Agricultural Technology and Structural Change

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Motivation

- Large share of population in LDCs work in the **agriculture** sector; Y_a/L_a in LDCs is a fraction of that in the developed world.
- 'Food problem' (Schultz, 1953) implies allocation of labour relies of **agricultural or aggregate TFP**.
- Growing literature on structural change driven by **non-homothetic preferences** (Echevarria, 1997; Duarte & Restuccia, 2010; Gollin et al, 2007;...).
- Agricultural **production technology** ($Y = AL^{\beta}X^{\gamma}$) assumed common across countries.
- Long-running recognition of **differences in agricultural technology** across climate zones and agricultural systems (Hayami & Ruttan, 1970, 1985; Ruthenberg, 1976).

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Roadmap and Preview of Findings

- **Empirics (i)**: Estimate agricultural CD production functions (N=128), addressing endogeneity concerns.
- **Empirics (ii)**: Illustrate technology heterogeneity (β_i^L) across agro-climatic zones.
- **Theory (i)**: Build simple dual economy model, establish standard comparative static results. Show that technology heterogeneity affects the speed of structural change.
- **Theory (ii)**: Calibrate model to South Korean data, provide counterfactuals for increase productivity or population growth. Counter-factual income for large sample taken from Caselli (2005).
- **Findings (i)**: Substantial difference for identical productivity increase (20%) between low ($L_a/L \downdownarrows$, Y_a/L_a $\times 2.3$) and high ($L_a/L \downarrow$, Y_a/L_a $\times 1.4$) β^L with change in income pc in the former more than twice that in the latter.

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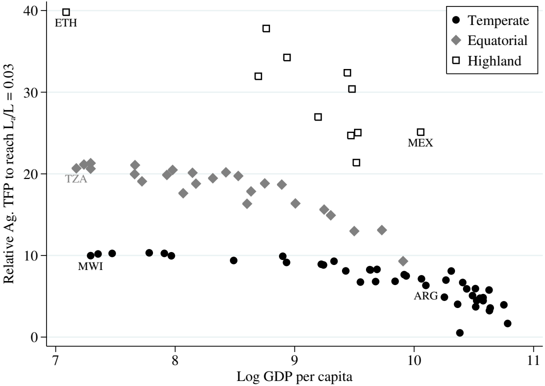
- **Findings (ii)**: technology heterogeneity accounts for between one-fifth and one-third of observed differences in aggregate income pc across countries



Notes: The figure shows the ratio that agricultural TFP (A) would have to increase by to reach $L_a/L = 0.03$ in each country. The 78 countries are from Caselli (2005), who provides the starting level of L_a/L and output per capita.

Data

- UN FAO data on inputs and output in **128 countries**.
- Time dimension: annual data **1961 to 2002** (fertilizer as constraint), average T 40.3.
- **Output**: Real agricultural net output (in thousand International $) based on all crops and livestock products adjusted for fodder and seed.
- **Inputs**: total economically active population in agriculture (L), tractor count (K), livestock ($Live$), fertilizer weight (F) and arable and permanent crop land (N).
- Large proportion of **estimated K** but absence of correlation with technology estimates indicates no systematic over-/underreporting.
- **Further data sources** include Mayer and Zignago (2006) and Caselli (2005).

Macro Panel Empirics

Common factor model framework for output and inputs:

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\gamma}_{Si}' \boldsymbol{f}_t^S + \boldsymbol{\gamma}_{Wi}' \boldsymbol{f}_t^W + \varepsilon_{it} \tag{1}$$

$$\boldsymbol{x}_{it} = \boldsymbol{\eta}_i + \boldsymbol{\Phi}_{Si}' \boldsymbol{f}_t^S + \boldsymbol{\Phi}_{Wi}' \boldsymbol{f}_t^W + \boldsymbol{\Psi}_i' \boldsymbol{g}_t + \boldsymbol{\Upsilon}_i' y_{it-1} + \boldsymbol{\epsilon}_{it} \tag{2}$$

Attempts at estimating the above raises well-known and somewhat less well-known issues:

- Endogeneity: $\mathbb{E}[\boldsymbol{x}u] \neq 0$ More
- Cross-section dependence: dto. plus correlation across i
- Simultaneity: if $\Upsilon \neq 0$ feedback from y to $\boldsymbol{x}$ More
- Technology heterogeneity: no pooled model IV approach (if instruments even exist in the panel) succeeds More
- Time series properties: $\boldsymbol{f}$ and $\boldsymbol{g}$ nonstationary processes.

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Identification strategy for β

Pesaran (2006) insight (for illustration applied to simpler setup)

$$y_{it} = \beta_i x_{it} + \alpha_i + \gamma_i f_t + \varepsilon_{it} \tag{3}$$

Proxy unobservable factors using cross-section averages (CA)

$$\bar{y}_t = \bar{\beta}\,\bar{x}_t + \bar{\alpha} + \bar{\gamma} f_t \quad \Leftrightarrow \quad f_t = \bar{\gamma}^{-1}(\bar{y}_t - \bar{\beta}\bar{x}_t - \bar{\alpha}) \tag{4}$$

...then augment models with these CA...

$$y_{it} = a_i + \beta_i' x_{it} + c_{0i}\bar{y}_t + c_i \bar{x}_t + e_{it} \tag{5}$$

...using heterogeneous parameters to capture γ_i.

Country regressions by OLS and averaging across i for consistent estimate of average β_i: Pesaran (2006) Common Correlated Effects Mean Group (CMG) estimator More

Production Function Estimates

	[1]	[2]	[3]	[4]	[5]	[6]
	2FE	MG	CMG	CMG	CMG	CMG
Weight matrix ♯			standard	neighbor	distance	agro-climate
Labor						
Tractors pw						
$\hat{\beta}_K$						
Livestock pw						
$\hat{\beta}_{Live}$						
Fertilizer pw						
$\hat{\beta}_F$						
Land pw						
$\hat{\beta}_N$						
Returns to Scale ♭						
Implied Avg $\hat{\beta}_L$						
$\hat{\varepsilon}$ Stationarity †						
$\hat{\varepsilon}$ CD Test (p) ‡						
RMSE						

Notes: Stationarity reports the (qualitative) result from panel unit root testing of the residuals (various lag lengths), CD provides the Pesaran (2004) CD test and p-value, H_0 cross-sectionally independent residuals. Results in [2]-[6] are robust mean coefficients across countries.

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	[1] 2FE	[2] MG	[3] CMG	[4] CMG	[5] CMG	[6] CMG
Weight matrix ♯			standard	neighbor	distance	agro-climate
Labor	-0.191					
	[10.60]**					
Tractors pw	0.058					
$\hat{\beta}_K$	[13.06]**					
Livestock pw	0.358					
$\hat{\beta}_{Live}$	[25.34]**					
Fertilizer pw	0.073					
$\hat{\beta}_F$	[19.87]**					
Land pw	0.294					
$\hat{\beta}_N$	[29.35]**					
Returns to Scale ♭						
Implied Avg $\hat{\beta}_L$						
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Land pw	0.294					
$\hat{\beta}_N$	[29.35]**					
Returns to Scale ♭	DRS					
Implied Avg $\hat{\beta}_L$	0.027					
	[2.34]*					
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$\hat{\varepsilon}$ Stationarity †	I(1)					
$\hat{\varepsilon}$ CD Test (p) ‡	9.64 (.00)					
RMSE	0.148					

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Weight matrix ♯			standard	neighbor	distance	agro-climate
Labor	-0.191	-0.357				
	[10.60]**	[2.23]*				
Tractors pw	0.058	0.075				
$\hat{\beta}_K$	[13.06]**	[3.31]**				
Livestock pw	0.358	0.246				
$\hat{\beta}_{Live}$	[25.34]**	[8.07]**				
Fertilizer pw	0.073	0.030				
$\hat{\beta}_F$	[19.87]**	[4.86]**				
Land pw	0.294	0.210				
$\hat{\beta}_N$	[29.35]**	[2.79]**				
Returns to Scale ♭	DRS	DRS				
Implied Avg $\hat{\beta}_L$	0.027	0.082				
	[2.34]*	[0.45]				
$\hat{\varepsilon}$ Stationarity †	I(1)	I(0)				
$\hat{\varepsilon}$ CD Test (p) ‡	9.64 (.00)	9.16 (.00)				
RMSE	0.148	0.066				

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Production Function Estimates

	[1] 2FE	[2] MG	[3] CMG standard	[4] CMG neighbor	[5] CMG distance	[6] CMG agro-climate
Weight matrix ♯						
Labor	-0.191	-0.357			-0.311	
	[10.60]**	[2.23]*			[2.62]**	
Tractors pw	0.058	0.075	0.109	0.096	0.078	0.086
$\hat{\beta}_K$	[13.06]**	[3.31]**	[5.13]**	[4.17]**	[3.60]**	[3.82]**
Livestock pw	0.358	0.246	0.321	0.321	0.278	0.339
$\hat{\beta}_{Live}$	[25.34]**	[8.07]**	[9.47]**	[8.22]**	[7.24]**	[9.97]**
Fertilizer pw	0.073	0.030	0.036	0.035	0.029	0.035
$\hat{\beta}_F$	[19.87]**	[4.86]**	[5.63]**	[5.19]**	[5.11]**	[5.63]**
Land pw	0.294	0.210	0.201	0.237	0.081	0.190
$\hat{\beta}_N$	[29.35]**	[2.79]**	[3.57]**	[4.14]**	[1.14]	[3.63]**
Returns to Scale ♭	DRS	DRS	CRS	CRS	DRS	CRS
Implied Avg $\hat{\beta}_L$	0.027	0.082	0.333	0.311	0.223	0.353
	[2.34]*	[0.45]	[4.81]**	[4.24]**	[1.53]	[5.26]**
$\hat{\varepsilon}$ Stationarity †	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) ‡	9.64 (.00)	9.16 (.00)	-0.23 (0.82)	2.02 (0.04)	-0.49 (0.62)	-1.01 (0.31)
RMSE	0.148	0.066	0.059	0.060	0.053	0.060

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$\hat{\varepsilon}$ CD Test (p) ‡	9.64 (.00)	9.16 (.00)	-0.23 (0.82)	2.02 (0.04)	-0.49 (0.62)	**-1.01 (0.31)**
RMSE	0.148	0.066	0.059	0.060	0.053	**0.060**

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Further Diagnostics and Robustness Checks

- **Simultaneity/reverse causality**: provide weak exogeneity tests for preferred CMG model(s) (highlighting FE model failure). More
- **Livestock rearing distorts estimates**: drop 22 countries with $Y_{live}/Y > .6$, results qualitatively unchanged. More
- **Factors fail to capture unobserved productivity**: add aggregate Y/L to our preferred CMG model(s), correlation between original and resulting $\hat{\beta}_i > .9$.
- **Further analysis of endogeneity concerns:** production function CMG estimates uncorrelated with each other and average inputs or output. More
- **Parameter stability over time:** Recursive estimates using increasing sample (two directions) provide evidence for stability. More

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- **Further analysis of endogeneity concerns:** production function CMG estimates uncorrelated with each other and average inputs or output. More
- **Parameter stability over time:** Recursive estimates using increasing sample (two directions) provide evidence for stability. More

Technology Heterogeneity Across Climate Zones

Clusters

	Panel A: Four Clusters					
Cluster	Arid & Temp/Cold	Temperate/ Cold		Equatorial		Equatorial & Highland
Mean $\hat{\beta}_L$	0.143	0.166		0.320		0.555
	[0.122]	[0.078]**		[0.104]***		[0.295]*
N	43	27		42		16
	Panel B: Five Clusters					
Cluster	Arid & Temp/Cold	Temperate/ Cold	Arid	Equatorial		Equatorial & Highland
Mean $\hat{\beta}_L$	0.011	0.166	0.183	0.382		0.537
	[0.177]	[0.084]*	[0.116]	[0.114]***		[0.236]**
N	28	25	18	40		17
	Panel C: Six Clusters					
Group/Cluster	Arid & Temp/Cold	Temperate/ Cold	Arid	Equatorial	Arid & Equatorial	Equatorial & Highland
Mean $\hat{\beta}_L$	-0.234	0.166	0.198	0.339	0.530	0.646
	[0.220]	[0.084]*	[0.132]	[0.108]***	[0.258]*	[0.146]***
N	15	25	16	43	19	10

Technology Heterogeneity Across Climate Zones

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Cluster	Arid & Temp/Cold	Temperate/ Cold	Arid	Equatorial		Equatorial & Highland
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N	15	25	16	43	19	10

Production

$$y_{it} = \beta_{Li} \ln L_{a,it} + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \quad \Leftrightarrow \quad Y_{it} = A_{it} L_{a,it}^{\beta_{Li}} \tag{6}$$

Production function in agriculture and non-agriculture ($\forall i,\ t$)

$$Y_a = A L_a^{\beta_L} \qquad Y_n = w L_n \qquad \text{with } L = L_a + L_n \tag{7}$$

Preferences and Individual Optimization

Utility over agricultural (c_a) and non-agricultural good (c_n)

$$U = \alpha \ln\left(c_a - \bar{c}_a\right) + (1 - \alpha) \ln\left(c_n + \bar{c}_n\right) \tag{8}$$

where $\bar{c}_a$ is subsistence constraint and $\bar{c}_n$ is an endowment.

$$w = p_a c_a + c_n \tag{9}$$

is the budget constraint, with w equal to income, p_a the relative price of agricultural good.

Preferences and Individual Optimization

Expenditures on the two goods

$$p_a c_a = \alpha(w - p_a\bar{c}_a + \bar{c}_n) + p_a\bar{c}_a \tag{10}$$
$$c_n = (1-\alpha)(w - p_a\bar{c}_a + \bar{c}_n) - \bar{c}_n.$$

Equilibrium Allocation of Labour

Free movement between sectors, assume agricultural wage is equal to the average product: no rents. Common setup in models of structural change. Here: removes the impact of β_L on labour allocation, s.t.

$$w = p_a \frac{Y_a}{L_a} \tag{11}$$

Equating supply and demand in both sectors we can then solve for the optimal allocation of labour L_a/L.

Comparative Statics

All standard results (Duarte & Restuccia, 2010; Alvarez-Cuadrado & Poschke, 2011) follow: increase in A

- Agricultural labor declines: $\frac{\partial L_a}{\partial A}\frac{A}{L_a} < 0$
- Agricultural consumption increases: $\frac{\partial c_a}{\partial A}\frac{A}{c_a} > 0$
- Agricultural labor productivity rises: $\frac{\partial Y_a/L_a}{\partial A}\frac{A}{Y_a/L_a} > 0$
- Relative price of agriculture falls: $\frac{\partial p_a}{\partial A}\frac{A}{p_a} < 0$

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- Relative price of agriculture falls: $\frac{\partial p_a}{\partial A}\frac{A}{p_a} < 0$

β_L affects the magnitudes of these changes

- $\left|\frac{\partial L_a}{\partial A}\frac{A}{L_a}\right|$ falls as β_L rises
- $\left|\frac{\partial c_a}{\partial A}\frac{A}{c_a}\right|$ falls as β_L rises
- $\left|\frac{\partial Y_a/L_a}{\partial A}\frac{A}{Y_a/L_a}\right|$ falls as β_L rises
- $\left|\frac{\partial p_a}{\partial A}\frac{A}{p_a}\right|$ falls as β_L rises

Calibration

- Calibrate model to 1963-2005 data for South Korea
- Why Korea?
  - Wanted to capture early stages of structural change and cover post-WWII period of increasing globalisation
  - In 1963 63% of Korea's workforce was employed in agriculture, by 2005 this had dropped to 8%
  - Y^a/L^a increased $\times 7.4$, non-agricultural output $\times 3.5$, population $\times 1.8$ (Timmer and De Vries, 2007)
- A, w, L set to unity, find values α, $\bar{c}_a$, $\bar{c}_n$ to deliver observed drop in L_a given observed labour productivity

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- A, w, L set to unity, find values α, $\bar{c}_a$, $\bar{c}_n$ to deliver observed drop in L_a given observed labour productivity

Counterfactual Exercise (i)

- For otherwise identical economies, how does β_L affect response to an increase in ★ (a) A, or (b) in L?

Heterogeneous Technology and Structural Change

		Equilibrium outcomes from:					
		20% Increase in Ag. TFP (A) with $\beta =$			5% Increase in Population (L) with $\beta =$		
Outcome	Baseline	0.15	0.35	0.55	0.15	0.35	0.55
Ag. labour share (L_a/L)	0.800						
Ag. relative price (p_a)	1.000						
Ag. labour productivity (Y_a/L_a)	1.000						
Ag. consumption p.c. (c_a)	1.000						
Non-ag. consumption p.c. (c_n)	1.000						
Real income p.c. (y)	1.000						

Heterogeneous Technology and Structural Change

		Equilibrium outcomes from:					
		20% Increase in Ag. TFP (A) with $\beta =$			5% Increase in Population (L) with $\beta =$		
Outcome	Baseline	0.15	0.35	0.55	0.15	0.35	0.55
Ag. labour share (L_a/L)	0.800	0.369					
Ag. relative price (p_a)	1.000	0.432					
Ag. labour productivity (Y_a/L_a)	1.000	2.314					
Ag. consumption p.c. (c_a)	1.000	1.069					
Non-ag. consumption p.c. (c_n)	1.000	3.153					
Real income p.c. (y)	1.000	1.485					

Heterogeneous Technology and Structural Change

		Equilibrium outcomes from:					
		20% Increase in Ag. TFP (A) with $\beta =$			5% Increase in Population (L) with $\beta =$		
Outcome	Baseline	0.15	0.35	0.55	0.15	0.35	0.55
Ag. labour share (L_a/L)	0.800	0.369	0.518				
Ag. relative price (p_a)	1.000	0.432	0.629				
Ag. labour productivity (Y_a/L_a)	1.000	2.314	1.591				
Ag. consumption p.c. (c_a)	1.000	1.069	1.030				
Non-ag. consumption p.c. (c_n)	1.000	3.153	2.408				
Real income p.c. (y)	1.000	1.485	1.306				

Heterogeneous Technology and Structural Change

		Equilibrium outcomes from:					
		20% Increase in Ag. TFP (A) with $\beta =$			5% Increase in Population (L) with $\beta =$		
Outcome	Baseline	0.15	0.35	0.55	0.15	0.35	0.55
Ag. labour share (L_a/L)	0.800	0.369	0.518	0.595			
Ag. relative price (p_a)	1.000	0.432	0.629	0.729			
Ag. labour productivity (Y_a/L_a)	1.000	2.314	1.591	1.371			
Ag. consumption p.c. (c_a)	1.000	1.069	1.030	1.019			
Non-ag. consumption p.c. (c_n)	1.000	3.153	2.408	2.026			
Real income p.c. (y)	1.000	1.485	1.306	1.221			

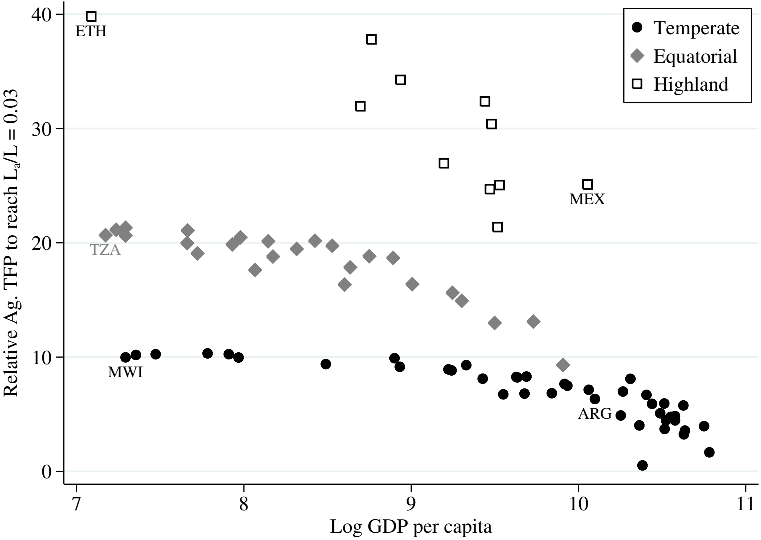
Heterogeneous Technology and Structural Change

		Equilibrium outcomes from:					
		20% Increase in Ag. TFP (A) with $\beta =$			5% Increase in Population (L) with $\beta =$		
Outcome	Baseline	0.15	0.35	0.55	0.15	0.35	0.55
Ag. labour share (L_a/L)	0.800	0.369	0.518	0.595	0.944	0.852	0.823
Ag. relative price (p_a)	1.000	0.432	0.629	0.729	1.189	1.068	1.031
Ag. labour productivity (Y_a/L_a)	1.000	2.314	1.591	1.371	0.841	0.936	0.970
Ag. consumption p.c. (c_a)	1.000	1.069	1.030	1.019	0.992	0.997	0.998
Non-ag. consumption p.c. (c_n)	1.000	3.153	2.408	2.026	0.281	0.740	0.882
Real income p.c. (y)	1.000	1.485	1.306	1.221	0.849	0.945	0.975

Counterfactual Exercise (ii)

- Adopt a sample of 78 countries from Caselli (2005) — overlap with our data; three groups: 11 equat./highland, 25 equat., 42 arid/temperate or temperate; pick representative β_L of $\{.55, .35, .15\}$ respectively.
- Normalise L, w, solve for A to yield observed L_a/L
- Counterfactuals
  (a) What increase in A is necessary to drive L_a/L to 3%?

Relative Ag. TFP Increase to Reach $L_a/L = .03$



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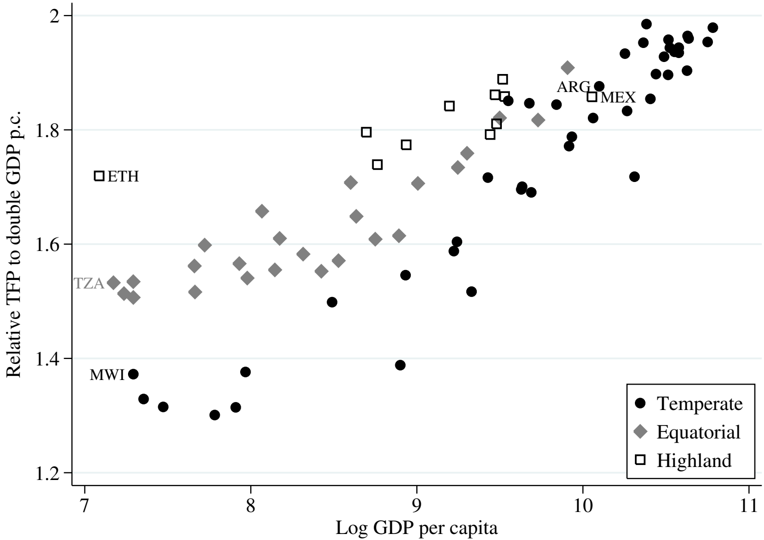
- Normalise L, w, solve for A to yield observed L_a/L
- Counterfactuals
  (a) What increase in A is necessary to drive L_a/L to 3%?
  (b) By how much do we need to scale up A and w to double output per worker?

Relative TFP Increase to Double Income pc



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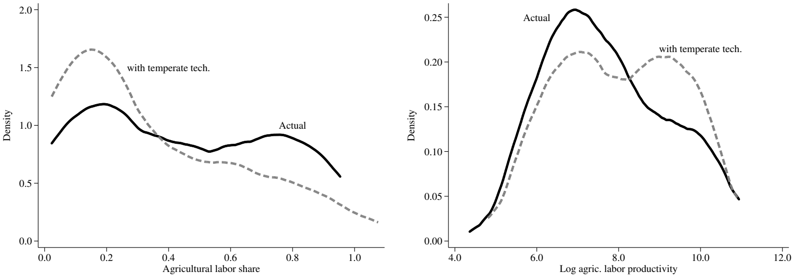
- Counterfactuals
  (a) What increase in A is necessary to drive L_a/L to 3%?
  (b) By how much do we need to scale up A and w to double output per worker?

Counterfactual Exercise (iii)

- How much variation in output pc remains once we eliminate heterogeneity in agricultural technology?
- "Apples and Oranges" problem (Bernard and Jones, 1996): counter-factual analysis where we set $A_1 = A_2$ for $\beta_{L,1} \neq \beta_{L,2}$ is not meaningful. More

Income Dispersion, Actual and Counterfactual

	Output per capita:		Ag. labour productivity:	
	$Var(\ln y)$	90/10 ratio	$Var(\ln Y_A/L_A)$	90/10 Ratio
Actual	1.185	21.7	2.206	46.0
Temperate technology	0.996	14.8	2.217	44.1



Notes: The figures show the actual distribution of the agricultural labor share and agricultural labour output for a sample of 78 countries from Caselli (2005) as well as the counterfactual values for the same countries when they are given a temperate-zone agricultural technology with $\beta = 0.15$.

The Quantitative Significance of Technology Heterogeneity

- **Agricultural technology varies widely** across countries. Seems to follow a pattern linked to agro-climatic conditions.
- Effect of technology heterogeneity in a standard two-sector model is **significant**.
- **No 'geographic determinism'**: fact that agricultural technology differs by climate does not imply anything about TFP or population levels.
- Short of fundamentally altering production technology — which may be biologically impossible and/or economically inefficient — **tropical countries will be slower to emulate the structural change witnessed in temperate regions** such as Korea or Japan.

Markus Eberhardt
GEP and CSAE

and

Dietrich Vollrath
Houston

Appendix: Identification Problem

Return

Simplified model setup

$$
\begin{aligned}
y_{it} &= \beta_i x_{it} + \alpha_i + \gamma_i f_t + \varepsilon_{it} && (12) \\
x_{it} &= \eta_i + \phi_i f_t + \psi_i g_t + \epsilon_{it} && (13)
\end{aligned}
$$

Solving the regressor for the common factor f and plugging into the production function yields

$$
\begin{aligned}
y_{it} &= \beta_i x_{it} + \alpha_i + \gamma_i \phi_i^{-1}(x_{it} - \eta_i - \psi_i g_t - \epsilon_{it}) + \varepsilon_{it} \\
&= \underbrace{\left(\beta_i + \gamma_i \phi_i^{-1}\right)}_{\varrho_i} x_{it} + \underbrace{\alpha_i + \gamma_i \phi_i^{-1} \alpha_i - \gamma_i \phi_i^{-1} \eta_i}_{\varpi_i} \\
&\quad + \underbrace{\varepsilon_{it} - \gamma_i \phi_i^{-1} \psi_i g_t - \gamma_i \phi_i^{-1} \epsilon_{it}}_{\varsigma_{it}} = \varrho_i x_{it} + \varpi_i + \varsigma_{it}
\end{aligned}
$$

Since in the standard case $\varrho_i = \beta_i + \gamma_i \phi_i^{-1} \neq \beta_i$ the slope coefficient on our regressor is not identified.

Appendix: Identification of Average β

Return 1 Return 2

- **Pesaran and Smith (1995)**: If true model is heterogeneous, then any pooled model misspecified by construction and there exists no instrument which is both valid and informative.
- **Price to pay for CMG**: unless T large difficult to estimate $\hat{\beta}_i$ precisely – weak signal-to-noise ratio. Averaging across i boosts the signal. Instead of full sample average we compute averages for specific subsamples.
- **CMG methodology and its consistency**: extends to multivariate and multifactor setup, nonstationary factors, structural breaks, and cointegration or noncointegration (Chudik, Pesaran and Tosetti, 2011; Kapetanios, Pesaran and Yamagata, 2011; Pesaran and Tosetti, 2011).

Appendix: Weak exogeneity testing

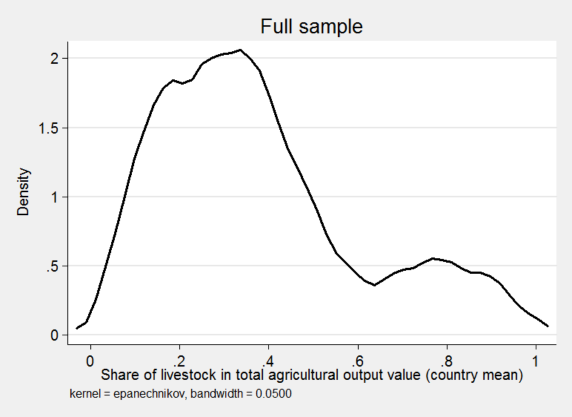
Return

2FE	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	*t-ratio*	*Verdict*
output equation	-0.97	0.00	485.2	0.00	-0.142	-7.91	$x \rightarrow y$
tractor equation	0.18	0.17	456.2	0.00	0.024	1.81	$x_{-tr}, y \rightarrow x_{tr}$
livestock equation	0.38	0.00	351.0	0.00	0.043	3.77	$x_{-live}, y \rightarrow x_{live}$
fertilizer equation	0.10	0.42	432.3	0.00	0.141	1.82	$x_{-f}, y \rightarrow x_f$
land equation	0.37	0.00	395.2	0.00	0.011	1.91	$x_{-n}, y \rightarrow x_n$
MG	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	*t-ratio*	*Verdict*
output equation	-2.93	0.00	1,612.1	0.00	-0.976	-24.00	$x \rightarrow y$
tractor equation	-0.16	0.87	274.7	0.20	-0.029	-0.98	$x_{-tr}, y \nrightarrow x_{tr}$
livestock equation	0.03	0.98	307.6	0.01	0.015	0.55	$x_{-live}, y \rightarrow x_{live}$
fertilizer equation	-0.06	0.96	257.2	0.47	-0.116	-0.85	$x_{-f}, y \nrightarrow x_f$
land equation	-0.06	0.95	286.5	0.09	-0.004	-0.33	$x_{-n}, y \rightarrow x_n$
CMG agro-climate	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	*t-ratio*	*Verdict*
output equation	-2.25	0.02	1,035.5	0.00	-0.935	-20.16	x, TFP $\rightarrow y$
tractor equation	-0.02	0.98	241.8	0.53	-0.013	-0.42	x_{-tr}, y, TFP $\nrightarrow x_{tr}$
livestock equation	0.15	0.88	380.0	0.00	0.048	1.23	x_{-live}, y, TFP $\rightarrow x_{live}$
fertilizer equation	0.07	0.94	242.5	0.52	-0.004	-0.02	x_{-f}, y, TFP $\nrightarrow x_f$
land equation	-0.09	0.93	227.3	0.77	-0.001	-0.08	x_{-n}, y, TFP $\nrightarrow x_n$

Appendix: Livestock rearing distorts estimates

Return

Using average 60% share of VA from livestock as cut-off:



Who drops out? Except for small number of LICs (e.g. Lesotho, Mongolia, Somalia) predominantly developed economies in the temperate or cold climate zones, including Denmark, Germany, and the United Kingdom.

Appendix: Further analysis of endogeneity concerns

Return

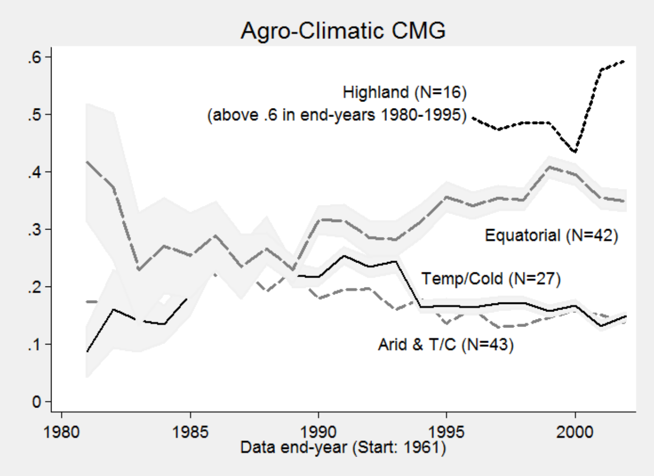
Correlation matrix: variable series averages and CMG estimates

Variable averages	$\overline{\mathrm{ly}}_i$	$\overline{\mathrm{ltr}}_i$	$\overline{\mathrm{llive}}_i$	$\overline{\mathrm{lf}}_i$	$\overline{\mathrm{ln}}_i$	$\hat{\beta}_i^{\mathrm{Tr}}$	$\hat{\beta}_i^{\mathrm{Live}}$	$\hat{\beta}_i^{\mathrm{F}}$	$\hat{\beta}_i^{\mathrm{N}}$
Output pw $\overline{\mathrm{ly}}_i$	1								
Tractors pw $\overline{\mathrm{ltr}}_i$	**0.911**	1							
Livestock pw $\overline{\mathrm{llive}}_i$	**0.816**	**0.738**	1						
Fertilizer pw $\overline{\mathrm{lf}}_i$	**0.902**	**0.917**	**0.695**	1					
Land pw $\overline{\mathrm{ln}}_i$	**0.780**	**0.718**	**0.677**	**0.673**	1				
Standard CMG	$\overline{\mathrm{ly}}_i$	$\overline{\mathrm{ltr}}_i$	$\overline{\mathrm{llive}}_i$	$\overline{\mathrm{lf}}_i$	$\overline{\mathrm{ln}}_i$	$\hat{\beta}_i^{\mathrm{Tr}}$	$\hat{\beta}_i^{\mathrm{Live}}$	$\hat{\beta}_i^{\mathrm{F}}$	$\hat{\beta}_i^{\mathrm{N}}$
$\hat{\beta}_i^{\mathrm{Tr}}$	0.089	0.124	0.052	0.072	0.051	1			
$\hat{\beta}_i^{\mathrm{Live}}$	0.003	-0.015	0.153	-0.051	-0.119	**-0.330**	1		
$\hat{\beta}_i^{\mathrm{F}}$	0.115	0.123	0.075	**0.223**	0.116	-0.067	-0.119	1	
$\hat{\beta}_i^{\mathrm{N}}$	0.105	0.139	0.076	**0.203**	0.108	**-0.203**	0.007	0.124	1
Agro-climatic CMG	$\overline{\mathrm{ly}}_i$	$\overline{\mathrm{ltr}}_i$	$\overline{\mathrm{llive}}_i$	$\overline{\mathrm{lf}}_i$	$\overline{\mathrm{ln}}_i$	$\hat{\beta}_i^{\mathrm{Tr}}$	$\hat{\beta}_i^{\mathrm{Live}}$	$\hat{\beta}_i^{\mathrm{F}}$	$\hat{\beta}_i^{\mathrm{N}}$
$\hat{\beta}_i^{\mathrm{Tr}}$	0.128	0.138	0.106	0.150	0.008	1			
$\hat{\beta}_i^{\mathrm{Live}}$	0.040	0.024	0.126	-0.047	-0.007	**-0.238**	1		
$\hat{\beta}_i^{\mathrm{F}}$	0.148	0.168	0.100	**0.282**	0.138	-0.002	**-0.218**	1	
$\hat{\beta}_i^{\mathrm{N}}$	0.098	0.125	0.037	0.128	0.145	-0.062	-0.053	0.094	1

Appendix: Further analysis of endogeneity concerns

Return

Average β_L by Climate Zone: Recursive Estimates



Appendix: Cluster makeup (examples)

Return

Panel A: Four Clusters

Climate Zone	A	B	C/D	H	*N*
Cluster					
Arid & Temperate/Cold	0.059 [0.215]	0.443 [0.396]	0.403 [0.411]	0.094 [0.214]	43
Temperate/Cold	0.004 [0.015]	0.037 [0.101]	0.920 [0.141]	0.038 [0.096]	27
Equatorial	0.799 [0.231]	0.099 [0.181]	0.074 [0.139]	0.028 [0.075]	42
Equatorial & Highland	0.668 [0.307]	0.023 [0.060]	0.050 [0.193]	0.260 [0.256]	16

Panel B: Five Clusters

Climate Zone	A	B	C/D	H	*N*
Cluster					
Arid & Temperate/Cold	0.072 [0.262]	0.285 [0.371]	0.589 [0.409]	0.053 [0.130]	28
Temperate/Cold	0.003 [0.013]	0.023 [0.065]	0.933 [0.121]	0.041 [0.099]	25
Arid	0.091 [0.140]	0.723 [0.228]	0.131 [0.214]	0.055 [0.149]	18
Equatorial	0.837 [0.202]	0.057 [0.107]	0.078 [0.142]	0.029 [0.077]	40
Equatorial & Highland	0.570 [0.357]	0.044 [0.094]	0.047 [0.188]	0.340 [0.301]	17

Appendix: Comparing Apples and Oranges

Return