Money Matters

The role of yields and profits in agricultural technology adoption

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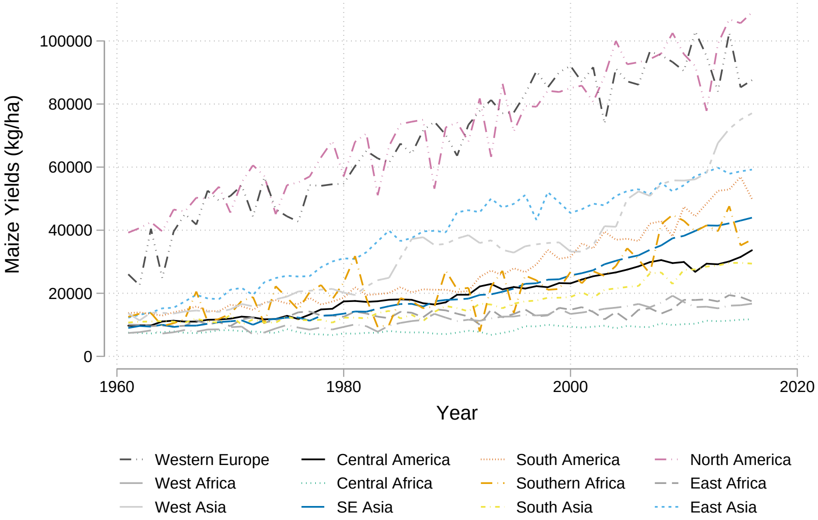
Development Economics Workshop, Madison, 22 February 2018

The Technology Adoption Puzzle



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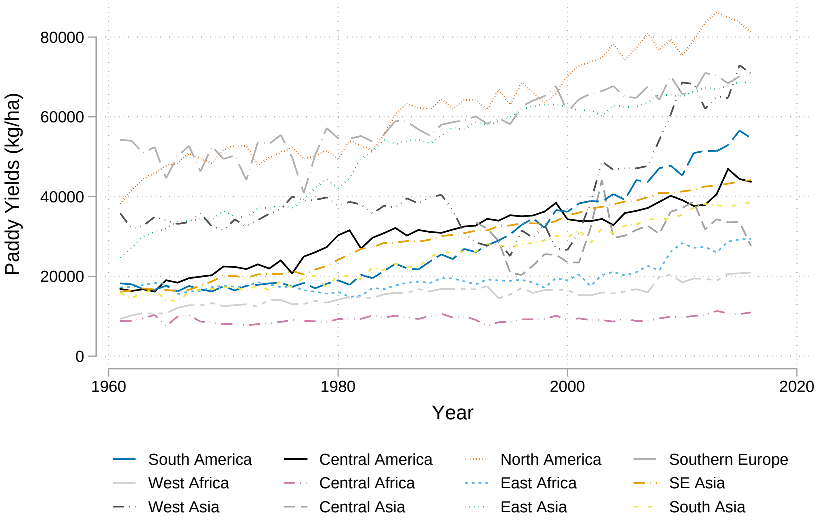

Constraints to Technology Adoption

- Why do adoption rates of many proven technologies remain low among smallholder farmers in developing countries?
  - Credit markets (Croppenstedt et al., 2003)
  - Property rights (Place and Swallow, 2000)
  - Learning externalities (Foster and Rosenzweig, 1995)
  - Lack of commitment (Kremer et al., 2011)

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    - Lack of commitment (Kremer et al., 2011)

An Empirical Puzzle?

- Suri (2011) proposed a “new” explanation: uncontrolled-for heterogeneity
  - Average returns to adoption are high
  - But returns to individual farmers may be heterogeneous
  - Heterogeneity is due to unobservable comparative advantage
  - Standard fixed effects only control for absolute advantage
  - Failing to control for unobserved comparative advantage biases results
- She shows this is the case for adoption of hybrid maize in Kenya
  - Average returns are positive and significant
  - Farmers with high returns adopt
  - Farmers with low returns do not adopt

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An Empirical Puzzle?

- The empirical puzzle is only a puzzle when we fail to account for the heterogeneity in returns
  - This is just an application of Becker and Chiswick (1966) and Griliches (1957, 1977) to technology adoption in developing countries
  - Heckman and Vytlacil (1998) solved the econometric problem using instrumental variables

Correlated Random Coefficients

The outcome y_i is a function of the rate of return, α_{1i}, to a choice variable h_i:

$$y_i = \alpha_{0i} + \alpha_{1i} h_i$$

Assume

- $\alpha_{0i} = \bar{\alpha}_0 + \epsilon_{0i}$
- $\alpha_{1i} = \bar{\alpha}_1 + \epsilon_{1i}$

where ϵ_{0i} and ϵ_{1i} are zero in expectation

$$y_i = \bar{\alpha}_0 + \bar{\alpha}_1 h_i + (\epsilon_{0i} + \epsilon_{1i} h_i)$$

The difficulty in identifying the model arises when α_{1i} is correlated with h_i

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Suri's (2011) CRC Model

- Suri (2011) develops a new method for estimating these Correlated Random Coefficients (CRC) models
  - The method is structural in nature
  - Eliminates the correlation by replacing the endogenous variable with its linear project
  - Similar to the Correlated Random Effects (CRE) approach developed in Mundlak (1978) and Chamberlain (1984)

Our Own Empirical Puzzle

1. What explains adoption of improved chickpea in Ethiopia?
   - Adoption has been very high $\approx 80\%$
   - With standard panel data methods, find that the technology does not increase yields
2. Is this result due to failure to control for unobserved heterogeneity?
   - Conduct an extension test of Suri (2011)
   - Find no evidence of a significant role for unobserved heterogeneity
3. What then explains the high adoption rates of a technology that does not significantly increase yields? Is the focus on physical returns is the wrong measure?
   - Many studies impute a value for production using market prices
   - But many households never actually receive this price
   - We explore the returns to adoption in terms of costs of production and profits from sale of agricultural goods in the market

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Methodological Approach

- Expand Suri's two-period model out to five-periods
- Estimate returns for yield using OLS, FE, CRE, and CRC
  - Fail to find evidence that adoption increases yields
  - Also fail to find heterogeneity in returns
- Estimate returns for costs and profits using OLS, FE, CRE, and CRC
  - Adoption reduces costs and increases profits
  - Again fail to find heterogeneity in returns
- Explore possible mechanisms

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Improved Chickpea

- Traditional variety: Desi, small brown seeds
- Recently introduced improved variety: Kabuli, large cream colored seeds
- From 2008-14 Kabuli adoption increased from 30% $\rightarrow$ 80%
- Ethiopia; world's 7^{th} largest producer of chickpea

Sources of Data

- Data collected in 2007, 2010, 2014
- Shewa region in central Ethiopia
- 678 households from 26 villages
- Use balance panel of 600 households
  - Measure yields as kg/ha
  - Measure costs as USD/ha using USD PPP with 2005 as base
  - Measure profits as USD/ha using net revenue from sale of agricultural goods in the market
- Use CHIRPS rainfall data

History of Adoption

	Transition of adoption			Fraction of sample (%)
	2007	2010	2014	($N = 600$)
Always adopter	Y	Y	Y	24.50
Early adopter	N	Y	Y	30.67
Late adopter	N	N	Y	20.00
Mixed adopter	Y	N	Y	4.00
Mixed dis-adopter	N	Y	N	6.33
Late dis-adopter	Y	Y	N	1.50
Early dis-adopter	Y	N	N	1.17
Never adopter	N	N	N	11.83

Variety Specific Yield Functions

$$y_{it}^{H} = \beta_{t}^{H} + X_{it}'\gamma_{j}^{H} + (\phi + 1)\,\theta_{i} + \zeta_{i} + \varepsilon_{it}^{H}$$
$$y_{it}^{L} = \beta_{t}^{L} + X_{it}'\gamma_{j}^{L} + \theta_{i} + \zeta_{i} + \varepsilon_{it}^{L}$$

- H and L are hybrid and local
- β_t variety specific aggregate returns
- X_{it} is a set of inputs with coefficients γ_j dependent on variety
- θ_i comparative advantage with coefficient ϕ
- ζ_i absolute advantage (household FE)
- ε_{it} variety specific idiosyncratic error

Generalized Yield Function

$$y_{it} = \beta_t^L + X_{it}'\gamma_j^L + \left(\beta_t^H - \beta_t^L\right) h_{it} + X_{it}' \left(\gamma_j^H - \gamma_j^L\right) h_{it} + \theta_i + \phi\theta_i h_{it} + \zeta_i + \varepsilon_{it}$$

Identification requires two assumptions:

1. Mean independence of the composite error $(\zeta_i + \varepsilon_{it})$ and unobserved comparative advantage terms (θ_i), and the exogenous regressors
   - Implies that farmer's absolute advantage is time constant, like FE
2. Strict exogeneity of the idiosyncratic error term
   - Implies transitory shocks do not affect decision to adopt (i.e., ε_{it} is realized after the planting decision)

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Basic DGP

- For ease of exposition, focus on three-year model without covariates
- Assume the data generating process is:

$$y_{it} = \delta + \beta h_{it} + \theta_i + \phi \theta_i h_{it} + \xi_{it},$$

- Where $\xi_{it} \equiv \zeta_i + \varepsilon_{it}$
- And $\beta \equiv \beta_t^H - \beta_t^L$

History of Adoption

- Project the θ_i on the history of the household's adoption behavior
- Similar to what Chamberlain (1984) does in his CRE model

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} + \lambda_4 h_{i1} h_{i2} + \lambda_5 h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} + \lambda_7 h_{i1} h_{i2} h_{i3} + \nu_i$$

- By including h_{it} $\forall t$ and $h_{it} hiq$ $\forall t, q$ s.t. $t \neq q$, we ensure that ν_i is uncorrelated with the adoption decision

Structural Equations

- Substitute the projection into the DGP
- Easer to write each period's structural equation

$$\begin{aligned}
y_{i1} &= (\delta + \lambda_0) + [\beta + \phi\lambda_0 + \lambda_1(1+\phi)]h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} \\
&+ [\phi\lambda_2 + \lambda_4(1+\phi)]h_{i1}h_{i2} + [\phi\lambda_3 + \lambda_5(1+\phi)]h_{i1}h_{i3} + \lambda_6 h_{i2}h_{i3} \\
&+ [\phi\lambda_6 + \lambda_7(1+\phi)]h_{i1}h_{i2}h_{i3} + (\nu_i + \phi\nu_i h_{i1} + u_{i1}) \\
y_{i2} &= (\delta + \lambda_0) + \lambda_1 h_{i1} + [\beta + \phi\lambda_0 + \lambda_2(1+\phi)]h_{i2} + \lambda_3 h_{i3} \\
&+ [\phi\lambda_1 + \lambda_4(1+\phi)]h_{i1}h_{i2} + \lambda_5 h_{i1}h_{i3} + [\phi\lambda_3 + \lambda_6(1+\phi)]h_{i2}h_{i3} \\
&+ [\phi\lambda_5 + \lambda_7(1+\phi)]h_{i1}h_{i2}h_{i3} + (\nu_i + \phi\nu_i h_{i2} + u_{i2}) \\
y_{i3} &= (\delta + \lambda_0) + \lambda_1 h_{i1} + \lambda_2 h_{i2} + [\beta + \phi\lambda_0 + \lambda_3(1+\phi)]h_{i3} \\
&+ [\phi\lambda_1 + \lambda_5(1+\phi)]h_{i1}h_{i3} + \lambda_4 h_{i1}h_{i2} + [\phi\lambda_2 + \lambda_6(1+\phi)]h_{i2}h_{i3} \\
&+ [\phi\lambda_4 + \lambda_7(1+\phi)]h_{i1}h_{i2}h_{i3} + (\nu_i + \phi\nu_i h_{i3} + u_{i3})
\end{aligned}$$

Reduced Form Equations

- From the structural equations we estimate the following reduced form equations

$$
\begin{aligned}
y_{i1} &= \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i3} \\
&\quad + \gamma_4 h_{i1} h_{i2} + \gamma_5 h_{i1} h_{i3} + \gamma_6 h_{i2} h_{i3} \\
&\quad + \gamma_7 h_{i1} h_{i2} h_{i3} + n_{i1} \\
y_{i2} &= \delta_2 + \gamma_8 h_{i1} + \gamma_9 h_{i2} + \gamma_{10} h_{i3} \\
&\quad + \gamma_{11} h_{i1} h_{i2} + \gamma_{12} h_{i1} h_{i3} + \gamma_{13} h_{i2} h_{i3} \\
&\quad + \gamma_{14} h_{i1} h_{i2} h_{i3} + n_{i2} \\
y_{i3} &= \delta_3 + \gamma_{15} h_{i1} + \gamma_{16} h_{i2} + \gamma_{17} h_{i3} \\
&\quad + \gamma_{18} h_{i1} h_{i2} + \gamma_{19} h_{i1} h_{i3} + \gamma_{20} h_{i2} h_{i3} \\
&\quad + \gamma_{21} h_{i1} h_{i2} h_{i3} + n_{i3}
\end{aligned}
$$

Restrictions

Gives us

- 21 reduced form coefficients ($\gamma_1 - \gamma_{21}$)
- 10 structural parameters ($\beta, \phi, \lambda_0 - \lambda_7$)

$$\begin{aligned}
\gamma_1 &= [\beta + \phi\lambda_0 + \lambda_1(1+\phi)] & \gamma_8 &= \lambda_1 & \gamma_{15} &= \lambda_1 \\
\gamma_2 &= \lambda_2 & \gamma_9 &= [\beta + \phi\lambda_0 + \lambda_2(1+\phi)] & \gamma_{16} &= \lambda_2 \\
\gamma_3 &= \lambda_3 & \gamma_{10} &= \lambda_3 & \gamma_{17} &= [\beta + \phi\lambda_0 + \lambda_3(1+\phi)] \\
\gamma_4 &= [\phi\lambda_2 + \lambda_4(1+\phi)] & \gamma_{11} &= [\phi\lambda_1 + \lambda_4(1+\phi)] & \gamma_{18} &= \lambda_4 \\
\gamma_5 &= [\phi\lambda_3 + \lambda_5(1+\phi)] & \gamma_{12} &= \lambda_5 & \gamma_{19} &= [\phi\lambda_1 + \lambda_5(1+\phi)] \\
\gamma_6 &= \lambda_6 & \gamma_{13} &= [\phi\lambda_3 + \lambda_6(1+\phi)] & \gamma_{20} &= [\phi\lambda_2 + \lambda_6(1+\phi)] \\
\gamma_7 &= [\phi\lambda_6 + \lambda_7(1+\phi)] & \gamma_{14} &= [\phi\lambda_5 + \lambda_7(1+\phi)] & \gamma_{21} &= [\phi\lambda_4 + \lambda_7(1+\phi)]
\end{aligned}$$

The OMD Estimator

- Estimate the period reduced form equations using SUR
- Save the 21 parameters in a vector $\pi_{[21\times 1]}$
- Save the variance-covariance matrices in a large symmetric block matrix $\mathbf{V}_{[21\times 21]}$
- Place the restrictions in a matrix $\mathbf{H}_{[21\times 9]}$

The Optimal Minimum Distance (OMD) function is then:

$$\min_{\delta} = \{\pi - \mathbf{H}\delta\}' \mathbf{V}^{-1} \{\pi - \mathbf{H}\delta\}$$

Solving for the minimum distance we get:

$$\delta^* = \left(\mathbf{H}'\mathbf{V}^{-1}\mathbf{H}\right)^{-1} \mathbf{H}'\mathbf{V}^{-1}\pi,$$

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Implementation

- Though Suri (2011) has been cited +400 times, only two papers actually use her CRC method
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OLS and FE Estimation of Yield Function

	Ln chickpea yield (kg/ha)			
	OLS	OLS	FE	FE
Improved chickpea	0.258***	0.128*	0.054	0.077
	(0.072)	(0.070)	(0.089)	(0.088)
Covariates	No	Yes	No	Yes
Year Controls	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes
District Controls	Yes	Yes	No	No
Household FE	No	No	Yes	Yes
Observations	1,408	1,408	1,408	1,408
R^2	0.043	0.163	0.006	0.058

CRE Estimation of Yield Function

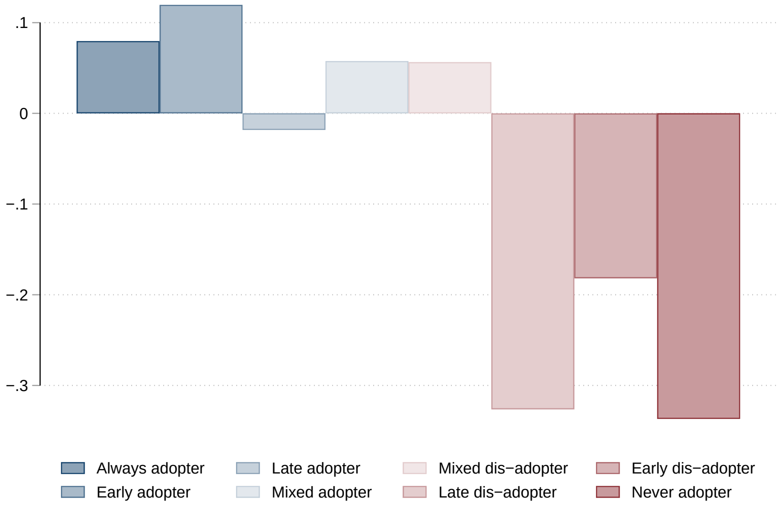
	Reduced Form Estimates					
	Without covariates			With covariates		
	2007	2010	2014	2007	2010	2014
Improved,	0.102	0.154***	0.222**	0.023	−0.072	0.068
2007	(0.078)	(0.060)	(0.105)	(0.080)	(0.060)	(0.116)
Improved,	0.044	0.023	−0.012	0.080	0.174**	−0.047
2010	(0.101)	(0.077)	(0.136)	(0.095)	(0.071)	(0.137)
Improved,	0.425***	0.131	0.306*	0.191	0.279**	−0.044
2014	(0.128)	(0.098)	(0.173)	(0.149)	(0.111)	(0.216)

	Optimal Minimum Distance (OMD) Structural Estimates	
	Without covariates	With covariates
β	-0.041	0.066
	(0.074)	(0.073)
λ_1	0.163***	-0.042
	(0.049)	(0.050)
λ_2	0.045	0.078
	(0.068)	(0.066)
λ_3	0.259***	0.196**
	(0.072)	(0.083)
Observations	1,011	1,011
χ^2	1,472	1,652***

CRC Estimation of Yield Function

	Without covariates	With covariates
β	−0.239	0.023
	(0.628)	(0.113)
ϕ	6.647	2.963
	(18.86)	(5.837)
λ_1	0.237	0.050
	(0.156)	(0.151)
λ_2	0.299***	0.139
	(0.109)	(0.110)
λ_3	0.272***	0.096
	(0.104)	(0.111)
λ_4	−0.297**	−0.198
	(0.120)	(0.182)
λ_5	−0.183	−0.017
	(0.265)	(0.180)
λ_6	−0.283***	−0.086
	(0.103)	(0.113)
λ_7	0.267**	0.152
	(0.122)	(0.155)
Observations	1,011	1,011
χ^2	4,341***	4,960***

Distribution of Returns for Yields



OLS and FE Estimation of Cost Function

	Ln production cost (USD/ha)			
	OLS	OLS	FE	FE
Improved chickpea	−0.027	−0.090***	0.038	−0.047**
	(0.026)	(0.015)	(0.029)	(0.019)
Covariates	No	Yes	No	Yes
Year Controls	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes
District Controls	Yes	Yes	No	No
Household FE	No	No	Yes	Yes
Observations	1,800	1,800	1,800	1,800
R^2	0.146	0.732	0.003	0.709

CRE Estimation of Cost Function

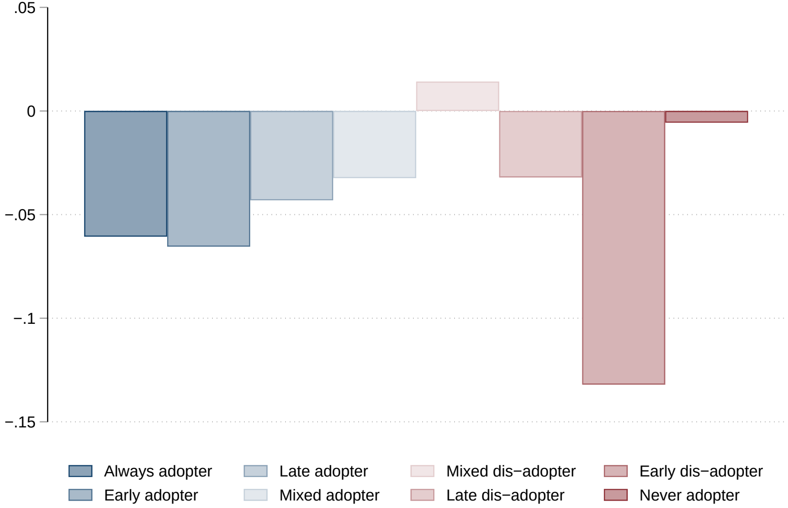
	Reduced Form Estimates					
	Without covariates			With covariates		
	2007	2010	2014	2007	2010	2014
Improved, 2007	0.272***	0.218***	0.153***	−0.055**	−0.006	0.016
	(0.046)	(0.047)	(0.041)	(0.026)	(0.024)	(0.018)
Improved, 2010	−0.058	−0.030	−0.054	−0.028	−0.039*	−0.014
	(0.045)	(0.046)	(0.040)	(0.025)	(0.023)	(0.018)
Improved, 2014	−0.077	−0.200***	0.149***	−0.006	−0.040	−0.065***
	(0.053)	(0.054)	(0.046)	(0.033)	(0.030)	(0.022)

	Optimal Minimum Distance (OMD) Structural Estimates	
	Without covariates	With covariates
β	0.038	-0.042**
	(0.036)	(0.018)
λ_1	0.198***	0.003
	(0.028)	(0.014)
λ_2	-0.060**	-0.013
	(0.028)	(0.014)
λ_3	-0.157***	-0.025
	(0.033)	(0.018)
Observations	1,800	1,800
χ^2	3,895***	1,427

CRC Estimation of Cost Function

	Without covariates	With covariates
β	0.032	−0.046*
	(0.038)	(0.024)
ϕ	−0.127	4.749
	(0.310)	(10.28)
λ_1	0.025	−0.023
	(0.116)	(0.039)
λ_2	−0.056	0.005
	(0.059)	(0.027)
λ_3	−0.154***	−0.007
	(0.045)	(0.021)
λ_4	0.213	0.015
	(0.164)	(0.032)
λ_5	0.145	0.026
	(0.135)	(0.043)
λ_6	−0.037	−0.009
	(0.073)	(0.032)
λ_7	−0.132	−0.016
	(0.177)	(0.034)
Observations	1,800	1,800
χ^2	6,591***	3,068***

Distribution of Returns for Costs



OLS and FE Estimation of Profit Function

	Ln on-farm profit (USD/ha)			
	OLS	OLS	FE	FE
Improved chickpea	2.834***	2.852***	2.485***	2.349***
	(0.310)	(0.313)	(0.391)	(0.401)
Covariates	No	Yes	No	Yes
Year Controls	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes
District Controls	Yes	Yes	No	No
Household FE	No	No	Yes	Yes
Observations	1,800	1,800	1,800	1,800
R^2	0.175	0.239	0.131	0.126

CRE Estimation of Profit Function

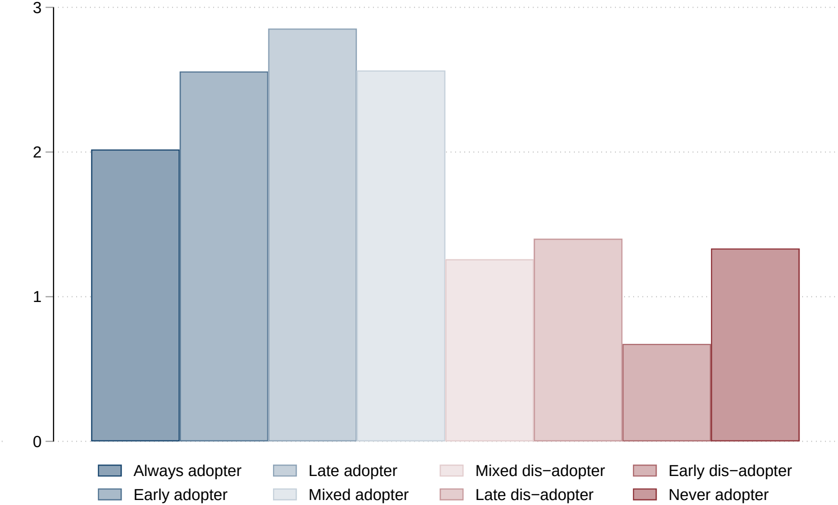
	Reduced Form Estimates					
	Without covariates			With covariates		
	2007	2010	2014	2007	2010	2014
Improved, 2007	0.728*	0.134	−1.479***	1.938***	−0.244	−0.540
	(0.447)	(0.530)	(0.574)	(0.460)	(0.569)	(0.546)
Improved, 2010	−0.395	0.305***	0.150	−0.135	2.530***	−0.617
	(0.436)	(0.517)	(0.560)	(0.447)	(0.553)	(0.531)
Improved, 2014	1.055**	2.315***	0.309***	0.670	1.455**	2.143***
	(0.508)	(0.602)	(0.652)	(0.564)	(0.697)	(0.670)

	Optimal Minimum Distance (OMD) Structural Estimates	
	Without covariates	With covariates
β	2.444***	2.283***
	(0.409)	(0.410)
λ_1	-1.086***	-0.375
	(0.343)	(0.346)
λ_2	0.055	-0.174
	(0.313)	(0.313)
λ_3	1.655***	0.645*
	(0.351)	(0.387)
Observations	1,800	1,800
χ^2	11,876***	3,028***

CRC Estimation of Profit Function

	Without covariates	With covariates
β	2.232***	2.249***
	(0.471)	(0.548)
ϕ	1.049	4.247
	(1.213)	(9.078)
λ_1	−0.153	−0.159
	(1.157)	(0.811)
λ_2	0.589	−0.040
	(0.656)	(0.608)
λ_3	1.741***	0.340
	(0.469)	(0.515)
λ_4	0.307	0.199
	(1.297)	(0.867)
λ_5	0.058	0.094
	(1.216)	(0.753)
λ_6	−0.524	−0.042
	(0.727)	(0.543)
λ_7	−0.984	−0.251
	(1.625)	(0.958)
Observations	1,800	1,800
χ^2	15,295***	7,763***

Distribution of Returns for Profits



In Brief

What is going on here?

- High levels of adoption
- No gains in terms of yields
- Some reduction in costs
- Large gains in terms of profits
- No significant heterogeneity in returns across all three measures

Potential Confounders

- Measurement error in valuing on-farm family labor
  - Measure family labor in days
  - Value family labor based on gov't rural wage data
  - Value family labor based on estimated shadow wage
- Bias due to endogeneity in measured inputs
  - Stata CRC package can accommodate an additional endogenous variable
  - Control for potential endogeneity in allocation of family labor
  - Control for potential endogeneity in application of chemical pesticide/herbicide
- None of these fundamentally change our results

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Potential Mechanisms

- If it is not yield gains, nor unobserved heterogeneity in returns, nor bias from confounding factors, what is driving the large gains in profitability?
  - Change in cropping patterns that help explain cost savings
  - Increased marketability of crop production that helps explain profit gains

Comparing Always Adopters to Future Dis-adopters

	2007			2014		
	Always adopter	Future dis-adopter	MW-test	Always adopter	Future dis-adopter	MW-test
Herfindahl Index	0.309	0.341		0.302	0.375	**
	(0.085)	(0.134)		(0.082)	(0.149)	
Shannon Index	-0.300	-0.329		-0.294	-0.361	**
	(0.078)	(0.118)		(0.076)	(0.129)	
Cultivated area allocated to chickpea (%)	27.14	29.02		25.81	21.32	
	(14.07)	(20.34)		(10.78)	(8.46)	
Agricultural sales income (USD)	4,874	4,350		2,098	918.6	***
	(3,915)	(4,493)		(2,336)	(1,064)	
Share of chickpea production sold (%)	63.61	59.91		48.65	22.22	***
	(29.37)	(24.51)		(24.63)	(9.94)	
Chickpea share of sales income (%)	38.97	31.82		31.94	25.04	
	(23.31)	(31.18)		(25.42)	(33.72)	
Observations	147	16		147	16	

Comparing Never Adopters to Future Adopters

	2007			2014		
	Never adopter	Future adopter	MW-test	Never adopter	Future adopter	MW-test
Herfindahl Index	0.393	0.409		0.409	0.331	***
	(0.126)	(0.141)		(0.151)	(0.093)	
Shannon Index	-0.377	-0.390		-0.391	-0.322	***
	(0.112)	(0.124)		(0.131)	(0.086)	
Cultivated area allocated to chickpea (%)	20.25	18.88		17.47	26.51	***
	(14.06)	(10.09)		(9.79)	(12.21)	
Agricultural sales income (USD)	2,227	2,727	*	683.0	1,521	***
	(1,724)	(2,212)		(875.7)	(1,253)	
Share of chickpea production sold (%)	59.23	58.90		29.56	57.77	***
	(14.42)	(23.17)		(18.67)	(25.30)	
Chickpea share of sales income (%)	24.42	22.67		18.25	39.24	***
	(23.00)	(18.36)		(29.74)	(27.09)	
Observations	71	304		71	304	

Conclusions

1. What explains adoption of improved chickpea in Ethiopia?
    - Not yield gains, which are not significant across a large number of regressions
2. Is this result due to failure to control for unobserved heterogeneity?
    - No evidence of significant heterogeneity in returns
3. What then explains the high adoption rates of a technology that does not significantly increase yields?
    - Adoption appears to be due to small cost savings and large gains in profit
    - Potentially due to reallocation from high cost to low cost crops
    - Potentially due to increased marketing of improved chickpea

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Implications

- Do Suri's (2011) results hold broadly for technology adoption in Africa?
  - Apparently not
  - At the very least, not for improved chickpea in Ethiopia
- What then explains these "adoption puzzles"?
  - Maybe the focus on physical gains to new technology is misguided
- Money/markets matters
  - Beyond a certain point, households won't care about physical gains unless they can store or sell the surplus
  - Most adoption studies value crop production at market prices
  - But if markets are imperfect, this may be overvaluing physical gains to new technologies
  - The empirical puzzle may disappear once we measure returns in economic terms

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