# Barriers to Technology Adoption:
## What We Know from Micro Empirics

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STEG Macro Development Course

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- Goals for TA section next week (Eleanor Wiseman)
  1. Review emerging evidence on intermediation in agriculture (new, ripe area for micro/macro interaction)

# Agricultural technology adoption

- Agriculture has a key role in the economy of many developing countries
- Low productivity. Agriculture is:
  - 64% of labor force but only 34% of GDP in SSA (2008)
  - 43% of labor force but only 20% of GDP in Asia (2008)
  - 2% of labor force and 2% of GDP in U.S.
- Lack of technology adoption (e.g. input usage) plays a key role in shaping these patterns
  - True in many regions, especially in SSA

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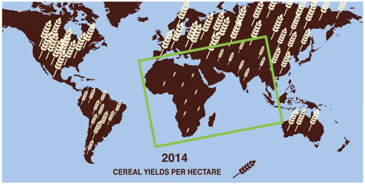
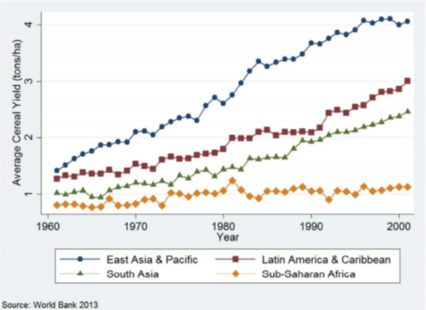
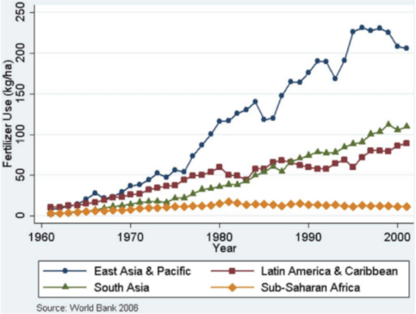
  - Credited with saving over a billion people from starvation
  - Norman Borlaug, the "Father of the Green Revolution," received the Nobel Peace Prize in 1970s
- But the Green Revolution did not transform agricultural productivity everywhere




**CGAP 2016 using FAO data; Infographic Data Source: World Development Indicators, FAO via the World Bank**

# Yields and fertilizer use




Graphs from McArthur and McCord (2017), "Fertilizing Growth," *Journal of Development Economics*, p. 135.

# Adoption and market inefficiencies

- Some technologies not adopted because they are not profitable
  - Increase in yields, but even more in costs (esp. labor)
  - Important here to take into account farmer heterogeneity (Suri 2011)
- Others would be adopted in world with perfect markets, but are not adopted because of one or more "market inefficiencies"

# Market inefficiencies (Jack, 2011 - ATAI)

| |
|---|
| **Externalities** – Some technologies create spillovers that affect others. If farmer decisions ignore these spillovers then technologies that create benefits for others may not be adopted, while technologies that impose costs on others may be adopted too widely. |
| **Input and output market inefficiencies** – Problems with infrastructure and with supply chains, compounded by weak contracting environments, make it more costly for farmers to access input and output markets and access the benefits from technology adoption. |
| **Land market inefficiencies** – In settings where land tenure is weak and property rights insecure, farmers may not have an incentive to invest in beneficial technologies. |
| **Labor market inefficiencies** – New technologies need different types and timing of labor input. Restrictions on labor mobility and high costs in the labor market will interfere with adoption opportunities. |
| **Credit market inefficiencies** – Many farmers have difficulty accessing credit and face high interest rates, which prevents investment in profitable technologies. Financial decisions may be difficult for farmers without high levels of financial literacy. |
| **Risk market inefficiencies** – Technologies that carry a small risk of a loss may not be worth large expected gains if risks cannot be offset. Psychological issues around risky decisions further lower levels of adoption. |
| **Informational inefficiencies** – If an individual does not know that a technology exists, does not know about its benefits or does not know how to use it effectively, then the technology will not be adopted. |

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# Agricultural Technology Adoption Initiative (ATAI)

atai AGRICULTURAL TECHNOLOGY ADOPTION INITIATIVE www.atai-research.org

Since 2009 have funded

- 48 evaluations in 15 countries in South Asia and Africa
- >100 affiliated researchers
- each study with field partners

Co-managed by:

CEGA Center for Effective Global Action at UC Berkeley

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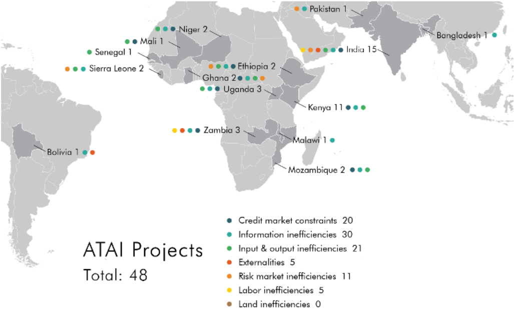


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UKaid from the British people

# Outline

- A model of agricultural technology adoption (Magruder 2018)
- Where we have good micro evidence (for macro to build on):
  - Credit and risk inefficiencies (Karlan et al., 2014)
  - Informational inefficiencies (Bold et al, 2017; Beaman et al., 2021)
- Where we have less micro evidence (and where macro can help):
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- Comment on potential synergies between micro and macro

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- Ex ante: farmer expects a choice of inputs $x$ will produce $E_{s,t}[f_{s,t}(x)]$

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Farmers maximize:

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Four constraints:

1. $c^0 = Y - x - a$
2. $c^1_s = f_{s,t}(x) + Ra$
3. $x >= 0$
4. $a >= \bar{a}$

# A model of agricultural technology adoption

Assumptions:

- Perfect info ($\pi_t \in \{0,1\} \forall t$) (will relax this in a moment)
- Inada conditions: $f_s'(x) > 0, f_s''(x) < 0, \lim_{x\to 0} f_s'(x) = \infty$

First order conditions:

$$u'(c^0) = \beta \sum_{s,\in S} \pi_s f_s'(x) u'(c_s^1)$$

and

$$u'(c^0) = \beta R E[u'(c_s^1)] + \lambda_a$$

# Implications

1. Credit constraints reduce input usage
   - Take the derivative of the FOC on $x$ with respect to $\bar{a}$
   - If credit constraints bind ($a = \bar{a}$), then optimal input use is increasing in the amount of available credit ($\frac{\partial x^*}{\partial \bar{a}} < 0$)

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   - If there were perfect insurance ($c_s^1 = c^{1I}$), then the two FOCs imply:

$$\beta R + \frac{\lambda_a^I}{u'(c^{1I})} = \beta E[f'(x)]$$

   - But without perfect insurance:

$$\beta R + \frac{\lambda_a^I}{E[u'(c_s^1)]} = \beta \left\{ E[f'(x)] + \frac{cov(f'(x), u'(c_s^1))}{E[u'(c_s^1)]} \right\}$$

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3. Can model information failures like more risk

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  - Risks are mostly aggregate risks (hard to informally insure)
  - Particularly hard for poor farmers
- Setting: Northern Ghana
  - Median farmer uses no chemical inputs
  - Agriculture almost exclusively rain-fed. Weather shocks translate directly to consumption fluctuations (Kazianga and Udry, 2006)

# Three year, multi-arm RCT

Year One (2x2 Design):

- Cash grants
- Grants of rainfall index insurance
  - Weather index insurance reduce moral hazard and adverse selection (though brings up basis risk)
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Year Three:

- Continued insurance-pricing experiment

# Demand for insurance in Year 2

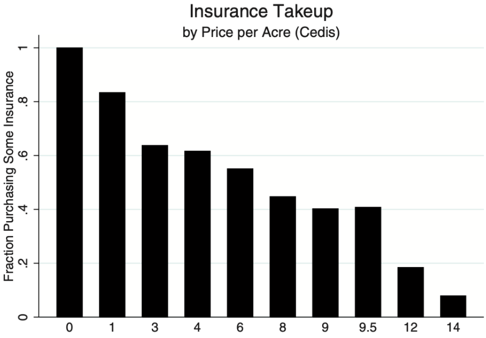


FIGURE II

Insurance Take-up

- At actuarially fair price, 40-50% of farmers demand index insurance
- Take-up in other settings typically much lower (Cole et al., 2013; Carter et al., 2017; Marr et al. 2016; Casaburi and Willis, 2018)
- Experience helps? Demand increases after either the farmer or others in his network receive an insurance payout

# Impacts on farm investment

TABLE IV

IMPACT ON INVESTMENT AND HARVEST (INSTRUMENTAL VARIABLES)

| Dependent variable: | (1) Land preparation costs | (2) # of Acres cultivated | (3) Value of chemicals used | (4) Wages paid to hired labor | (5) Opportunity cost of family labor | (6) Total costs | (7) Value of harvest |
|---|---|---|---|---|---|---|---|
| Insured | 25.53** | 1.02** | 37.90** | 83.54 | 98.16 | 266.15** | 104.27 |
| | (12.064) | (0.420) | (14.854) | (59.623) | (84.349) | (134.229) | (81.198) |
| Insured * capital grant treatment | 15.77 | 0.26 | 66.44*** | 39.76 | −52.65 | 72.14 | 129.24 |
| | (13.040) | (0.445) | (15.674) | (65.040) | (86.100) | (138.640) | (81.389) |
| Capital crant treatment | 15.36 | 0.09 | 55.63*** | 75.61 | −130.56 | 2.44 | 64.82 |
| | (13.361) | (0.480) | (17.274) | (68.914) | (92.217) | (148.553) | (89.764) |
| Constant | 169.38*** | 8.12*** | 171.70*** | 201.88*** | 1,394.58*** | 2,033.11*** | 1,417.52*** |
| | (10.603) | (0.399) | (13.804) | (45.383) | (84.786) | (124.294) | (90.635) |
| Observations | 2,320 | 2,320 | 2,320 | 2,320 | 2,320 | 2,320 | 2,320 |
| $R$-squared | 0.017 | 0.143 | 0.041 | 0.005 | 0.006 | 0.009 | 0.012 |
| Mean for control | 189.1 | 5.921 | 158.3 | 327.9 | 1,302 | 2,058 | 1,177 |
| Chi$^2$ test of insured and insured + capital grant treatment | 8.889 | 7.125 | 36.15 | 3.136 | 0.239 | 5.091 | 6.618 |
| $p$-value | .003 | .008 | .000 | .077 | .625 | .024 | .010 |

*Notes.* Robust standard errors in parentheses. "Insured" instrumented by full set of prices (Table III, column (1) presents first-stage regressions). Total costs (column (6)) includes sum of chemicals, land preparatory costs (e.g., equipment rental but not labor), hired labor, and family labor (valued at gender/community/year-specific wages). Harvest value includes own-produced consumption, valued at community-specific market value. All specifications include controls for full set of sample frame and year interactions. ***$p < .01$, **$p < .05$, *$p < .1$.

# For more on credit and risk

- On credit, see: Beaman et al, 2014; Crepon et al. 2015; Tarozzi et al. 2015. Take-aways:
  - Take-up is far from universal (17-36%)
  - Fertilizer use generally goes up with credit access (11-35%)
  - But the increase in input usage accounts for a small fraction of the average loan size (13-20%)
  - $\Rightarrow$ A substantial minority of farmers would consume substantially more inputs if credit constraints were lifted

- On risk, see: Mobarak & Rosenzweig, 2012; Cai et al., 2015; Emerick et al., 2016. Take-aways:
  - Reducing risk leads farmers to invest more in inputs and high-risk, high-return crops/livestock
  - But getting take-up of insurance is hard! (Cole et al., 2013; Carter et al., 2017; Marr et al. 2016; Casaburi and Willis, 2018)

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# Learning models

(Example: Foster and Rosenzweig, 1995)

- An agent is trying to learn about the return to a certain technology, $\theta^*$
- She has prior:

$$\theta_0 \sim N(\theta^*, \sigma_0^2) = N(\theta^*, 1/h_0)$$

- In each period $t$, she receives a signal

$$\tilde{\theta}^t \sim N(\theta^*, 1/h_u)$$

- Things to note:
  - Both prior and signal are centered at the "right" value
  - Relative precision of signal vs. prior is $h_u/h_0$
  - How does an agent update her beliefs? Bayesian updating

# Learning models (continued)

- It can be shown that the posterior belief, conditional on receiving signal $\tilde{\theta}_1$ is

$$\theta_1|\tilde{\theta}_1 \sim N(\frac{h_u\tilde{\theta}_1 + h_0\theta_0}{h_u + h_0}, \frac{1}{h_u + h_0})$$

- What about after $T$ periods? (normality simplifies algebra!)

$$\theta_T|\tilde{\theta}_1, \tilde{\theta}_2..., \tilde{\theta}_T \sim N(\frac{h_u\sum_{i=1}^{T}\tilde{\theta}_i + h_0\theta_0}{Th_u + h_0}, \frac{1}{Th_u + h_0})$$

- Take aways:
  - Beliefs converge to the true value $\theta^*$ as $T$ grows
    - N.B. Other models predict failure of info diffusion, even in long run (e.g. Herd Behavior, Banerjee 1992)
  - Learning is faster as $h_u$ increases

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- Confirm in agronomic trials that return to authentic inputs would be much higher (though even at market-rates of quality, positive returns to using inputs) Trials Returns
- Farmers' inference problem: yields vary due to a number of factors not fully observable to the farmer Go to
  - Quality of the inputs
  - Weather, fertility status of the soil, etc.

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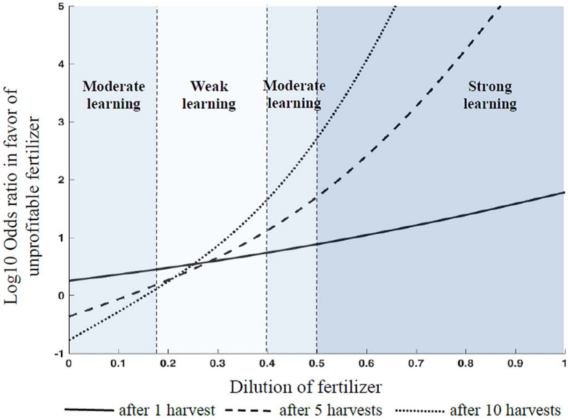


Panel A: Evidence in favor of fertilizer being profitable or not

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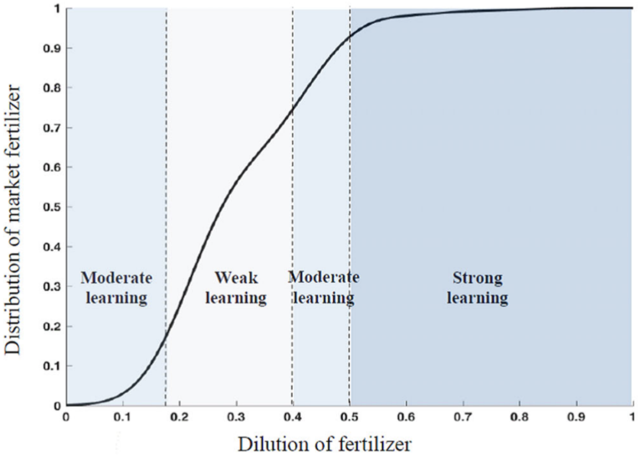


Panel B: Learning about fertilizer quality and distribution of market fertilizers

$\sim$ 60% of the samples located in the range where learning is weak

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- Simple contagion ($\lambda = 1$): an agent adopts as long as one of her peers adopts
- Complex contagion ($\lambda \geq 2$): an agent adopts as long as $\lambda$ of their peers adopt

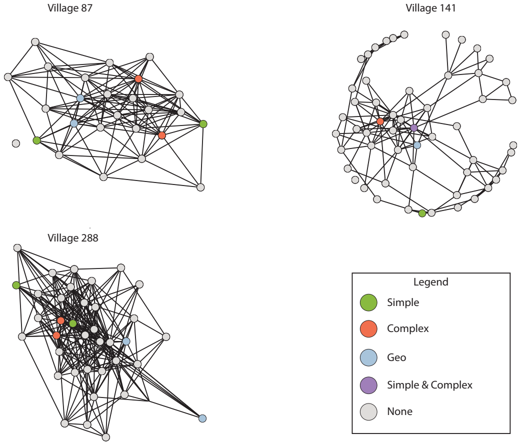
# Peer learning (Beaman et al., 2021)

- But can't people learn more quickly if learn from peers?
- And can targeting speed up peer learning?
- Simple contagion ($\lambda = 1$): an agent adopts as long as one of her peers adopts
- Complex contagion ($\lambda \geq 2$): an agent adopts as long as $\lambda$ of their peers adopt
- Now consider an intervention that aims to reach 2 "seed farmers" in each network. The optimal entry points will depend on the contagion model
  - Simple: first seed in dense part of network, second seed to diffuse to the more distant periphery
  - Complex ($\lambda = 2$): choose both seeds in central part of the network

# Adoption of pit-planting in Malawi

- Nice features of the papers
  - Collect *complete* network data in 200 villages (Chandrashekar and Lewis, 2011)
  - Simulate the various models to identify optimal entry points and then experimental treatment are based on the models
- Treatments vary at the village level based on the model used to select seed farmers
  - Simple contagion
  - Complex contagion based on network data
  - Complex contagion based on geographical proximity network
  - Selection made by extension officers (status quo)

# Seed farmers under different scenarios




- Note: some overlap.

# Adoption by non-seed farmers: individual-level regs

Table 5: Diffusion Within the Village

| | Heard of PP | | | Knows how to PP | | | Adopts PP | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Connected to 1 seed | 0.002 | 0.030 | 0.016 | 0.017 | 0.021 | -0.031 | 0.008 | 0.012 | 0.004 |
| | (0.024) | (0.022) | (0.029) | (0.016) | (0.017) | (0.023) | (0.011) | (0.015) | (0.017) |
| Connected to 2 seeds | 0.084 ** | 0.124 *** | 0.064 | 0.062 ** | 0.068 ** | 0.110 ** | 0.016 | 0.039 ** | 0.014 |
| | (0.038) | (0.040) | (0.064) | (0.028) | (0.029) | (0.051) | (0.014) | (0.019) | (0.035) |
| Within path length 2 of at least one seed | -0.018 | 0.016 | 0.067 | 0.005 | 0.022 | 0.028 | 0.013 | 0.022 * | 0.037 * |
| | (0.028) | (0.027) | (0.042) | (0.018) | (0.021) | (0.028) | (0.008) | (0.013) | (0.021) |
| Season | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| N | 4155 | 4532 | 3103 | 4155 | 4532 | 3103 | 4203 | 3931 | 2998 |
| Mean of Reference Group (No connection to any seed) | 0.223 | 0.286 | 0.391 | 0.057 | 0.095 | 0.147 | 0.013 | 0.044 | 0.043 |
| SD of Reference Group | 0.416 | 0.452 | 0.488 | 0.232 | 0.293 | 0.355 | 0.113 | 0.206 | 0.203 |
| *p-value* for 2 connections = 1 connection | 0.018 | 0.013 | 0.442 | 0.072 | 0.091 | 0.004 | 0.522 | 0.164 | 0.760 |

Notes

1 Sample excludes seed and shadow farmers. Only connections to simple, complex and geo seed farmers are considered (no connections to benchmark farmers included).

2 The dependent variable in columns (1)-(3) is an indicator for whether the respondent reported being aware of a plot preparation method other than ridging and then subsequently indicated awareness of pit planting in particular. In columns (4)-(6), the dependent variable is an indicator for whether the farmer reported knowing how to implement pit planting. The dependent variable in (7)-(9) is an indicator for the household having adopted pit planting in that season.

3 In all columns, additional controls include indicators for the respondent being connected to: one Simple partner, two Simple partners, one Complex partner, two Complex partners, one Geo partner, two Geo partners, within 2 path length of a Simple partner, within 2 path length of a Complex Partner, and within 2 path length of the geo partner.

4 Also included in both panels are village fixed effects. Standard errors clustered at the village level.

5 The reference group is comprised of individuals with no direct or 2-path-length connections to a seed farmer.

6 *** p<0.01, ** p<0.05, * p<0.1

- N.B. Important to control for features of the individual's network (footnote 3)

# Adoption by non-seed farmers: village-level regs

Table 6: Village-Level Regressions of Adoption Outcomes Across Treatment Arms

| | Any Non-Seed Adopters | | | | Adoption Rate | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| Simple Contagion Treatment | 0.155 | | 0.189 | * | 0.036 | ** | 0.006 | |
| | (0.100) | | (0.111) | | (0.017) | | (0.022) | |
| Complex Contagion Treatment | 0.252 | *** | 0.304 | *** | 0.036 | ** | 0.036 | |
| | (0.093) | | (0.101) | | (0.016) | | (0.026) | |
| Geographic treatment | 0.107 | | 0.188 | * | 0.038 | | 0.013 | |
| | (0.096) | | (0.110) | | (0.027) | | (0.034) | |
| Year | 2 | | 3 | | 2 | | 3 | |
| N | 200 | | 141 | | 200 | | 141 | |
| Mean of Benchmark Treatment (omitted category) | 0.420 | | 0.543 | | 0.038 | | 0.075 | |
| SD of Benchmark | 0.499 | | 0.505 | | 0.073 | | 0.109 | |
| *p-values for equality in coefficients:* | | | | | | | | |
| Simple = Complex | 0.300 | | 0.240 | | 0.981 | | 0.173 | |
| Complex = Geo | 0.102 | | 0.220 | | 0.937 | | 0.491 | |
| Simple = Geo | 0.623 | | 0.990 | | 0.950 | | 0.783 | |

Notes

1 The reference group is the Benchmark treatment.

2 The adoption rate in columns (1)-(2) include all radomly sampled farmers, excluding seed and shadow farmers. The "Any non-seed adopters" indicator in columns (3)-(4) excludes only seed farmers.

3 Sample for year 3 (columns 2 and 4) excludes Nkhotakota district.

4 All columns include controls used in the re-randomization routine (percent of village using compost at baseline; percent village using fertilizer at baseline; percent of village using pit planting at baseline); village size and its square; and district fixed effects. Standard errors are clustered at the village level.

5 *** p<0.01, ** p<0.05, * p<0.1

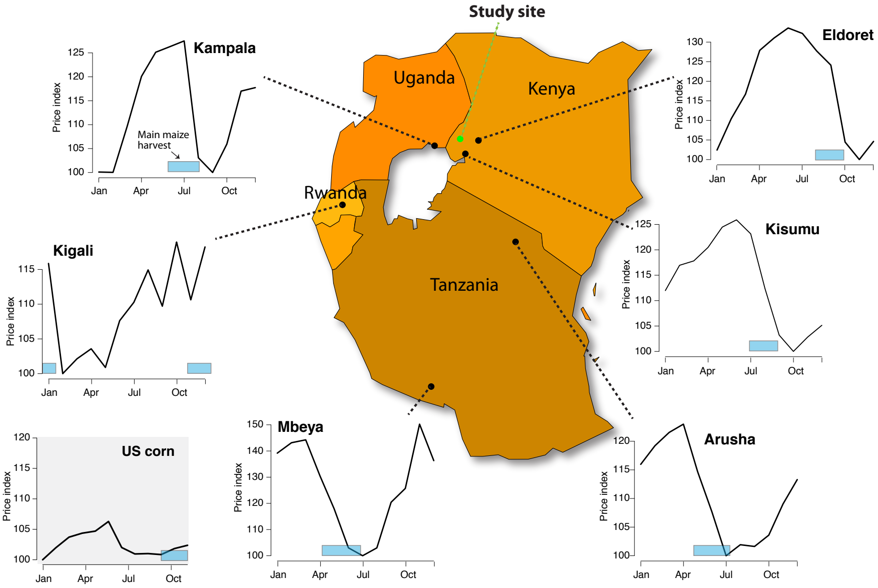
- Geo treatment poor substitute for network data, but (somewhat) better than benchmark

# For more on info constraints

- Learning can be helped or hampered depending on the gender of the communicator (BenYishay et al. 2016, Kondylis et al. 2016)
- With financial incentives, farmers selected by peers can encourage greater adoption than a lead farmer selected by extension agents, but without these incentives, the lead farmer outperforms the peer farmers (BenYishay & Mobarak, 2017)
- Farmers are more likely to adopt new seeds when when their land quality is more similar to their peers who (randomly) receive new seeds (Tjernstrom, 2017)
- Mobile phone-based farming advice lines can increase farmers use of fertilizer and encourage crop diversification (Cole & Fernando, 2012)

# Outline

- A model of agricultural technology adoption (Magruder 2018)
- Where we have good micro evidence (for macro to build on):
  - Credit and risk inefficiencies (Karlan et al., 2014)
  - Informational inefficiencies (Bold et al, 2017; Beaman et al., 2021)
- Where we have less micro evidence (and where macro can help):
  - **Externalities/GE effects (Burke et al., 2019)**
- Comment on potential synergies between micro and macro


Study site
Uganda
Kenya
Rwanda
Tanzania
Kampala
Main maize harvest
Eldoret
Kisumu
Kigali
US corn
Mbeya
Arusha
Price index
Jan
Apr
Jul
Oct

# Storage

So: staple food prices not fixed within the season.

Storage should allow the movement of grain intertemporally

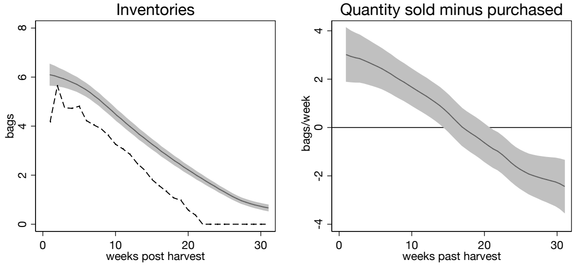
An unconstrained intertemporal profit maximizer should store a unit of grain if:

$$\delta E[p_{t+1}] > p_t + c \tag{1}$$

You might think: use storage to *buy low, sell high*

# Instead: Sell Low, Buy High

**Sell low, buy high:** farm households appear to be selling low at harvest or buying high later in the season – and often both




⇒ Modal HH in our sample appears to be giving up equivalent of 1-2 months of agricultural wages by selling low/ buying high, instead of the reverse

# Paper Overview

Why are farmers not using storage to arbitrage these price fluctuations?

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Data:

- Three rounds of household surveys throughout the year
- Monthly price data at 52 local markets

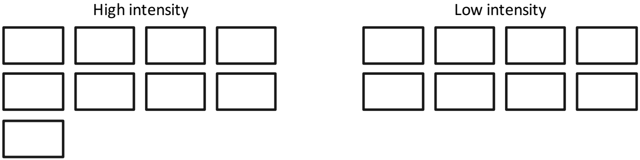
Study timeline:

- Two years of replication
- Long-run follow-up survey 1-2 years after loan ended

# Experimental Design

**Sublocation-level randomization**

High intensity = 9 locations
Low intensity = 8 locations



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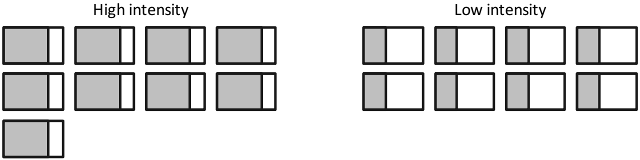
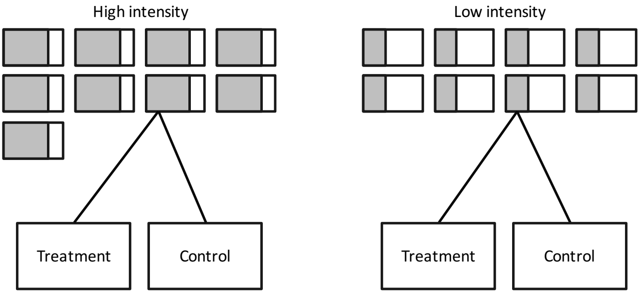


# Experimental Design

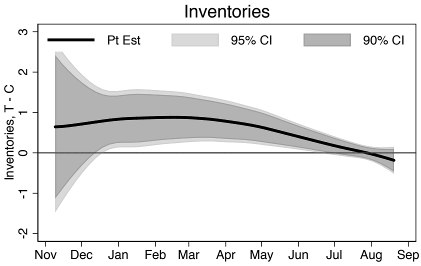
**Sublocation-level randomization**
High intensity = 9 locations
Low intensity = 8 locations

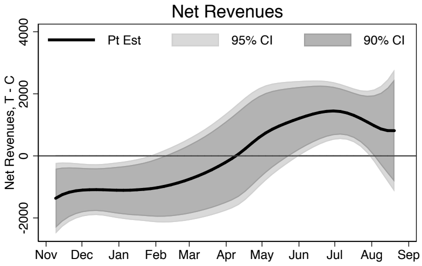
**Group-level randomization**

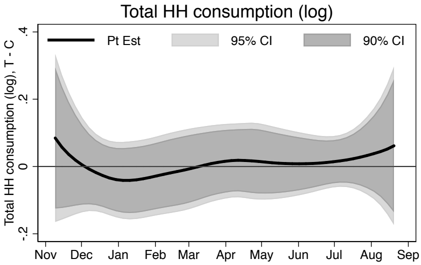



Y1 Y2 Timeline Balance

# Individual Level Effects: Graphical Results



# Individual Level Effects: Regression Results

| | Inventory | | Net Revenues | | Consumption | |
|---|---|---|---|---|---|---|
| | Overall | By rd | Overall | By rd | Overall | By rd |
| Treat | 0.56*** | | 533.44*** | | 0.04 | |
| | (0.10) | | (195.49) | | (0.02) | |
| Treat - R1 | | 1.05*** | | -613.58** | | 0.01 |
| | | (0.18) | | (271.61) | | (0.03) |
| Treat - R2 | | 0.55*** | | 1187.97*** | | 0.05* |
| | | (0.12) | | (337.41) | | (0.03) |
| Treat - R3 | | 0.09 | | 998.67*** | | 0.04 |
| | | (0.16) | | (291.06) | | (0.03) |
| Observations | 6780 | 6780 | 6730 | 6730 | 6736 | 6736 |
| Mean DV | 2.16 | 2.16 | -1616.12 | -1616.12 | 9.55 | 9.55 |
| SD DV | 3.23 | 3.23 | 6359.06 | 6359.06 | 0.64 | 0.64 |
| R squared | 0.33 | 0.33 | 0.12 | 0.12 | 0.06 | 0.06 |

Specification Other Results

# Market Effects: Predictions

By encouraging greater storage, the loan shifted supply at different points in the season. Does this affect local market prices?

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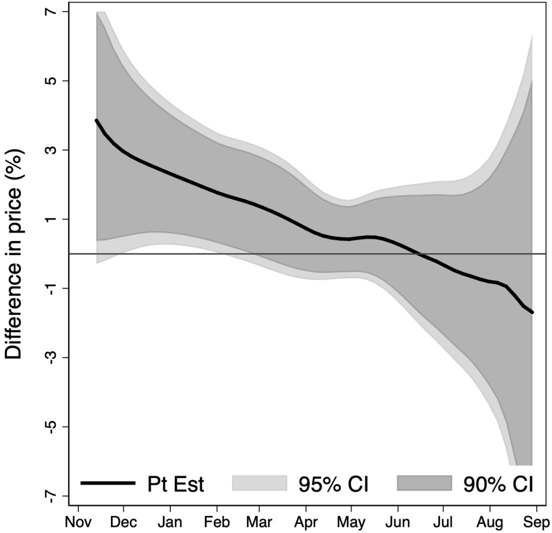
By encouraging greater storage, the loan shifted supply at different points in the season. Does this affect local market prices?

When more individuals engage in arbitrage, we predict that:

- Prices will be higher immediately after harvest, as maize in storage rather than on market
- Prices will be lower later, as stored maize is released

# Market Effects: Graphical Results



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- *N.B. smoother prices could benefit non-borrowers!*
- To explore this, estimate:

$$Y_{ijry} = \alpha + \beta_1 T_{jy} + \beta_2 Hi_s + \beta_3 T_{jy} * Hi_s + \eta_{ry} + \varepsilon_{ijry}$$

# Treatment Spillovers

| | (1) Inventory | (2) Net Revenues | (3) Consumption |
|---|---|---|---|
| Treat | 0.74*** | 1101.39** | -0.01 |
| | (0.15) | (430.09) | (0.02) |
| Hi | 0.02 | 164.94 | -0.05 |
| | (0.24) | (479.68) | (0.04) |
| Treat * Hi | -0.29 | -816.77 | 0.07* |
| | (0.19) | (520.04) | (0.04) |
| Observations | 6780 | 6730 | 6736 |
| Mean DV | 2.59 | -1055.15 | 9.54 |
| R squared | 0.29 | 0.09 | 0.03 |
| p-val T+TH=0 | 0.01 | 0.41 | 0.08 |

Effects by year IV Effects

# Implications

- Revenue effects are concentrated among low-intensity treated individuals
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- Methodologically, impacts captured in a small pilots may not correspond to impacts at scale
  - We would have overestimated the direct impacts of credit if evaluated just among a few farmers
- What implications do GE effects have for the distribution of gains?
  - Small indirect gains per-person could be a large part of the total gains
  - In this context, high saturation appears to provide larger social gains but lower private gains

Gains Distribution

# Outline

- A model of agricultural technology adoption (Magruder 2018)
- Where we have good micro evidence (for macro to build on):
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- **Comment on potential synergies between micro and macro**

# “From Micro to Macro Development”

Buera, Kaboski, and Townsend (2021):

- Each has their strengths:
    - Micro: causality revolution (e.g. RCTs), deeply grounded in realities and data of developing countries
    - Macro: focused on policies that have aggregate or economy-wide distributional and welfare implications
- Common (though not inherent) critiques:
    - Micro: not enough focus on aggregate effects at scale, disconnect from theory
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- Common (though not inherent) critiques:
  - Micro: not enough focus on aggregate effects at scale, disconnect from theory
  - Macro: rely on strong structural assumptions, calibrated parameters may not be well-identified or locally relevant
- Methodological tools to bridge the gap:
  - Randomized saturation
  - Randomization at scale
  - Embedding RCTs/natural experiments in structural models

# Examples from agricultural tech adoption

- Burke at el (2019): storage loans shift supply of grain across time, dampening seasonal price fluctuations
- Fink et al (2020): seasonal loan to farmers increase on-farm labor and agricultural output, driving up wages in local labor markets
- Brooks and Donovan (2020): bridges lower risk of market access, affects labor market choices, farm investment, and savings
- Caunedo and Kala (2020): farm mechanization reduces labor demand, including family labor in supervision activities
- Casaburi and Willis (2020): randomizing subsidies to rent out land
- Bergquist et al (2020): agriculture policies at scale can shift wages and output prices, changing their average and distribution impacts
- *Your paper next...*

# Substantial variation in input quality

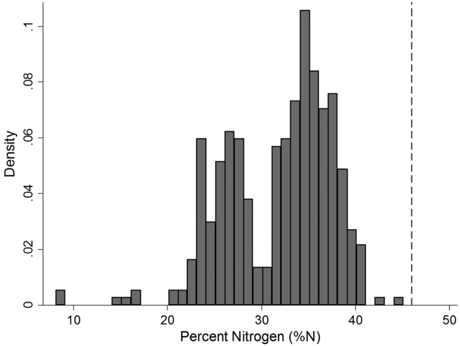


FIGURE I

The Distribution of Nitrogen Content in Fertilizer

(N.B. Other studies find limited evidence of adulteration, e.g. Michelson et al. (2021))

Back

# But not much variation in price

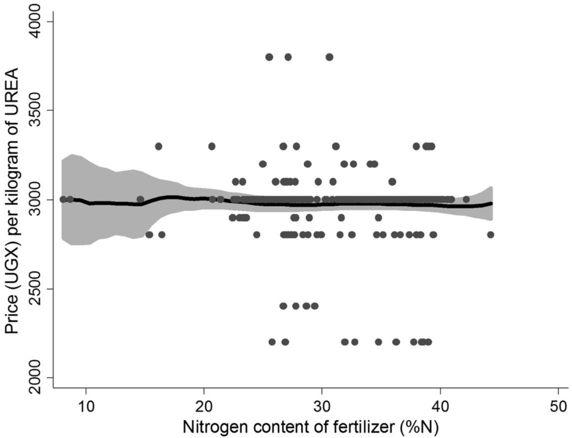


FIGURE II

The Relationship between Price and Quality of Fertilizer

Back

# Quality matters for yields

- Do consumers not care about quality?
- Bold et al. run agronomic trials to experimentally vary inputs
- 40% loss in yields at average input quality (retail hybrid, 32%N vs. authentic hybrid, 46%N)

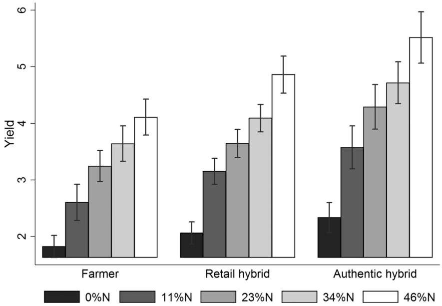


FIGURE III
The Yield Return to Nitrogen Content in Fertilizer

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# Returns to retail and authentic input use

TABLE V

ECONOMIC RETURNS TO FERTILIZER AND HYBRID SEEDS ADOPTION

| Source | Technologies available in the market (1) | Authentic technologies (2) |
|---|---|---|
| Panel A: Adoption of UREA fertilizers and hybrid seeds | | |
| Mean rate of return | 6.5% | 83.6% |
| Median rate of return | 10.8% | 83.1% |
| Fertilizer samples yielding positive net return | 65.6% | 100.0% |
| Fertilizer samples yielding rate of return > 25% | 8.9% | 100.0% |
| Fertilizer samples yielding rate of return > 50% | 0.0% | 100.0% |
| Panel B: 25% lower complementary expenses | | |
| Mean rate of return | 15.8% | 99.6% |
| Median rate of return | 20.5% | 99.0% |
| Fertilizer samples yielding positive net return | 76.7% | 100.0% |
| Fertilizer samples yielding rate of return > 25% | 37.1% | 100.0% |
| Fertilizer samples yielding rate of return > 50% | 1.1% | 100.0% |
| Panel C: 50% lower complementary expenses | | |
| Mean rate of return | 26.9% | 118.7% |
| Median rate of return | 31.9% | 117.9% |
| Fertilizer samples yielding positive net return | 89.2% | 100.0% |
| Fertilizer samples yielding rate of return > 25% | 62.3% | 100.0% |

Back

# Inference problem

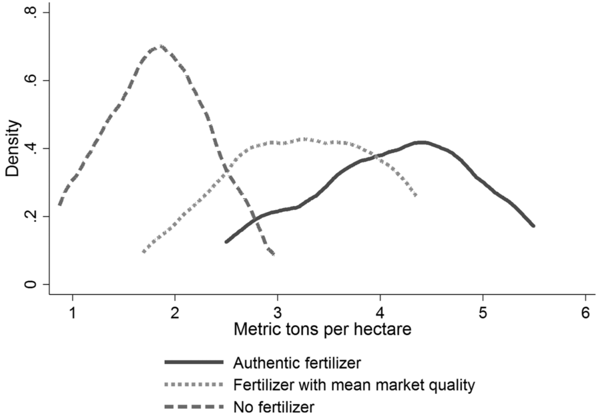


FIGURE VII

Densities of Yield for Different Input Qualities

Back

# A model of learning about quality

- Consider a farmer who wants to adopt fertilizer and starts experimenting with it on a small plot.
- The farmer knows that fertilizer of sufficiently high quality, say, with a rate of dilution $\theta < \theta^*$, where $\theta^*$ is the threshold level, is profitable.
- However, the dilution level $\theta \in [0, 1]$ is unknown
- The farmer must therefore infer quality based on the yields on her plot using Bayes' rule

# Characteristics of Seed Farmers

Table 1: Characteristics of the Seeds Chosen by Each Treatment Arm

| | Wealth Measures | | Social Network Measures | | |
|---|---|---|---|---|---|
| | Farm Size | Total Index (PCA) | Degree | Betweenness Centrality | Eigenvector Centrality |
| | (1) | (2) | (3) | (4) | (5) |
| Treatment arm: | | | | | |
| Simple Contagion | -0.152 | 0.113 | 0.455 | 156.009 ** | 0.009 |
| | (0.19) | (0.23) | (1.03) | (67.93) | (0.01) |
| Complex Contagion | -0.037 | 0.380 | 3.725 *** | 146.733 ** | 0.064 *** |
| | (0.19) | (0.23) | (1.02) | (67.74) | (0.01) |
| Geographic | -0.614 *** | -0.740 *** | -3.616 *** | -90.204 | -0.046 *** |
| | (0.19) | (0.23) | (1.03) | (68.04) | (0.01) |
| **p-values for tests of equality in seed characteristics** | | | | | |
| Simple = Complex | 0.335 | 0.067 | 0.000 | 0.815 | 0.000 |
| Complex = Geographic | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Simple = Complex = Geographic | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| N | 1248 | 1248 | 1232 | 1232 | 1232 |
| Mean Value for Seeds in Benchmark Treatment (omitted category) | 2.06 | 0.626 | 11.9 | 169 | 0.173 |
| SD for Seeds in Benchmark Treatment | 2.97 | 1.7 | 6.77 | 343 | 0.0961 |

Notes

1 The sample includes all seeds and shadows. The sample frame includes 100 Benchmark farmers (2 partners in 50 villages), as we only observe Benchmark farmers in Benchmark treatment villages, and up to 6 additional partner farmers (2 Simple partners, 2 Complex partners, and 2 Geo partners) in all 200 villages.

2 Benchmark treatment seeds are the omitted category.

3 *** p<0.01, ** p<0.05, * p<0.1

*Degree*: number of other people a person is connected to; *Betweenness centrality*: captures that a person is important if one has to go through him to connect to other people; *Eigenvector centrality*: weighted sum of connections, where each connection's weight is determined by its own eigenvector centrality

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# Adoption Rates for Seed Farmers (Relative to Shadow)

Table 2: Adoption Rates of Actual Seeds Relative to Shadow (Counterfactual) Farmers

| | Adopted Pit Planting | | | | | | Adopted Crop Residue Management | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (5) |
| Seed | 0.258 | *** | 0.230 | *** | 0.183 | *** | 0.137 | *** | 0.047 |
| | (0.03) | | (0.03) | | (0.04) | | (0.04) | | (0.04) |
| N | 686 | | 672 | | 490 | | 686 | | 467 |
| Mean of Shadows | 0.054 | | 0.093 | | 0.139 | | 0.320 | | 0.207 |
| Season | 1 | | 2 | | 3 | | 1 | | 2 |

Notes

[1] Also included are village fixed effects. Sample includes only seed farmers (chosen by the simulations and trained on the technologies through our intervention) and shadow (counterfactual) farmers with the same network characteristics but not trained by the experiment. The sample excludes Benchmark villages. Standard errors are clustered at the village level.

- What are "shadow farmers"?

# Adoption by Seed Farmersby Treatment Group

Table 3: Difference in Adoption Rates Across Seed Farmers chosen through Different Targeting Strategies

| | Adopted Pit Planting | | | Adopted Crop Residue Management | |
|---|---|---|---|---|---|
| Treatment: | (1) | (2) | (3) | (4) | (5) |
| Simple Contagion | -0.006 | 0.129 * | 0.176 ** | 0.078 | -0.097 |
| | (0.07) | (0.07) | (0.09) | (0.08) | (0.09) |
| Complex Contagion | -0.020 | 0.002 | 0.037 | -0.001 | -0.077 |
| | (0.08) | (0.07) | (0.08) | (0.08) | (0.09) |
| Geographic | -0.095 | -0.064 | -0.003 | -0.011 | -0.075 |
| | (0.08) | (0.07) | (0.08) | (0.08) | (0.10) |
| N | 353 | 352 | 259 | 353 | 243 |
| Mean Adoption for Seeds in Benchmark Treatment (the omitted category) | 0.337 | 0.276 | 0.238 | 0.442 | 0.339 |
| *p-value for tests of equality in adoption rates across treatment cells:* | | | | | |
| Simple = Complex | 0.862 | 0.077 | 0.108 | 0.311 | 0.808 |
| Complex = Geographic | 0.360 | 0.358 | 0.625 | 0.886 | 0.977 |
| Joint test of 3 treatments | 0.252 | 0.008 | 0.049 | 0.235 | 0.795 |
| Season | 1 | 2 | 3 | 1 | 2 |

- How does this affect our interpretation of the results?

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