

APPENDIX — NOT INTENDED FOR PUBLICATION

A. DATA SOURCES AND CONSTRUCTION

The principal data source for our empirical analysis is the Food and Agriculture Organisation's *FAOSTAT* database (FAO, 2007), from which we obtain annual observations for agricultural net output, economically active labor force in agriculture, number of tractors used in agriculture, arable and permanent crop land and fertilizer use in 128 countries from 1961 to 2002. The total number of observations is 5,162 with an average T of 40.3. Real agricultural net output (in thousand International \$) is based on all crops and livestock products originating in each country. Intermediate primary inputs of agricultural origin are deducted, including fodder and seed. The quantities for each commodity are weighted by the respective 1999-2001 average international commodity prices and then summed for each year by country. The prices are in international dollars, derived using a Geary-Khamis formula for the agricultural sector.³⁵ The labor variable represents the annual time series for total economically active population in agriculture. For capital stock in agriculture we follow a common convention and use total number of agricultural tractors in use as a proxy. The livestock variable is constructed from the data for asses (donkeys), buffalos, camels, cattle, chickens, ducks, horses, mules, pigs, sheep & goats and turkeys. Following convention we use a formula detailed in Hayami and Ruttan (1970) to convert the numbers for individual animal species into cattle-equivalent livestock. The fertilizer variable represents agricultural fertilizer consumed in metric tons, which includes 'crude' and 'manufactured' fertilizers. The land variable represents arable and permanent crop land (in hectare).

Descriptive statistics are presented in Table A-1. The countries in our sample are listed in Table A-2, with 'cluster affiliation' presented in Table F-4. The clusters (4, 5 or 6) were created from the country-pair Jaffe measure of agro-climatic similarity described in the maintext of the paper. Each country has N Jaffe measures and the grouping of countries is then computed from 'partition-clustering,' which breaks the observations into a distinct number of non-overlapping groups: we adopt 'kmeans' clustering in Stata 11, where following the choice of number of groups to be created each observation is assigned to the group whose mean is closest. Based on this categorization the new group means are determined and the entire process is iterated until the group affiliation is stable (see Stata 11 Multivariate Statistics Manual p.85ff).

³⁵Refer to the Technical Appendix to Restuccia, et al. (2008), available on Restuccia's website.

As a robustness check we drop all countries where livestock (in value terms) on average exceeds 60% of total agricultural output, adopting recently-developed FAO data for net output and livestock in 2004-2006 I\$ value terms. Figure H-1 below indicates that this cutoff point represents a natural choice given the distribution of the data. The dependent variable for these models is net output less livestock value and we drop the headcount livestock variable (described above) from these regressions.

Table A-1: Descriptive statistics

Variables in untransformed level terms					
Variable	mean	median	std. dev.	min.	max.
<i>logs</i>					
output	14.24	14.24	1.71	8.07	19.57
labor	14.01	14.09	1.84	8.01	20.05
tractors	9.01	8.87	2.79	0.69	15.51
livestock	14.90	14.92	1.71	8.80	19.51
fertilizer	10.82	10.97	2.69	1.61	17.49
land	14.69	14.78	1.80	6.91	19.07
<i>annual growth rate</i>					
output	2.3%	2.4%	8.8%	-83.0%	87.6%
labor	0.3%	0.8%	2.6%	-28.8%	28.8%
tractors	4.4%	2.0%	9.9%	-121.8%	138.6%
livestock	1.4%	1.6%	6.4%	-93.3%	182.9%
fertilizer	5.6%	3.5%	40.1%	-626.3%	393.2%
land	0.8%	0.1%	3.6%	-41.8%	79.0%

Variables in per worker terms					
Variable	mean	median	std. dev.	min.	max.
<i>logs</i>					
output	0.23	-0.03	1.42	-2.22	4.00
tractors	-5.00	-4.97	3.01	-13.67	0.68
livestock	0.89	0.81	1.38	-2.77	4.63
fertilizer	-3.19	-2.87	2.67	-11.56	1.95
land	0.68	0.67	1.15	-2.20	4.95
<i>annual growth rate</i>					
output	2.0%	2.0%	9.0%	-80.3%	109.9%
tractors	4.1%	2.1%	10.1%	-120.2%	136.5%
livestock	1.2%	1.2%	6.6%	-93.5%	182.9%
fertilizer	5.4%	4.2%	40.0%	-627.8%	390.8%
land	0.5%	0.0%	4.1%	-43.0%	81.6%

Notes: We report the descriptive statistics for net output (in I\$1,000), labor (headcount), tractors (number), livestock (cattle-equivalent numbers), fertilizer (in metric tonnes) and land (in hectare) for the full sample ($n = 5,162$; $N = 128$).

Analysing agricultural production for a large number of countries inevitably raises concerns over data reliability. In contrast to macro data provided in for instance the Penn World Table (GGDC Groningen) FAOSTAT does not offer a data quality grade for each country, but instead labels each observation. Most output data used in our analysis carries the note ‘[a]ggregates may include official, semi-official or estimates.’ For inputs we obtain more details, which suggest that tractor data is least reliable, with around 45% of observations estimated.³⁶ Thus data is far from perfect for cross-country comparison, although estimating production functions country by country and accounting for unobserved common factors should go some way to ward against systematic over-/underreporting of variable magnitudes. We find that there is no statistically significant relationship between countries’ share of tractor data estimated and the coefficients on tractor, livestock, fertilizer or land in our preferred agro-climatic CMG model, which could be viewed as evidence to that end.

Additional time-invariant data on geographical distance between countries and contiguity (neighborhood) is taken from Mayer and Zignago (2006), and data on the share of agricultural land by climatic zone from Matthews (1983), available in Gallup, et al. (1999) — see Table B-1 for details.

³⁶We report Penn World Table country quality grade and share of non-estimated tractor data in Table A-2.

Table A-2: Sample of countries and number of observations

Country	Code	Obs	PWT-Q	FAO-Q	Country	Code	Obs	FAO-Q	FAO-Q
Afghanistan	AFG	40		5%	Cambodia	KHM	33	D	25%
Angola	AGO	40	D	45%	South Korea	KOR	42	B	95%
Albania	ALB	42	C	69%	Kuwait †	KWT	24	C	43%
United Arab Emirates	ARE	31	D	23%	Lao PDR	LAO	38	D	52%
Argentina	ARG	42	B	50%	Lebanon	LBN	42	C	13%
Australia †	AUS	42	A	100%	Liberia	LBR	30	D	
Austria †	AUT	42	A	76%	Libya	LBY	42		15%
Burundi	BDI	37	C	28%	Sri Lanka	LKA	42	C	50%
Benin	BEN	42	C	13%	Lesotho †	LSO	42	D	20%
Burkina Faso	BFA	42	C	17%	Morocco	MAR	42	C	56%
Bangladesh	BGD	42	C	5%	Madagascar	MDG	42	C	17%
Bulgaria	BGR	42	C	79%	Mexico	MEX	42	C	21%
Belgium-Luxembourg †	BLX	39	A	85%	Mali	MLI	42	C	12%
Belize	BLZ	42	C	36%	Myanmar	MMR	42	D	88%
Bolivia	BOL	42	C	28%	Mongolia †	MNG	34	D	80%
Brazil	BRA	42	C	12%	Mozambique	MOZ	42	D	20%
Botswana †	BWA	42	C	33%	Mauritania †	MRT	33	C	14%
Central African Republic	CAF	42	D	22%	Malawi	MWI	42	C	63%
Canada	CAN	42	A	62%	Malaysia	MYS	42	C	51%
Switzerland †	CHE	42	A	17%	Niger	NER	34	D	63%
Chile	CHL	42	B	33%	Nigeria	NGA	42	C	5%
China	CHN	42	C	90%	Nicaragua	NIC	42	C	16%
Côte d'Ivoire	CIV	42	C	27%	Netherlands †	NLD	42	A	29%
Cameroon	CMR	42	C	32%	Norway †	NOR	42	A	71%
Congo, Republic	COG	41	C	93%	Nepal	NPL	42	C	23%
Colombia	COL	42	C	68%	New Zealand †	NZL	42	B	62%
Costa Rica	CRI	42	C	31%	Oman	OMN	30	C	38%
Cuba	CUB	42	D	57%	Pakistan	PAK	42	C	43%
Cyprus	CYP	42	D	50%	Panama	PAN	42	C	13%
Germany †	DEU	42	B	93%	Philippines	PHL	42	C	53%
Denmark †	DNK	42	A	90%	Papua New Guinea	PNG	42	D	62%
Dominican Republic	DOM	42	C	5%	Poland	POL	42	B	100%
Algeria	DZA	42	D	48%	Korea, DPR	PRK	42		50%
Ecuador	ECU	42	C	33%	Portugal	PRT	42	B	33%
Egypt	EGY	42	C	45%	Paraguay	PRY	42	C	2%
Spain	ESP	42	B	100%	Qatar †	QAT	27	C	45%
Ethiopia	ETH	42	C	25%	Romania	ROM	42	C	100%
Finland †	FIN	30	A	62%	Rwanda	RWA	34	C	24%
France	FRA	42	A	79%	Saudi Arabia	SAU	42	D	21%
Gabon	GAB	31	C		Sudan	SDN	42	D	21%
United Kingdom †	GBR	42	A	76%	Senegal	SEN	42	C	10%
Ghana	GHA	42	C	5%	Sierra Leone	SLE	42	C	35%
Guinea	GIN	41	C	10%	El Salvador	SLV	42	C	9%
Gambia	GMB	39	C	22%	Somalia †	SOM	36	D	33%
Guinea-Bissau	GNB	26	D	14%	Suriname	SUR	42	D	14%
Equatorial Guinea	GNQ	19	D		Sweden †	SWE	42	A	52%
Greece	GRC	42	B	100%	Swaziland	SWZ	42	C	74%
Guatemala	GTM	42	C	30%	Syria	SYR	42	C	100%
Guyana	GUY	42	D	6%	Chad	TCO	41	D	100%
Honduras	HND	42	C	25%	Togo	TGO	37	D	19%
Haiti	HTI	42	D	8%	Thailand	THA	42	C	45%
Hungary	HUN	42	C	79%	Trinidad & Tobago	TTO	42	C	0%
Indonesia	IDN	42	C	28%	Tunisia	TUN	42	C	33%
India	IND	42	C	83%	Turkey	TUR	42	C	100%
Ireland †	IRL	42	A	50%	Tanzania	TZA	42	C	10%
Iran	IRN	42	C	33%	Uganda	UGA	39	D	59%
Iraq	IRQ	42	D	45%	Uruguay †	URY	42	B	17%
Iceland †	ISL	42	B	79%	United States	USA	42	A	40%
Israel	ISR	42	B	83%	Venezuela	VEN	42	C	71%
Italy	ITA	42	A	100%	Vietnam	VNM	42	C	65%
Jamaica	JAM	42	C	70%	Yemen, Republic	YEM	37	D	15%
Jordan	JOR	42	C	83%	South Africa	ZAF	42	C	60%
Japan	JPN	42	A	85%	Congo, DR	ZAR	41	D	18%
Kenya	KEN	42	C	60%	Zimbabwe	ZWE	42	C	32%

Notes: The full sample contains $n = 5,162$ observations, from 1961 to 2002. † indicates countries dropped in the reduced sample (see maintext). PWT-Q reports a data quality rating for aggregate economy data from the Penn World Table project (Heston, et al., 2009), where A denotes the highest and D the lowest score (<http://pwt.econ.upenn.edu/Documentation/append61.pdf>, Table A, column 11). FAO-Q reports the share of observations for the tractor variable which are not estimated but taken from official publications or international organisations (FAO codes: I, W, Q), which is reported for most FAO observations.

B. CLIMATE ZONES

Table B-1: Climate Zones following Köppen-Geiger

A	Equatorial climates	Af	Equatorial rainforest, fully humid
		Am	Equatorial monsoon
		As	Equatorial savannah with dry summer
		Aw	Equatorial savannah with dry winter
B	Arid climates	Bs	Steppe climate
		Bw	Desert climate
C	Warm temperate climates	Cf	Warm temperate climate, fully humid
		Cs	Warm temperate climate with dry summer
		Cw	Warm temperate climate with dry winter
D	Snow climates	Df	Snow climate, fully humid
		Ds	Snow climate with dry summer
		Dw	Snow climate with dry winter
E	Polar climates	Ef	Frost climate
		Et	Tundra climate
H	Highland climate	above 2,500m elevation	

Notes: This classification is taken from Kottke et al (2006). The Highland category was added after the creation of the Köppen-Geiger classification, with an elevation cut-off of 2,500m suggested in a number of online databases. The Matthews (1983) data has a marginally different classification where As and Ds are not classified and the two polar climates are combined to a single category — this results in 12 rather than 15 categories.

C. PROOF OF PROPOSITION 1

To begin the proof, first define the following elasticities:

$$\epsilon_A^{c_a} = \frac{\partial c_a}{\partial A} \frac{A}{c_a} \quad (25)$$

$$\epsilon_A^{Y_a} = \frac{\partial Y_a/L_a}{\partial A} \frac{A}{Y_a/L_a} \quad (26)$$

$$\epsilon_A^{L_a} = \frac{\partial L_a}{\partial A} \frac{A}{L_a} \quad (27)$$

$$\epsilon_A^{p_a} = \frac{\partial p_a}{\partial A} \frac{A}{p_a}. \quad (28)$$

Market clearing requires that $c_a L_a = Y_a$, which can be re-written using the production function $Y_a = AL_a^{\beta_L}$ as

$$L_a = \left(\frac{c_a L_a^{1-\beta_L}}{A} \right)^{\beta_L}. \quad (29)$$

Taking the derivative of L_a with respect to A , and allowing for the fact that c_a is a function of A as well, with some manipulation we have

$$\epsilon_A^{L_a} = \frac{1}{\beta_L} (\epsilon_A^{c_a} - 1). \quad (30)$$

Holding that result for a moment, consider that expenditure on agricultural goods must satisfy

$$p_a c_a = \alpha(w - p_a \bar{c}_a + \bar{c}_n) + p_a \bar{c}_n. \quad (31)$$

Rearranging this and using the labor-market clearing condition that $w = p_a Y_a / L_a$ as well as the production function for Y_a yields

$$c_a = \alpha \left(1 + \frac{\bar{c}_n}{w} \right) AL_a^{\beta_L-1} + (1 - \alpha) \bar{c}_n. \quad (32)$$

Taking the derivative of c_a with respect to A , accounting for the fact that L_a is a function of A yields after some manipulation

$$\epsilon_A^{c_a} = \Omega (1 + (\beta_L - 1) \epsilon_A^{L_a}) \quad (33)$$

where

$$\Omega = \frac{\alpha \left(1 + \frac{\bar{c}_n}{w} \right)}{L_a/L}. \quad (34)$$

Solving (33) with (30) yields the following expression for the elasticity of agricultural labor with respect to agricultural productivity

$$\epsilon_A^{L_a} = \frac{\Omega - 1}{\beta_L(1 - \Omega) + \Omega}. \quad (35)$$

This is clearly decreasing in β_L , as claimed in the proposition. Using this result in (33) yields that

$$\epsilon_A^{c_a} = \frac{\Omega}{\beta_L(1 - \Omega) + \Omega}, \quad (36)$$

and this is also decreasing in β_L , matching the second claim of the proposition. From market clearing we have that $Y_a/L_a = (c_a L)/L_a$, which indicates that $\epsilon_A^{Y_a} = \epsilon_A^{c_a} - \epsilon_A^{L_a}$. That makes it straightforward to see that

$$\epsilon_A^{Y_a} = \frac{1}{\beta_L(1 - \Omega) + \Omega}. \quad (37)$$

This is declining in β_L , as claimed in the proposition. Finally, the labor market clearing condition $w = p_a Y_a/L_a$ shows that $\epsilon_A^{p_a} = -\epsilon_A^{Y_a}$, as w is held constant. Thus the absolute value of $\epsilon_A^{p_a}$ is decreasing in β_L , as claimed, given that $\epsilon_A^{Y_a}$ is declining in β_L .

D. COUNTRY-SPECIFIC COUNTER-FACTUAL RESULTS

We performed a counter-factual simulation for each country where we set $\beta_L = 0.15$, the temperate zone value, and recalculated several measures of development including output per worker, agricultural labor productivity, and the agricultural labor share. The following table D-1 shows for each individual country in that simulation the actual and counter-factual values.

Table D-1: Country Data, Actual and with Temperate Technology

Country	Output p.w.		Ag. labor prod.		Ag. labor share	
	Actual	Temp.	Actual	Temp.	Actual	Temp.
<i>Equatorial cluster:</i>						
Angola	4,558	8,405	354	446	0.82	0.65
Bangladesh	4,085	7,002	513	717	0.74	0.54
Bolivia	8,151	11,478	1,706	3,542	0.47	0.24
Brazil	16,808	20,299	3,853	9,742	0.28	0.13
Burundi	1,389	936	443	433	0.92	0.97
Cameroon	7,272	12,272	78	122	0.67	0.44
Costa Rica	13,340	16,053	4,072	10,523	0.27	0.12
Cote d'Ivoire	5,624	8,503	1,377	2,395	0.59	0.35
Dominican Republic	10,368	14,072	2,124	4,776	0.42	0.20
El Salvador	10,960	14,444	1,746	4,196	0.38	0.17
Ghana	3,187	4,724	899	1,609	0.57	0.33
Guinea	5,053	8,947	508	683	0.77	0.58
Haiti	2,257	3,616	624	920	0.70	0.48
India	3,546	5,758	592	908	0.68	0.45
Kenya	2,918	5,252	532	642	0.85	0.71
Madagascar	2,123	3,498	682	887	0.79	0.61
Mozambique	1,469	2,701	231	272	0.87	0.74
Nigeria	2,781	4,832	451	596	0.78	0.60
Rwanda	2,129	3,898	475	526	0.92	0.83
Senegal	3,445	6,201	442	562	0.81	0.64
Sri Lanka	5,438	7,676	957	1,997	0.47	0.24
Tanzania	1,303	2,196	495	581	0.87	0.75
Thailand	6,307	10,375	858	1,309	0.68	0.45
Uganda	1,469	2,401	617	659	0.94	0.89
Venezuela	20,074	21,979	4,460	13,567	0.13	0.06

Table continued overleaf.

Table D-1: Country Data, Actual and with Temperate Technology (cont'd)

Country	Output p.w.		Ag. labor prod.		Ag. labor share	
	Actual	Temp.	Actual	Temp.	Actual	Temp.
<i>Equatorial/Highland cluster:</i>						
Colombia	13,583	17,623	2,746	15,361	0.28	0.07
Ecuador	12,972	18,119	2,721	13,366	0.35	0.09
Ethiopia	1,196	2,589	351	590	0.79	0.48
Guatemala	12,594	22,287	1,426	4,433	0.56	0.19
Honduras	7,599	14,088	1,412	3,810	0.61	0.24
Indonesia	5,976	10,351	839	2,692	0.54	0.18
Malaysia	13,743	19,391	2,460	11,891	0.36	0.09
Mexico	23,256	32,995	2,341	11,283	0.36	0.09
Nicaragua	9,855	14,535	1,806	7,604	0.41	0.11
Papua New Guinea	6,387	13,436	1,246	2,504	0.72	0.37
Paraguay	13,090	20,982	3,820	13,648	0.50	0.15

Notes: Actual data is from Caselli (2005). The ‘Temp.’ columns refer to counter-factual values calculated using our calibrated model and assuming the country has temperate agricultural technology with $\beta = 0.15$. See text for details.

E. SYSTEMATIC PATTERNS IN THE TECHNOLOGY ESTIMATES

We analyse the correlation between the country-specific means of log inputs and the country-specific estimated coefficient for that input. Our findings in Table E-1 indicate very limited correlation in the preferred standard and agro-climatic CMG models, which implies that there is no systematic relationship between the size of the estimated coefficient on an input and the amount of that input used.

Table E-1: Correlation matrix – variable averages and CMG estimates

<i>Variable averages</i>	\overline{ly}_i	\overline{ltr}_i	\overline{llive}_i	\overline{lf}_i	\overline{ln}_i	$\hat{\beta}_i^{Tr}$	$\hat{\beta}_i^{Live}$	$\hat{\beta}_i^F$	$\hat{\beta}_i^N$
Output pw \overline{ly}_i	1								
Tractors pw \overline{ltr}_i	0.910	1							
Livestock pw \overline{llive}_i	0.818	0.735	1						
Fertilizer pw \overline{lf}_i	0.903	0.918	0.698	1					
Land pw \overline{ln}_i	0.778	0.718	0.675	0.671	1				
<i>Standard CMG</i>	\overline{ly}_i	\overline{ltr}_i	\overline{llive}_i	\overline{lf}_i	\overline{ln}_i	$\hat{\beta}_i^{Tr}$	$\hat{\beta}_i^{Live}$	$\hat{\beta}_i^F$	$\hat{\beta}_i^N$
$\hat{\beta}_i^{Tr}$	0.089	0.124	0.052	0.072	0.051	1			
$\hat{\beta}_i^{Live}$	0.003	-0.015	0.153	-0.051	-0.119	-0.330	1		
$\hat{\beta}_i^F$	0.115	0.123	0.075	0.223	0.116	-0.067	-0.119	1	
$\hat{\beta}_i^N$	0.105	0.139	0.076	0.203	0.108	-0.203	0.007	0.124	1
<i>Agro-climatic CMG</i>	\overline{ly}_i	\overline{ltr}_i	\overline{llive}_i	\overline{lf}_i	\overline{ln}_i	$\hat{\beta}_i^{Tr}$	$\hat{\beta}_i^{Live}$	$\hat{\beta}_i^F$	$\hat{\beta}_i^N$
$\hat{\beta}_i^{Tr}$	0.128	0.138	0.106	0.150	0.008	1			
$\hat{\beta}_i^{Live}$	0.040	0.024	0.126	-0.047	-0.007	-0.238	1		
$\hat{\beta}_i^F$	0.148	0.168	0.100	0.282	0.138	-0.002	-0.218	1	
$\hat{\beta}_i^N$	0.098	0.125	0.037	0.128	0.145	-0.062	-0.053	0.094	1

Notes: We correlate the country-specific variable series (means) with the standard and agro-climatic CMG technology estimates. Significant coefficients (5% level) are in bold (except for the diagonals). We employ the CRS-based estimates for the standard and agro-climate CMG respectively (Table 1, columns [3] and [6]). Coefficient estimates are for ‘Tr’ tractors, ‘Live’ livestock, ‘F’ fertilizer and ‘N’ land; ‘pw’ refers to variables in ‘per worker’ terms.

F. ROBUSTNESS CHECK: ALTERNATIVE GROUPINGS

In our baseline specification, we used cluster analysis to group countries into four climate types: arid/temperate, temperate/cold, equatorial, and equatorial/highland. Here we show that alternative ways of grouping countries by climate type yield similar heterogeneity in the average $\hat{\beta}_L$ coefficient to what we found using the four clusters.

Table F-1: Labor Coefficients and Climate Zones

	B Arid	C/D Temperate	A Equatorial	H Highland
<i>Panel A: Any share of land in climatic zone</i>				
Mean $\hat{\beta}_L$	0.185 [0.086]**	0.137 [0.071]*	0.397 [0.089]***	0.240 [0.082]***
Sample	57	67	70	47
<i>Panel B: Share above zone mean</i>				
Mean $\hat{\beta}_L$	0.178 [0.114]	0.184 [0.083]**	0.432 [0.115]***	0.484 [0.100]***
Sample	38	53	53	26
<i>Panel C: Share above 40%</i>				
Mean $\hat{\beta}_L$	0.103 [0.100]	0.161 [0.086]*	0.419 [0.117]***	0.357 [0.220]
Sample	23	51	52	12
<i>Panel D: Share above 50%</i>				
Mean $\hat{\beta}_L$	-0.001 [0.083]	0.150 [0.087]*	0.409 [0.124]***	0.558 [0.150]***
Sample	20	49	47	7
<i>Panel E: Share above 60%</i>				
Mean $\hat{\beta}_L$	0.035 [0.115]	0.082 [0.098]	0.413 [0.131]***	0.734 [0.168]**
Sample	17	43	43	4

Notes: Each cell in this Table presents the robust mean of the estimated labor coefficient $\hat{\beta}_L$ given the criterion indicated. All criteria refer to the share of agricultural land in the respective climatic zones (denoted by their Köppen-Geiger letters), e.g. each robust mean computed in Panel B only includes countries which have a share of land above the full sample mean in the specific climatic zone — this indicates the skewness of distribution in the equatorial and temperate/cold zones. Sample indicates the number of observations from which the robust mean is constructed.

Table F-2: Clusters – Descriptives

<i>Panel A: Four Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster Name</i>					
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
<i>Panel B: Five Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster Name</i>					
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
<i>Panel C: Six Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster Name</i>					
Arid & Temperate/Cold	0.000 [0.000]	0.146 [0.153]	0.800 [0.190]	0.054 [0.127]	15
Temperate/Cold	0.003 [0.013]	0.023 [0.065]	0.933 [0.121]	0.041 [0.099]	25
Arid	0.102 [0.145]	0.730 [0.218]	0.147 [0.223]	0.022 [0.057]	16
Arid & Equatorial	0.358 [0.462]	0.329 [0.469]	0.278 [0.426]	0.036 [0.082]	19
Equatorial	0.833 [0.202]	0.053 [0.104]	0.072 [0.138]	0.042 [0.102]	43
Equatorial & Highland	0.259 [0.283]	0.164 [0.189]	0.002 [0.008]	0.575 [0.196]	10

Notes: The table presents the mean share of land in each of the four climatic zones (denoted by their Köppen-Geiger letters) for groups of countries determined endogenously using the cluster analysis technique described in the main test. The standard deviations of these means are in brackets.

First are ad hoc methods, using arbitrary cut-off levels for the share of land in a climate zone to group countries. These ad hoc groups allow for the possibility of double-counting, as a country could have more than 40% (for example) of their land in two different groups. Table F-1 shows the results of these different ad hoc methods.

Second, our cluster analysis groups the countries according to their agro-climatic distance, but the number of clusters we used (four) is arbitrary. Here we show that allowing for either 5 or 6 clusters of countries does not materially change the heterogeneity found by climate type.

Table F-2 shows the share of land in each of the Köppen-Geiger zones for a given cluster. Table F-3 shows the average value of $\hat{\beta}_L$ for each associated cluster. Table F-4 shows the actual assignment of countries to each cluster.

Table F-3: Labor Coefficients by Clusters

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

Notes: We present robust mean estimates (standard errors in brackets) for the labor coefficients (using estimates from Model [6] in Table 1) based on various groupings. In Panels A-C we use cluster analysis specifying 4, 5 and 6 clusters, respectively, to create our groups (see Table F-2 for group descriptives).

Table F-4: Country Clusters

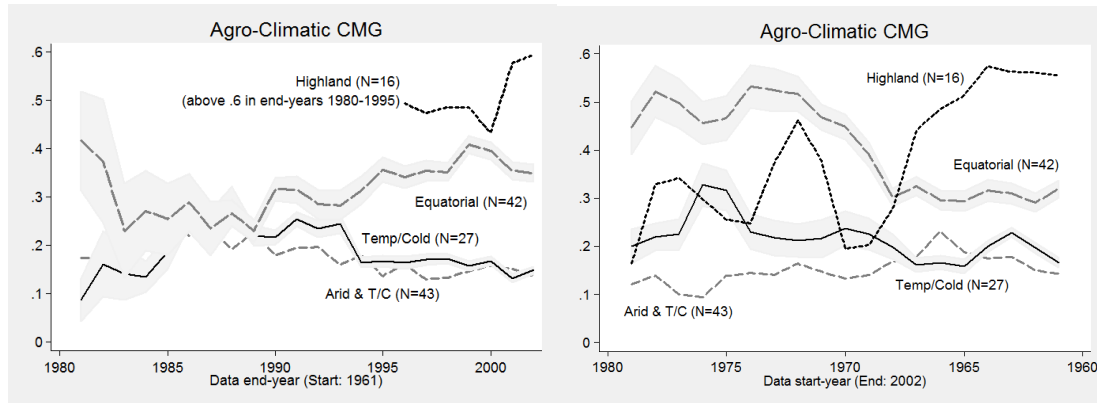
	Country	Number of Clusters				Country	Number of Clusters				Country	Number of Clusters			
		wbcode	Four	Five	Six		wbcode	Four	Five	Six		wbcode	Four	Five	Six
1	Afghanistan	AFG	A&T/C	Eq&Hi	Eq&Hi	44	Gambia	GMB	Eq&Hi	Eq&Hi	87	Netherlands	NLD	T/C	T/C
2	Angola	AGO	Eq&Hi	Eq&Hi	Eq&Hi	45	Guinea-Bissau	GNB	Eq&Hi	Eq&Hi	88	Norway	NOR	T/C	T/C
3	Albania	ALB	A&T/C	A&T/C	A&T/C	46	Equatorial Guinea	GNQ	Eq&Hi	Eq&Hi	89	Nepal	NPL	A&T/C	A&T/C
4	United Arab Emirates	ARE	A&T/C	A&T/C	A&Eq	47	Greece	GRC	A&T/C	A&T/C	90	New Zealand	NZL	T/C	T/C
5	Argentina	ARG	T/C	T/C	T/C	48	Guatemala	GTM	Eq&Hi	Eq&Hi	91	Oman	OMN	A&T/C	A&Eq
6	Australia	AUS	T/C	T/C	T/C	49	Guyana	GUY	Eq&Hi	Eq&Hi	92	Pakistan	PAK	A&T/C	A&Eq
7	Austria	AUT	T/C	T/C	T/C	50	Honduras	HND	Eq&Hi	Eq&Hi	93	Panama	PAN	Eq&Hi	Eq&Hi
8	Burundi	BDI	Eq&Hi	Eq&Hi	Eq&Hi	51	Haiti	HTI	Eq&Hi	Eq&Hi	94	Philippines	PHL	A&T/C	A&Eq
9	Benin	BEN	Eq&Hi	Eq&Hi	Eq&Hi	52	Hungary	HUN	T/C	T/C	95	Papua New Guinea	PNG	Eq&Hi	Eq&Hi
10	Burkina Faso	BFA	A&T/C	Arid	Arid	53	Indonesia	IDN	Eq&Hi	Eq&Hi	96	Poland	POL	T/C	T/C
11	Bangladesh	BGD	Eq&Hi	Eq&Hi	Eq&Hi	54	India	IND	Eq&Hi	Eq&Hi	97	Korea, DPR	PRK	A&T/C	A&Eq
12	Bulgaria	BGR	T/C	T/C	T/C	55	Ireland	IRL	T/C	T/C	98	Portugal	PRT	A&T/C	A&T/C
13	Belgium-Luxembourg	BLX	T/C	T/C	T/C	56	Iran	IRN	A&T/C	Arid	99	Paraguay	PRY	Eq&Hi	Eq&Hi
14	Belize	BLZ	Eq&Hi	Eq&Hi	Eq&Hi	57	Iraq	IRQ	A&T/C	Arid	100	Qatar	QAT	A&T/C	A&Eq
15	Bolivia	BOL	Eq&Hi	Eq&Hi	Eq&Hi	58	Iceland	ISL	T/C	T/C	101	Romania	ROM	T/C	T/C
16	Brazil	BRA	Eq&Hi	Eq&Hi	Eq&Hi	59	Israel	ISR	A&T/C	A&T/C	102	Rwanda	RWA	Eq&Hi	Eq&Hi
17	Botswana	BWA	A&T/C	Arid	Arid	60	Italy	ITA	T/C	A&T/C	103	Saudi Arabia	SAU	A&T/C	A&T/C
18	Central African Republic	CAF	Eq&Hi	Eq&Hi	Eq&Hi	61	Jamaica	JAM	Eq&Hi	Eq&Hi	104	Sudan	SDN	Eq&Hi	Arid
19	Canada	CAN	A&T/C	A&T/C	A&Eq	62	Jordan	JOR	A&T/C	A&T/C	105	Senegal	SEN	Eq&Hi	Arid
20	Switzerland	CHE	T/C	T/C	T/C	63	Japan	JPN	T/C	T/C	106	Sierra Leone	SLE	Eq&Hi	Eq&Hi
21	Chile	CHL	A&T/C	A&T/C	A&T/C	64	Kenya	KEN	Eq&Hi	Eq&Hi	107	El Salvador	SLV	Eq&Hi	Eq&Hi
22	China	CHN	T/C	T/C	T/C	65	Cambodia	KHM	Eq&Hi	Eq&Hi	108	Somalia	SOM	A&T/C	Arid
23	Côte d'Ivoire	CIV	Eq&Hi	Eq&Hi	Eq&Hi	66	South Korea	KOR	T/C	T/C	109	Suriname	SUR	Eq&Hi	A&Eq
24	Cameroon	CMR	Eq&Hi	Eq&Hi	Eq&Hi	67	Kuwait	KWT	A&T/C	A&T/C	110	Sweden	SWE	T/C	T/C
25	Congo, Republic	COG	Eq&Hi	Eq&Hi	Eq&Hi	68	Lao PDR	LAO	Eq&Hi	Eq&Hi	111	Swaziland	SWZ	T/C	T/C
26	Colombia	COL	Eq&Hi	Eq&Hi	Eq&Hi	69	Lebanon	LBN	A&T/C	A&T/C	112	Syria	SYR	A&T/C	A&T/C
27	Costa Rica	CRI	Eq&Hi	Eq&Hi	Eq&Hi	70	Liberia	LBR	Eq&Hi	Eq&Hi	113	Chad	TCO	A&T/C	Arid
28	Cuba	CUB	Eq&Hi	Eq&Hi	Eq&Hi	71	Libya	LBY	A&T/C	Arid	114	Togo	TGO	Eq&Hi	Eq&Hi
29	Cyprus	CYP	A&T/C	A&T/C	A&T/C	72	Sri Lanka	LKA	Eq&Hi	Eq&Hi	115	Thailand	THA	Eq&Hi	Eq&Hi
30	Germany	DEU	T/C	T/C	T/C	73	Lesotho	LSO	T/C	T/C	116	Trinidad & Tobago	TTO	A&T/C	A&Eq
31	Denmark	DNK	T/C	T/C	T/C	74	Morocco	MAR	A&T/C	A&T/C	117	Tunisia	TUN	A&T/C	A&T/C
32	Dominican Republic	DOM	Eq&Hi	Eq&Hi	Eq&Hi	75	Madagascar	MDG	Eq&Hi	Eq&Hi	118	Turkey	TUR	A&T/C	A&T/C
33	Algeria	DZA	A&T/C	A&T/C	A&T/C	76	Mexico	MEX	Eq&Hi	Eq&Hi	119	Tanzania	TZA	Eq&Hi	Eq&Hi
34	Ecuador	ECU	Eq&Hi	Eq&Hi	Eq&Hi	77	Mali	MLI	A&T/C	Arid	120	Uganda	UGA	Eq&Hi	Eq&Hi
35	Egypt	EGY	A&T/C	A&T/C	A&T/C	78	Myanmar	MMR	Eq&Hi	Eq&Hi	121	Uruguay	URY	T/C	T/C
36	Spain	ESP	A&T/C	A&T/C	A&T/C	79	Mongolia	MNG	A&T/C	Arid	122	United States	USA	T/C	T/C
37	Ethiopia	ETH	Eq&Hi	Eq&Hi	Eq&Hi	80	Mozambique	MOZ	Eq&Hi	Eq&Hi	123	Venezuela	VEN	Eq&Hi	Eq&Hi
38	Finland	FIN	A&T/C	A&T/C	A&T/C	81	Mauritania	MRT	A&T/C	Arid	124	Vietnam	VNM	Eq&Hi	Eq&Hi
39	France	FRA	T/C	T/C	T/C	82	Malawi	MWI	A&T/C	A&T/C	125	Yemen, Republic	YEM	A&T/C	Eq&Hi
40	Gabon	GAB	Eq&Hi	Eq&Hi	Eq&Hi	83	Malaysia	MYA	Eq&Hi	Eq&Hi	126	South Africa	ZAF	A&T/C	Arid
41	United Kingdom	GBR	T/C	T/C	T/C	84	Niger	NER	A&T/C	Arid	127	Congo, DR	ZAR	Eq&Hi	Eq&Hi
42	Ghana	GHA	Eq&Hi	Eq&Hi	Eq&Hi	85	Nigeria	NGA	Eq&Hi	Eq&Hi	128	Zimbabwe	ZWE	Eq&Hi	Arid
43	Guinea	GIN	Eq&Hi	Eq&Hi	Eq&Hi	86	Nicaragua	NIC	Eq&Hi	Eq&Hi					

Notes: This table reports the cluster affiliation from our analysis imposing four, five or six clusters, respectively. Group names (stylised): A&T/C – Arid & Temperate/Cold; T/C – Temperate/Cold; Arid; Eq&Hi – Equatorial; A&Eq – Arid & Equatorial; Eq&Hi – Equatorial & Highland.

G. ROBUSTNESS CHECK: PARAMETER STABILITY

In Figure G-1 we present average labour coefficients for each of the four clusters used in the main text of the paper where the country-specific estimates of β_L are based on recursive estimates: in the left panel we estimate the agricultural production function with a sample from 1961 to 1980, compute the average β_L by agro-climatic cluster and then increase the end date of the sample by one year at a time until we reach 2002. Each line plot charts, from left to right, the evolution of the cluster-specific mean labor coefficient as the sample size is increased. In the right sample we do the same beginning with a sample from 1981 to 2002, then shifting the start year of the sample one year at a time until we reach the full sample starting in 1961 – again sample size increases from left to right. In either plot we can see that mean coefficient estimates for each cluster stabilize once the time series reaches around 30 years.

Figure G-1: Average Labor Coefficient by Climate Zone – Recursive Estimates



Notes: Shaded areas represent 90% confidence intervals for the robust mean estimates within each cluster, where clusters are defined as detailed in Table F-4 above. In the left plot we omit the early estimates of the Highland cluster (all above .6) in order to aid presentation in the graph.

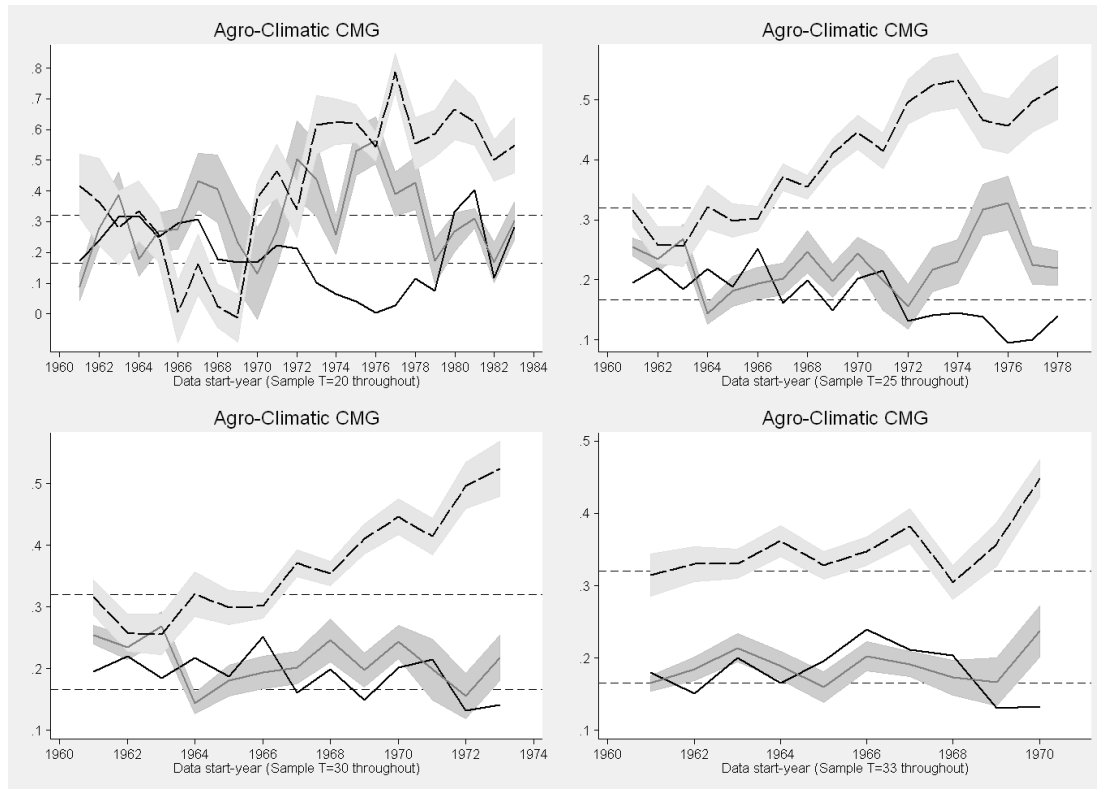
We also carried out robustness checks using a moving sample window of different length. In Figure G-2 we adopt $T_j = \{20, 25, 30, 33\}$ years for the estimation window. The x -axis in each plot indicates the start-year for each window T_j , on the y -axis we plot the robust mean labor estimate (empirical specification: Agro-Climate CMG, column [6] in Table 1 in the main body of the paper) for the arid (solid black line), equatorial (dashed black line) and the temperate/cold (solid grey line) clusters, together with a 90% confidence interval for the latter two. We omit the small sample highland cluster for ease of illustration.

Two forces are at play in this data mining exercise: firstly, small sample bias, and secondly, potential true technology heterogeneity over time. We should think it uncon-

troversial to suggest that the estimates for the arid and temperate/cold clusters are fairly stable across all four plots: the obvious variation in the estimates for the 20-year window smoothen once the sample size is increased, with the 25, 30 and 33 year windows fluctuating around the robust full time series mean for the temperate/cold cluster indicated by the lower dashed line in all plots. Here we would argue is a good case for small sample bias rather than genuine technology heterogeneity *over time* causing the observed fluctuations in the cluster-specific means. For the equatorial cluster we observe a systematic pattern over time, whereby we can suggest that there is some evidence that the technology coefficient *increased* over time. Nevertheless it appears that for longer time horizons our robust full sample estimate — indicated by the upper dashed line in all plots — represents an *average* technology over time.³⁷ Further, this finding, assuming it is not an artifact of small sample bias, does not fundamentally challenge our discussion in the main body of the paper: for moving window results beginning from $T = 25$ years the average equatorial technology parameter is higher than that for the temperate zone in virtually all subsamples analysed.

³⁷Note that the results presented in Figure G-2 do not account for entry and exit into the sample. Once we limit the sample to countries with 39 to 42 observations this aspect is more easily observed in the plot — results available on request.

Figure G-2: Average Labor Coefficient by Climate Zone – Moving Window

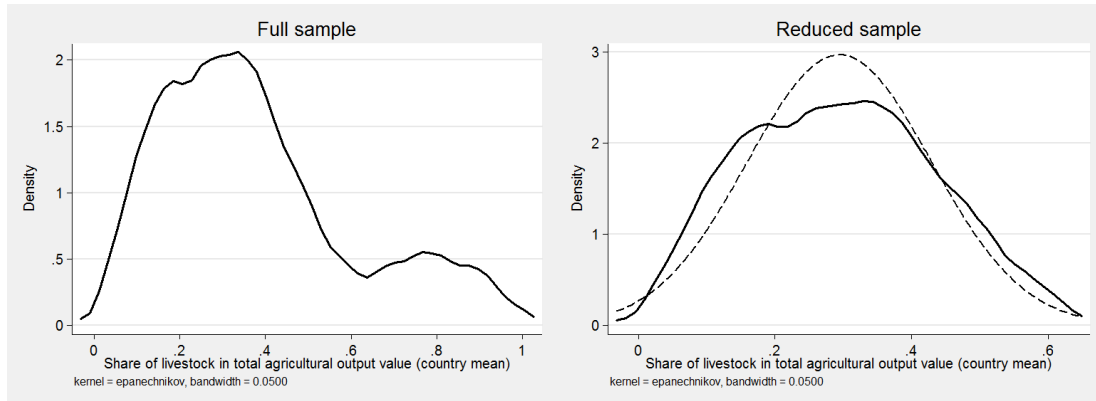


Notes: We plot robust mean labor estimates within agro-climatic clusters as detailed in Table F-4 above (4 cluster case). Shaded areas represent 90% confidence intervals for the robust mean estimates within clusters, where clusters are defined as detailed in Table F-4 above. We only present these for the equatorial and temperate/cold estimates, for ease of illustration. For the same reason we omit the estimates for the (small sample) highland cluster throughout. Note that in the computation of the averages presented we do *not* account for changes in the makeup of the cluster-specific sample over time. We convinced ourselves that the findings were not driven by this phenomenon by restricting the sample to countries which had between 39 and 42 time series observations (results available on request).

H. ROBUSTNESS CHECK: NON-LIVESTOCK SAMPLE

The dominance of livestock breeding in some economies may be seen to have a distorting impact on our agricultural production function estimation. As a robustness check we therefore attempt to exclude those economies from the sample where livestock rearing appears to account for a significant share of total agricultural output. In the left panel of Figure H-1 we plot the country-specific averages of livestock share in total agricultural output (in value terms) for our sample of $N = 128$ countries. The clear bi-modal nature of the distribution is driven by 22 economies with an average livestock share of more than 60% – with the exception of a small number of low income countries (e.g. Lesotho, Mongolia, Somalia) these are predominantly developed economies in the temperate or cold climate zones, including Denmark, Germany, and the United Kingdom. If we exclude these economies, the distribution of livestock share is unimodal and normal, with a mean/median just under 30% and a standard deviation of 14% (right panel of Figure H-1).

Figure H-1: Distribution of Livestock Share in Total Agricultural Output



Notes: We plot the distribution of country-specific averages for the share of livestock in total agricultural output value. Left panel: full sample of $N = 128$; right panel: we drop 22 countries for which this average share exceeds 60%.

Table H-1 provides agricultural production function estimates for a model of agricultural output net of livestock, where we have dropped the previous ‘livestock’ variable (the cattle-equivalent headcount). Patterns of returns to scale as well as average coefficients for capital stock and fertilizer are next to identical to the alternative specification with the full sample data in Table 1 of the maintext. Land coefficients are however substantially elevated, and with the exception of the ‘distance’ specification the CMG estimates for labor are considerably higher as well. Taking diagnostics into account

the agro-climatic distance version of the CMG still emerges as the preferred specification.

Table H-2 presents the labor coefficient analysis for the four broad climatic zones, where like in the full sample case the highland zone appears to have the highest labor coefficients, followed by the equatorial zone. In contrast to the earlier results the arid zone now has clearly higher average labor coefficients across the various scenarios than the temperate/cold zone.

We carry out cluster analysis on the agro-climatic similarity measures for the reduced sample of $N = 106$ countries and present cluster characteristics in Table H-3 and averaged labor coefficients in Table H-4. We pick 3 to 5 clusters – due to the one-sided reduction in the sample, which almost exclusively (15/22) dropped temperate/cold zone countries, the emerging clusters are no longer quite as clear-cut as in the full sample specification (note the presence of a ‘diverse’ group in the five cluster case). Average labor coefficients still broadly follow the patterns of the earlier results, with the highest labor coefficients in equatorial and highland climate zones and significantly lower coefficients in the temperate/cold and arid zones.

Table H-1: Production Function Estimates – Non-Livestock

	[1] 2FE	[2] MG	[3] CMG standard	[4] CMG neighbor	[5] CMG distance	[6] CMG agro-climate
Weight matrix ‡						
Labor	-0.143 [4.63]**	-0.502 [2.73]**			-0.440 [2.99]**	
Tractors pw $\hat{\beta}_K$	0.072 [13.78]**	0.062 [2.43]*	0.120 [5.27]**	0.098 [4.24]**	0.075 [2.85]**	0.093 [3.54]**
Fertilizer pw $\hat{\beta}_F$	0.097 [20.12]**	0.041 [5.25]**	0.043 [5.15]**	0.050 [5.32]**	0.034 [4.45]**	0.043 [4.75]**
Land pw $\hat{\beta}_N$	0.565 [16.46]**	0.307 [3.43]**	0.417 [6.26]**	0.391 [5.37]**	0.230 [2.66]**	0.368 [5.15]**
Returns to Scale ^b	DRS	DRS	CRS	CRS	DRS	CRS
Implied Avg $\hat{\beta}_L$	0.123 [7.48]**	0.088 [0.43]	0.420 [5.92]**	0.460 [5.98]**	0.221 [1.28]	0.497 [6.48]**
Avg implied $\hat{\beta}_L$		0.136 [0.91]	0.356 [5.15]**	0.396 [4.77]**	0.225 [2.06]*	0.431 [5.52]**
# rejecting CRS		49			34	
$\hat{\varepsilon}$ Stationarity [†]	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-2.00 (.05)	4.64 (.00)	-1.83 (.07)	3.80 (.00)	-0.01 (.99)	-1.06 (.29)
RMSE	0.187	0.074	0.070	0.071	0.062	0.070

Notes: Results for $n = 4,309$ observations from $N = 106$ countries – we omitted the countries with a dominance in livestock breeding. Estimators: 2FE – 2-way fixed effects, MG – Pesaran and Smith (1995) Mean Group, CMG – Pesaran (2006) Common Correlated Effects Mean Group. We present robust sample means for model parameters in [2]-[6]; [1] is a pooled model. * and ** indicate statistical significance at the 5% and 1% level respectively. Terms in square brackets are absolute t -statistics based on standard heteroskedasticity-robust standard errors in [1] and based on the variance estimator following Pesaran and Smith (1995) in [2]-[6]. RMSE reports the root mean squared error.

Dependent variable – log output per worker, [1] dto. in 2FE transformation as described in Coakley, et al. (2006).

Independent variables – all variables are in log per worker terms with the exception of ‘Labor,’ for which the coefficient estimate indicates deviation from constant returns (formally: $\hat{\beta}_L + \hat{\beta}_K + \hat{\beta}_{Live} + \hat{\beta}_F + \hat{\beta}_N - 1$). This is not the technology coefficient on labor, which is reported under ‘Implied $\hat{\beta}_L$ ’ in a lower panel of the Table.

^b The implied returns to scale are labeled decreasing (DRS) if the coefficient on Labor is negative significant, and constant (CRS) if this coefficient is insignificant. We present models with CRS imposed if the unrestricted model cannot reject this specification. For heterogeneous models we present two robust mean estimates for the implied labor coefficient: the first is computed from the averages presented in the upper panel of the Table, while the second is constructed at the country level and then averaged.

‡ We apply different $N \times N$ weight matrices to construct the cross-section averages as described in the main text.

[†] Pesaran (2007) CIPS test results for residual nonstationarity: I(0) — stationary, I(1) — nonstationary. Full results available on request. [‡] Pesaran (2004) test for cross-section dependence (CD) in the residuals, H_0 : no CD.

Table H-2: Labor Coefficients and Climate Zones – Non-Livestock

	B	C/D	A	H
<i>Panel A: Any share of land in climatic zone</i>				
Mean $\hat{\beta}_L$	0.329 [0.110]***	0.218 [0.114]*	0.589 [0.090]***	0.497 [0.103]***
Sample	50	50	69	41
<i>Panel B: Share above zone mean</i>				
Mean $\hat{\beta}_L$	0.363 [0.137]**	0.165 [0.133]	0.589 [0.114]***	0.717 [0.102]***
Sample	34	38	51	22
<i>Panel C: Share above 40%</i>				
Mean $\hat{\beta}_L$	0.251 [0.191]	0.179 [0.143]	0.574 [0.112]***	0.660 [0.120]***
Sample	16	35	52	11
<i>Panel D: Share above 50%</i>				
Mean $\hat{\beta}_L$	0.255 [0.212]	0.169 [0.143]	0.561 [0.120]***	0.729 [0.125]***
Sample	15	33	47	7
<i>Panel E: Share above 60%</i>				
Mean $\hat{\beta}_L$	0.461 [0.195]**	0.094 [0.153]	0.566 [0.127]***	1.040 [0.042]***
Sample	12	29	43	4

Notes: We analyse labor coefficients obtained from the analysis of the reduced sample ($N = 106$) where we exclude countries where livestock output makes up a large share of total agricultural output (in value terms) – production function results in Table H-1. Each cell in this Table presents the robust mean of the estimated labor coefficient $\hat{\beta}_L$ given the criterion indicated. All criteria refer to the share of agricultural land in the respective climatic zones (denoted by their Köppen-Geiger letters), e.g. each robust mean computed in Panel B only includes countries which have a share of land above the full sample mean in the specific climatic zone — this indicates the skewness of distribution in the equatorial and temperate/cold zones. Sample indicates the number of observations from which the robust mean is constructed.

Table H-3: Clusters – Non-Livestock

<i>Panel A: Three Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster</i>					
Arid & Temperate/Cold	0.070 [0.220]	0.285 [0.348]	0.556 [0.414]	0.089 [0.201]	50
Equatorial & Highland	0.683 [0.299]	0.034 [0.070]	0.026 [0.094]	0.257 [0.264]	15
Equatorial	0.807 [0.229]	0.097 [0.183]	0.067 [0.133]	0.029 [0.076]	41
<i>Panel B: Four Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster</i>					
Arid & Temperate/Cold	0.063 [0.211]	0.288 [0.361]	0.618 [0.390]	0.032 [0.080]	45
Arid & Equatorial	0.797 [0.228]	0.092 [0.177]	0.069 [0.136]	0.041 [0.100]	45
Equatorial	0.947 [0.083]	0.000 [0.000]	0.000 [0.000]	0.053 [0.083]	6
Equatorial & Highland	0.245 [0.255]	0.164 [0.189]	0.002 [0.008]	0.588 [0.169]	10
<i>Panel C: Five Clusters</i>					
<i>Climate Zone</i>	A	B	C/D	H	N
<i>Cluster</i>					
Arid & Temperate/Cold	0.000 [0.000]	0.179 [0.199]	0.770 [0.219]	0.051 [0.124]	16
Diverse	0.177 [0.355]	0.253 [0.365]	0.442 [0.447]	0.128 [0.245]	35
Arid & Equatorial	0.293 [0.112]	0.497 [0.298]	0.075 [0.172]	0.135 [0.238]	11
Equatorial	0.874 [0.157]	0.045 [0.088]	0.056 [0.114]	0.026 [0.076]	31
Equatorial & Highland	0.795 [0.221]	0.012 [0.042]	0.045 [0.114]	0.148 [0.202]	13

Notes: The table presents the mean share of land in each of the four climatic zones (denoted by their Köppen-Geiger letters) for groups of countries determined endogenously using the cluster analysis technique described in the main test. The standard deviations of these means are in brackets.

Table H-4: Labor Coefficients by Clusters – Non-Livestock

Panel A: Three Clusters					
Cluster	Arid & temperate/cold	Arid & Equatorial	Equatorial & Highland		
Mean $\hat{\beta}_L$	0.287 [0.115]**	0.482 [0.126]***	0.762 [0.135]***		
N	50	41	15		
Panel B: Four Clusters					
Cluster	Arid & temperate/cold	Arid & Equatorial	Equatorial	Equatorial & Highland	
Mean $\hat{\beta}_L$	0.253 [0.118]**	0.506 [0.117]***	0.876 [0.705]	0.813 [0.123]***	
N	45	45	6	10	
Panel C: Five Clusters					
Cluster	Arid & temperate/cold	Diverse	Arid & Equatorial	Equatorial	Equatorial & Highland
Mean $\hat{\beta}_L$	-0.225 [0.202]	0.512 [0.139]***	0.796 [0.261]**	0.382 [0.132]***	0.802 [0.182]***
N	16	35	11	31	13

Notes: We present robust mean estimates (standard errors in brackets) for the labor coefficients (using estimates from Model [6] in Table 1) based on various groupings. In Panels A-C we use cluster analysis specifying 3, 4 and 5 6 clusters, respectively, to create our groups (see Table H-3 for group descriptives).

I. ROBUSTNESS CHECK: CLUSTER-SPECIFIC PRODUCTION FUNCTIONS

In our main empirical approach we look at the average of the coefficient estimates for each cluster to establish that $\hat{\beta}_L$ varies by climate zone. An alternative is to estimate the average coefficient for each cluster. In this case we estimate the production function separately for each cluster, after separating countries into clusters by agro-climatic distance. Table I-1 presents the summary results for the implied $\hat{\beta}_L$ for each of five different agro-climatic clusters. The tables that follow show the full results for each separate climate zone.

In this analysis we make use of the pooled version of the CCE estimator (Pesaran, 2006): since cluster sample size is relatively small we may see some improvement in precision from this pooled over the Mean Group estimator since it significantly reduces the number of parameters to be estimated. The CCEP is specified as

$$y_{it} = a_i + \beta x_{it} + c_{0i} \bar{y}_t + \sum_{m=1}^k c_{mi} \bar{x}_{mt} + e_{it}, \quad (38)$$

which is estimated in a pooled model with each of the cross-section averages carrying country-specific coefficients. In this specification we do not obtain unique technology coefficients $\hat{\beta}_i$ for each country individually, but the average $\hat{\beta}$ for each climate group.

In Table I-1 we shaded the preferred pooled and heterogeneous specification, which again follow the patterns discussed in the main part of the paper. Our decision rule for ‘preferred specification’ here is (i) cross-sectionally independent residuals; (ii) smaller number of parameters to estimate; (iii) more precise estimates. Focusing on the CCEP results, we can see that while the technology estimates for the five clusters are not all statistically significantly *different* from each other, their confidence intervals overlap only marginally, if at all. Given the small sample size for each cluster, these findings are remarkably in line with our previous results.

Table I-1: Production functions by Cluster – Summary Results

	[1]	[2] CMG	[3]	[4]	[5] CCEP	[6]
(Weighted) CA [†]	Cluster	Ag-Clim	Both	Cluster	Ag-Clim	Both
<i>Panel A</i> Arid & Temperate/Cold ($n = 1,108; N = 28$)						
Implied Avg $\hat{\beta}_L$	0.036 [0.25]	0.103 [0.55]	0.157 [1.09]	-0.046 [0.49]	-0.108 [1.60]	-0.066 [0.55]
90% CI lower & upper bound	-0.203 0.275	-0.203 0.409	-0.080 0.394	-0.199 0.107	-0.220 0.004	-0.265 0.133
$\hat{\varepsilon}$ CD Test (p)	-1.78 (.08)	-0.75 (.45)	-0.89 (.37)	-2.30 (.02)	-0.84 (.40)	-2.40 (.02)
# parameters	280	280	420	172	172	312
<i>Panel B</i> Temperate/Cold ($n = 1,047; N = 25$)						
Implied Avg $\hat{\beta}_L$	0.200 [1.99]**	0.168 [1.91]*	0.170 [1.52]	0.250 [4.42]***	0.164 [3.21]**	0.286 [3.71]***
90% CI lower & upper bound	0.034 0.366	0.023 0.313	-0.014 0.354	0.156 0.344	0.080 0.248	0.159 0.413
$\hat{\varepsilon}$ CD Test (p)	-1.05 (.29)	0.84 (.40)	3.88 (.00)	-0.71 (.48)	2.74 (.01)	3.62 (.00)
# parameters	250	250	375	154	154	279
<i>Panel C</i> Arid ($n = 724; N = 18$)						
Implied Avg $\hat{\beta}_L$	-0.044 [0.31]	0.224 [1.95]*	0.173 [1.27]	0.049 [0.94]	0.205 [2.75]**	0.091 [0.87]
90% CI lower & upper bound	-0.278 0.190	0.035 0.413	-0.051 0.397	-0.037 0.135	0.082 0.328	-0.080 0.262
$\hat{\varepsilon}$ CD Test (p)	-2.00 (.05)	0.92 (.36)	-0.88 (.38)	-3.77 (.00)	-0.02 (.98)	-1.96 (.05)
# parameters	180	180	270	112	112	202
<i>Panel D</i> Equatorial ($n = 1,599; N = 40$)						
Implied Avg $\hat{\beta}_L$	0.329 [3.27]**	0.411 [3.43]**	0.404 [3.31]**	0.398 [6.82]***	0.386 [5.07]***	0.378 [3.91]***
90% CI lower & upper bound	0.163 0.495	0.214 0.608	0.203 0.605	0.303 0.493	0.261 0.511	0.218 0.538
$\hat{\varepsilon}$ CD Test (p)	-1.58 (.12)	-0.14 (.89)	0.90 (.37)	-0.77 (.44)	-0.48 (.63)	0.90 (.37)
# parameters	400	400	600	244	244	444
<i>Panel E</i> Equatorial & Highland ($n = 684; N = 17$)						
Implied Avg $\hat{\beta}_L$	0.509 [2.43]**	0.445 [1.54]	0.645 [2.80]**	0.575 [9.04]***	0.297 [2.46]**	0.513 [4.53]***
90% CI lower & upper bound	0.165 0.853	-0.030 0.920	0.265 1.025	0.470 0.680	0.100 0.494	0.327 0.699
$\hat{\varepsilon}$ CD Test (p)	-1.31 (.19)	-0.76 (.45)	-1.29 (.20)	-0.80 (.42)	2.21 (.03)	-0.50 (.62)
# parameters	170	170	255	106	106	191

Notes: Models [1]-[3] employ the Pesaran (2006) Mean Group CCE estimator, [4]-[6] its pooled variant. We report (i) the implied labor coefficients (averages in [1]-[3]); (ii) absolute t -statistics following Pesaran and Smith (1995) (in [1]-[3]) and absolute t -statistics based on bootstrapped standard errors (in [4]-[6]); (iii) 90% confidence bounds based on the respective standard errors; (iv) the Pesaran (2004) CD test (H_0 cross-section independence) and p -value; (v) information on the number of parameters estimated in each model. All model residuals were found to be stationary (results available on request).

[†] Cross-section averages employed: (i) ‘Cluster’ specific means; (ii) ‘Ag-Clim’ – weighted full sample CA where weights reflect agro-climatic distance (as in Table 1 Column [6]); (iii) both. Shading indicates the preferred CMG and CCEP estimates based on diagnostic tests.

Table I-2: Cluster-specific Production Functions – Full Results

	[1]	[2] CMG	[3]	[4]	[5] CCEP	[6]
(Weighted) CA [†]	Cluster	Ag-Clim	Both	Cluster	Ag-Clim	Both
<i>Cluster</i>	<i>Arid & Temperate/Cold ($n = 1,108; N = 28$)</i>					
Tractors pw	0.125 [2.17]*	0.081 [1.17]	0.125 [1.97]*	0.157 [3.87]***	0.070 [2.04]*	0.178 [3.25]**
Livestock pw	0.241 [3.19]**	0.223 [2.56]*	0.230 [3.16]**	0.483 [6.02]***	0.548 [8.00]***	0.452 [5.51]***
Fertilizer pw	0.069 [4.05]***	0.074 [3.87]***	0.078 [3.99]***	0.056 [4.43]***	0.079 [4.91]***	0.042 [2.63]**
Land pw	0.528 [3.67]***	0.519 [3.17]**	0.409 [3.20]**	0.350 [3.54]***	0.411 [4.86]***	0.394 [2.64]**
Implied Avg $\hat{\beta}_L$	0.036 [0.25]	0.103 [0.55]	0.157 [1.09]	-0.046 [0.49]	-0.108 [1.60]	-0.066 [0.55]
90% CI lower & upper bound	-0.203 0.275	-0.203 0.409	-0.080 0.394	-0.199 0.107	-0.220 0.004	-0.265 0.133
$\hat{\varepsilon}$ Stationarity [†]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-1.78 (.08)	-0.75 (.45)	-0.89 (.37)	-2.30 (.02)	-0.84 (.40)	-2.40 (.02)
RMSE	0.071	0.075	0.062	0.099	0.107	0.089
N	1,108	1,108	1,108	1,108	1,108	1,108
# parameters	280	280	420	172	172	312
<i>Cluster</i>	<i>Temperate/Cold ($n = 1,047; N = 25$)</i>					
Tractors pw	0.140 [2.17]*	0.117 [2.20]*	0.079 [1.38]	0.062 [3.47]***	0.057 [3.05]**	0.041 [1.35]
Livestock pw	0.309 [5.53]***	0.374 [7.10]***	0.38 [5.48]***	0.327 [8.75]***	0.335 [8.55]***	0.292 [5.06]***
Fertilizer pw	0.027 [1.85]	0.042 [2.66]**	0.043 [2.28]*	0.051 [3.64]***	0.068 [5.33]***	0.059 [3.48]***
Land pw	0.323 [2.86]**	0.298 [3.37]***	0.328 [2.75]**	0.311 [6.62]***	0.376 [8.54]***	0.322 [4.24]***
Implied Avg $\hat{\beta}_L$	0.200 [1.99]**	0.168 [1.91]*	0.170 [1.52]	0.250 [4.42]***	0.164 [3.21]**	0.286 [3.71]***
90% CI lower & upper bound	0.034 0.366	0.023 0.313	-0.014 0.354	0.156 0.344	0.080 0.248	0.159 0.413
$\hat{\varepsilon}$ Stationarity [†]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-1.05 (.29)	0.84 (.40)	3.88 (.00)	-0.71 (.48)	2.74 (.01)	3.62 (.00)
RMSE	0.040	0.041	0.031	0.049	0.051	0.041
N	1,047	1,047	1,047	1,047	1,047	1,047
# parameters	250	250	375	154	154	279

Notes: Continued overleaf.

Table I-2: Cluster-specific Production Functions – Full Results (cont'd)

	[1]	[2]	[3]	[4]	[5]	[6]
		CMG			CCEP	
(Weighted) CA [†]	Cluster	Ag-Clim	Both	Cluster	Ag-Clim	Both
<i>Cluster</i>	Arid ($n = 724; N = 18$)					
Tractors pw	0.170 [3.18]**	0.105 [2.04]*	0.115 [2.44]*	0.143 [6.17]***	0.107 [4.23]***	0.110 [2.94]**
Livestock pw	0.484 [4.57]***	0.465 [5.10]***	0.440 [4.62]***	0.496 [10.64]***	0.474 [11.13]***	0.465 [6.78]***
Fertilizer pw	0.055 [1.72]	0.067 [2.57]*	0.057 [1.97]*	0.029 [3.63]***	0.022 [2.75]**	0.038 [3.20]**
Land pw	0.335 [2.28]*	0.139 [1.37]	0.215 [1.74]	0.283 [5.76]***	0.192 [3.23]**	0.297 [4.11]***
Implied Avg $\hat{\beta}_L$	-0.044 [0.31]	0.224 [1.95]*	0.173 [1.27]	0.049 [0.94]	0.205 [2.75]**	0.091 [0.87]
90% CI lower & upper bound	-0.278 0.190	0.035 0.413	-0.051 0.397	-0.037 0.135	0.082 0.328	-0.080 0.262
$\hat{\varepsilon}$ Stationarity [†]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-2.00 (.05)	0.92 (.36)	-0.88 (.38)	-3.77 (.00)	-0.02 (.98)	-1.96 (.05)
RMSE	0.063	0.070	0.056	0.082	0.088	0.075
N	724	724	724	724	724	724
# parameters	180	180	270	112	112	202
<i>Cluster</i>	Equatorial ($n = 1,599; N = 40$)					
Tractors pw	0.085 [1.48]	0.103 [1.84]	0.062 [1.39]	0.057 [5.00]***	0.064 [7.50]***	0.045 [3.17]**
Livestock pw	0.349 [4.15]***	0.352 [4.14]***	0.351 [4.10]***	0.229 [8.34]***	0.264 [9.46]***	0.178 [4.22]***
Fertilizer pw	0.031 [3.21]**	0.031 [3.19]**	0.032 [3.36]***	0.020 [4.26]***	0.021 [4.74]***	0.024 [3.81]***
Land pw	0.206 [2.35]*	0.103 [0.98]	0.151 [1.52]	0.296 [4.62]***	0.265 [3.41]***	0.375 [3.75]***
Implied Avg $\hat{\beta}_L$	0.329 [3.27]**	0.411 [3.43]**	0.404 [3.31]**	0.398 [6.82]***	0.386 [5.07]***	0.378 [3.91]***
90% CI lower & upper bound	0.163 0.495	0.214 0.608	0.203 0.605	0.303 0.493	0.261 0.511	0.218 0.538
$\hat{\varepsilon}$ Stationarity [†]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-1.58 (.12)	-0.14 (.89)	0.90 (.37)	-0.77 (.44)	-0.48 (.63)	0.90 (.37)
RMSE	0.053	0.054	0.042	0.071	0.074	0.061
N	1,599	1,599	1,599	1,599	1,599	1,599
# parameters	400	400	600	244	244	444

Notes: Continued overleaf.

Table I-2: Cluster-specific Production Functions – Full Results (cont'd)

	[1]	[2]	[3]	[4]	[5]	[6]
		CMG			CCEP	
(Weighted) CA [†]	Cluster	Ag-Clim	Both	Cluster	Ag-Clim	Both
<i>Cluster</i>	Equatorial & Highland ($n = 684; N = 17$)					
Tractors pw	0.172 [1.19]	0.194 [1.52]	0.155 [0.96]	0.124 [4.12]***	0.095 [4.77]***	0.052 [1.29]
Livestock pw	0.333 [4.20]***	0.367 [4.39]***	0.388 [3.00]**	0.221 [5.09]***	0.387 [6.69]***	0.322 [6.00]***
Fertilizer pw	0.044 [2.54]*	0.037 [1.70]	0.016 [1.19]	0.041 [3.78]***	0.034 [2.92]**	0.018 [1.34]
Land pw	-0.058 [0.36]	-0.043 [0.23]	-0.203 [0.92]	0.038 [0.65]	0.187 [1.54]	0.095 [0.81]
Implied Avg $\hat{\beta}_L$	0.509 [2.43]**	0.445 [1.54]	0.645 [2.80]**	0.575 [9.04]***	0.297 [2.46]**	0.513 [4.53]***
90% CI lower	0.165	-0.030	0.265	0.470	0.100	0.327
& upper bound	0.853	0.920	1.025	0.680	0.494	0.699
$\hat{\varepsilon}$ Stationarity [†]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) [‡]	-1.31 (.19)	-0.76 (.45)	-1.29 (.20)	-0.80 (.42)	2.21 (.03)	-0.50 (.62)
RMSE	0.050	0.057	0.040	0.068	0.083	0.057
N	684	684	684	684	684	684
# parameters	170	170	255	17	17	17

Notes: We ran cluster-specific (five clusters, Tables F-2 and 2, Panel B respectively) Cobb-Douglas production functions (CRS imposed) adopting the same set of inputs as in our main results. Models [1]-[3] employ the Pesaran (2006) Mean Group CCE estimator, [4]-[6] its pooled variant. We report the production function (mean) estimates, along with (i) the implied labor coefficients (averages in [1]-[3]); (ii) absolute t -statistics based on outlier-robust standard errors (in [1]-[3]) and absolute t -statistics based on 100 bootstraps (in [4]-[6]); (iii) 90% confidence bounds based on the respective standard errors; (iv) the Pesaran (2004) CD test (H_0 cross-section independence) and p -value; (v) the model root mean squared error (RMSE); (vi) the number of parameters estimated in each model. All model residuals were found to be stationary (results available on request).

[†] Cross-section averages employed: (i) 'Cluster' specific means; (ii) 'Ag-Clim' – weighted full sample CA where weights reflect agro-climatic distance (as in Table 1 Column [6]); (iii) both.

J. WEAK EXOGENEITY TESTS

In Table J-1 we provide some evidence that our preferred CMG specifications (standard and agro-climatic distance models) can be interpreted as production functions and do not suffer from bias due to reverse causality. These results represent weak exogeneity tests following Canning and Pedroni (2008). An error correction specification incorporating the residuals from our empirical models in Table 1 of the maintext is estimated for output and each production input. For any causal relation to exist between x and y at least one of the coefficients on the residuals in these five equations (we impose constant returns to scale) has to be statistically significant. If this ‘error correction’ (EC) term is significant in the output but not the input equations, we can suggest that the inputs ‘cause’ output ($x \rightarrow y$). Note how the misspecified 2FE and MG models find multiple causal relationships between the variables.

Table J-1: Canning & Pedroni (2008) tests for direction of causation

2FE	<i>GM</i>	(<i>p</i>)	<i>Fisher</i>	(<i>p</i>)	<i>mean</i> $\hat{\lambda}_i$	<i>t-ratio</i>	<i>Verdict</i>
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	<i>GM</i>	(<i>p</i>)	<i>Fisher</i>	(<i>p</i>)	<i>mean</i> $\hat{\lambda}_i$	<i>t-ratio</i>	<i>Verdict</i>
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 standard	<i>GM</i>	(<i>p</i>)	<i>Fisher</i>	(<i>p</i>)	<i>mean</i> $\hat{\lambda}_i$	<i>t-ratio</i>	<i>Verdict</i>
output equation	-2.09	0.04	938.4	0.00	-0.925	-18.63	$x, \text{TFP} \rightarrow y$
tractor equation	-0.08	0.94	189.3	1.00	-0.045	-1.28	$x_{-tr}, y, \text{TFP} \nrightarrow x_{tr}$
livestock equation	0.12	0.91	331.1	0.00	0.011	0.27	$x_{-live}, y, \text{TFP} \rightarrow x_{live}$
fertilizer equation	-0.04	0.97	232.7	0.69	0.023	0.14	$x_{-f}, y, \text{TFP} \nrightarrow x_f$
land equation	0.06	0.95	225.7	0.79	0.010	0.68	$x_{-n}, y, \text{TFP} \nrightarrow x_n$
CMG agro-climate	<i>GM</i>	(<i>p</i>)	<i>Fisher</i>	(<i>p</i>)	<i>mean</i> $\hat{\lambda}_i$	<i>t-ratio</i>	<i>Verdict</i>
output equation	-2.25	0.02	1,035.5	0.00	-0.935	-20.16	$x, \text{TFP} \rightarrow y$
tractor equation	-0.02	0.98	241.8	0.53	-0.013	-0.42	$x_{-tr}, y, \text{TFP} \nrightarrow x_{tr}$
livestock equation	0.15	0.88	380.0	0.00	0.048	1.23	$x_{-live}, y, \text{TFP} \rightarrow x_{live}$
fertilizer equation	0.07	0.94	242.5	0.52	-0.004	-0.02	$x_{-f}, y, \text{TFP} \nrightarrow x_f$
land equation	-0.09	0.93	227.3	0.77	-0.001	-0.08	$x_{-n}, y, \text{TFP} \nrightarrow x_n$

Notes: We report various test statistics for the null of no long-run causal impact between sets of different variables. In each case ‘*variable* equation’ refers to the ECM regression with ‘*variable*’ on the LHS. GM gives the group-mean average of country-specific *t*-ratios for the coefficient on the disequilibrium term ($\hat{\lambda}_i$) which is distributed $N(0, 1)$. Fisher gives $-2 \sum_i \log \pi_i$ where π_i is the probability value of the country-specific *t*-ratio on the disequilibrium term. The Fisher statistic is distributed $\chi^2(2N)$. The final two columns but one report the mean estimate for $\hat{\lambda}_i$ and the associated *t*-ratio. In the ‘Verdict’ column we summarise the analysis, using x_{-tr} for ‘all inputs other than tractors’ and \rightarrow as short-hand for ‘does cause’ and \nrightarrow for ‘does not cause’. TFP is included implicitly in the CMG models via cross-section averages. For comparability we impose constant returns on all models tested.