Networks and learning about an agricultural technology

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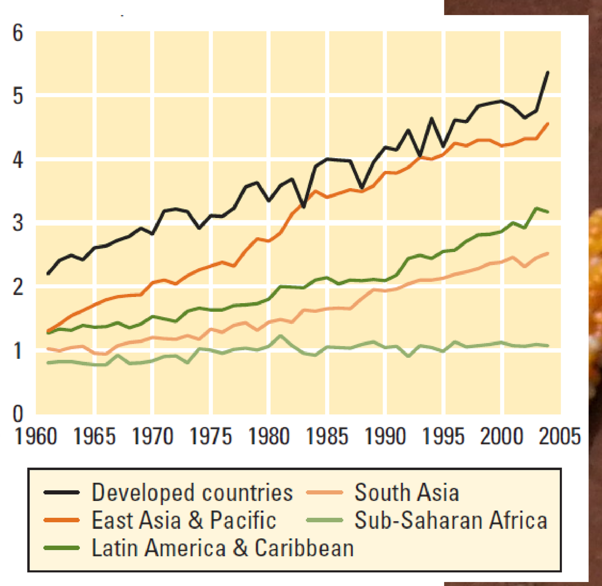
Motivation

- GDP growth originating in agriculture benefits the poor substantially more than growth originating outside ag (Ligon & Sadoulet, 2007)
- Ag yields and productivity have remained low and flat in sub-Saharan Africa, resulting in a widening yield gap with the rest of the world
- Part of the reason is low adoption of improved technologies
- Kenya's ag sector employs >75% of workforce, and accounts for >50% of GDP; maize accounts for a substantial portion of ag GDP & caloric consumption (in Kenya, more than 100 kg/person) (Feed the Future, 2013)
- Despite relatively high hybrid adoption rates, and many improved varieties on the market, Kenyan maize yields have stalled
- Average age of hybrids is 20+ years (Tegemeo, TAPRA survey data, 2010), so recent advances don't seem to spread



Cereal yields, tons per hectare

Source: World Development Report, 2008

Compelling reason to study technology diffusion in this context!

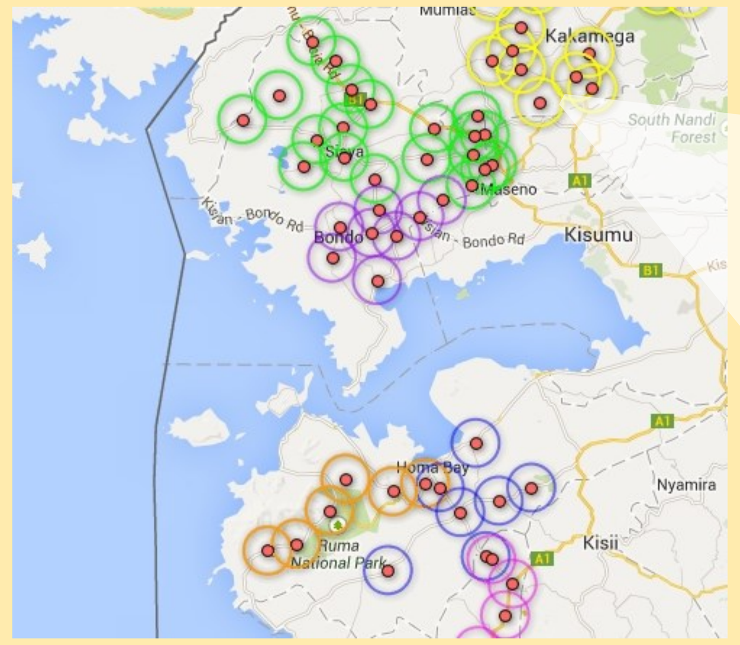
Three different aspects of learning

1 Learning by doing

		Information intervention	
		Control (18 learning zones / 53 villages / 900 hhs)	**Treatment** (18 learning zones / 54 villages / 900 hhs)
Liquidity intervention	Control	*Central Kenya*: 300 hhs *Western Kenya*: 300 hhs	*Central Kenya*: 300 hhs *Western Kenya*: 300 hhs
	Treatmt.	*Western Kenya*: 300 hhs	*Western Kenya*: 300 hhs

Main study: Can improved maize seeds move farmers out of poverty?

- Western Seed Company produces locally adapted hybrids; field trial suggest could increase yields in Western Kenya 6-8 times
- Company recently expanded into new districts, thanks to infusion of capital by investors
- They market using demonstration plots, providing info and sample packs of seeds
- For main season 2013, they over-identified demo plots & gave research team the GPS coordinates of planned plots
- We drew 5-km 'learning zones' around the demonstration plots & selected some for exclusion (pair-wise matching on rainfall, altitude and 'seed kit')
- Exclusion means no demo plot & no marketing within 5-km radius for 2 years
- In treatment villages, sampled hhs were invited to an **information session**, were told the **location of the demo plot**, and received a **sample pack** (250g) of seeds
- We will be able to attribute differences in uptake to farmers' **learning by doing** based on on-farm experimentation using sample seed packs (+ demo plots—a bit hard to separate)

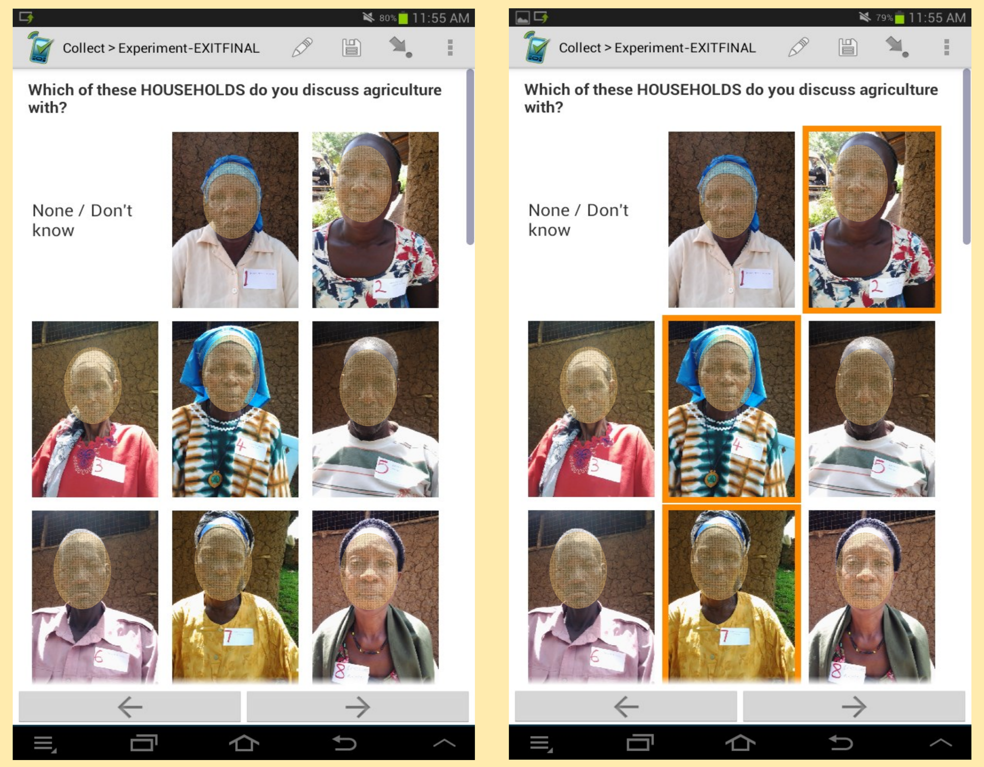


- Within each 5-km learning zone, we selected **3 villages**

- Within each village, we sampled ca. **17 farm households**
- Detailed household surveys + phone surveys beginning in 2013, with 1st main follow-up in 2015, 2nd follow-up in 2016

2 Learning from others

- In addition to treatment and control farmers, we have a third group: **'neighbors'** - *un*treated farmers in treatment villages
- Did not receive samples or attend info session
- But may have talked to treated farmers & could have seen demonstration plot
- Treated farmers were randomly selected, so number of treated in a farmer's social network is also random
- After a 2nd selection (among 'neighbors'), we collect social network information using **photo matrices**
- Selection is intuitive and quick, allowing us to ask more questions than usual
- Among other things, we elicit
  - **frequency** of communication
  - **similarity** of farming practices & soil types
  - **knowledge** about farmers in the social network (what seed variety did contacts plant this season?)



Social network characteristics:

- We can therefore move beyond examining the impact of how many treated people a farmer speaks with about agriculture by also looking at the strength of the connections (frequency of communication)
- Another measure of the strength of a connection is the amount of information that is *actually* transmitted between two farmers — farmer A may speak with farmer B about agriculture, but if she does not know what maize seed farmer B planted, or whether farmer B would recommend the new hybrid, the information link is weak
- Finally, the amount that you can learn from your contacts depends on how similar you are to your contacts: we compare subjective perceptions to objective info — we have measures of soil quality plus history of hybrid and fertilizer use)

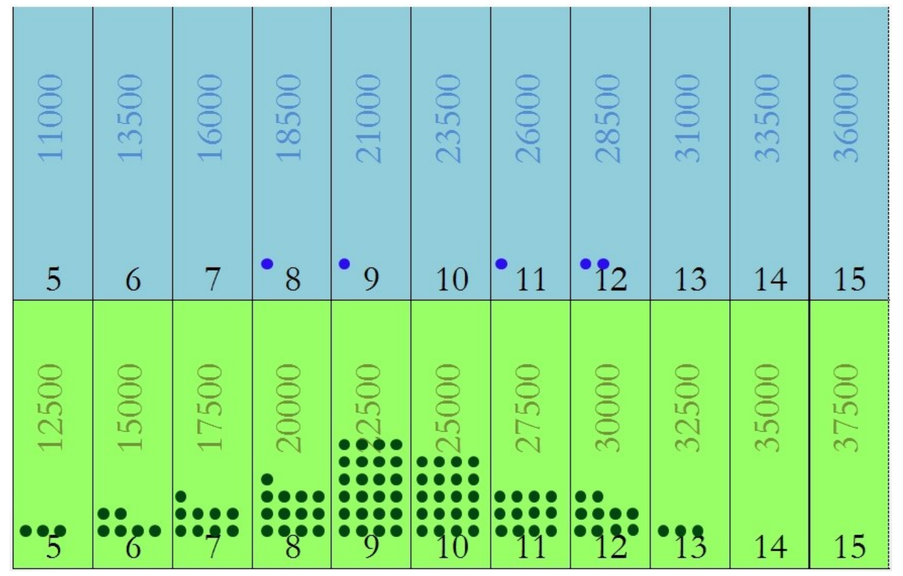
Measures of what treated farmers actually learned:

Collected info on what treated learned from their sample—knowing someone whose sample performed well transmits different info about the new technology than speaking with one whose experience was poor

- How well did your sample seed pack perform?
- Would you recommend the new seeds to friends and neighbors?

3 Individual characteristics

- In addition to who you know, and what information they transmitted to you, there may be individual characteristics that influence how you learn and whether you adopt a new technology
- In a sub-sample of villages, treated farmers & neighbors participated in an experimental game to classify their learning types in a manner disassociated from the social network context
- The framed, incentivized experiment asked farmers to imagine planting maize on 1 acre; they draw their yields from a bag (in private!) to represent their harvest but at the end of each round, everyone's yields are represented on a board in the front of the room
- After numerous practice rounds with the green seed, a 'new' (blue) seed is introduced—but it is more costly than the green seed
- After observing only 5 draws of the blue seed, farmers have to choose what seed to plant



- Participants choose which seed to plant over 10 seasons; at the end of each season, yields is displayed on the board, color-coded by which seed was chosen
- The blue seed first-order stochastically dominates the green seed, even after accounting for the higher cost

Experience-Weighted Attraction (EWA) learning model

- We can model participants' decisions using a modified version of the EWA learning model (Camerer and Ho, 1998)
- Typically used to study how individuals learn about other players' strategies in games of strategic interaction—here, payoffs are independent of other players' decisions
- Instead, participants are learning about Nature's strategy, i.e. the pdf of the yields of the two different technologies

- Strategies have different *attractions*, which are updated after each round as the sum of a depreciated, experience-weighted previous attraction, plus the weighted payoff from the most recent period
- Unchosen attractions are weighted by a fraction, δ, of their potential payoff (δ is thus a sort of 'imagination-parameter') while chosen strategies receive the additional weight (1-δ)

I modify the model to allow farmers to update attractions not only based on the true/expected payoffs (the ones shown on the board at the front of the room), but rather on a *subjective* payoff that takes into account the individual payoffs that the individual has received when playing that strategy

- This allows participants to *overweight* their own history of payoffs
- Individual parameters are estimated using maximum likelihood and used to predict individuals' technology adoption decisions

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