Can Diffusion Theory Improve Extension?

Jeremy Magruder with Lori Beaman, Ariel BenYishay, and A. Mushfiq Mobarak

June 2017

Social Learning and Extension

- Social Learning is the last mile of extension systems
  - Practically, too difficult to train all farmers in a new technology
  - Empirically supported: lots of good evidence that farmers learn from each other (e.g. Griliches 1957, Foster and Rosenzweig 1995, Conley and Udry 2010, BenYishay and Mobarak 2014)
- 2 common designs
  1. Bring (some) farmers to demo plots outside of the village
  2. Train one or a few lead farmers in a village to make their own demo plots
- Do these systems effectively generate social learning?

Our Context

- Working with the Ministry of Agriculture and Food Security in Malawi
- Current system: extension agents train lead farmers in new technologies
    - Selected either through village elections or village head appointments
- Ministry wants extension to promote pit planting: an unknown, new technology
- Can we tweak lead farmer system to improve social learning on pit planting?

A simple model of Technological learning

- Suppose (some) farmers have a signal about a new technology
- Other farmers see the signals of their contacts
- Farmers adopt the new technology if the aggregated signals are sufficiently positive A simple representation:

$$A_{it} = I(\Omega X_{t-1} > \tau_i) \tag{1}$$

entry points matter

- Several recent studies: selecting entry points with different institutions lead to more effective information transmission (e.g. Banerjee et al 2012, Kremer et al 2011, Miller and Mobarak 2014, BenYishay and Mobarak 2014)
- if different institutions are differentially effective, signal aggregation process must be important
    - Everyone is not learning equally from everyone else in village (Ω is fairly sparse)
- Suggests a potential, practical application of results from learning on networks
- We designed an experiment to test whether results from diffusion and learning theory can improve the effectiveness of extension

Threshold theory

- Threshold diffusion theory (Granovetter 1978, Centola and Macy 2007): Individuals adopt a behavior if a threshold λ of their connections have adopted it.
- if $\lambda = 1$, then the behavior spreads via a "simple contagion."
  - For simple contagions, new behaviors spread quickly
  - actual choice of entry points is not too important, even with sparse networks
- if $\lambda > 1$, then the behavior spreads via a "complex contagion"
  - most pairs of entry points will lead in no adoption of a new behavior.
  - critical to cluster entry points in a network to yield any adoption

thresholds in technology adoption

- 2 steps to technology adoption
  1. Farmers learn that the characteristics of the technology by soliciting signals from neighbors
  2. Farmers make an informed adoption decision by aggregating those signals via Ω
- This process leads to simple or complex contagion models, depending on the accuracy of signals and strength of priors
  - Step 2 means that farmers know that they will need a certain amount of information to be persuaded to adopt
  - if there is a small cost to seeking information, farmers will not seek information unless they have enough informed connections that they could be persuaded to adopt
  - A simple contagion is one where persuasion is relatively easy (because signals are accurate, or priors are weak); A complex contagion is one where signals are weaker or priors against adoption are stronger.

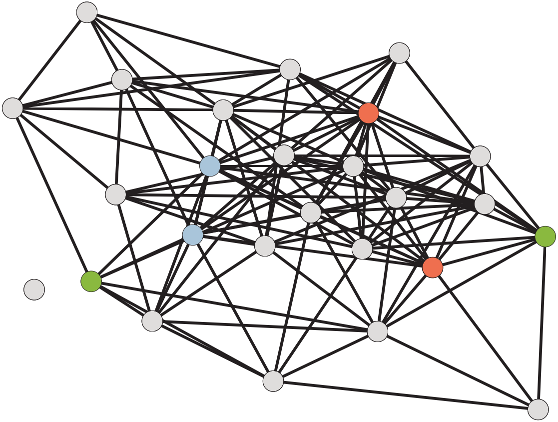
Our Approach

- We mapped networks in 200 villages to measure Ω
- Working with threshold theory
  1. microfound the theory by adapting some new results on learning about new technologies (Banerjee et al 2017)
  2. Identify optimal partners under different parameterizations of the theory
  3. Randomly assigned villages to receive different pairs of optimal partners
  4. Government Extension agents trained the identified partners
  5. We measure adoption 2-3 years later and compare to a business-as-usual control

Treatment

- 50 villages: business as usual. Extension agent selects 2 lead farmers by "usual methods"
- 50 villages: Simple contagion. We identify the best 2 partners if $\lambda = 1$ and the extension agent trains them
- 50 villages: Complex contagion. We identify the best 2 partners if $\lambda = 2$ and the extension agent trains them
- 50 villages: Geographic Complex contagion. We pretend that the network is defined by geography, and pick the best two partners if $\lambda = 2$ For time reasons won't say much about this.

Mapping Ω



- Results not shown
    1. Trained Seed Farmers adopt Pit Planting
    2. Trained Seed Farmers have (much) higher yields
    3. Other farmers talk to seed farmers about pit planting, and those who are close to the seed farmers in the network are differentially likely to adopt
        - especially if they are close to both seeds.

Table 8: Simple and Complex Learning in Pit Planting

	Adoption Rate				Number Adopters				Any Non-Seed Adopters			
	(1)		(2)		(3)		(4)		(5)		(6)	
Simple Treatment	0.035	**	0.006		1.04		0.43		0.158		0.189	*
	(0.017)		(0.022)		(.71)		(1.31)		(0.101)		(0.111)	
Complex Treatment	0.027	*	0.038		2.37	**	2.23		0.210	**	0.304	***
	(0.016)		(0.026)		(1.21)		(1.71)		(0.095)		(0.101)	
Geo treatment	0.038		0.015		0.54		-0.73		0.068		0.188	*
	(0.026)		(0.030)		(.71)		(1.11)		(0.096)		(0.110)	
Year	2		3		2		3		2		3	
N	200		141		200		141		200		141	
Mean Benchmark	0.044		0.077		1.940		4.100		0.46		0.543	
Simple = Complex	0.684		0.177		0.313		0.341		0.581		0.240	
Complex = Geo	0.670		0.442		0.142		0.077		0.113		0.220	
Simple = Geo	0.898		0.723		0.552		0.331		0.352		0.990	

Table XX: Learning Heterogeneity

	Sloped Land		Flat Land		Familiar Technology		Unfamilliar Technology	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Simple	-0.013	-0.039	0.057 ***	0.033	0.023	0.005	0.049	0.029
	(0.024)	(0.038)	(0.019)	(0.022)	(0.017)	(0.031)	(0.030)	(0.022)
Complex	0.005	-0.029	0.050 ***	0.054 **	0.016	-0.035	0.054 **	0.094 ***
	(0.024)	(0.036)	(0.018)	(0.025)	(0.016)	(0.030)	(0.024)	(0.030)
Geo	0.000	-0.068 **	0.042 *	0.013	0.032	-0.048	0.025	0.040
	(0.031)	(0.032)	(0.023)	(0.024)	(0.035)	(0.030)	(0.024)	(0.029)
Year	2	3	2	3	2	3	2	3
N	1313	912	1855	1380	2026	1263	1928	1760
mean	0.0658	0.123	0.0207	0.0457	0.0462	0.104	0.0278	0.0493
sd	0.248	0.33	0.143	0.209	0.21	0.305	0.165	0.217
Simple = Complex	0.419	0.782	0.742	0.311	0.677	0.0797	0.896	0.0296
Complex = Geo	0.869	0.169	0.762	0.0957	0.642	0.451	0.301	0.109
Simple = Geo	0.667	0.327	0.523	0.34	0.786	0.0174	0.424	0.662

Conclusions

- Both Simple and (particularly) Complex contagion targeting increases adoption relative to the elections and appointments in business as usual
- particularly among those with the greatest benefits to learning.
- Very high probability of no social learning at all in business as usual also supports idea of complex contagion
- suggests the need for multiple lead farmers, clustered in the same part of the network.

Policy Directions and discussion

- Rather than extrapolate from an institution that works someplace, we identified the goal for policy makers
  - Using local institutional knowledge, find an institution that will pick multiple partners in the same (dense) part of the network.
  - Emphasize depth rather than breadth of coverage
- Some ideas on how to achieve:
  - Multiple farmers from the same farmer's group
  - algorithm from simulations - identify high degree friends of a high degree farmer.
  - gossip-type data collection
- Social learning is not automatic, and network theory has practical importance for extension.