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Models to Action: Proactive Integration of Social Learning Theory

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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?

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• • •/• • • 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:

$$Y^k_{t+1} = \Omega_k X^k_t$$

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.

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.

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 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

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

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 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 farmers are

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").

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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