adopting the new technology[1] and the signal has additional effects on both WTP and on the probability of planting a hybrid. This lends support to the notion that farmers are indeed learning from each other and not merely mimicking what others are trying.

Further supporting this notion, I find that the observed social network effects are weaker in villages where soil quality is more varied. Observing or talking to one's neighbor may be more or less useful depending on how similar they are along dimensions that matter for the profitability of the technology. In other words, it is harder for individuals to learn from their network members about a technology that is sensitive to characteristics (such as soil quality) that are difficult to condition on if those characteristics vary in the population. Large variation in unobserved characteristics, like soil quality, could therefore negatively impact social learning.

For this analysis, I take advantage of detailed soil quality data on the treated farmers' fields. I interact the coefficient of variation in soil quality (proxied by the Cation Exchange Capacity, or CEC, a common measure of soil fertility). At low levels of soil quality variation, the average information signal in an individual's network positively influences adoption. As the variation increases, the impact of the average signal decreases. These results suggest that farmers are aware of this particular type of heterogeneity and that it affects how much they can learn from their social contacts.

Finding that this type of underlying heterogeneity handicaps social learning gives additional confidence that the social network effects that I observe are due to learning rather than imitation. It is unlikely that we would find a negative relationship between unobserved soil heterogeneity and social network effects if farmers were merely imitating their peers.

Implications for policy

Results showing that farmers talk to and learn from each other should come as no surprise. The extent to which heterogeneity in soil quality seems to handicap these social network effects, however, suggests that it is much harder for a farmer to make inference about how well a new technology will do on her own soil if she only observes its returns on soils that are very different from hers.

A better understanding of the complexities that farmers face when making input decisions is therefore key to understanding why some innovations diffuse more slowly than would be socially optimal. Farmers react to heterogeneity by relying less on information from their peers when making agricultural decisions. The more variable the environment, the more important learning-by-doing becomes. In this study, seed packet recipients were much more likely – ten percentage points – to purchase and plant the seeds in the next main season than the untreated in the same village.

1. The effect on WTP is mostly seen for the indirectly treated farmers (the untreated farmers in treatment villages).

This implies that in areas where soil type and other production variables varies significantly across farms, policy-makers should consider focusing their attention (and subsidies) on encouraging learning-by-doing, while in homogenous areas they might get bigger impact from the same spending by leveraging social learning. In the case of hybrids, this could be achieved by subsidizing learning or by making samples of seeds available to farmers for on-farm trials.

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Chapter 9

Learning-by-doing and learning-from-others: evidence from agronomical trials in Kenya

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Abstract

This research analyzes the dynamic processes underlying farmers' learning about heterogeneous returns to new inputs. A RCT was designed to provide an exogenous increase in the farmers' information on input quality and suitability through agronomical trials on their own farm. We study the dynamic impacts of farmers' experimentation with multiple products over three seasons and test whether this leads to an increase in the use of high quality and suitable inputs and yields. Preliminary results show that farmers' learning is slow but matches well the agronomic findings of the trials. After several seasons many identify which inputs worked best and increase the demand for those specific inputs. The increased willingness to purchase the inputs is however only partially translated into purchase, suggesting important remaining constraints on the supply side. Evidence further suggests that farmers participating in the trial are learning from each other, but learning by non-participating neighboring farmers appears more limited.

1. Motivation

Information barriers can be an important constraint preventing adoption of a profitable technology. Whether such information constraints exist and persist likely depends on farmers' ability to learn about the use of, and the returns to new technologies, through learning-by-doing or through learning-from-others. However farmers' experimentation and learning does not always happen, which can be puzzling given that in many cases the cost to experiment a technology may seem relatively small compared to the long-term benefits of technology adoption. This research explores a number of reasons that can explain this puzzle.

First, farmers do not consider one input in isolation, but a large number of inputs and input combinations. If a large share of possible input combinations has low returns it may become too costly to experiment with enough products to identify the few good ones. Second, because the return to each input combination is a function of soil and other farm characteristics, each farmer may need to find the one that is most suitable to their own farm, thus reducing the potential for learning-from-others. Third, learning about the return of an input combination can be a challenging dynamic process because yields can be affected by multiple observed and unobserved factors. Identifying the right signal about returns can hence be complex and might well take multiple seasons, and farmers are likely to differ in their willingness and ability to do so. Finally, imperfect communication within the household, and the fact that the person exposed to new information is not necessarily the one who can use it adds to the household's difficulty to use its experience to make the right decisions about technology adoption.

This research hence focuses on the dynamic processes underlying farmers' learning about heterogeneous returns to new inputs. As numerous interventions aim at increasing technology adoption through learning, a better understanding of how these different factors affect farmers' learning arguably is key for effective policy design. We provide strong causal evidence on the impact of providing information on the returns to specific combination of inputs that rely on experimentation on the farmer's own land. We pay special attention to the heterogeneity in returns and learning due to local soil conditions and differences in skill levels of farmers. Beyond providing unique evidence on learning-by-doing regarding input quality and suitability, the research also contributes by analyzing learning-from-others. First of all, we analyze learning within the household, building on a rich baseline datasets with individual skill measures for the two main farmers in the household. Second, we analyze learning by other farmers in the village, and how differences between neighbors and participating farmers affect the learning process. As such, the research will provide evidence on potential hidden constraints to information dissemination within and across households.

2. Setting for the research

The research builds on the findings of COMPRO I, a BMG funded project, which analyzed the cost-effectiveness of 100 commercial inputs in Kenya, Nigeria and Ethiopia, through lab-analysis of the content for active ingredients, trials in research stations and on-farm trials. Only a small proportion of tested inputs were found to have sufficiently high benefit-costs ratios to unambiguously warrant adoption by smallholder farmers. Agronomic research results further show that the returns to inputs can vary a lot depending on soil conditions, the use of complementary inputs, farming practices and weather conditions, implying there can be low returns to many inputs for a large share of farmers. With a high likelihood of low returns, farmers' own experimentation with many products will often turn out to be a costly mistake, and anticipation of such costs might well entirely prevent such experimentation. This can lead to low demand, and in turn low supply of new products, including of the few high return ones.

We analyze these potential constraints to learning in the context of COMPRO II, a program implemented by IITA (the International Institute for Tropical Agriculture, one of the CGIAR centers) in 6 sub-Saharan African countries. Within this context, IITA and PSE set up an agronomical research RCT in Siaya (Western Kenya), where smallholder farmers were invited to participate in an agronomical trial on one of their plots that lasted for three seasons. While the study is set up as a proof-of-concept study, encouraging experimentation by farmers is at the core of the technology dissemination approach of Compro II and many other extension programs. The insights of the study hence aim to contribute to the literature on extension, where rigorous evidence on scalable cost-effective interventions remains scarce.

3. Methodology

The RCT was designed to provide an exogenous increase in the farmers' information on input quality and suitability. We study the dynamic impacts of farmers' experimentation with multiple products over three seasons and test whether this leads to an increase in the use of high quality and suitable inputs and yields. Prior to the long rain season 2014, we identified ten farmers per village in 96 villages and the plots that they would dedicate to the research trials. Half of the villages were randomly selected to the control group, and in the other half all identified farmers were selected to apply the research trials during three seasons. In the first (random) 24 villages, trials started in the long rain season 2014, in the second batch of 24 villages trials started in the short rain season 2014. Within each village, we sampled 5 random farmers, as well as 5 farmers specifically selected as promising farmers for the trials, so lessons can be drawn for both average and highly skilled or motivated farmers. Following standard agronomical protocols, agronomical scientists from IITA then worked with each farmer in the treatment group to implement an agronomical trial. Each plot was randomly divided into a control sub-plot without inputs and

5 treatment sub-plots where different combinations of inputs were tested. Inputs were selected to ensure variation in the quality and suitability of the inputs tested by each farmer, ranging from inputs of known stable high returns to inputs with more uncertain quality signals. The inputs were varied randomly by farmer, but each farmer tested a set of inputs that satisfy the same function.

The trials tested different combinations of seeds and fertilizer packages, for soya and maize. The packages were selected based on insights from the ISFM (integrated soil fertility management) literature. The returns to the different packages are further illustrated through the agronomical trials, with important heterogeneity across locations (subdivisions) and farmers in Siaya county. The packages include both some inputs with which farmers were familiar, as well as fertilizer more recently introduced in the market. The use of these inputs at baseline was low. When using an optimal fertilizer package, maize yields increased between 30-200%, with important heterogeneity between locations and maize varieties; yield gains in soya varied between 50-150%. These yield gains were calculated based on comparison of control and treatment subplots of the same farmers, and the results for different subplots allows disentangling the importance of different inputs. The trial yield data also illustrated important heterogeneity across farmers within the same village. Overall compliance with the randomized design was good, though some farmers did not complete all three seasons. In general take-up was good during the long-rain seasons (~90%) but lower (~ 80%) during the short-rain seasons, when weather conditions increase the risk of crop failure.

The protocol was designed so that the agronomist working with the farmers did not provide any signals about which input is expected to perform better. As a result, a significantly higher use of the high quality inputs in the treatment villages should indicate that farmers learned about the return to inputs from observations of the trials. Indeed, the design of the RCT is based on an assumption that, due to possible heterogeneity in soil and farmer characteristics, dissemination of information on input quality through experimentation may be more credible than merely telling farmers which inputs to use. In particular, the research trials offer a rare occasion to analyze learning from observation and yield comparison of farmer's own experimentation, in absence of any behavioral marketing. To do so we collected data at baseline and after each season of the agricultural trials. This intensive data collection during and after the implementation of the RCTs allows the analysis of the dynamic learning and adoption decisions. The data collected after the end of the trial allows studying the sustainability of the adoption patterns, as well as any potential dis-adoption. Attrition was kept to a minimum, at less than 5% in each of the follow-up rounds.

We also surveyed the second farmer in the household after 3 seasons on their agricultural knowledge, perceptions about the new technologies, and their related investments and decisions, after their spouses have participated three seasons in the agricultural trials. This allows testing for intra-household learning. To further shed light on the relative importance of own experimentation for learning, we organized field days in the last season of the trials in the treatment villages, where the results and experiences of the trails were discussed among participating farmers and presented to other interested farmers in the village. We subsequently study spillovers in the wider village population by surveying non-participating farmers randomly selected from the village population. Further evidence on learning-from-others comes from studying changes in soya input use and practices among farmers that were randomly assigned to maize treatment, and vice versa.

4. Preliminary results

The findings show that experimentation on farmers' own plots results in clear learning gains. Farmers' learning is slow but it matches well the agronomic findings and after several seasons many identify which inputs worked best and increase the demand for those specific inputs. Community selected farmers learn faster and more, but differences with randomly farmers decrease over time. And learning is not limited to specific inputs, but farmers' also grasp wider lessons regarding optimal agronomical practices, and apply those on their own plots. Learning increased the willingness to purchase the inputs, but only partially translates into purchase, pointing to important remaining constraints, in particular on the supply side.

Learning-by-doing is to a certain extent accompanied by learning from others. Indeed learning is strong across treatments: farmers with maize trials learn about soya and vice versa, suggesting high communication among participating farmers in the village. We find that participation in the trials increases the communication among the participating farmers, and this increases over time. Yet learning of neighboring farmers that themselves did not participate in any trials appears more limited. In contrast, we find significant learning spillovers within the participating households. Future work will deepen the analysis of returns and learning, conditional on soil characteristics and on the skills of farmers, measured at baseline. The analysis will also aim to derive lessons for the design of extension interventions.

Chapter 10

Improving Yields with Improved Recommendations

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Abstract
We report preliminary results of an intervention that aims to promote the adoption of new technologies by small producers in the state of Tlaxcala. The intervention was carried out during the 2015-2017 agricultural cycle. The producers received a soil analysis, visits from specialized technicians and subsidized inputs in order to increase the per hectare productivity of their maize plots.
The results show that, on average, the producers increased their productivity by 100-250 kilograms per hectare in comparison to those who did not receive the intervention.

Introduction

According to the World Development Report (2008), GDP growth originating in agriculture is about four times more effective in reducing poverty than GDP growth originating outside agriculture. For this reason, policies that increase agricultural productivity can have a significant impact on poverty reduction.

Technology adoption is an important mechanism for improving agricultural productivity in poor countries. The Green revolution introduced high-yield crop varieties, chemical fertilizer and other modern agricultural practices to developing countries but the take-up of these technologies has been uneven. In many areas traditional farming practices still predominate and take-up of new agricultural technologies remains limited.

There has been considerable debate in both academic and policy circles about the sources of incomplete technology adoption in agriculture. In a recent review, Foster and Rosenzweig (2010) argue that limited adoption could reflect heterogeneity in costs or returns to the technology so that observed (low) adoption rates do not imply substantial unrealized gains. They argue that observational studies, even with panel data, typically face formidable endogeneity problems so that observed positive partial correlations between input use and yields or profits may not in fact be causal. In contrast, others argue that because of informational problems, market failures or behavioral biases there is substantial under-adoption of agricultural technologies. Both sides of the argument are, however, in agreement that the returns to input use, particular fertilizer, are likely to be heterogeneous and this heterogeneity has implications for adoption.

The Intervention

In this brief we summarize work in progress (Corral et al., In Progress) where we examine one particular source of heterogeneity in detail — heterogeneity in land quality — and its link to input use and hence technology adoption. In particular, we test whether heterogeneity in soil quality leads to a corresponding heterogeneity in the optimal recommended mix of fertilizers and whether such tailored recommendations improve outcomes in field conditions. This is particularly relevant in the developing world where fertilizer recommendations are usually of a generic nature, untailored to agro-climactic variations. In contrast, we provided localized recommendations (shopping list) and in addition examine the effect of varying the level of localization on outcomes. In addition to providing localized input recommendations we also offered in-kind grants to farmers to purchase inputs.

In particular, we designed an intervention in the state of Tlaxcala, Mexico for rainfed maize farmers with five arms experimental arms:

- T1: Individualized soil analysis and recommendations and an inflexible in-kind grant along with agricultural extension services.

- T2: Average soil analysis and recommendations and an inflexible in-kind grant along with agricultural extension services.
- T3: Average soil analysis and recommendations and a flexible in-kind grant along with agricultural extension services.
- T4: Average soil analysis and recommendations and no grant along with agricultural extension services.
- Control arm

The in-kind grants provided 2000 pesos (U.S $150) worth of inputs for half of average per-hectare cost. The inflexible grant restricted purchases to items on shopping list. The grant was applied sequentially, starting with sowing drill (800 pesos) and then used towards the fertilizer package. If total shopping list cost more than 2000 pesos, farmer were responsible for paying the difference. Farmers offered the flexible grant could purchase any inputs in dealer store and did not have to hire the sowing drill. Extension services consisted of 3 plot visits by extension workers along with 3 group training sessions (at sowing, 40 days after sowing and pre-harvest).

The program was widely advertised in all municipalities of Tlaxcala during 34 promotional meetings conducted in Jan. 2015. Eligibility was restricted to farmers that planned to sow maize with land less than 15 ha. and age between 18 and 70 years old. We ended up with a sample of 981 eligible farmers randomized into program in February 2015. Study farmers have on average lower yields than the Mexican average, are less likely to use hybrid seeds and more likely be rainfed. They are however more likely to use fertilizers and herbicides.

Results

Take-up rates of the recommendations and extension services are around 80 percent and significantly higher in T1-T3. This means that they apply significantly less Urea and DAP but more KCl. Thus fertilizer use among T1-T3 is significantly closer to the recommended dosages. We also find that T1-T3 have higher density of maize plants, partly due to the fact that the use of mechanized precision drills uses a higher density than the semi-precision drills that farmers typically use. Despite a severe drought in the area, T1-T3 managed to get higher yields relative to farmers in the control group. There are no differences in take-up, plant density, fertilizer use or yields among T1-T3 groups.

Interestingly, farmers appear more certain about the quality of their plots. We asked to rank their plots where 0 was the worst plot in the area and 10 the best plot and we then asked them how certain they were of their assessment. After the recommendations were given farmers update little their assessment but they report being more certain about it. Consistent with their more accurate assessment, farmers report lower CV of yields after the recommendations. Put differently, the recommendations provided a signal of the quality of their land that led to a decline in the expected volatility of yields. If farmers are risk averse, this decline in volatility should translate into higher investments. In 2015, an increase in investment could come from the tighter priors just discussed or from the grant farmers received in T1-T3. In 2016/17 we will ask again about practices and investments to see if they are indeed higher.

Conclusions and Policy Recommendations

The project is still ongoing as we are following farmers in 2016/17 to see if any of the practices and recommendations learned actually stick and are disseminated. From the analysis thus far, we can draw a couple of conclusions:

- First, the level of localization does not seem to matter for take-up, plant density or yields. As a result, and because individualized recommendations are more expensive, using area recommendations seems more desirable. We note that the area used to compute average recommendations is smaller than the state-wide recommendations currently used.
- Second, localized recommendations alone may not foster technology adoption. These interventions have to be supplemented with extension services, agro-dealer coordination so that the optimal input mixes will be available and in-kind grants.

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Chapter 11

Technology adoption under uncertainty

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Abstract

Many technology adoption decisions require investment at two or more points in time. The first investment is typically associated with take-up and subsequent investments with the use or implementation of the technology. After take-up, new information about the cost of subsequent investments is acquired, and adopters may decide to abandon the technology if they learn that following-through will not be worth it after all. We study this dynamic adoption problem in the case of agroforestry in Zambia. A field experiment that varies the payoffs from taking up seedlings and following through to keep the trees alive allows us to estimate the new information that arrives after take-up. We observe that, while farmers are responsive to the incentives offered in the experiment, a large share of the payoffs from adoption are not known to them at the time they make their take-up decision.

Importantly, this makes it difficult for farmers to self-select into the take-up decision, meaning that a higher initial cost for the technology does not make follow-through more likely. As a result, subsidies for take-up are less cost effective, but also less necessary since many farmers facing uncertainty about the costs of follow-through choose to take-up so that they have the option to follow-through should the new information that arrives after take-up contain good news about the profitability of the technology.

Policy Issue

Many technology adoption decisions require investment by adopters at two or more points in time. The first investment is typically associated with take-up and subsequent investments with the use or implementation of the technology (referred to here as "follow-through"). For example, agricultural technologies such as herbicides or crop varieties all require farmers to purchase inputs and follow-through with the recommended usage or cultivation instructions. This two-part adoption structure is not limited to agricultural technologies. For example, health treatments and many energy saving investments also require a follow-through step.

Subsidies are a common tool to increase the adoption of many of these technologies. However, many policy-makers worry that subsidizing the initial take-up decision may lower subsequent follow-through. In most cases, both the policy maker and the adopter are most interested in the follow-through step, which is required for the technology to generate private or social benefits. If follow-through is lower when take up is subsidized, subsidies are less cost effective, since everyone who takes up receives the subsidy even if they do not follow through. Research on the cost effectiveness of subsidizing take-up, when follow-through is also necessary, has shown mixed results.

There are a number of reasons why subsidizing take-up might result in lower follow-through among those who take-up. The most obvious one is that subsidies might simply attract users who value the technology less and are less likely to make the necessary follow-through investments. This is often referred to as a selection effect. Other possibilities include psychological channels, such as sunk cost effects, anchoring and time inconsistent preferences.

This paper focuses on the dynamic aspects of technology adoption. Specifically, even though potential adopters may have some information about their costs and benefits of adoption, there might be a component of these that is unknown at the time they decide whether or not to take-up. After take-up, new information about the cost of follow-through is acquired, and adopters may decide to abandon the technology if they learn that following-through will not be worth it after all. For example, some attribute of the technology or some external factor such as weather or pests could make follow-through more of a hassle than originally anticipated. This could occur even among adopters who take-up the technology at a positive price, leading to seemingly irrational behavior – some pay for the technology but never use it – if the dynamics of adoption are not taken into consideration.

This study proposes and tests a framework that allows for uncertainty in the costs of the follow-through stage at the time of the take-up decision, and assumes that adopters can "change their minds" about the technology even after they have taken it up. We investigate the implications of this type of dynamic adoption problem for the use of subsidies to increase adoption.

The technology

Faidherbia albida is an agroforestry species endemic to Zambia that fixes nitrogen, a limiting nutrient in agricultural production, in its roots and leaves. Optimal spacing of *Faidherbia* is around 100 trees per hectare, or at intervals of 10 meters. The relatively wide spacing, together with the fact that the tree sheds its leaves at the onset of the cropping season, means that planting *Faidherbia* does not displace other crop production.

Agronomic studies suggest significant yield gains from *Faidherbia*. However, these private benefits take 7-10 years to reach their full value, and may be insufficient to justify the front-loaded investment costs, particularly if farmers have high discount rates. In the first year after trees are planted on the field, the farmer has to invest time to weed, water and protect the trees from pests and other threats. Survey data indicate around 38 hours devoted to cultivation activities in the first year, though it may be hard for farmers to anticipate how costly this extra effort will be, since it will depend on available family labor, agricultural conditions, and other things that affect their opportunity cost of time. Once a seedling survives the first dry season, costs decrease substantially. In the baseline survey, less than 10 percent of the study households reported any *Faidherbia* on their land. This could be explained by low perceived private net-benefits, by high costs associated with accessing inputs – there is no existing market for *Faidherbia* seedlings – or cultivating the trees, or by a lack of information.

Subsidies may therefore be necessary to increase take-up rates, and are justified by positive environmental externalities and market failures that contribute to high private discount rates. Environmental benefits include erosion control, wind breaks, and carbon sequestration. Based on allometric equations adapted to the growth curves for *Faidherbia*, we estimate that a tree sequesters around 4 tons of carbon dioxide equivalent over 30 years. The combination of private and public benefits has led to renewed interest in agroforestry and afforestation in developing countries in recent years.

Context

The study was implemented in coordination with Dunavant Cotton Ltd., a large cotton growing company with over 60,000 outgrower farmers in Zambia, and with an NGO, Shared Value Africa. The project, based in Chipata, Zambia, targeted approximately 1,300 farmers growing cotton under contract with Dunavant, alongside other subsistence crops. The project is part of the NGO partner's portfolio of carbon market development projects in Zambia.

Dunavant organizes its farmers into groups of approximately 15 geographically clustered households, with 125 groups involved in the study. Each group has one lead farmer who, under the Dunavant system, is responsible for training his farmer group on cotton production and, in the case of this project, on *Faidherbia* planting and management.

Agriculture in Eastern Zambia relies on an annual monsoon and small scale farmers plant the main staple crop of maize, alongside cash crops including cotton, tobacco and soya. Most production is done by hand and small farming households make little or no profit.

Study design and implementation

Around 1,300 cotton farmers associated with the partner organization received training on *Faidherbia albida* and were given the opportunity to purchase a package of 50 tree seedlings (the take-up decision) at the training, which was held at the start of the planting season. Also at the training, farmers learned that they might be eligible to receive a reward for keeping trees alive for at least a year (the follow-through decision). One year later, households were re-visited to measure tree survival and administer rewards. The subsidies and rewards were varied as follows:

(1) Take-up subsidy – Farmer groups were randomly assigned to receive one of four input prices that range from fully subsidized (free) to the cost-recovery price for the implementing organization (approximately $2.50 US, which is still a subsidy relative to alternative ways of acquiring the seedlings). Farmers' response to the variation in the take-up price helps reveal the variation in expected costs and benefits of the technology across farmers.

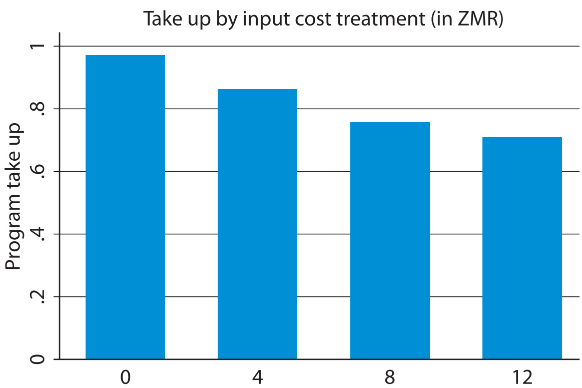
(2) Reward for follow-through – Individual farmers were randomly assigned to receive different levels a conditional reward, based on tree survival, which farmers are informed of either before or after making their take-up decision. The range of rewards ranged from $0 - $30 (0 - 150,000 ZMK), and pays out conditional on keeping 35 of the 50 trees alive through the first year. The tree survival outcomes in response to the rewards helps reveal the variation in costs and benefits of the technology across farmers one year after take-up.

In summary, the randomly varied take-up subsidy together with the randomly varied reward for follow-through are informative of the costs and benefits perceived by farmers at two different points in time. The difference between these reveals the new information that farmers received between their take-up and their follow-through decisions. In addition to recording the take-up and follow-through (tree survival) decisions, farmers participate in a baseline and endline survey.

Results

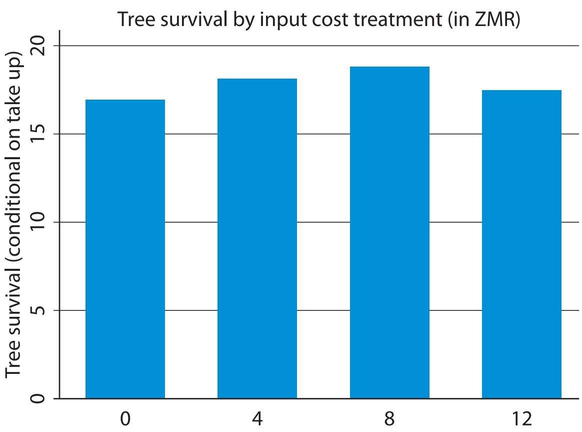
Our data analysis is guided by a theoretical model of the dynamic adoption process. The model highlights that, provided that the technology can be abandoned after take-up, a higher degree of uncertainty makes take-up more attractive, everything else held constant. This is because the adopter can keep options open – whether to follow-through or not – by taking-up in the first place. If instead, he or she chooses not to take-up, then there is no option to follow-through later. Thus, take-up provides option value when there is uncertainty in the costs or benefits of follow-through. The model also shows that subsidies are less likely to decrease follow-through in the presence of uncertainty. This is because subsidies cannot attract low valuation (and therefore low follow-through) types because adopters do not know whether they are low valuation types or not at the time of their take-up decision.

Figure 1. Take-up, by subsidy condition ('000 ZMK)



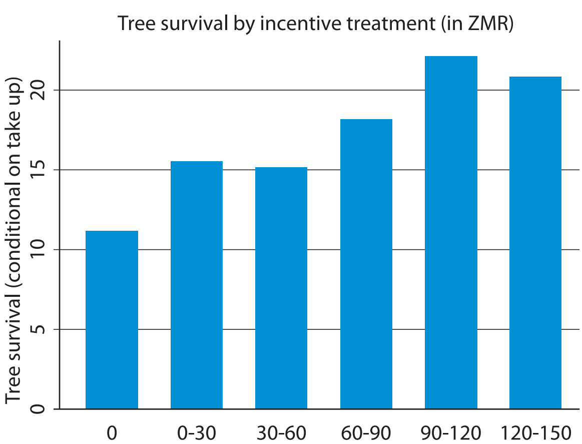
The raw data show patterns that are consistent with dynamic adoption framework that we propose. First, not surprisingly, farmers respond to economic incentives: they take-up at higher rates under higher subsidies and follow-through at higher rates under higher rewards (Figures 1 and 2). Second, the price at which each individual takes up is not predictive of the follow-through outcome (Figure 3). In other words, charging farmers more for the seedlings does not lead to more surviving trees per farmer after a year. In addition, a large share (37%) of farmers who paid a positive price end up abandoning the technology altogether.

Figure 2. Follow-through by reward condition ('000 ZMK)



Fitting the data to our model provides additional support for the interpretation that the results are driven by uncertainty rather than other explanations. We use these results to further investigate the relationship between subsidies by simulating what would happen to program outcomes at higher or lower levels of uncertainty. Relative to the study setting, eliminating uncertainty altogether (i.e. farmers know all of their costs and benefits of keeping trees alive for a year at the time they decide whether or not to take-up), would increase follow-through by 33%.

Figure 3. Follow-through, by take-up subsidy condition ('000 ZMK)
Conditional on take-up



Policy implications

The findings highlight insights into how policies designed to increase technology adoption should consider uncertainty in the follow-through stage:

1. When adopters have to pay to take-up a technology, uncertainty lowers the rates of follow-through conditional on take-up, and lowers the cost effectiveness of subsidies applied to take-up.

2. At low levels of uncertainty, charging a higher price may result in higher follow-through.

3. When uncertainty is high, rewarding follow-through is more effective than subsidizing take-up, providing the costs of monitoring follow-through are not too high.

Overall, uncertainty is neither good nor bad news for subsidies – it depends on the policy objective. On the one hand, subsidies become less cost-effective because take-up is driven up by the "option value" associated with take up, and everyone who takes up gets the subsidy. On the other hand, the selection problem – that adopters with lower valuations are attracted by the subsidy – is lower when the costs of follow-through are uncertain. Importantly, uncertainty has the effect of transferring benefits from the implementer, who would like follow-through, and the adopter, who would like to choose whether to follow-through depending on the new information that arrives after take-up. Thus, there are clear tradeoffs a sociated with the design of subsidies to increase follow-through.

Learning for adopting: Technology adoption in developing country agriculture

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