Heterogeneous farmers' technology adoption decisions: Good on average is not good enough

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Motivation

Despite the importance of the agriculture sector, farmers in Sub-Saharan African countries persistently use traditional farming methods and face low agricultural productivity [7].

A large share of current studies focus on obstacles that have caused the insufficient usages of modern technology, such as information failure [1] [4] [6], supply shortages [5], credit constraints [2], and behavior constraints [3]. Those factors contribute to the low and stagnant rate of technology adoption, but they cannot fully account for it.

Objectives

- Understand the rationale behind farmers' technology adoption decisions. Specifically, can heterogeneous farmer characteristics and heterogeneous technologies explain the adoption patterns?
- Construct a structure model that could be used to examine technology adoption decisions under uncertainty.

Theoretical model

At the beginning of each farming season, farmers consider various existing agricultural technologies (h^N_{ijt}, h^F_{ijt}, h^I_{ijt}, h^B_{ijt}) and choose which one to adopt for each plot.

Assume that farmers are expected utility maximizers and care about both the expected value and the variance of profits, which are defined as yields minus costs:

$$\max_{h^N_{ijt},h^F_{ijt},h^I_{ijt},h^B_{ijt}} EU_{ijt} = m\mu_{ijt} + \rho v_{ijt} \tag{1}$$

$$s.t. \quad \mu_{ijt} = \mathbb{E}[\pi_{ijt}]$$

$$v_{ijt} = \mathbb{E}[(\pi_{ijt})^2] - (\mathbb{E}[\pi_{ijt}])^2, \tag{2}$$

where i represents farmer, j refers to plot, t stands for agriculture season, and π is the profit.

I build farmer's production function with four special proprieties: 1) heterogeneous returns, 2) selection bias, 3) heterogeneous variances, and 4) multiple technology choices:

$$y^D_{ijt} = \beta^D_t + \boldsymbol{x_{ijt}}'\boldsymbol{\gamma} + u^D_{ijt}, \tag{3}$$

where y^D_{ijt} is the log of technology-specific yield (dollars per acre), β^D_t is technology-specific aggregate returns to yield, $\boldsymbol{x}_{ijt}$ is a $k \times 1$ vector of log of exogenous observable farming inputs, and u^D_{ijt} is technology-specific error term.

I decompose the technology-specific error term (u^D_{ijt}) into two parts - productivity and shock. The observed yield can be written as:

$$\begin{aligned} y_{ijt} = \sum_D h^D_{ijt} y^D_{ijt} &= \beta^N_t + \boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \theta_{ij} \\ &+ [(\beta^F_t - \beta^N_t) + \theta^F_{ij}]h^F_{ijt} + [(\beta^I_t - \beta^N_t) + \theta^I_{ij}]h^I_{ijt} \\ &+ [(\beta^B_t - \beta^N_t) + \theta^B_{ij}]h^B_{ijt} + \varepsilon_{ijt}\{(\alpha^N)^{\frac{1}{2}} + [(\alpha^F)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^F_{ijt} \\ &+ [(\alpha^I)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^I_{ijt} + [(\alpha^B)^{\frac{1}{2}} - (\alpha^N)^{\frac{1}{2}}]h^B_{ijt}\}, \end{aligned} \tag{4}$$

where θ_{ij} is farmer-plot-specific general farming productivity, θ^D_{ij} farmer-plot-technology-specific productivity, α^D is technology-specific characteristic, and ε_{ijt} is farmer-plot-time-specific idiosyncratic shock.

Data

- A national panel survey: Tanzania Living Standards Measurement Study, round 2010-2011 and 2012-2013.
- It includes 1628 households and 2523 plots (unit of anlysis).
- Farmers face 4 technology decision choices: adopting neither technology (N), fertilizer only (F), intercropping only (I), both technologies (B).

Empirical strategies

To empirically study farmers' decisions about agricultural technology adoption, I estimate the farmer's decision-making model through four steps.

1. Evaluate the farmer's production function as a correlated random coefficient (CRC) model and substitute farmer's unobserved and endogenous productivity with its linear projection on the farmer's full history of adoptions and their interactions.
2. Decompose the previously estimated residual term of the farmer's production function through the feasible generalized least squares (FGLS) method, to separate out the intrinsic characteristic of the technology set that affects the variance of production.
3. Re-estimate the production function with a weight derived from the previous step, thereby all coefficients are updated to be both consistent and asymptotically efficient.
4. Calculate farmers' responses to the expected value of profit and the variance of profit and analyze factors that influence farmers' technology adoption decisions using the alternative-specific conditional logit method.

Results

Expected returns justify the adoption of fertilizer and both technologies, but cannot justify the adoption of intercropping.

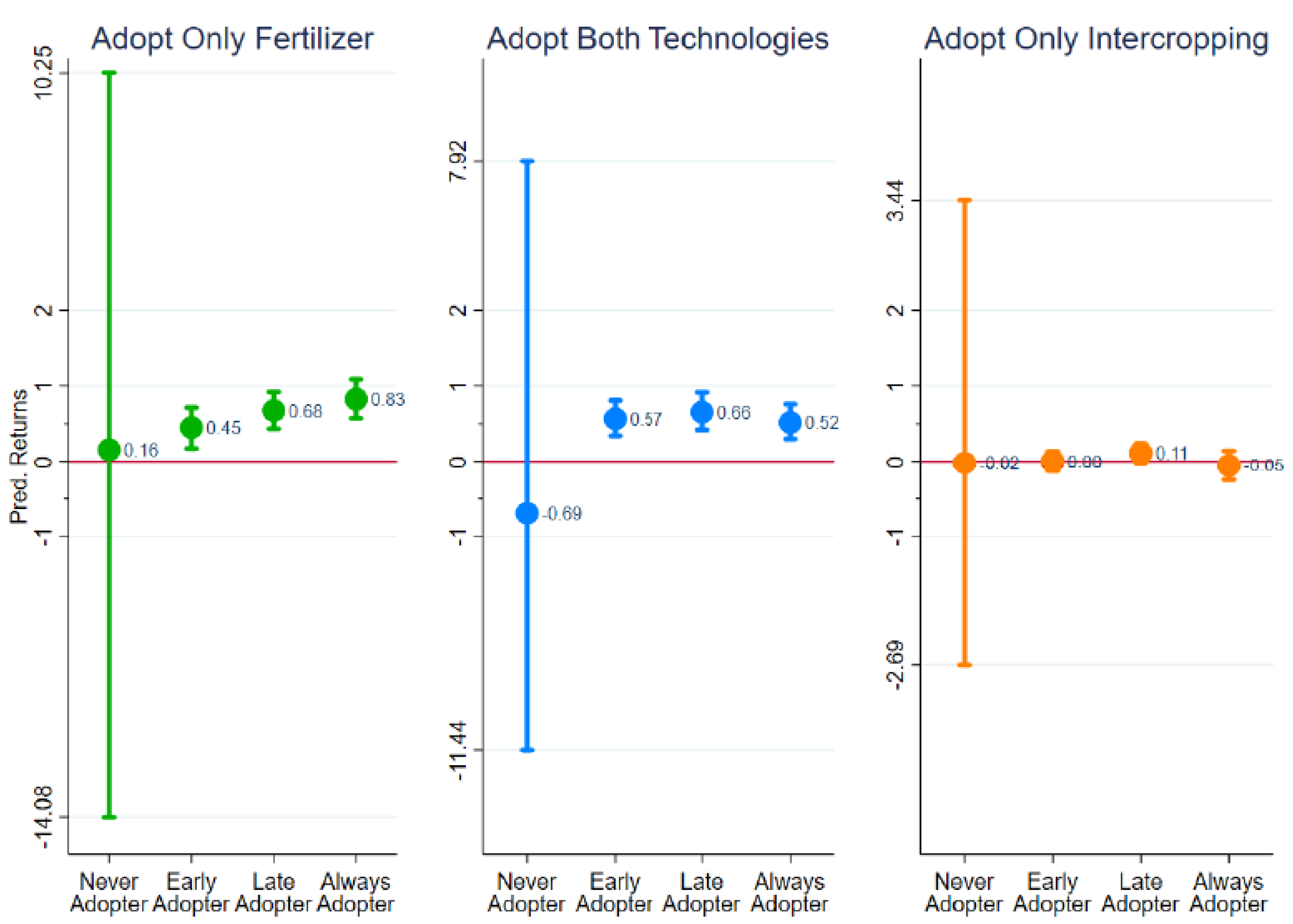

Fig. 1: Predicted returns with weights to technology adoption

Variance of returns justify the adoption of intercropping and the non-adoption of fertilizer.

	Ln of Conditional Variance of Ln of Yield $log\{Var(y_{ijt}\|\mathbf{x_{ijt}}, h^D_{ijt})\}$
Adopt only fertilizer	0.158
	[0.143]
Adopt only intercropping	-0.131**
	[0.057]
Adopt both technologies	-0.110
	[0.143]
N	5046
R^2	0.002
Intercropping = Fertilizer ($P-Value$)	0.031**

The expected value of profit and the variance of profit have positive and negative impacts on farmers' expected utility, respectively.

	(1) Basic	(2) Enhanced	(3) Mean-Only
Expected value of profit	0.059**	0.062**	0.040***
($/acre)	[0.031]	[0.032]	[0.019]
Variance of profit	-1.446***	-1.615***	
(1S.D.)	[0.000]	[0.000]	
Alternative-Specific Variables	Y	Y	Y
Case-Specific Variables	N	Y	Y
N	2523×2×4=20168		
Likelihood-ratio test between (2) and (3): Prob > χ^2 = 0.000.			

Policy implications

1. Given the high variation in yields and profits, providing crop insurance to insure production risk could increase fertilizer adoption and therefore overall yields.
2. Given the importance of variance on farmer's decision making, it is beneficial to have more agronomic research aimed at inventing low-variance technologies.

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