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Eberhardt, Markus and Teal, Francis

Centre for the Study of African Economies (CSAE), Department of Economics, Oxford University

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Markus Eberhardt[a,b†] Francis Teal[b]

[a] *St. John's College, Oxford*
[b] *Centre for the Study of African Economies, Department of Economics, University of Oxford*

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Abstract:

In this paper we investigate a 'global' production function for agriculture, using FAO data for 128 countries from 1961-2002. Our review of the empirical literature in this field highlights that existing cross-country studies largely neglect variable time-series properties, parameter heterogeneity and the potential for heterogeneous Total Factor Productivity (TFP) processes across countries. We motivate the case for technology heterogeneity in agricultural production and present statistical tests indicating nonstationarity and cross-section dependence in the data. Our empirical approach deals with these difficulties by adopting the Pesaran (2006) Common Correlated Effects estimators, which we extend by using alternative weight-matrices to model the nature of the cross-section dependence. We furthermore investigate returns to scale of production and production dynamics. Our results support the specification of a common factor model in intercountry production analysis, highlight the rejection of constant returns to scale in pooled models as an artefact of empirical misspecification and suggest that agro-climatic environment, rather than neighbourhood or distance, drives similarity in TFP evolution across countries. The latter finding provides a possible explanation for the observed failure of technology transfer from advanced countries of the temperate 'North' to arid and/or equatorial developing countries of the 'South'.

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†Correspondence: St. John's College, Oxford OX1 3JP; markus.eberhardt@economics.ox.ac.uk

"[A]ssumptions of a common production function, and perfect and competitive factor markets ... get in the way of understanding international differences in productivity — particularly differences between advanced and underdeveloped economies."
Nelson (1968, p.1229)

"Techniques developed in advanced countries were not generally directly transferable to less developed countries with different climates and resource endowments."
Ruttan (2002, p.162)

Ever since Hayami and Ruttan (1970) introduced the use of panel data to estimate cross-country production functions for the agriculture sector, academic studies have emphasised the conceptual desirability of technology heterogeneity across the diverse range of agro-climatic environments across countries. The literature further highlighted the potential for barriers to technology transfer between countries which are specific to the agricultural sector, in particular the problems of transfers between the developed countries of the temperate 'North' and the developing countries of the arid or equatorial 'South': innovations in the former did not seem to yield the desired productivity boost in the latter context. In practice, however, empirical investigation was typically based on models which impose technology homogeneity across the diverse sample of countries under analysis, or only allowed for heterogeneity by splitting the sample into crude geographical groups of countries. Further to this choice of empirical specification, many studies opted to impose constant returns to scale on their regressions, despite concerns that the supply of one factor input, land, is essentially fixed.

In this paper we extend the insights gained from the emerging literature on multi-factor models in nonstationary panels (Bai & Ng, 2004; Coakley, Fuertes, & Smith, 2006; Pesaran, 2006; Kapetanios, Pesaran, & Yamagata, 2008) to cross-country empirical productivity analysis in the agricultural sector — to the best of our knowledge this is the first empirical study to do so. We adopt a common factor model approach and estimate production functions for a panel of 128 developing and developed countries using annual data from 1961 to 2002 (FAO, 2007). Our focus is on the changes in the parameter estimates and diagnostic tests when we move between pooled and heterogeneous estimators, between methods which ignore cross-section dependence and those which accommodate it, and between approaches that put different emphasis on the time-series properties of long T panels. This aside, the nature of the data for agriculture allows us to investigate the cross-section dependence properties in a formal manner.

These innovations aside we particularly focus on three issues: *firstly*, we do not restrict the returns to scale of production, given that with a fixed input (land) part of the production function we do not have any priors about whether returns can assumed to be constant, decreasing or increasing.

Secondly, in an extension to the Pesaran (2006) common correlated effects estimators, we set out to identify what these 'common effects' might actually represent in the case of agriculture. In the standard CCE approach the nature of the cross-sectional dependence across countries is unspecified; in our extension to this approach, which we believe represents a further original contribution to the empirical literature, we apply a number of weighting schemes in the construction of the cross-section averages, based on neighbourhood, geographical distance and agro-climatic distance. The application of weight matrices in essence imposes more structure on the factor loadings across countries, which in the standard CCE estimators are left unconstrained. The first two of our extensions investigated essentially mimic standard spatial econometric approaches using geographical distance measures, the third represents a more complex cross-section correlation. The economic interpretation of our extension would be that the set of unobserved factors influencing productivity in each country is the same for its neighbours, countries in close(r) proximity or countries with similar agro-climatic environment respectively. Thus, countries that are *not* neighbours, are geographically *more distant* or have a very *dissimilar* agro-climatic conditions are argued to to be driven by different sets of factors.

Thirdly, we check the robustness of our empirical results by comparing them with those derived from a dynamic specification of the production function. Again, the majority of studies in the literature concentrate on static models.

Our empirical analysis thus investigates the interplay and salience of time-series properties of the data, parameter heterogeneity, returns to scale assumptions and the presence as well as potential structure of cross-section dependence in the estimation of cross-country production functions in agriculture.

The remainder of the paper is organised as follows: Section 1 briefly reviews the existing literature on cross-country production function estimation for agriculture. Section 2 presents a number of graphs to highlight agro-climatic heterogeneity across our sample of 128 countries and provides the motivation for the empirical approach. Section 3 introduces the empirical model adopted, develops our extension to the Pesaran (2006) CCE estimators and introduces the data. Section 4 presents and discusses the empirical results,[1] before we conclude our findings in Section 5.

[1]The analysis of data time-series and cross-section dependence properties is presented in Appendices B and C respectively.

1 Literature review

Following the seminal contribution by Hayami and Ruttan (1970) and a later update by the same authors (Hayami & Ruttan, 1985), the literature on agricultural productivity analysis across countries using panel data or 'repeated cross-sections' can be broadly distinguished by two aspects. The first of these does not relate to methodological approach, but to the dataset used, whereas the second major aspect relates to the empirical restrictions placed on production technology: whether countries are allowed to have differential technology parameters, TFP levels and evolvement, and whether constant returns to scale are imposed. While our short overview of the literature claims by no means to be exhaustive, we believe that the indicative literature presented in Table 1 and briefly discussed below does represent the breadth of the empirical field at the present time.

Most cross-country studies on agriculture use the data provided by the Food and Agriculture Organisation (FAO) which provides output and input variables for a large number of countries from 1961 onwards but relies on tractors and agricultural machinery as proxy for agricultural capital. Examples include Craig, Pardey, and Roseboom (1997); Cermeño, Maddala, and Trueblood (2003); Bravo-Ortega and Lederman (2004) and Fulginiti, Perrin, and Yu (2004). The alternative to this is a dataset developed by a World Bank team of researchers which provides agricultural fixed capital stock data for a maximum of 57 developing and developed countries (although in practice only 37 or 48 countries are used) from 1967-1992 (Larson, Butzer, Mundlak, & Crego, 2000).[2] An updated version of the dataset provides agricultural fixed capital stock from 1972-2000 for 30 countries.[3] The use of the two World Bank datasets is to our knowledge limited to Mundlak, Larson, and Butzer (1997, 1999), as well as Martin and Mitra (2002), Gutierrez and Gutierrez (2003) and Mundlak, Larson, and Butzer (2008).

We highlight this difference since with the noteworthy exception of Martin and Mitra (2002) *all* empirical studies which use the World Bank dataset(s) obtain very high capital coefficients, typically between .35 and .6. The Martin and Mitra (2002) paper arrives at a much lower coefficient of .12.[4] In contrast, all studies using the FAO data with tractors proxying for fixed capital stock obtain capital coefficients in the range .05 to .2.

The second major aspect relating to technology heterogeneity has commonly been limited to the modelling of TFP. Technology parameter heterogeneity across countries has either been ignored (Hayami & Ruttan, 1970; Craig et al., 1997; Mundlak et al., 1999; Martin & Mitra, 2002; Mundlak et al., 2008) or approached by splitting the sample into 'homogeneous groups', e.g. by level of development (Hayami & Ruttan, 1985; Cermeño et al., 2003; Gutierrez & Gutierrez, 2003). Although many of these studies stress the importance of allowing for technology differences across country groups, none of them investigates this in an approach which allows for full technology heterogeneity.

[2] Other variables, such as sectoral value added, arable land and agricultural are taken from World Bank, FAO and the ILO data (see Martin & Mitra, 2002).

[3] At present the updated data is not publicly available, although the it seems the World Bank team headed by Don Larson is happy to provide the data if approached.

[4] Given that the methods applied are very similar this discrepancy may be caused by the alternative deflation strategy applied in Martin and Mitra (2002). Similar to the practice in the FAO data, the authors advocate the use of a single LCU-US$ exchange rate (in their case for 1990) in favour of the practice of using annual exchange rates as implemented in the Larson et al. (2000) data.

Closely linked to the empirical specification of production technology is the returns to scale assumption imposed on the regression model or tested. The underlying returns to scale of agricultural production affect the size-distribution of farms within an economy (Mundlak, Larson, & Crego, 1997). However, in addition we can think of a number of constraints, for instance insecure legal environment and variations in land tenure arrangements, that influence both of these processes in a similar fashion. For cross-country production analyses in agriculture findings of increasing, decreasing or constant returns to scale (all of which are present as can be seen in Table 1) are typically justified with reference to micro-economic studies of production or the structural change within countries witnessed over the sample period. Hayami and Ruttan (1985), for instance, report increasing returns to scale for a subsample of developed countries (DC),[5] while their developing country (LDC) sample cannot reject constant returns. They argue that increasing returns are linked to the indivisibility of fixed capital, which has played an increasingly important role in the substitution of labour in developed countries (labour-saving technology). The result for their LDC sample is said to be the outcome of increasing population pressure on land over the sample period, resulting in a decline in the land-labour ratio. Efforts to increase productivity were therefore directed toward saving land by applying more inputs that acted as land-substitutes, such as fertilizer, chemicals or improved seeds (land-saving technology). Since these inputs are highly divisible, the authors argue, it is not surprising to encounter constant returns in this subsample. Although some LDCs also witnessed labour-saving technological change, it is argued that this must have been dominated by the scale-neutral impact of land-saving technical change.

Mundlak, Larson, and Butzer (1997) in contrast argue that the "contribution of inputs to growth should be judged by their contribution to output under a constant technology, attributing the rest of the growth to technical change [TFP]" (paper summary). Their specification "succeeds in capturing the impact of cross-country differences in technology and thus eliminates the spurious result of increasing returns to scale." (p.13)

With regard to our own analysis it is important to point out that once the empirical implementation allows for heterogeneous technology across countries, the standard *ceteris paribus* property of regression parameters alluded to by Mundlak, Larson, and Butzer (1997) breaks down. The implications are beyond the scope of this paper.

The study by Gutierrez and Gutierrez (2003) to the best of our knowledge represents the only analysis which accounts for time-series properties of the data (nonstationarity, cointegration), using nonstationary panel econometric methods (Kao, Chiang, & Chen, 1999). Phillips and Moon (1999) have shown that even panel regressions can lead consistent 'long-run average' estimates even if the error terms are nonstationary, such that the danger nonsense 'spurious' regression is mitigated in the panel (Fuertes, 2008)— a result which depends on the units of the panel being independent of each other. As in common with the vast majority of cross-country empirical analysis, none of the studies reviewed considers the impact of cross-section dependence in the data on empirical estimates. The presence of such dependence can result in misleading inference and even inconsistency in standard fixed effects panel estimators favoured in this literature (Phillips & Sul, 2003). Furthermore, if common factors drive both the regressors and the error terms this will lead to inconsistent panel estimators due to the correlation between the regressors and the error components (Pesaran, 2006).

[5]Only if data is deflated by the number of farms. They remark that their national aggregate data however displays constant returns for both subsamples — unfortunately results are not presented.

Table 1: Selective Review of the Literature

	Hayami & Ruttan (1970)	**Hayami & Ruttan (1985)**	**Craig et al (1997)**	**Mundlak et al (1999)**	**Martin & Mitra (2002)**	**Cermeño et al (2003)**	**Gutierrez & Gutierrez (2003)**	**Bravo-Ortega & Lederman (2004)**	**Mundlak et al (2008)**
Data									
Countries	36	43	98	37	49	84	47	86	30
Observations	108	129	588	777	1248	2604	1081	2993	870
Year(s)/Period	1955, 1960, 1965	1960, 1970, 1980	1961-1990	1970-1990	1967-1992	1961-1991	1970-1992	1961-1997	1972-2000
Data source	own, annual	own, annual	FAO, 5-year avg.	WB, annual	WB, annual	FAO, annual	WB, annual	FAO, annual	WB, annual
Specification									
Model	pooled	pooled	pooled	pooled	pooled	pooled by region	pooled	pooled	pooled
Estimation method	POLS	POLS	POLS	2FE	POLS	POLS	panel DOLS	POLS	2FE
Covariates:									
'standard'	L, N, Live, F, K	L, N, Live, F, K †	L, N, Live, F, K	L, N, K, F	L, N, K	L, N, K, Live, F	L, N, K	L, N, P, K, F, Live,	L, N, Live, K, F
'non-standard'	School, Tech Edu	School, Tech Edu	Lit, Life, Infra (all quality-adjusted)	School, Dev, Yield, Prices				irrigated land	
Year dummies	✓	✓		implicit	N trends	✓	✓	✓	implicit
Country dummies			✓	implicit	✓	✓	✓	✓	implicit
Returns to scale	CRS imposed	unrestricted	unrestricted	unrestricted	CRS imposed	unrestricted	unrestricted	CRS imposed	CRS imposed
Findings									
labour	.40	.50	.25	.08	.64		.29	.11	.12
land	.07	.03	.40	.42	.24	.02 – .47	.14	.04	.33
pastures								.53	
irrigated land								.03	
capital/machinery	.11	.07	.05	.36	.12	.02 – .08	.58	.04	.34
livestock	.29	.31	.35			.03 – .40		.25	.08
traction animals			-.06						
fertilizer	.14	.15	.04	.08		.00 – .10		.05	.13
TFP			no difference across i or over t	accounted via 2FE transformation	sign. diff. across i, 1.4-3.5% growth pa	sign. diff. across i and over t	accounted via DOLS method	sign. trend term (1%pa)	accounted via 2FE transformation
Returns to scale	(CRS imposed)	not tested	DRS	CRS not rejected	not tested	differs across regions	CRS	(CRS imposed)	(CRS imposed)
Reference	Table 2, (17)	Table 6-2, (Q14)	Table 1, (1)	Table 4	Table 1, footnote	Tables 1-4, (7)	Table 2, DOLS	Table 6(A), (2)	Table 2, Within

Notes: The table compares Cobb-Douglas production function estimates from studies as indicated. Since many studies report results for more than one specification we concentrate on the most general model for 'standard' production inputs with panel data. The specific reference for each study's entry is stated at the bottom of the table. The studies by Hayami and Ruttan (1985) and Gutierrez and Gutierrez (2003) also provide separate estimations by country groups (developed, developing), finding production technology differences to be considerable and negligible respectively.
Datasets: The Hayami and Ruttan (1970, 1985) studies use data from a wider range of sources which includes the FAO, OECD and other international institutions. FAO — the various databases provided by the Food and Agriculture Organisation of the UN, WB — the Larson et al. (2000) dataset and its updated version.
Output is agricultural output (expressed in some type of constant 'international' monetary terms) in all studies.
Inputs: L — agricultural labour, N — (crop) land, Live — livestock, F — fertilizer, K — capital stock/machinery/tractors, P — pastures, School — school enrolment, Tech Edu — technical education, Lit — literacy, Life — life expectancy, Dev — development level, Yield — peak yield, Infra — various infrastructure variables, Prices — various price indicators.
Estimators: POLS — pooled OLS (we indicate separately whether the regression equation contains country fixed effects), 2FE — Two-way Fixed Effects, see Section 3.2.1 for details, DOLS — Dynamic OLS, following Kao et al. (1999). This estimator imposes a homogeneous cointegration vector but allows for country-specific short-run dynamics.
†For this study the reported coefficients are derived from data deflated by the number of farms. Regressions for national aggregates are alluded to but not presented.

2 Technology Heterogeneity and the Analysis of Agricultural Production

2.1 Heterogeneity in the Agro-Climatic Environment

In this section we attempt to create an impression of the differential agro-climatic environment across different countries. Our focus is here on the differences in the share of arable land[6] in climatic zones across regions of the globe. The data is taken from FAO (2007) and Gallup, Mellinger, and Sachs (1999). The sample is made up of 128 developing and developed countries; the measures presented are essentially time-invariant. Detailed information about data construction and sample coverage is presented in Appendix A.

In Figure 1 we present the average share of agricultural land in the four major climatic zones (equatorial, arid, temperate & cold, highland) for a number of country groups.[7] The means are computed as weighted means within regions, where the weights are the size of arable land for each country. The bar chart provides a strong sense of the heterogeneity in agro-climatic environment across regions: Sub-Saharan Africa (SSA), for instance, at 52% has the highest average share of land in the equatorial zone, higher even than the Latin America & Caribbean group (LAC), which includes Brazil. In contrast, this agro-climatic zone is (virtually) absent from the developed (EU & WIC) and MENA countries. Developed countries are dominated by agricultural land in the temperate & cold zone (>80%), which in turn makes up only around 10% of land in the average Sub-Saharan African country — the lowest share across all regions. It would thus be difficult to refer to any of these groupings as 'similar' to each other, as far as agro-climatic environment is concerned.

In order to get an alternative, more refined visualisation of these geographical differences across individual countries, rather than crude groupings, we compute a 'Jaffe-measure' (Jaffe, 1986) for agro-climatic environment. This measure is computed for every possible country-pair and can be interpreted as a multi-variate correlation coefficient which varies between zero and unity, where a low (high) value indicates little (high) similarity in the distribution of cultivated land across climatic zones in the two countries (Pardey et al., 2007). From the Matthews (1983) data we obtain the share of cultivated land within each of twelve climatic zones ($h_i = (h_{i1}, \ldots, h_{i12})$), such that for each country i the values in the twelve zones sum up to unity ($\sum_m h_{im} = 1$). The Jaffe measure for 'agro-climatic distance' between countries i and j is then

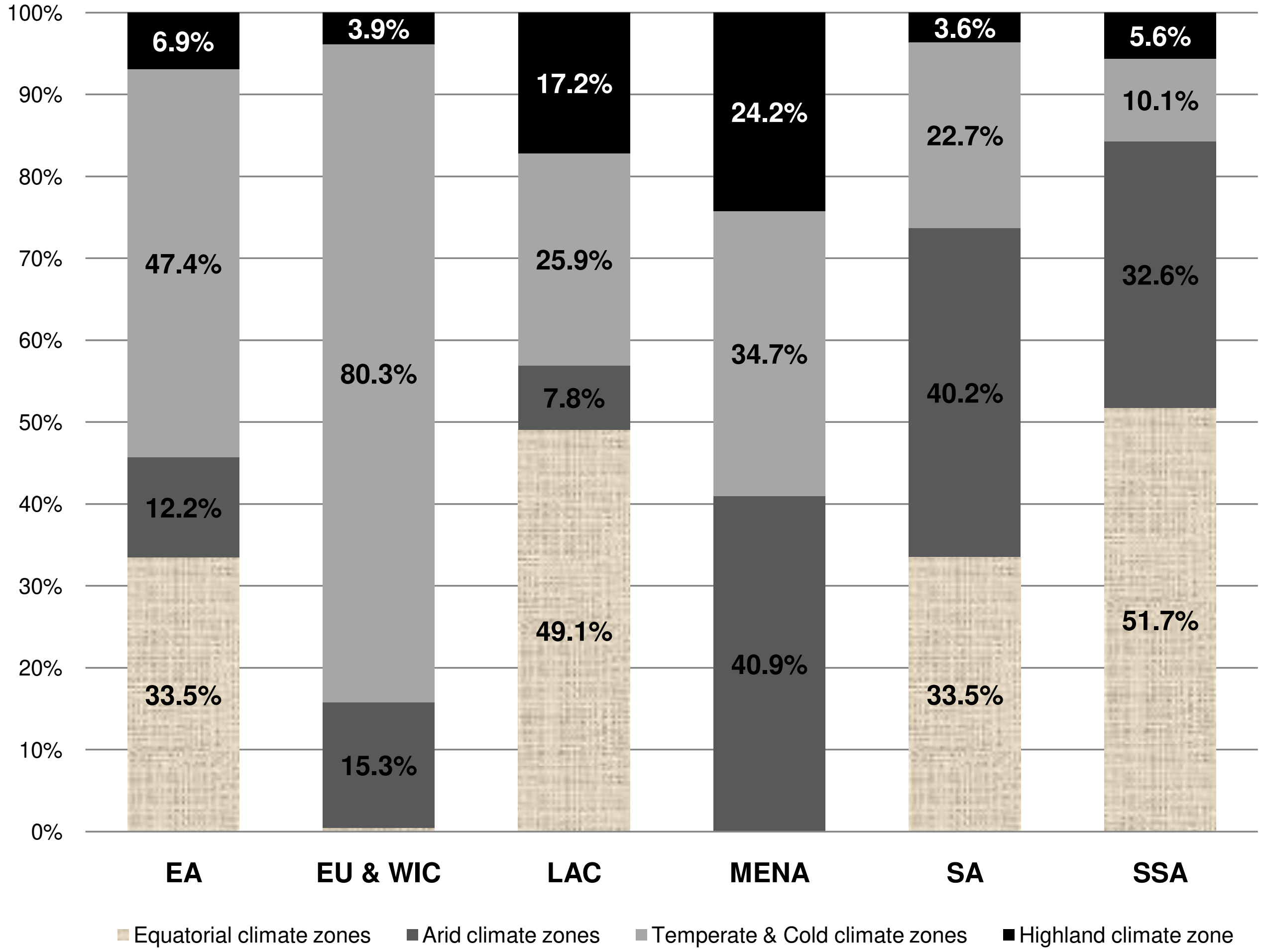
$$\omega_{ij} = \frac{\sum_m h_{im} h_{jm}}{\left(\sum_m h_{im}^2\right)^{1/2} \left(\sum_m h_{jm}^2\right)^{1/2}}$$

In Figure 2 we plot the Jaffe-measures for Kenya: countries with dark green shading, such as Ethiopia, Sudan or Ghana, as well as some Central American countries have an agro-climatic makeup (distribution of agricultural land across climate zones) very similar to that of Kenya, whereas countries with lighter, yellow and orange shading are progressively different. At the other end of the scale, countries in red, such as the UK, Ireland or Japan have an agro-climatic environment which is entirely different from the Kenyan one.

[6]Instead of using the full definition of 'arable land and permanent crop area', throughout this paper we refer to land or 'arable land' for simplicity.

[7]See Appendix A for the makeup of each grouping.

Figure 1: Geographical regions and climate zones — weighted means



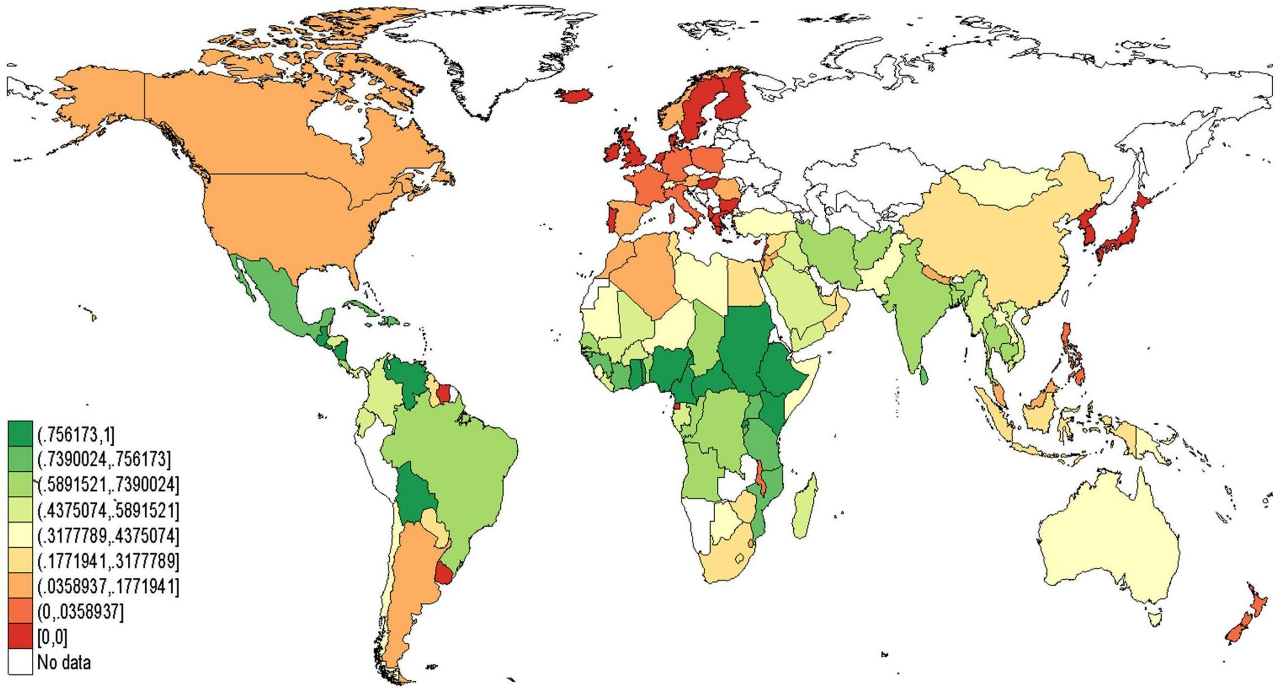
Notes:
This figure shows the weighted group mean for the share of arable land in each climate zone, where the weights are the area of arable and permanent crop land. The groups are East Asia (EA), Europe & other Western Industrialised Countries (EU & WIC), Latin America & Caribbean (LAC), Middle East & North Africa (MENA), South Asia (SA) and Sub-Saharan Africa (SSA).

We may now find the tales of failed agricultural technology transfer from developed to developing countries (Ruttan, 2002; Gutierrez, 2002) rather unsurprising: many of the former have very different agro-climatic characteristics from the latter thus making it rather intuitive that technology between (and even within) these two groups differs and the potential for successful technology transfer *without adaptation* may be limited.

2.2 The Case for Technology Heterogeneity and Cross-section Dependence in the Data

The previous section highlighted the stark differences in the agro-climatic environment for agricultural production across different countries. In our econometric implementation we translate this into the need to allow for *technology heterogeneity* across countries. The assumption of a homogeneous production function may mask or distort important insights into development, as the comment by Nelson (1968) at the beginning of this paper suggests. Hayami and Ruttan (1970) state that Nelson's comment (referring to the analysis of manufacturing data) equally

Figure 2: Agro-climatic 'distance' — the view from Kenya



Notes:
Kenya's cultivated land: 40% is located in zone Aw (Equatorial savannah, dry winters), 19% in zone BS (steppe), 17% in zone BW (desert) and 25% in zone H (highland climate). Source: Matthews (1983), in Gallup et al. (1999).

applies to the analysis of agricultural production. Their approach further highlights the implications of and anecdotal evidence for technology being endogenous to the prevailing 'economic system', namely the "differential diffusion of agricultural technology... [and] of the scientific and technical capacity to invent and develop new mechanical, biological, and chemical technology specifically adapted to the factor endowments and prices in a particular country or region" (Hayami & Ruttan, 1970, p.898). In addition to technology heterogeneity, this highlights potential limits to technological spillover from innovations between countries with very different agro-climatic makeup and resource endowment: we indicated the vast differences for the former in our visualisation of agro-climatic 'distance' in the case of Kenya. Much of agricultural technology has to be viewed as location-specific, with attempts at direct technology transfer from one agro-climatic region to another largely doomed to failure (Gutierrez, 2002; Ruttan, 2002). By the early 1960s it had become increasingly clear that "[t]echniques developed in advanced countries were not generally directly transferable to less developed countries with different climates and resource endowments" (Ruttan, 2002, p.162). However, this insight does not seem to have affected the specification of empirical models in any way.

We incorporate these ideas into our empirical model in three ways: *firstly*, we allow for parameter heterogeneity in the observable variables in our empirical model. At present no intercountry production analysis in agriculture has considered this specification.

Secondly, we adopt a common factor approach to model TFP, which we interpret in the Abramowitz (1956) fashion as 'measure of ignorance': all time-variant processes, inputs, 'factors' and characteristics which are not captured by the observable covariates in our model are arguably captured by unobserved common factors, which are allowed to possess heterogeneous 'factor loadings' across countries. This common factor representation enables us to account for cross-section dependence between countries — this dependence can be hypothesised to arise from common shocks and/or spillover effects, the latter determined for instance by trade, policy or technology (Costantinia & Destefanis, 2008). The importance of accounting for cross-section dependence in estimation and inference has become a major theme in the recent nonstationary panel econometric literature (Bai & Ng, 2004; Pesaran, 2004; Breitung & Pesaran, 2005; Coakley et al., 2006; Baltagi, Bresson, & Pirotte, 2007) and this paper represents our second empirical example of these themes.

Thirdly, we use the above arguments of potential barriers to technology spillovers to motivate an extension to the Pesaran (2006) CCE estimators. In the standard setup these estimators account for the impact of unobserved factors by augmenting the regression equation with a vector of cross-section averages at time t for each of the variables, whereby the averages are constructed from equally weighted observations across all countries. The economic interpretation of this approach would be that the set of unobserved factors which influences productivity is common to all countries — this is not to say that their impact is the same (in fact their heterogeneity is the major contribution of the Pesaran (2006) approach), it is just required that across all countries the impact of each factor is on average non-zero. In our extension we chose to impose some more structure on this framework by investigating three alternative scenarios:

(i) **The 'Neighbourhood Effect'**: many empirical studies have argued that the economic performance of contiguous neighbours to country i has a significant effect on the latter's total factor productivity, and attempted to measure the impact of this spillover empirically by specifying spatially-lagged dependent variables in a production function model (e.g. Ertur & Koch, 2007). In our empirical models we will allow for a conceptually similar relationship in the data using the alternative CCE estimation approach.

(ii) **The 'Gravity Model Effect'**: gravity models are common in empirical trade analysis where they suggest geographical distance as a powerful determinant of the magnitude of economic exchange between countries (e.g. Frankel & Romer, 1999; Redding & Venables, 2004). We adopt this approach to hypothesise that distance between countries (a crude proxy for factors such as climatic, soil, cultural, ethnic and socio-economic differences) can explain the effects of unobserved heterogeneity across countries. Existing examples in the spatial econometric literature are reviewed in Magrini (2004), Abreu, de Groot, and Florax (2005) and Bode and Rey (2006).

(iii) **The 'Agro-Climatic Distance Effect'**: much of the existing literature on intercountry production functions in agriculture particularly highlights the differential agro-climatic characteristics across countries and even explicitly links the failure of technology transfer between diverse countries to heterogeneity in resource endowment and climate. Our third alternative to the standard CCE approach hypothesises that countries with similar agro-climatic makeup are influenced by similar unobserved factors.

In the following section we show somewhat more formally how these ideas are introduced into our econometric model.

3 Empirical Model and Implementation

3.1 Common factor model representation

We adopt an unobserved common factor model as our empirical framework. For $i = 1, \ldots, N$ and $t = 1, \ldots, T$, let

$$
\begin{aligned}
y_{it} &= \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} && (1)\\
x_{mit} &= \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \rho_{1mi} f_{1mt} + \ldots + \rho_{nmi} f_{nmt} + v_{mit} && (2)\\
&\quad \text{where} \qquad m = 1, \ldots, k \qquad \text{and} \qquad \boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t \\
&\quad \boldsymbol{f}_t = \boldsymbol{\varrho}' \boldsymbol{f}_{t-1} + \boldsymbol{e}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t && (3)
\end{aligned}
$$

We assume a production function with observed inputs $\boldsymbol{x}_{it}$ (labour, agricultural capital stock, livestock, fertilizer, land under cultivation) and observed net output y_{it} (all in logarithms). Technology parameters on the inputs can vary across countries ($\boldsymbol{\beta}_i$). Unobserved agricultural TFP is represented by a combination of country-specific TFP levels α_i and a set of common factors $\boldsymbol{f}_t$ with factor loadings that can differ across countries ($\boldsymbol{\lambda}_i'$). We also introduce an empirical representation of the observed inputs in equation (2) in order to indicate the possibility for endogeneity: the input variables $\boldsymbol{x}_{it}$ are driven by a set of common factors $\boldsymbol{g}_{mt}$ as well as an additional set of factors $\boldsymbol{f}_{nmt}$, whereby the latter as indicated represent a subset of the factors driving output in equation (1). The intuition is that some unobserved factors driving agricultural production are likely to similarly drive (at least in parts) the evolution of the inputs. This overlap of common factors creates severe difficulties for the identification of the technology parameters $\boldsymbol{\beta}_i$ (see Remark 4 in Kapetanios et al., 2008) and our empirical estimators set out to address this issue: previous simulation exercises (Coakley et al., 2006; Kapetanios et al., 2008) as well as our own investigations (available on request) indicate that the newly-developed CCE-type estimators are able to accommodate this type of endogeneity in the estimation equation to arrive at consistent parameter estimates for common $\boldsymbol{\beta}$ coefficients or the means of heterogeneous $\boldsymbol{\beta}_i$. Equation (3) indicates that the factors are persistent over time, which allows for the setup to accommodate nonstationarity in the factors ($\boldsymbol{\varrho} = 1$, $\boldsymbol{\kappa} = 1$) and thus the observables. It further allows for various combinations of cointegration: between output y and inputs $\boldsymbol{x}$, and between output $\boldsymbol{y}$, inputs $\boldsymbol{x}$ and (some of) the unobserved factors $\boldsymbol{f}_t$. The latter alternative is of particular interest, since it will allow us to specify a cointegrating relationship *without even knowing its individual elements.*

The above empirical framework allows for the maximum level of flexibility, with regard to parameter heterogeneity, cross-section dependence induced by the common factors, and nonstationarity in the observables and unobserved factors.

3.2 Empirical estimators

3.2.1 Estimators imposing homogeneous parameters

We first use the full time-series of the data to estimate pooled OLS (POLS), two-way fixed effects (2FE), and pooled OLS for data in first differences (FD-OLS). In order to capture the unobserved common processes the POLS and FD-OLS estimation equations contain a set of $T-1$ year dummies (in first differences in the FD-OLS equation); the 2FE estimator captures the common processes by transforming all variables into deviations from the cross-section mean.

Formally, the above estimators are defined as

$$\text{POLS} \qquad y_{it} = a + \boldsymbol{b}\boldsymbol{x}_{it} + \sum_{s=2}^{T} c_s D_s + e_{it} \tag{4}$$

$$\text{FD-OLS} \qquad \Delta y_{it} = \boldsymbol{b}\Delta\boldsymbol{x}_{it} + \sum_{s=2}^{T} c_s \Delta D_s + \Delta e_{it} \tag{5}$$

$$\text{2FE} \qquad \breve{y}_{it} = \boldsymbol{b}\breve{\boldsymbol{x}}_{it} + \breve{e}_{it} \tag{6}$$

where $\breve{z}_{it} = z_{it} - \bar{z}_i - \bar{z}_t + \bar{z}$ with $\bar{z}_i = T^{-1}\sum_{t=1}^{T} z_{it}$ (country average), $\bar{z}_t = N^{-1}\sum_{i=1}^{N} z_{it}$ (cross-section average) and $\bar{z} = (NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}$ (full sample average).

None of the above estimators explicitly addresses cross-section dependence in the data. This is addressed in the pooled version of the Pesaran (2006) Common Correlated Effects estimator (CCEP), where the pooled fixed effects equation is augmented by cross-section averages of the dependent and the independent variables, in a fashion such that the impact of the unobserved common factors is allowed to vary across countries. Formally,

$$\text{CCEP} \qquad y_{it} = a + \boldsymbol{b}\boldsymbol{x}_{it} + \sum_{j=2}^{N} d_j D_j + \sum_{j=1}^{N} c_{1i}\{\bar{y}_t D_j\} + \sum_{j=1}^{N} \boldsymbol{c}_{2i}\{\bar{\boldsymbol{x}}_t D_j\} + e_{it} \tag{7}$$

where the first three terms represent a standard fixed effects estimator and the last two terms represent the augmentation with cross-section averages at time t ($\bar{z}_t = N^{-1}\sum_{i=1}^{N} z_{it}$) interacted with a set of N country dummies D_j. This combination creates $k+1$ matrices of dimensions $NT \times N$ where k is the number of observed variables in the model.

The intuition why this rather simple augmentation can do away with the impact of unobserved common factors (with heterogeneous factor loadings) is as follows: take the cross-section averages of our hypothesised DGP in equation (1) for each point in time to yield

$$\begin{aligned} \bar{y}_t &= \bar{\alpha} + \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t + \bar{\gamma}'\bar{\boldsymbol{f}}_t \\ \Leftrightarrow &\quad \bar{\boldsymbol{f}}_t = \bar{\gamma}^{-1}(\bar{y}_t - \bar{\alpha} - \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t) \qquad \text{since} \qquad \bar{\varepsilon}_t = 0 \end{aligned} \tag{8}$$

This indicates that provided the average impact of each factor across all countries is non-zero ($\bar{\gamma} \neq 0$), the use of cross-section averages of the dependent ($\bar{y}_t$) and independent variables ($\bar{\boldsymbol{x}}_t$) can act as a representation of the unobserved common factors $\boldsymbol{f}_t$ since as the cross-section dimension (N) becomes large $\bar{\boldsymbol{f}}_t \to \boldsymbol{f}_t$ in probability. To allow for heterogeneity in the factor loadings this representation must be implemented in the fashion outlined above.

Pesaran (2006) shows that the asymptotic consistency of the CCEP estimator is based on any weighted cross-section aggregates ($\bar{z}_t = \sum_i w_i z_{it}$) provided the weights w_i satisfy the conditions

$$w_i = O\left(\frac{1}{N}\right) \qquad \sum_{i=1}^{N} w_i\gamma_i \neq 0 \qquad \sum_{i=1}^{N} |w_i| < K \tag{9}$$

where K is a finite positive constant (Coakley et al., 2006). In the standard CCE estimator the weights are the same for all countries ($1/N$) as $\bar{z}_t$ represents the arithmetic mean. In an extension to this standard practice we experiment with a number of weight-matrices to develop alternative CCE estimators. We present three variants of the standard approach:

1. The Neighbourhood CCE approach — for country i the cross-section averages (means) for y and $\boldsymbol{x}$ are constructed from the values for i's *contiguous* neighbours.

2. The Gravity CCE approach — for country i the observations for countries $j = 1, \ldots, N-1$ are weighted by the inverse of the population-weighted distance between i and j (these weights were normalised so that they sum to unity) before computing the cross-section aggregate.

3. The Agro-Climatic CCE approach — for country i the observations for countries $j = 1, \ldots, N-1$ are weighted by Jaffe's measure for agricultural distance (see below) between i and j (these weights were normalised so that they sum to unity) before computing the cross-section aggregate.[8]

Our conceptual justification for these variants of the CCEP (and also the CCEMG) estimator is the situation where the average of factor loadings across countries is non-zero, but systematic patterns drive the data. In the distance case we implicitly test the hypothesis that country i is driven by unobserved common factors which are the same in countries in close proximity, but is much less affected by other factors which drive countries further away from it. The neighbourhood case represents an extreme extension of this argument whereby only countries which share a common border are driven by the same factors. Finally, in the agro-climatic case we test the hypothesis that countries with similar agro-climatic environment are affected by a shared set of common factors, but that these countries are not (or only to a very limited degree) affected by a separate set of common factors, which in turn influences countries in very different agro-climatic environments.

All of the above estimators impose parameter homogeneity on the production technology (observed variables) and TFP (unobserved common factors), with the exception of the CCEP estimator which allows for heterogeneity in TFP evolvement. If variables $(y, \boldsymbol{x})$ and factors $(\boldsymbol{f})$ are nonstationary the POLS, FE and 2FE estimators require that the cointegrating relation between $y, \boldsymbol{x}$ and $\boldsymbol{f}$ is homogeneous across countries. Similarly, if only y and $\boldsymbol{x}$ are nonstationary their cointegrating relationship is required to be common across countries. As our simulation study reveals[9] the use of year dummies can greatly reduce the misspecification bias in a range of scenarios when these assumptions are violated, however the regression equations fundamentally are misspecified and contain nonstationary errors.[10] We now turn to a number of estimators which allow for parameter heterogeneity in both the production technology and TFP evolvement.

3.2.2 Estimators allowing for parameter heterogeneity

All of the following estimators are based on individual country regressions. A starting point is the Pesaran and Smith (1995) Mean Group estimator (MG) which assumes cross-section independence (absence of unobserved common factors) and in the presence of nonstationary variable series requires heterogeneous cointegration, i.e. that the country regression model is correctly specified and encompasses the cointegrating relationship.

[8] For the Jaffe (1986) measure see Section 2.1 for details. For the distance and agro-climatic distance we normalise the weights (across i) so that they sum to unity.

[9] Available on request.

[10] The CCEP estimator seems to be the exception with regard to the latter.

We thus estimate N country regressions

$$\begin{aligned} \text{MG} \qquad y_{it} &= a_i + \boldsymbol{b}_i \boldsymbol{x}_{it} + c_i t + e_{it} \\ &\hat{\boldsymbol{b}}_{MG} = N^{-1} \sum_i \hat{\boldsymbol{b}}_i \end{aligned} \tag{10}$$

where t is a linear trend term with parameter coefficient c_i and a_i is the intercept. By construction all parameters can differ across countries, indicated by the subscript i. The linear trend term is included to capture unobserved idiosyncratic processes which are time-invariant. The MG estimates are then derived as averages of the individual country estimates.

3.2.3 Estimators allowing for parameter heterogeneity and common factors

We also present results for the Augmented Mean Group estimator (AMG), which we developed in Eberhardt and Teal (2008). This estimator accounts for potential cross-section dependence by inclusion of a 'common dynamic effect' in the country regression. This variable is extracted from the year dummy coefficients of the pooled regression in first differences and (following transformation) represents a levels-equivalent average evolvement of unobserved common factors across all countries. Provided that the unobserved common factors form part of the country-specific cointegrating relation, the augmented country regression model thus encompasses the cointegrating relationship, which is allowed to differ across countries.

$$\text{AMG Stage (i)} \qquad \Delta y_{it} = \boldsymbol{b} \Delta \boldsymbol{x}_{it} + \sum_{s=2}^{T} c_s \Delta D_s + \Delta e_{it} \tag{11}$$

$$\Rightarrow \hat{\boldsymbol{c}}_s \equiv \hat{\mu}_t^{\bullet}$$

$$\begin{aligned} \text{AMG Stage (ii)} \qquad & y_{it} = a_i + \boldsymbol{b}_i \boldsymbol{x}_{it} + \kappa_i \hat{\mu}_t^{\bullet} + c_i t + e_{it} \\ & \hat{\boldsymbol{b}}_{AMG} = N^{-1} \sum_i \hat{\boldsymbol{b}}_i \end{aligned} \tag{12}$$

The first stage represents a standard FD-OLS regression with $T - 1$ year dummies in first differences, from which we collect the year dummy coefficients which are labelled as $\hat{\mu}_t^{\bullet}$. In the second stage this variable is included in each of N standard country regression which also includes a linear trend term to capture unobserved idiosyncratic processes which are time-invariant. The AMG estimates are then derived as averages of the individual country estimates.

This approach is conceptually close to the Mean Group version of the Pesaran (2006) Common Correlated Effects (CCEMG) estimator, which is a variant on the pooled estimator CCEP introduced above. For CCEMG we obtain N country regression equations, each of which contains the cross-section average terms for y and $\boldsymbol{x}$

$$\begin{aligned} \text{CCEMG} \qquad y_{it} &= a_i + \boldsymbol{b}_i \boldsymbol{x}_{it} + c_{1i} \bar{y}_t + \boldsymbol{c}_{2i} \bar{\boldsymbol{x}}_t + e_{it} \\ &\hat{\boldsymbol{b}}_{CCEMG} = N^{-1} \sum_i \hat{\boldsymbol{b}}_i \end{aligned} \tag{13}$$

As was detailed above the cross-section averages can account for unobserved common factors with heterogeneous factor loadings. The CCEMG estimates are then averaged across countries. We develop the three variants of the CCEMG estimator in analogy to the pooled estimator case.

3.3 Data

The principal data source for our empirical analysis is the Food and Agriculture Organisation's *FAOSTAT* panel database (FAO, 2007), from which we obtain annual observations for agricultural net output, economically active labour force in agriculture, number of tractors used in agriculture, arable land and permanent crop land and fertilizer use in 128 countries from 1961 to 2002 (average $T = 40.3$).

Additional time-invariant data on geographical distance between countries and contiguity (neighborhood) is taken from CEPII (2006), and data on the share of agricultural land by climatic zone from Matthews (1983) available in Gallup et al. (1999). Data construction is discussed in Appendix A which also contains the descriptive statistics.

4 Empirical Results

4.1 Time-Series Properties and Cross-Section Dependence

We carry out a set of stationarity and nonstationarity tests for individual country time-series as well as the panel as a whole, results for which are presented in Appendix B. Ultimately, in case of the present data dimensions and characteristics, and given all the problems and caveats of individual country and panel unit root tests, we can suggest *most conservatively* that nonstationarity cannot be ruled out in this dataset. Investigation of the time-series properties of the data was not intended to select a subset of countries which we can be reasonably certain display nonstationary variable series like in Pedroni (2007); instead, our aim was to indicate that the sample (possibly due to the limited time-series dimension, as argued in Pedroni, 2007) is likely to be made up of a mixture of some countries with stationary and others with nonstationary variable series.

The results for the cross-section dependence (CSD) analysis are presented in Appendix C. Our analysis provides strong evidence for the presence of cross-section dependence within the full sample dataset, based on average variable cross-country correlation coefficients, principal component analysis and the Pesaran (2004) CD test. This result holds for both the individual variables as well as residuals from regressions which do not address cross-section correlation: the pooled OLS (POLS), two-way fixed effects (2FE) and Mean Group (MG) estimators.[11] The CD test for residuals from standard CCEMG regressions cannot reject cross-section independence, indicating that this approach successfully deals with the presence of unobserved common factors. It is noteworthy that the average cross-section correlation for residuals from the pooled OLS regression with variables in first differences (FD-OLS) drops considerably and like in the CCEMG case cross-section independence cannot be rejected. This result is surprising — Coakley et al. (2006) did not investigate the FD-OLS estimator in their study and we further noted its performance in our dedicated Monte Carlo analysis (available on request). We also carry out the same testing procedures for various subsamples of the data, based on geographic and climatic categories. The standard CCEMG estimator seems to achieve the elimination of cross-section dependence even within and across narrower subsamples, while most other estimation approaches (now including FD-OLS) are subject to considerable residual correlation within

[11] POLS is augmented with $T - 1$ year dummies, MG country regressions with a linear trend term.

and across country groupings. CD tests and mean absolute residual correlation are reported in the results section below for each of the empirical specifications considered.

4.2 Pooled estimation results

We present the estimation results for the pooled specifications in Table 2. The dependent variable and the independent variables are expressed in per worker term, such that the addition of the labour variable indicates deviation from constant returns to scale. In the lower panels of the table we report the implied returns to scale and labour coefficients as well as various diagnostic test results. Recall for the following discussion that the 2FE estimator represents the empirical implementation of choice in the present literature.

We first discuss parameter coefficients: most empirical models presented indicate large decreasing returns to scale in agriculture. In common with many studies using the FAO data, the coefficients on capital (tractors) are relatively low across all models, ranging from .04 (FD-OLS) to .13 (POLS). The land coefficients are high and relatively stable across specifications (between .21 and .33), whereas the fertilizer coefficients range from .01 to .17. Livestock again has a rather large coefficient across all specifications (.22 to .37).

Regarding the implied labour coefficients, we find very low magnitudes across all specifications, with the standard and distance-weighted CCEP even providing nonsensical negative parameter values. Certainly the most striking pattern in these results is the general magnitude of the implied decreasing returns to scale: based on this analysis we can conclude that in a pooled specification the data in all but two of the weighted CCE estimators rejects constant returns emphatically, with input elasticities in the commonly favoured 2FE estimator adding up to around .80. This finding may reflect a global production function with substantial decreasing returns to scale, possibly due to the presence of a fixed factor (median land per worker growth rate for the sample: 0.0%); alternatively, it may reflect empirical misspecification.

Turning to the diagnostics, we can see that with the exception of the models in first differences, *all* models seem to display serial correlation in the residuals. Unit root tests indicate that the CCEP-type and first difference estimators seem to yield stationary residuals, in contrast to the standard panel estimators in levels (POLS, 2FE) for which nonstationary residuals cannot be rejected. Recall that t-statistics are invalid in the presence of nonstationary errors (Kao, 1999). Mean absolute residual correlations for POLS and 2FE are relatively high, at around .4, whereas this measure drops to around .16 in all other regression models. Nevertheless the Pesaran (2004) CD-test for cross-section dependence yields very mixed results: only the residuals for the agro-climate CCEP and the FD-OLS estimator suggest cross-section independence. Further specification tests emphatically reject residual normality and homoskedasticity in all models. These diagnostics indicate that the commonly preferred 2FE estimator has serially correlated errors, which are nonstationary, nonnormal, heteroskedastic and correlated across countries. Note that input parameter estimates for this estimator are reasonably close to those in Craig et al. (1997), the closest match for this dataset and specification.

Table 2: Pooled regressions (unrestricted returns to scale)

Pooled regressions

dependent variable: [1] & [3]-[6] log output per worker, [2] dto. in 2FE transformation♮,
[7] Δlog output per worker, [8] dto. in 2FE transformation♮

	[1] **POLS**	[2] **2FE**♮	[3] **CCEP**	[4] **CCEP**	[5] **CCEP**	[6] **CCEP**	[7] **FD-OLS**	[8] **FD-2FE**♮
weight matrix‡			none	neighbour	distance	agro-climate		
labour†	-0.0586	-0.1908	-0.3194	-0.0659	-0.2684	-0.2157	-0.3797	-0.1946
Δ in [7]&[8]	[17.50]**	[14.79]**	[2.35]**	[0.39]	[2.52]*	[1.70]	[3.60]**	[3.54]**
tractors pw	0.1315	0.0577	0.0740	0.0898	0.0765	0.0440	0.0383	0.0718
Δ in [7]&[8]	[24.12]**	[13.76]**	[4.86]**	[4.13]**	[4.02]**	[2.68]**	[3.21]**	[5.71]**
livestock pw	0.2189	0.3579	0.3601	0.2984	0.3669	0.3715	0.2861	0.3012
Δ in [7]&[8]	[28.61]**	[30.85]**	[7.00]**	[3.95]**	[10.03]**	[7.26]**	[6.87]**	[7.80]**
fertilizer pw	0.1690	0.0726	0.0255	0.0497	0.0277	0.0258	0.0086	0.0103
Δ in [7]&[8]	[28.08]**	[23.63]**	[4.67]**	[4.97]**	[2.59]*	[4.68]**	[2.48]*	[3.00]**
land pw	0.2529	0.2936	0.2415	0.2854	0.3321	0.2452	0.2101	0.2831
Δ in [7]&[8]	[30.42]**	[21.07]**	[2.34]*	[2.86]**	[3.17]**	[3.23]**	[2.71]**	[4.33]**
We included $(T-1)$ year dummies in equations [1] and (in first differences) [7].								
Constant	1.9084		2.8646	0.9223	4.2520	2.6092		
	[28.93]**		[1.78]	[0.39]	[2.92]**	[1.49]		
Observations	5,162	5,162	5,162	5,162	5,162	5,162	5,013	5,013
groups	128	128	128	128	128	128	128	128
average T	40.3	40.3	40.3	40.3	40.3	40.3	39.2	39.2
R-squared	0.91	0.66	0.96	0.94	0.98	0.96	0.16	0.12

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Returns to scale implications of the parameter estimates ♭								
Implied β_L	0.1691	0.0274	-0.0205	0.2108	-0.0716	0.0978	0.0772	0.1390
Returns	DRS	DRS	DRS	CRS	DRS	CRS	DRS	DRS
Arellano-Bond Serial Correlation Test — H_0: no serial correlation in the residuals								
AR(1) (p)	36.72 (.00)	56.21 (.00)	7.62 (.00)	16.20 (.00)	12.82 (.00)	11.40 (.00)	-9.52 (.00)	-9.67 (.00)
AR(2) (p)	36.19 (.00)	49.01 (.00)	0.78 (.44)	10.96 (.00)	5.05 (.00)	3.80 (.00)	-0.61 (.54)	-0.69 (.49)
AR(3) (p)	35.63 (.00)	43.30 (.00)	-3.04 (.00)	6.66 (.00)	-0.67 (.50)	-0.50 (.61)	0.49 (.62)	0.40 (.69)
Nonstationarity: Pesaran (2007) CIPS test applied to residuals♯ — H_0: residuals are I(1)								
lags	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)
none	-7.94 (.00)	-9.54 (.00)	-40.38 (.00)	-31.21 (.00)	-32.76 (.00)	-33.63 (.00)	-48.92 (.00)	-48.78 (.00)
1 lag	-2.67 (.00)	-3.47 (.00)	-32.11 (.00)	-21.03 (.00)	-23.73 (.00)	-24.07 (.00)	-38.06 (.00)	-37.83 (.00)
2 lags	0.01 (.50)	0.39 (.65)	-24.66 (.00)	-15.41 (.00)	-18.45 (.00)	-16.75 (.00)	-24.40 (.00)	-24.21 (.00)
3 lags	1.79 (.96)	2.05 (.98)	-20.39 (.00)	-11.28 (.00)	-14.49 (.00)	-13.18 (.00)	-14.87 (.00)	-15.32 (.00)
4 lags	3.91(1.00)	4.20 (1.00)	-15.83 (.00)	-5.96 (.00)	-8.72 (.00)	-9.26 (.00)	-8.79 (.00)	-8.94 (.00)
Cross-Section Dependence: Mean (Absolute) Correlation & Pesaran (2004) CD test — H_0: no CSD								
Mean ρ_{ij}	-0.01	0.02	0.01	0.01	0.07	0.00	0.00	0.02
Mean $\lvert\rho_{ij}\rvert$	0.42	0.41	0.18	0.15	0.17	0.16	0.15	0.15
CD (p)	-2.49 (.01)	9.64 (.00)	4.97 (.00)	4.06 (.00)	38.52 (.00)	-0.25 (.80)	0.04 (.97)	12.84 (.00)
Further residual diagnostic tests⋆ — H_0: no heteroskedasticity, regular skewness/kurtosis								
(A) Joint test χ^2 (p)	119.9 (.00)	238.8 (.00)	585.4 (.00)	534.9 (.00)	439.6 (.00)	471.72 (.00)	976.1 (.00)	975.5 (.00)
(B) Joint test χ^2 (p)	1128.1 (.00)	459.4 (.00)	-	-	-	-	1064.8 (.00)	334.6 (.00)

Notes: The values in square brackets are absolute t-statistics of the estimates, based on heteroskedasticity-robust standard errors.
* and ** indicate statistical significance at the 5% and 1% level respectively.
♮ In the 2FE model we transform all variables as follows: $(z_{it} - \bar{z}_i - \bar{z}_t + \bar{z})$, where

$$\bar{z}_i = T^{-1}\sum_{t=1}^{T} z_{it} \quad \text{and} \quad \bar{z}_t = N^{-1}\sum_{i=1}^{N} z_{it} \quad \text{and} \quad \bar{z} = (NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}$$

† All variables are in log per worker terms with the exception of the log labour variable: this specification allows for convenient determination of the returns to scale, whereby a positive (negative) significant coefficient on log labour is evidence for increasing (decreasing) returns to scale and an insignificant coefficient implies constant returns to scale.
‡ We apply different $N \times N$ weight matrices to construct the cross-section averages: in [4] averages are constructed for each country i from the values of itself and its neighbours, in [5] we use the inverse of the population-weighted distance between two countries, in [6] the Jaffe correlation coefficient for the 12 agro-climatic zones between two countries. See main text for details.
♭ The implied returns to scale are labeled decreasing (DRS) if the coefficient on labour is negative, statistically significant, and constant (CRS) if this coefficient is insignificant, see previous note. The implied labour coefficient is computed by adding up all the coefficients on the RHS variables (except for labour), subtracting them from unity (the result is the implied labour coefficient if constant returns were to hold) and then adding the coefficient on labour.
♯ The Pesaran (2007) CIPS test results are for the ADF equation with an intercept and the indicated augmentation with lagged first differences. The test results for the ADF equation with intercept and trend follow the same pattern of rejection and are therefor omitted. The CIPS accounts for cross-section dependence in the residuals.
⋆ The D'Agostino et al. (1990) test *(A)* investigates skewness and kurtosis. The Cameron and Trivedi (1990) decomposition test in *(B)* analyses residual heteroskedasticity, skewness and kurtosis. Both tests provide joint hypothesis tests. If a test rejects skewness or kurtosis we can no longer assume normality for the residual distribution. Note that we cannot compute the Cameron and Trivedi (1990) for all CCEP estimators due to the large number of parameters in these models.

Table 3: Pooled regressions (CRS imposed)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	POLS	**2FE**♮	**CCEP**	**CCEP**	**CCEP**	**CCEP**	**FD-OLS**	**FD-2FE**♮
weight matrix‡			none	neighbour	distance	agro-climate		
Pooled regressions — dependent variable: [1] & [3]-[6] log output per worker, [2] dto. in 2FE transformation♮, [7] Δlog output per worker, [8] dto. in 2FE transformation♮								
tractors pw	0.1437	0.0650	0.0989	0.0982	0.0879	0.0787	0.0542	0.0788
Δ in [7]&[8]	[25.96]**	[15.27]**	[5.63]**	[5.35]**	[6.37]**	[4.93]**	[4.00]**	[5.93]**
livestock pw	0.2472	0.4147	0.3869	0.3103	0.4120	0.3994	0.3191	0.3248
Δ in [7]&[8]	[29.59]**	[37.10]**	[7.53]**	[4.49]**	[9.30]**	[8.94]**	[7.84]**	[8.61]**
fertilizer pw	0.1616	0.0647	0.0289	0.0485	0.0333	0.0326	0.0084	0.0100
Δ in [7]&[8]	[26.72]**	[20.94]**	[5.19]**	[5.10]**	[3.39]**	[5.72]**	[2.46]*	[2.97]**
land pw	0.2503	0.3955	0.3326	0.3311	0.4550	0.3198	0.3129	0.3239
Δ in [7]&[8]	[28.68]**	[32.01]**	[3.87]**	[4.74]**	[6.49]**	[4.17]**	[4.68]**	[5.12]**
We included $(T-1)$ year dummies in equations [1] and (in first differences) [7].								
Constant	1.1077		-0.1508	0.2140	0.3488	0.0397		
	[23.50]**		[2.62]**	[1.73]	[6.50]**	[0.65]		
Observations	5,162	5,162	5,162	5,162	5,162	5,162	5,013	5,013
groups	128	128	128	128	128	128	128	128
average T	40.3	40.3	40.3	40.3	40.3	40.3	39.2	39.2
R-squared	0.90	0.64	0.95	0.93	0.98	0.95	0.15	0.11
Implications for labour coefficient♭								
Implied β_L	0.1972	0.0601	0.1527	0.2119	0.0118	0.1695	0.3054	0.2625
Arellano-Bond Serial Correlation Test — H_0: no serial correlation in the residuals								
AR(1) (p)	36.67 (.00)	56.81 (.00)	11.17 (.00)	17.96 (.00)	15.46 (.00)	14.10 (.00)	-9.57 (.00)	-9.60 (.00)
AR(2) (p)	36.18 (.00)	49.72 (.00)	4.70 (.00)	12.97 (.00)	7.61 (.00)	6.61 (.00)	-0.57 (.57)	-0.62 (.53)
AR(3) (p)	35.67 (.00)	44.01 (.00)	-0.09 (.93)	8.62 (.00)	1.25 (.21)	1.50 (.13)	0.45 (.65)	0.39 (.69)
Nonstationarity: Pesaran (2007) CIPS test applied to residuals♯ — H_0: residuals are I(1)								
lags	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)
none	-7.77 (.00)	-5.83 (.00)	-34.17 (.00)	-27.74 (.00)	-30.88 (.00)	-30.98 (.00)	-49.10 (.00)	-48.99 (.00)
1 lag	-2.47 (.01)	-0.01 (.50)	-24.10 (.00)	-18.15 (.00)	-21.66 (.00)	-21.41 (.00)	-37.52 (.00)	-37.75 (.00)
2 lags	0.01 (.50)	2.74 (1.00)	-17.44 (.00)	-12.01 (.00)	-16.91 (.00)	-15.48 (.00)	-24.85 (.00)	-23.64 (.00)
3 lags	-0.41 (.34)	3.17 (1.00)	-13.51 (.00)	-9.57 (.00)	-13.04 (.00)	-11.36 (.00)	-15.90 (.00)	-14.73 (.00)
4 lags	0.06 (.52)	3.99 (1.00)	-9.47 (.00)	-4.76 (.00)	-6.54 (.00)	-8.72 (.00)	-7.66 (.00)	-7.84 (.00)
Cross-Section Dependence: Mean (Absolute) Correlation & Pesaran (2004) CD test — H_0: no CSD								
Mean ρ_{ij}	-0.01	0.00	0.00	0.01	0.07	0.00	0.00	0.02
Mean $\|\rho_{ij}\|$	0.43	0.42	0.19	0.16	0.17	0.17	0.14	0.15
CD (p)	-3.79 (.01)	-0.71 (.48)	1.46 (.14)	5.51 (.00)	38.48 (.00)	-1.28 (.20)	-0.19 (.85)	9.21 (.00)
Further residual diagnostic tests⋆ — H_0: no heteroskedasticity, regular skewness/kurtosis								
(A) Joint test χ^2 (p)	179.4 (.00)	229.3 (.00)	557.5 (.00)	452.1 (.00)	368.4 (.00)	461.7 (.00)	1002.5 (.00)	990.4 (.00)
(B) Joint test χ^2 (p)	1078.9 (.00)	424.5 (.00)	-	-	-	-	967.8 (.00)	268.2 (.00)

Notes: See Table 2 for further details.

In line with much of the literature, we run regressions with CRS imposed to provide a reference point — as just reported this imposition is *rejected* by the data in most models — and report the results in Table 3. Interestingly the parameter estimates for tractors, livestock (moderate increase) and fertilizer are relatively stable compared with the unrestricted models. In contrast the land coefficients shoot up (in the 2FE case from .29 to .40) in all specification safe for POLS. Implied labour coefficients remain relatively stable for POLS and 2FE but rise substantially for the difference and CCEP regressions. Serial correlation tests and the unit root tests display rejection patterns next to identical to those in the unrestricted case. With regard to the CD test, 2FE and CCEP errors now indicate cross-section independence. Again the normality and homoskedasticity tests reject across the all estimators. Existing results for the FAO data and a comparable empirical specification in Bravo-Ortega and Lederman (2004) show similar patterns (albeit with an even higher land-coefficient).

We can see from these results that the the erroneous imposition of CRS (the unrestricted models reject CRS) has led to larger magnitudes for either the land or the implied labour coefficient — in the commonly preferred 2FE model the implied labour coefficient has merely risen from .03 to .06 — albeit with diagnostics that reject the most common regression assumptions for this estimator (residuals which are stationary, serially uncorrelated, normal and homoskedastic). Note that our empirical setup implies that factor-input parameters are unidentified in the POLS and 2FE *if* the same unobserved common factors drive output *and* inputs.

Regarding the Pesaran (2006) CCEP and our extensions, our results show that the former emphatically rejects CRS and yields summed input elasticities of around .68, with *negative* implied labour coefficient; of the other CCE estimators the distance version behaves in a similar fashion, whereas the other two cannot reject CRS. Serial correlation remains a concern in all four models. Surprisingly the agro-climate version is the only model that cannot reject cross-section independence. Once CRS is (despite previous results) imposed, all models yield somewhat similar coefficients, with the land coefficient again rising considerably — most obviously so in the distance model. Diagnostics remain similar, although residuals in the standard CCEP now cannot reject cross-sectional independence.

In conclusion, our pooled models largely reject constant returns to scale, yield very low values for the implied coefficient on labour and over a range of specification tests indicate a combination of non-normality and heteroskedasticity, cross-section dependence, nonstationarity and/or serial correlation in the residuals. Allowing for heterogeneity in the unobserved common factors (CCEP) although alleviating a potential identification problem does not seem to provide an overall panacea; in fact for the most part the CCEP-type estimators are suggested to continue suffering from cross-section dependence. Our next analytical step is therefore to investigate how the parameter estimates and diagnostic tests change if we allow for technology heterogeneity across countries.

4.3 Averaged country regression estimates

We present the results from Mean-Group type estimators in the unrestricted regression model (CRS not imposed) in Table 4. For all estimators we present the mean and robust mean across N country parameters — the latter uses weights to reduce the impact of outliers. In practice the median estimates (not reported) are very close to the robust estimates. In our discussion below we focus on the robust means. The t-statistics reported for each average estimate test whether the average parameter is statistically different from zero, following Pesaran, Smith, and Yamagata (2008).

The MG, as well as our two Augmented Mean Group estimators display large decreasing returns, although in the AMG version (i) only at the 10% level of significance. The standard, neighbour and agro-climate CCEMG in contrast have insignificant coefficients on labour, indicating constant returns *in the average country regression.* Around 30 to 40 countries reject CRS at 5% level of significance in each of these models. The distance CCEMG indicates very large and highly significant decreasing returns to scale.

Regarding average parameter estimates on the factor inputs, the MG and AMG estimators yield next to identical results: capital around .07, livestock around .25, fertilizer around .03

Table 4: Mean Group type estimators (no restrictions on returns to scale)

Average country regression estimates (means and robust means)
Returns to scale are left unrestricted (CRS, DRS, IRS); N=128, average T=40.3, $n = 5,126$;
dependent variable: [1],[3]-[7] log output per worker, [2] log output per worker less $\hat{\mu}_t^\bullet$

	[1]		[2]		[3]		[4]		[5]		[6]		[7]	
	MG		**AMG(i)**		**AMG(ii)**		**CCEMG**		**CCEMG**		**CCEMG**		**CCEMG**	
weight matrix†							none		neighbour		distance		agro-climate	
	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust
labour	-0.5393	-0.3574	-0.5438	-0.3039	-0.5438	-0.3664	-0.2162	-0.1257	-0.309	-0.1814	-0.5309	-0.5014	-0.2101	-0.1192
	[1.87]	[2.23]*	[1.83]	[1.90]	[1.96]	[2.34]*	[1.38]	[1.04]	[1.66]	[1.55]	[4.42]**	[5.85]**	[1.15]	[1.12]
tractors pw	-0.0611	0.0748	-0.045	0.0797	-0.0351	0.0721	0.0489	0.0641	-0.0301	0.0561	0.0524	0.0419	-0.0088	0.0612
	[0.51]	[3.31]**	[0.40]	[3.52]**	[0.36]	[3.34]**	[1.19]	[3.26]**	[0.31]	[2.08]*	[2.51]*	[2.83]**	[0.13]	[2.74]**
livestock pw	0.2757	0.2456	0.2853	0.2719	0.2761	0.2508	0.3803	0.3237	0.3044	0.2779	0.3219	0.3336	0.3056	0.2760
	[5.87]**	[8.07]**	[6.08]**	[8.28]**	[6.38]**	[7.82]**	[7.04]**	[9.44]**	[6.34]**	[7.22]**	[7.66]**	[9.48]**	[5.78]**	[7.91]**
fertilizer pw	0.0370	0.0299	0.0379	0.0315	0.0367	0.0309	0.0366	0.0310	0.0394	0.0274	0.0409	0.0413	0.0467	0.0299
	[5.10]**	[4.86]**	[5.10]**	[4.91]**	[4.99]**	[4.64]**	[5.39]**	[5.02]**	[4.97]**	[4.59]**	[6.15]**	[6.74]**	[5.85]**	[5.26]**
land pw	0.2549	0.2102	0.2363	0.1952	0.2617	0.1695	0.0935	0.1999	-0.0327	0.1623	0.1235	0.1414	0.2316	0.1966
	[2.12]*	[2.79]**	[1.88]	[2.60]*	[2.06]*	[2.27]*	[0.82]	[2.68]**	[0.27]	[2.17]*	[1.39]	[2.07]*	[2.05]*	[3.13]**
Common factors			imposed		1.0569	0.7741								
					[7.38]**	[7.72]**								
Country trend	0.013	0.0123	-0.0013	-0.0031	-0.0015	-0.0015								
	[2.69]**	[4.82]**	[0.25]	[1.20]	[0.30]	[0.30]								
$\hat{t}_i$ sign. at 10%	78		68		42									
Constant	7.0818	5.366	7.2221	4.7029	7.2654	5.6869	0.9917	0.8964	3.442	2.1018	7.5518	7.1717	2.0287	1.6316
	[1.79]	[2.30]*	[1.75]	[2.05]*	[1.87]	[2.51]*	[0.38]	[0.41]	[1.49]	[1.27]	[4.33]**	[6.11]**	[0.82]	[1.09]

Returns to scale implications of the parameter estimates‡

	[1]		[2]		[3]		[4]		[5]		[6]		[7]	
implied β_L	-0.0458	0.0821	-0.0583	0.1178	-0.0832	0.1103	0.2245	0.2556	0.4100	0.2949	-0.0696	-0.0596	0.2148	0.3171
Returns	CRS	DRS	CRS	CRS	CRS	DRS	CRS	CRS	CRS	CRS	DRS	DRS	CRS	CRS
reject CRS	47		47		46		28		36		53		40	

Pedroni (1999) panel t-statistics

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
$N^{-1/2}\sum_i t_{\hat{\beta}_{L,i}}$	[7.20]**	[6.33]**	[6.83]**	[2.10]*	[2.84]**	[14.04]**	[2.54]**
$N^{-1/2}\sum_i t_{\hat{\beta}_{tr,i}}$	[6.57]**	[7.11]**	[7.27]**	[8.36]**	[5.41]**	[4.81]**	[7.24]**
$N^{-1/2}\sum_i t_{\hat{\beta}_{live,i}}$	[21.42]**	[22.22]**	[20.30]**	[21.53]**	[20.09]**	[23.52]**	[18.88]**
$N^{-1/2}\sum_i t_{\hat{\beta}_{f,i}}$	[9.39]**	[9.22]**	[8.93]**	[7.57]**	[9.49]**	[11.16]**	[9.36]**
$N^{-1/2}\sum_i t_{\hat{\beta}_{n,i}}$	[8.06]**	[7.36]**	[6.87]**	[3.41]**	[5.11]**	[6.71]**	[7.04]**
$N^{-1/2}\sum_i t_{\hat{\beta}_{TFP,i}}$			[10.37]**				
$N^{-1/2}\sum_i t_{\hat{t}_i}$	[33.60]**	[28.84]**	[15.70]**				

Serial correlation in the residuals♯ — H_0: no serial correlation (except for DW d)

	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Ljung-Box	912.3	(.00)	902.1	(.00)	1005.8	(.00)	47.8	(1.00)	407.0	(.00)	201.3	(1.00)	170.5	(1.00)
Durbin AR(1)	778.9	(.00)	929.0	(.00)	758.0	(.00)	356.6	(.00)	545.3	(.00)	387.6	(.00)	431.5	(.00)
Durbin AR(2)	782.2	(.00)	771.1	(.00)	782.9	(.00)	508.6	(.00)	683.9	(.00)	521.8	(.00)	531.4	(.00)
BGod AR(1)	755.9	(.00)	738.9	(.00)	701.0	(.00)	437.3	(.00)	578.1	(.00)	449.6	(.00)	486.4	(.00)
BGod AR(2)	750.6	(.00)	746.6	(.00)	720.0	(.00)	623.2	(.00)	723.8	(.00)	613.8	(.00)	611.9	(.00)
	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79
DW d statistic #	29	43	26	42	25	47	4	82	13	76	10	70	8	74
(in %)	23%	34%	20%	33%	20%	37%	3%	64%	10%	59%	8%	55%	6%	58%

Nonstationarity: Pesaran (2007) CIPS test applied to residuals — H_0: residuals are I(1)

lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
none	-35.9	(.00)	-36.6	(.00)	-36.2	(.00)	-43.9	(.00)	-42.0	(.00)	-42.1	(.00)	-44.2	(.00)
1 lag	-27.2	(.00)	-29.2	(.00)	-28.4	(.00)	-33.6	(.00)	-32.3	(.00)	-31.4	(.00)	-35.0	(.00)
2 lags	-20.4	(.00)	-20.1	(.00)	-19.7	(.00)	-23.9	(.00)	-22.5	(.00)	-24.7	(.00)	-25.8	(.00)
3 lags	-17.2	(.00)	-16.2	(.00)	-16.4	(.00)	-18.8	(.00)	-18.9	(.00)	-19.6	(.00)	-21.2	(.00)
4 lags	-10.2	(.00)	-9.7	(.00)	-9.4	(.00)	-14.1	(.00)	-12.3	(.00)	-13.5	(.00)	-16.8	(.00)

Cross-section Dependence: Mean (absolute) correlations and Pesaran (2004) test — H_0: no CSD in the residuals

	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$	ρ_{ij}	$\lvert\rho_{ij}\rvert$
Mean Correl.	0.02	0.15	0.00	0.15	0.00	0.15	0.00	0.15	0.00	0.14	0.07	0.15	0.00	0.14
CD statistic (p)	9.16	(.00)	-1.12	(.26)	-2.47	(.02)	0.21	(.83)	2.24	(.03)	37.16	(.00)	-1.72	(.09)

Further residual diagnostic tests⋆ — H_0: no heteroskedasticity, regular skewness/kurtosis

d'Agostini et al	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	379.2	(.00)	343.4	(.00)	355.4	(.00)	318.8	(.00)	299.8	(.01)	258.3	(.45)	308.3	(.03)
Cam & Tri	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	374.1	(.00)	368.7	(.00)	293.8	(.05)	245.2	(.68)	236.4	(.80)	233.5	(.84)	256.1	(.49)
homosk.	317.6	(.00)	314.9	(.01)	253.3	(.54)	218.8	(.96)	228.2	(.89)	218.8	(.96)	218.8	(.96)
skewness	374.0	(.00)	367.7	(.00)	342.2	(.00)	300.7	(.03)	259.6	(.43)	275.3	(.19)	324.6	(.00)
kurtosis	264.2	(.35)	254.4	(.52)	256.7	(.48)	242.5	(.72)	256.7	(.48)	248.4	(.62)	252.2	(.55)

Notes: All variables are in logs. * and ** indicate statistical significance at the 5% and 1% level respectively. We present the sample mean and the robust sample mean estimates of all model parameters. Terms in brackets are absolute t-statistics (H_0: $N^{-1}\sum_i \hat{\beta}_i = 0$) following Pesaran et al. (2008). An alternative panel t-test by Pedroni (1999) is also provided. The 'common factors' variable refers to $\hat{\mu}_t^\bullet$.
† Weight matrix: we use the same approach to construct cross-section averages as in the pooled regressions.
‡ We compute implied labour coefficients and report returns to scale (DRS, CRS are decreasing and constant returns respectively).
♯ The Ljung-Box, Durbin 'alternative' and Breusch-Godfrey procedures test first- and higher-order serial correlation in time-series regression residuals. We convert the p-statistics of the N results into a Fisher-statistic p_λ which is distributed $\chi^2(2N)$. For the Durbin-Watson d statistic we report the number of time-series tests with a d statistic larger than 1.79 (smaller than 1.23) which is deemed to (be unable to) reject the null of first order serial correlation (under the strong assumption of exogenous regressors).
For all other test statistics please refer to definitions in the footnotes of Table 2.

and land around .20. In comparison to the parameter differences across models in the *pooled* specifications, the MG and AMG parameter estimates are relatively similar to those in the CCEMG models, with the crucial exception of the returns to scale coefficient and thus the implied labour elasticity: in the former group of models the labour coefficient is around .10, whereas in the latter group it is closer to .30 (leaving the nonsensical results produced by the distance CCEMG to one side). Within the CCEMG group the standard and the agro-climate estimators yield very similar results.

Turning to the diagnostics, *all* models reject nonstationary errors in the Pesaran (2007) CIPS test. The panel t-statistic following Pedroni (1999) suggests that all coefficients are significant at the 5% level, in contrast to the t-statistic following Pesaran et al. (2008) which we used for our discussion above. Mean absolute error correlation is uniformly low at .15 for all estimators, but cross-section independence is rejected in the MG and AMG(ii), as well as in the alternative CCEMG estimators (marginally in case of the agro-climate CCEMG). For the serial correlation tests we need to take recourse to statistics constructed from country-regression diagnostics. In each case these are Fisher (1932)-type statistics (labelled p_λ), derived from p-values for the test statistics in each country.[12] As can be seen the Durbin 'alternative' and Breusch-Godfrey procedures reject the absence of serially correlated errors, whereas for the Ljung-Watson and Durbin-Watson statistics (see table footnotes) there is some evidence for serially uncorrelated errors in the CCEMG-type estimators. Furthermore, the error normality and homoskedasticity tests (similarly expressed as Fisher-statistics) suggest these properties are rejected in the MG and AMG estimators, and offer conflicting evidence across the CCEMG-type models.

Taking the results for all diagnostic tests into account and recognising the potential problems of the use of time-series tests adjusted for the panel context via computation of the Fisher (1932) statistic, we suggest that evidence in favour of the standard CCEMG and agro-climate CCEMG seems most convincing: compared to the other models these provide some evidence of serially uncorrelated and normal residuals. Since neither of these estimators can reject CRS for the average country production function, we rerun all heterogeneous parameter models with CRS imposed.

The CRS country regression averages in Table 5 produce very similar results across *all* estimators: it can be seen that the imposition of CRS in heterogeneous regression models does not create the same dramatic changes to the estimates as in the pooled estimator case. It can also be seen that the individual country-estimates for each model now contain less outliers, as is evidenced by the precision of the mean estimates and their proximity in parameter value to the robust mean estimates. We focus on the models for which on average we had not rejected CRS: AMG(i), standard, neighbour and agro-climate CCEMG. Factor elasticities in the AMG(i) are close to the unrestricted model ones, with the obvious exception of implied labour, which with CRS imposed is around .33 rather than .12. The standard and agro-climate CCEMG now match each other's (robust) mean parameters even closer than in the unrestricted case, while the neighbour CCEMG in comparison has an inflated land coefficient. Panel t-statistics are significant at the 1% level for all parameters in all models and CIPS tests continue to reject nonstationarity in the residuals. AMG(i) as well as standard and agro-climate CCEMG residuals appear cross-sectionally independent.

[12]Constructed as $p_\lambda = -2\sum_i log(p_i)$, distribution $\chi^2(2N)$.

In comparison to the unrestricted versions, the models now however seem *more* likely to be subject to serially correlated errors, as evidenced by the fall in the share of countries with a Durbin-Watson statistic above 1.79, as well as the Ljung-Box and other test statistics. The CCEMG now all 'pass' the Cameron and Trivedi (1990) normality/homoskedasticity test, while all models continue to fail the D'Agostino et al. (1990) normality test.

Table 5: Mean Group type estimators (CRS imposed)

Average country regression estimates (means and robust means)
CRS imposed for all country regressions; N=128, average T=40.3;
dependent variable: [1],[3]-[7] log output per worker, [2] log output per worker less $\hat{\mu}_t^\bullet$

	[1] **MG**		[2] **AMG(i)**		[3] **AMG(ii)**		[4] **CCEMG**		[5] **CCEMG**		[6] **CCEMG**		[7] **CCEMG**	
weight matrix†							none		neighbour		distance		agro-climate	
	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust
tractors pw	0.0700	0.0814	0.0887	0.0903	0.0780	0.0842	0.0879	0.1093	0.0673	0.0972	0.1317	0.1078	0.1247	0.0977
	[2.08]*	[3.57]**	[2.57]*	[3.71]**	[2.27]*	[3.65]**	[2.50]*	[5.23]**	[1.72]	[4.27]**	[4.67]**	[5.59]**	[3.88]**	[4.48]**
livestock pw	0.3051	0.2917	0.3106	0.3075	0.3099	0.2905	0.3424	0.3214	0.3231	0.3124	0.3726	0.3682	0.3257	0.3298
	[7.80]**	[8.82]**	[7.89]**	[8.90]**	[8.40]**	[8.66]**	[8.33]**	[9.47]**	[7.53]**	[8.44]**	[11.29]**	[11.52]**	[8.02]**	[9.53]**
fertilizer pw	0.0373	0.0328	0.0414	0.0378	0.0376	0.0348	0.0435	0.0358	0.0437	0.0376	0.0393	0.0365	0.0501	0.0352
	[5.29]**	[5.17]**	[5.52]**	[5.58]**	[5.32]**	[5.31]**	[5.76]**	[5.63]**	[5.34]**	[5.26]**	[5.25]**	[5.15]**	[6.83]**	[5.87]**
land pw	0.2884	0.2636	0.2653	0.2234	0.2811	0.1919	0.2104	0.2008	0.2364	0.2623	0.3478	0.2905	0.2465	0.2139
	[4.86]**	[4.55]**	[4.32]**	[3.78]**	[4.30]**	[3.34]**	[3.57]**	[3.57]**	[3.41]**	[4.71]**	[6.25]**	[5.62]**	[4.27]**	[4.02]**
Common factors			imposed		1.0590	0.7808								
					[6.56]**	[6.77]**								
Country trend	0.0100	0.0107	-0.0029	-0.0019	-0.0035	-0.0035								
	[6.18]**	[7.86]**	[1.78]	[1.38]	[1.43]	[1.43]								
$\hat{t}_i$ sign. at 10%	82		65		37									
Constant	-0.3487	-0.2095	-0.2145	-0.1052	-0.2871	-0.1604	-0.2011	0.2874	-0.0917	-0.0603	0.0431	0.1377	-0.0580	-0.0582
	[1.49]	[1.11]	[0.89]	[0.55]	[1.19]	[0.90]	[0.44]	[1.02]	[0.38]	[0.39]	[0.13]	[0.95]	[0.26]	[0.33]

Returns to scale implications of the parameter estimates‡														
implied β_L	0.2992	0.3305	0.2940	0.3410	0.2934	0.3986	0.3158	0.3327	0.3295	0.2905	0.1086	0.1970	0.2530	0.3234
Pedroni (1999) panel *t*-statistics														
$N^{-1/2}\sum_i t_{\hat{\beta}_{tr,i}}$	[11.17]**		[13.16]**		[11.35]**		[13.46]**		[9.15]**		[12.91]**		[12.01]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{live,i}}$	[24.88]**		[26.03]**		[24.16]**		[24.68]**		[25.75]**		[28.7]**		[22.35]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{f,i}}$	[10.34]**		[10.94]**		[9.27]**		[9.83]**		[11.33]**		[9.85]**		[11.00]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{n,i}}$	[13.45]**		[11.83]**		[11.28]**		[9.66]**		[10.93]**		[14.22]**		[9.61]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{TFP,i}}$					[11.85]**									
$N^{-1/2}\sum_i t_{\hat{t}_i}$	[38.89]**		[33.02]**		[14.83]**									
Serial correlation in the residuals — H_0: no serial correlation														
	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Ljung-Box	1579.7	(.00)	1542.7	(.00)	1426.8	(.00)	380.2	(.00)	830.6	(.00)	443.5	(.00)	312.2	(.01)
Durbin AR(1)	1017.6	(.00)	1162.2	(.00)	843.5	(.00)	455.6	(.00)	715.8	(.00)	471.0	(.00)	484.1	(.00)
Durbin AR(2)	964.1	(.00)	952.3	(.00)	812.4	(.00)	502.2	(.00)	757.3	(.00)	557.3	(.00)	560.6	(.00)
BGod AR(1)	914.5	(.00)	908.5	(.00)	780.2	(.00)	513.5	(.00)	663.3	(.00)	523.3	(.00)	534.0	(.00)
BGod AR(2)	853.6	(.00)	855.3	(.00)	751.7	(.00)	573.5	(.00)	699.2	(.00)	628.1	(.00)	631.6	(.00)
	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79
DW d statistic #	42	33	42	32	35	41	18	63	21	58	19	62	17	61
(in %)	33%	26%	33%	25%	27%	32%	14%	49%	16%	45%	15%	48%	13%	48%
Nonstationarity: Pesaran (2007) CIPS test applied to residuals — H_0: residuals are I(1)														
lag-augmentation	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
none	-33.57	(.00)	-34.67	(.00)	-34.32	(.00)	-44.26	(.00)	-42.06	(.00)	-41.62	(.00)	-43.34	(.00)
1 lag	-24.56	(.00)	-27.02	(.00)	-25.55	(.00)	-35.24	(.00)	-31.87	(.00)	-31.33	(.00)	-34.59	(.00)
2 lags	-18.29	(.00)	-19.13	(.00)	-17.87	(.00)	-25.55	(.00)	-23.61	(.00)	-24.79	(.00)	-25.46	(.00)
3 lags	-15.74	(.00)	-16.33	(.00)	-15.89	(.00)	-21.35	(.00)	-21.24	(.00)	-19.31	(.00)	-21.65	(.00)
4 lags	-9.45	(.00)	-11.25	(.00)	-9.12	(.00)	-16.54	(.00)	-13.57	(.00)	-12.28	(.00)	-17.13	(.00)
Cross-section Dependence: Mean correlations and Pesaran (2004) test — H_0: no CSD in the residuals														
	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$
Mean Correl.	0.02	0.15	0.00	0.15	0.00	0.15	0.00	0.15	0.00	0.14	0.06	0.15	0.00	0.14
CD statistic (p)	8.98	(.00)	-0.08	(.93)	-1.56	(.12)	-0.23	(.82)	1.69	(.05)	31.34	(.00)	-1.51	(.13)
Further residual diagnostic tests* — H_0: no heteroskedasticity, regular skewness/kurtosis														
d'Agostini et al	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	383.1	(.00)	344.2	(.00)	343.2	(.00)	337.0	(.00)	334.6	(.00)	263.8	(.36)	336.2	(.00)
Cam & Tri	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	458.5	(.00)	447.7	(.00)	355.5	(.00)	259.5	(.43)	260.7	(.41)	247.1	(.63)	248.2	(.62)
homosk.	392.7	(.00)	385.7	(.00)	310.6	(.01)	218.8	(.96)	221.2	(.94)	218.8	(.96)	218.8	(.96)
skewness	396.9	(.00)	393.5	(.00)	356.4	(.00)	337.8	(.00)	324.2	(.00)	311.0	(.01)	305.6	(.02)
kurtosis	262.3	(.38)	245.4	(.67)	251.2	(.57)	247.9	(.63)	294.5	(.05)	254.3	(.52)	278.3	(.16)

Notes: See Table 4 for details.

In summary, while parameter estimates for the four models which could not reject CRS did not change considerably (in magnitude) compared to the unrestricted models, their precision has improved while some diagnostic test results have deteriorated. Given that in any finite sample the cointegrating relationship may be affected by short-run dynamics, and furthermore on the back of the serial correlation test results we carry out the country-regressions in a dynamic specification, focusing on long-run coefficients in the MG (as a benchmark) and the four CCEMG estimators. Table 6 presents these results.

It can be seen that the robust mean long-run parameter estimates[13] are again virtually identical between the standard and agro-climate CCEMG in columns [2] and [5]. Furthermore, there is only one small deviation from the respective parameter estimates in the static models, namely the increase in the mean fertilizer elasticities. According to the Pedroni (1999) panel t-statistics all parameters are significant at the 1% level in these two models. The results for the MG estimator in contrast show considerable differences and crucially cannot arrive at a statistically significant capital estimate. Both the neighbour and distance CCEMG collapse in the dynamic specification and yield largely insignificant long-run coefficients — in this case the panel t-statistics support this insignificance emphatically. We interpret this breakdown in the shift from static to dynamic specification as a strong indication for the invalidity of the weighting strategy adopted. This suggests that neither neighbourhood nor geographical distance drive the impact of the unobserved common factors in this data.

Comparing diagnostic test results across the dynamic models and with their static versions in Table 5 we can see that while parameter estimates have not changed a great deal for our two preferred estimators (standard and agro-climate CCEMG), the serial correlation tests now provide more reassuring evidence of serially uncorrelated errors. Furthermore, the agro-climate CCEMG now 'passes' both tests for homoskedasticity and normality. Residuals from both estimators continue to show no evidence of nonstationarity and/or cross-section dependence — the latter in contrast to all other models presented. We provide an interpretation of the similarity between standard and agri-climate CCEMG in the next section.

We also estimated the *pooled* version of the dynamic specification with CRS imposed. Results presented in Table D-1 in Appendix D are still broadly in line with those from the *static* pooled CRS models. Focusing on the 2FE as the commonly preferred estimator in the literature, the dynamic equation yields very similar long-run coefficients for capital ($\approx$.07), livestock ($\approx$.40) and fertilizer ($\approx$.08), with the land elasticity dropping from .40 in the static to .31 in the dynamic equation. As a result the implied labour coefficient rises from .06 to .13. Crucially, however, the dynamic 2FE rejects cross-section independence, normality/homoskedasticity and the null of no serial correlation in the residuals, thus not improving on the diagnostic results of the static model.

[13]These long-run parameters are derived from an error correction model regression, in the MG case

$$\Delta y_{it} = -(1-r_i)\, y_{i,t-1} + (1-r_i)\, a_i + (1-r_i)\, c_i t + (1-r_i)\boldsymbol{b}_i\, \boldsymbol{x}_{i,t-1} + \boldsymbol{b}_i\, \boldsymbol{\Delta x}_{it}$$

where in practice the common factor restrictions indicated are not imposed. $\boldsymbol{x}$ and $\boldsymbol{\Delta x}$ represent all observed regressors in levels and first differences respectively; a_i and c_i capture country-specific TFP level and constant growth rate. Long-run coefficients are then computed as the negative difference of the coefficient on the lagged $\boldsymbol{x}$-variables in levels and the lagged dependent variable.
For the CCEMG regressions we include cross-section averages of the dependent variable ($\Delta\bar{y}_t$), the lagged level of the dependent variable ($\bar{y}_{t-1}$), the set of $\boldsymbol{x}$-variables in lagged levels ($\bar{\boldsymbol{x}}_{t-1}$) and in first difference ($\boldsymbol{\Delta}\bar{\boldsymbol{x}}_t$). No trend is included here and the long-run coefficients are computed as in the MG case.

Table 6: Dynamic Specification — MG-type estimators (CRS imposed)

Average country long-run coefficient estimates (means and robust means)
CRS imposed for all country regressions; N=128, average T=39.2;
dependent variable: growth of output per worker

	[1] **MG**		[2] **CCEMG**		[3] **CCEMG**		[4] **CCEMG**		[5] **CCEMG**	
weight matrix†			none		neighbour		distance		agro-climate	
	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust	Mean	Robust
long-run coefficients										
tractors pw	0.346	0.043	0.099	0.088	0.125	0.019	-2.780	-0.116	0.121	0.085
	[1.19]	[1.50]	[1.37]	[3.18]**	[0.24]	[0.14]	[0.78]	[1.39]	[1.67]	[2.85]**
livestock pw	0.405	0.288	0.304	0.307	1.203	-0.381	-5.298	-0.597	0.316	0.327
	[3.33]**	[6.97]**	[3.71]**	[6.82]**	[0.51]	[1.75]	[1.66]	[3.43]**	[3.46]**	[6.67]**
fertilizer pw	0.123	0.046	0.070	0.054	0.576	-0.016	-0.546	-0.015	0.081	0.077
	[1.67]	[4.50]**	[5.41]**	[4.84]**	[0.86]	[0.39]	[0.84]	[0.48]	[6.59]**	[6.42]**
land pw	-4.940	0.188	0.244	0.215	0.623	-0.055	-3.026	0.007	0.102	0.191
	[0.95]	[2.50]*	[2.42]*	[2.73]**	[0.49]	[0.23]	[0.64]	[0.03]	[0.72]	[2.33]*
trend	0.007	0.006								
	[4.00]**	[4.96]**								
$\hat{t}_i$ sign. at 10%	58									
Constant	-0.476	-0.098	-1.242	0.056	-0.053	0.061	0.151	0.002	0.030	0.020
	[1.76]	[0.71]	[2.00]*	[0.16]	[0.15]	[0.34]	[0.65]	[0.01]	[0.09]	[0.10]
Returns to scale implications of the parameter estimates‡										
implied β_L	5.066	0.436	0.284	0.335	-1.526	1.433	12.649	1.721	0.381	0.321
Serial correlation in the residuals — H_0: no serial correlation										
	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Ljung-Box	72.9	(1.00)	0.6	(1.00)	21.0	(1.00)	2.1	(1.00)	0.9	(1.00)
Durbin AR(1)	299.3	(.03)	332.4	(.00)	487.5	(.00)	488.3	(.00)	493.2	(.00)
Durbin AR(2)	370.5	(.00)	525.8	(.00)	678.2	(.00)	741.9	(.00)	775.2	(.00)
BGod AR(1)	366.7	(.00)	573.0	(.00)	781.9	(.00)	715.4	(.00)	775.2	(.00)
BGod AR(2)	465.6	(.00)	902.7	(.00)	1072.3	(.00)	1158.5	(.00)	1130.6	(.00)
	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79
DW d statistic #	0	111	0	115	0	124	0	124	0	124
(in %)	0%	87%	0%	90%	0%	97%	0%	97%	0%	97%
Pedroni (1999) panel *t*-statistics										
$N^{-1/2}\sum_i t_{\hat{\beta}_{tr,i}}$	[6.18]**		[7.72]**		[0.58]		[2.01]*		[5.94]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{live,i}}$	[15.42]**		[12.06]**		[1.03]		[1.46]		[15.91]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{f,i}}$	[8.20]**		[7.40]**		[1.43]		[0.97]		[8.98]**	
$N^{-1/2}\sum_i t_{\hat{\beta}_{n,i}}$	[6.48]**		[5.74]**		[1.81]		[0.70]		[6.25]**	
$N^{-1/2}\sum_i t_{\hat{t}_i}$	[19.50]**									
Nonstationarity: Pesaran (2007) CIPS test applied to residuals — H_0: residuals are I(1)										
lag-augmentation	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
none	-48.9	(.00)	-50.0	(.00)	-51.1	(.00)	-50.8	(.00)	-50.8	(.00)
1 lag	-32.1	(.00)	-38.9	(.00)	-38.8	(.00)	-38.8	(.00)	-40.8	(.00)
2 lags	-24.6	(.00)	-30.5	(.00)	-29.2	(.00)	-28.0	(.00)	-31.7	(.00)
3 lags	-20.3	(.00)	-25.2	(.00)	-22.3	(.00)	-22.1	(.00)	-25.8	(.00)
4 lags	-11.5	(.00)	-15.1	(.00)	-14.0	(.00)	-13.6	(.00)	-15.5	(.00)
CSD: Mean correlations and Pesaran (2004) test — H_0: no CSD in the residuals										
	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$	ρ_{ij}	$\|\rho_{ij}\|$
Mean Correl.	0.02	0.14	0.00	0.16	0.00	0.14	0.07	0.15	0.00	0.15
CD statistic (p)	7.07	(.00)	-0.22	(.83)	2.57	(.01)	38.31	(.00)	-0.42	(.67)
Further residual diagnostic tests⋆ — H_0: no heteroskedasticity, regular skewness/kurtosis										
d'Agostini et al	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	402.2	(.00)	336.7	(.00)	347.4	(.00)	303.3	(.02)	280.1	(.14)
Cameron & Trivedi	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)	p_λ	(p)
Fisher stat (joint)	246.4	(.66)	199.7	(.99)	194.3	(.99)	210.6	(.98)	248.7	(.62)

Notes: The values in square brackets are absolute t-statistics of the estimates, based on heteroskedasticity-robust standard errors (Pesaran et al., 2008). An alternative 'panel t-test' by Pedroni (1999) is also provided — both are with reference to the long-run coefficients computed for each country regression. * and ** indicate statistical significance at the 5% and 1% level respectively. Long-run coefficients are computed from the lagged levels estimates using the `nlcom` command in `Stata`.
For the diagnostic tests refer to Table 4 for more details. Residuals tested are those from the ECM regressions for each country.

5 Conclusions

In this paper we investigated the impact of variable nonstationarity, technology heterogeneity, cross-section dependence and imposition of returns to scale on the results for cross-country production functions in agriculture for a large sample of countries. Our review of the literature indicated that the empirical implementations of the intercountry production functions for agriculture are dominated by the two-way fixed effects (2FE) model, with constant returns to scale often imposed without formal testing. Variable and residual analysis indicates that all of the aforementioned properties may be present in the data for 128 countries in our empirical analysis. Our estimation results display considerable differences in the estimated parameters when moving from pooled models to averaged country regressions, and between equations ignoring and accounting for cross-section dependence, and we use diagnostic testing to determine the most favourable specification and estimator(s).

We draw the following conclusions from our empirical analysis:

(i) Parameter heterogeneity plays an important role in cross-country productivity investigation for agriculture. The use of pooled models is largely rejected by the diagnostic tests we apply. These tests further indicate that the standard pooled estimator applied in the literature (2FE) is seriously misspecified.

(ii) The imposition of constant returns to agricultural production (CRS) on pooled regression equations — e.g. in the commonly preferred two-way fixed effects model — is rejected by the data and further leads to qualitatively different empirical results. In contrast, the imposition of CRS on individual country regressions does not change average parameter coefficients considerably compared with the unrestricted results: thus the observed decreasing returns in the pooled models is an artefact of empirical misspecification.

(iii) The presence of unobserved common factors with heterogeneous factor loadings *does* matter, as is highlighted by diagnostic tests comparing the MG and CCEMG-type estimators: the standard CCEMG estimator yields very favourable test statistics and shows robustness across various specifications (static, dynamic; unrestricted, CRS imposed). As was suggested in Kapetanios et al. (2008) estimators which do not account for cross-section correlation are unable to identify the technology parameters $\boldsymbol{\beta}$ or mean of $\boldsymbol{\beta}_i$ separately from the impact of the factor loadings $\boldsymbol{\lambda}_i$ if the same common factors drive both inputs and output.

(iv) Our own AMG estimator yields results much closer to the standard MG than the Pesaran (2006) CCEMG estimator, often failing specification tests in a similar fashion to the MG — Monte Carlo simulations (available on request) indicate a set of circumstances in which the AMG yields biased estimates but the CCEMG remains unbiased. We would speculate that the explicit, common TFP estimate $\hat{\mu}_t^\bullet$ applied in the AMG estimation may be unable to capture the heterogeneity in the underlying factor structure of the agriculture data, where heterogeneous factors play a much more prominent role (see next point).

(v) Our extension to the CCEMG estimator of applying (exogenous) weight matrices before computing the cross-section averages and in effect imposing more structure on the nature of cross-section correlation in the data has provided very interesting insights. We suggest that given the close match between the standard and agro-climate CCEMG that the common correlated effects driving the cross-section dependence are closely proxied by our measure for agro-climatic distance. In contrast, neighbourhood or geographical distance measures do not seem to play a major role. The implication of this finding is that agricultural TFP is affected by different factors and has different levels of responsiveness across geographic regions of the world due to agro-climatic diversity. Furthermore, technology transfer between countries is limited by the adaptiveness of technology to the local environment — both of these statements are widely accepted in the literature but prior to this study were ignored in empirical analyses of cross-country productivity.

(vi) While the preferred standard and agro-climate CCEMG estimators yielded very similar results across static and dynamic specifications, the other heterogeneous parameter estimators collapse to a larger or smaller extent when we introduce a dynamic specification. In our mind this is strong evidence for the robustness of the standard and agro-climate CCEMG.

In future research we will investigate the patterns of parameter values across countries as well as those of the TFP residuals derived from our preferred specification. Methods such as principal component analysis could be employed to obtain and investigate the underlying factors and country-specific factor loadings that make up TFP.

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Appendix

A Data construction and descriptives

The principal data source for our empirical analysis is the Food and Agriculture Organisation's *FAOSTAT* panel database (FAO, 2007), from which we obtain annual observations for agricultural net output, economically active labour force in agriculture, number of tractors used in agriculture, arable land and permanent crop land and fertilizer use in 128 countries from 1961 to 2002. The specific sources and definitions are detailed below. Descriptive statistics for all variables are presented in Table A-1. The countries in our sample (ordered by country iso-code) and the number of country observations for the regressions in levels and first differences respectively are presented in Table A-2. The total number of observations is 5,162 in the levels and 5,013 in the first difference specification, minimum T is 19 and 17 respectively, and average T 40.3 and 39.2 respectively.

Real agricultural net output (in thousand International $), taken from *ProdSTAT* is based on all crops and livestock products originating in each country: "practically all products are covered, with the main exception of fodder crops." (FAO, 2007). 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, which are derived using a Geary-Khamis formula for the agricultural sector. The labour variable is taken from *PopSTAT* and 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. This variable can be found in the 'Machinery' section of *ResourceSTAT*. The **livestock** variable is constructed from the data for asses (donkeys), buffalos, camels, cattle, chickens, ducks, horses, mules, pigs, sheep & goats and turkeys in the 'Live animals' section of *ProdStat*. Following convention we use the below formula to convert the numbers for individual animal species into the livestock variable:

$$\begin{aligned}\text{livestock} = {} & 1.1^*\text{camels} + \text{buffalos} + \text{horses} + \text{mules} + 0.8^*\text{cattle} + 0.8^*\text{asses} \\ & +0.2^*\text{pigs} + 0.1^*(\text{sheep}+\text{goats}) + 0.01^*(\text{chickens}+\text{ducks}+\text{turkeys})\end{aligned}$$

The fertilizer variable is taken from the 'Fertilizers archive' of *ResourceSTAT* and represents **agricultural fertilizer consumed in metric tons**, which includes 'crude' and 'manufactured' fertilizers. The land variable is taken from *ResourceSTAT* and represents **arable and permanent crop land (in 1000 hectare)**.

Additional time-invariant data on geographical distance between countries and contiguity (neighbourhood) is taken from CEPII (2006), and data on the share of agricultural land by climatic zone from Matthews (1983), available in Gallup et al. (1999). For a number of diagnostics we group the data by region or climate zone — Table A-3 details these groupings using country iso-codes.

Finally, Table A-4 provides an overview of the climatic zones referred to in the the Köppen-Geiger classification, taken from Kottek, Grieser, Beck, Rudolf, and Rubel (2006).

Table A-1: Descriptive statistics

Variables in untransformed level terms					
Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**
levels					
output	6,659,293	1,523,753	19,900,000	3,196	317,000,000
labour	8,528,396	1,317,000	42,400,000	3,000	511,000,000
tractors	149,528	7,124	512,278	2	5,470,000
livestock	11,800,000	3,031,056	31,900,000	6,644	298,000,000
fertilizer	721,176	58,000	2,680,786	5	39,600,000
land	9,799,731	2,628,500	25,500,000	1,000	191,000,000
logs					
output	14.24	14.24	1.71	8.07	19.57
labour	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
annual growth rate					
output	2.3%	2.4%	8.8%	-83.0%	87.6%
labour	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.**
levels					
output	3.86	0.97	7.40	0.11	54.85
tractors	0.13	0.01	0.29	0.00	1.97
livestock	6.60	2.24	12.76	0.06	102.28
fertilizer	0.43	0.06	0.94	0.00	7.05
land	4.88	1.96	12.87	0.11	140.47
logs					
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
annual growth rate					
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 output (in I$1,000), labour (headcount), tractors (number), livestock (cattle-equivalent numbers), fertilizer (in metric tonnes) and land (in hectare) for the full regression sample ($n = 5,162$; $N = 128$).

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

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

Notes: The full levels sample contains n=5,162 observations, the sample with variables in first differences (FD) contains n=5,013 observations. The sample period is from 1961 to 2002.

Table A-3: Country groupings

Regional country groups		
Grouping	N	Country Codes
East Asia	14	CHN, IDN, JPN, KHM, KOR, LAO, MMR, MNG, MYS, PHL, PNG, PRK, THA, VNM
Europe & other WIC	28	ALB, AUS, AUT, BGR, BLX, CAN, CHE, CYP, DEU, DNK, ESP, FIN, FRA, GBR, GRC, HUN, IRL, ISL, ITA, NLD, NOR, NZL, POL, PRT, ROM, SWE, TUR, USA
Latin America & Caribbean	24	ARG, BLZ, BOL, BRA, CHL, COL, CRI, CUB, DOM, ECU, GTM, GUY, HND, HTI, JAM, MEX, NIC, PAN, PRY, SLV, SUR, TTO, URY, VEN
South America	11	ARG, BOL, BRA, CHL, COL, ECU, GUY, PRY, SUR, URY, VEN
C. America & Caribbean	13	BLZ, CRI, CUB, DOM, GTM, HND, HTI, JAM, MEX, NIC, PAN, SLV, TTO
Middle East & North Africa	17	ARE, DZA, EGY, IRN, IRQ, ISR, JOR, KWT, LBN, LBY, MAR, OMN, QAT, SAU, SYR, TUN, YEM
North Africa	5	DZA, EGY, LBY, MAR, TUN
South Asia	6	AFG, BGD, IND, LKA, NPL, PAK
Sub-Saharan Africa	39	AGO, BDI, BEN, BFA, BWA, CAF, CIV, CMR, COG, ETH, GAB, GHA, GIN, GMB, GNB, GNQ, KEN, LBR, LSO, MDG, MLI, MOZ, MRT, MWI, NER, NGA, RWA, SDN, SEN, SLE, SOM, SWZ, TCD, TGO, TZA, UGA, ZAF, ZAR, ZWE
Eastern Africa	9	BDI, ETH, KEN, MOZ, MWI, RWA, SOM, TZA, UGA
Western Africa	16	BEN, CAF, CIV, CMR, COG, GAB, GHA, GIN, GMB, GNB, GNQ, LBR, NGA, SEN, SLE, TGO
Southern Africa	7	AGO, BWA, LSO, MDG, SWZ, ZAR, ZWE (does not include ZAF)
Sahel	6	BFA, MLI, MRT, NER, SDN, TCD

Climate-zone country groups		
Grouping	N	Country Codes
Equatorial (EQ)	52	AGO, BDI, BEN, BGD, BLZ, BOL, BRA, CAF, CIV, CMR, COG, COL, CRI, CUB, DOM, GAB, GHA, GIN, GMB, GNB, GNQ, GTM, GUY, HND, HTI, IDN, JAM, KHM, LAO, LBR, LKA, MDG, MMR, MOZ, MYS, NGA, NIC, PAN, PHL, PNG, RWA, SLE, SLV, SUR, TGO, THA, TTO, TZA, UGA, VEN, VNM, ZAR
Arid (AR)	19	AUS, BEN, BFA, BWA, EGY, IRQ, LBY, MLI, MNG, MRT, NER, PAK, SAU, SDN, SEN, SOM, TCD, ZAF, ZWE
Temperate & Cold (TEMP)	51	ALB, ARG, AUS, AUT, BGR, BLX, CAN, CHE, CHL, CHN, CYP, DEU, DNK, DZA, ESP, FIN, FRA, GBR, GRC, HUN, IRL, ISL, ISR, ITA, JOR, JPN, KOR, LAO, LBN, LSO, MAR, MWI, NLD, NOR, NPL, NZL, POL, PRK, PRT, PRY, ROM, SWE, SWZ, SYR, TUN, TUR, URY, USA, VNM, ZAF, ZWE
Highland	12	AFG, CHE, CHL, ECU, ETH, GTM, HND, IRN, MEX, NIC, SAU, YEM
Inbetween categories[1]	2	IND, KEN
Multiple categories	11	AUS, BEN, CHL, GTM, HND, LAO, NIC, SAU, VNM, ZAF, ZWE
Not classified	4	ARE, OMN, KWT, QAT

Notes: [1] India has around 30-35% of arable land in each of the equatorial, arid and temperate & cold zones; Kenya has around 39% in the equatorial, 36% in the arid and 25% in the highland zones respectively.

Table A-4: Climate Zones following Köppen-Geiger

Köppen-Geiger Classification			
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	Cs	Warm temperate climate with dry summer
		Cw	Warm temperate climate with dry winter
		Cf	Warm temperate climate, fully humid
D	Snow climates	Ds	Snow climate with dry summer
		Dw	Snow climate with dry winter
		Df	Snow climate, fully humid
E	Polar climates	ET	Tundra climate
		EF	Frost climate
H	Highland climate		above 2,500m elevation

Notes: This classification is taken from Kottek et al. (2006). The H category for Highland climate was added after the creation of the Köppen-Geiger classification, however it was impossible to establish the elevation cut-off definitively. The 2,500m mark is implicitly suggested in a number of online databases.

B Time-series properties of the data

In this section we report results relating to the time-series properties of the data. Since the time dimension of the panel is sizeable (T ranges from 19 to 42, average $T = 40.3$), we first carry out Augmented Dickey-Fuller (Dickey & Fuller, 1979) and KPSS (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) tests for the variable series within each individual country.[14] We use this combination of tests since the ADF test has the null of nonstationary variable series, whereas the KPSS test has the null of stationary variable series. The **time-series unit root test** rejection frequencies for variables in *levels* and in *first differences* are shown in Table B-1: we report the share of countries (in %) for which the null hypothesis (stationarity or nonstationarity as indicated) is rejected. The theoretical rejection frequencies at our sample size are 12.8% (H_0 : nonstationarity) and 87.2% (H_0 : stationarity) for the 10% significance level we adopted.

Table B-1: Time-series unit root tests — rejection frequency

Unit root tests
share of country tests which reject H_0 (stationarity or nonstationarity as indicated);
no adjustment for cross-sectional dependence; all variables in logs

Testing for levels-stationarity								
Test			log output pw	labour	tractors pw	livestock pw	fertilizer pw	land pw
ADF without trend	H_0: nonstationary	H_1: levels-stationary	9%	9%	48%	16%	41%	10%
KPSS without trend	H_0: levels-stationary	H_1: nonstationary	82%	91%	81%	85%	70%	82%

Testing for trend-stationarity								
Test			output pw	labour	tractors pw	livestock pw	fertilizer pw	land pw
ADF with trend	H_0: nonstationary	H_1: trend-stationary	16%	15%	24%	12%	21%	11%
KPSS with trend	H_0: trend-stationary	H_1: nonstationary	65%	71%	88%	65%	74%	66%

Testing for difference-stationarity								
Test			output pw	labour	tractors pw	livestock pw	fertilizer pw	land pw
ADF with drift	H_0: nonstationary	H_1: stationary	94%	16%	48%	88%	78%	67%
KPSS with drift	H_0: stationary	H_1: nonstationary	13%	38%	81%	81%	70%	82%

Notes: All variables are in logs. We report the share of countries (out of $N = 128$) for which the respective unit root test is rejected at the 10% level of significance. All unit root tests for variables in levels contain an intercept term in the estimating equation. ADF refers to the augmented Dickey-Fuller test, which has the null of nonstationarity. KPSS refers to the Kwiatkowski et al. (1992) unit root test, which has the null of (trend-)stationarity. Lag-augmentation or bandwidth selection in these tests to account for serial correlation in the variables is allowed to vary by country. For the ADF test we determined 'ideal' lag-augmentation using the Akaike Information Criterion (AIC). For the KPSS tests an automated bandwidth selection following Newey and West (1994) and discussed in Hobijn et al. (2004) is used. For KPSS we use the `kpss` command in `Stata` written by Kit Baum.

For the majority of countries the ADF tests for the variables in levels cannot reject nonstationarity, with the notable exceptions of tractors per worker and fertilizer per worker. Consistently with this finding the majority of country KPSS tests reject the null of level stationarity. The tests for trend stationarity reveal a similar pattern. The difference stationarity tests show considerable differences across variables: in the ADF tests the labour and tractors per worker variables reject the nonstationarity null in far less countries than we would expect (87.2%) and the KPSS tests reject stationarity in the vast majority of countries for the tractors, livestock, fertilizer and land (all in per worker terms) variables.

Our analysis based on standard time-series (non)stationarity tests therefore has no clearcut message regarding variable properties. It needs to be emphasised that country-specific unit root tests suffer from low power, in particular in the case where the persistence in the variable is high — i.e. in the case when the test matters most (Harris, 1994).

[14] Whereas the `Stata` command for ADF allows us to run country regressions with gaps in the data, this is not possible for the KPSS tests. We interpolate data in order to run the KPSS for a balanced panel.

Next we apply **'first generation' panel unit root tests** to the data. These were developed due to the desirable property of increased power from pooling the results from many low-powered country unit root tests. It is important to stress that rejection of the unit root null hypothesis does not imply that the panel is stationary, but rather that the variable series does not follow a unit root process *in all countries*. Table B-2 presents the results for the Maddala and Wu (1999) (MW) panel unit root test and a panel version of Phillips and Perron (1988) (PP) test, for which serial correlation is accounted for using nonparametric methods rather than lagged differences. Following Fisher's suggestion the MW statistic is constructed as $P = -2\sum_i log(p_i)$, where p_i is the p-value for the individual country ADF statistics. The PP test is constructed in analogy. For both tests the theoretical distribution of the statistic is $\chi^2(2N)$, s.t. critical values are 97.35 for 5% and 92.16 for 10%.

For both tests tractors per worker and fertilizer per worker in levels reject nonstationarity in both the standard ADF equation and the ADF equation with a trend. All other variables in levels seemingly cannot reject the null of nonstationarity once augmented with sufficient lags or once a trend is added to the ADF equation. For the variables in first differences the tests unanimously reject nonstationarity.

Similarly to the above analysis we cannot definitely reject nonstationarity in all variables. However, as Baltagi et al. (2007) point out the first generation panel unit root tests which do not account for cross-section dependence can be subject to considerable size distortions, such that the test tends to overreject. This issue led to the development of **'second generation' panel unit root tests**, namely the Im, Pesaran, and Shin (2003) and the Pesaran (2007) tests, results for which are presented in Table B-3. These tests explicitly allow for cross-sectional dependence in the data and therefore have better performance than the 'classic' panel unit root tests that assume cross-sectional independence.

Our results now seem to provide a more consistent theme across the different variables and specifications: following augmentation with lags or a linear trend term the levels variables cannot reject the null of nonstationarity. For the variables in first differences all variables reject nonstationarity with the exception of labour.

It should be noted that our preferred panel unit root test by Pesaran (2007) can only account for a single unobserved common factor as the cause for cross-sectional dependence in the data. More recent extensions of this test (Pesaran et al., 2008) can accommodate multiple unobserved common factors, but this development was too recent for the test to be included in this paper. Further issues which have received attention in the recent panel unit root literature such as structural breaks in data series (Westerlund, 2006; Kao, Trapani, & Urga, 2007) and changes in the volatility of the innovations (Hanck, 2008) could also not be accommodated.

Table B-2: First generation panel unit root tests: Fisher tests

Maddala & Wu (1999) unit root test												
Variables in levels: ADF equation contains intercept												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	264.33	.35	836.91	.00	2776.92	.00	318.88	.00	713.80	.00	202.25	.99
1	248.31	.62	212.39	.98	897.70	.00	269.52	.27	672.69	.00	174.36	1.00
2	216.15	.97	161.97	1.00	716.62	.00	298.71	.03	593.96	.00	185.48	1.00
3	205.40	.99	137.31	1.00	707.83	.00	274.18	.21	561.27	.00	172.74	1.00
4	198.13	1.00	139.56	1.00	614.63	.00	236.64	.80	586.15	.00	252.63	.55
5	217.60	.96	138.40	1.00	663.07	.00	236.17	.81	551.27	.00	189.16	1.00
6	180.78	1.00	140.82	1.00	532.05	.00	219.06	.95	399.06	.00	159.21	1.00
Variables in levels: ADF equation contains intercept & trend												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	473.86	.00	205.02	.99	916.00	.00	272.79	.22	411.14	.00	160.72	1.00
1	322.37	.00	676.49	.00	499.77	.00	326.65	.00	319.24	.00	340.40	.00
2	241.67	.73	293.71	.05	423.53	.00	318.07	.00	256.12	.49	255.62	.50
3	230.43	.87	266.99	.31	335.91	.00	319.78	.00	235.53	.82	269.17	.27
4	224.20	.92	249.02	.61	449.23	.00	286.63	.09	256.61	.48	305.17	.02
5	205.05	.99	254.56	.51	479.71	.00	286.74	.09	313.58	.01	290.07	.07
6	184.29	1.00	230.35	.87	436.98	.00	248.59	.62	190.53	1.00	275.99	.19
Variables in first differences: ADF equation contains drift												
variable ‡	**Δly**		**ΔlL**		**Δltr**		**Δllive**		**Δlf**		**Δln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	5893.19	.00	513.12	.00	2092.88	.00	2780.22	.00	5138.24	.00	2408.11	.00
1	2875.38	.00	538.34	.00	1206.83	.00	1561.93	.00	2475.73	.00	1153.82	.00
2	1571.83	.00	414.45	.00	773.43	.00	1052.88	.00	1437.93	.00	806.68	.00
3	1048.43	.00	338.69	.00	603.03	.00	867.15	.00	956.45	.00	616.82	.00
4	779.00	.00	289.06	.08	534.76	.00	669.12	.00	662.53	.00	473.58	.00
5	564.99	.00	312.39	.01	627.47	.00	601.37	.00	517.31	.00	441.97	.00
6	425.31	.00	341.73	.00	534.53	.00	504.60	.00	420.91	.00	426.10	.00

Philipps & Perron (1988)-type unit root test (panel version)												
Variables in levels: ADF equation contains intercept												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	264.33	.35	836.91	.00	2776.92	.00	318.88	.00	713.80	.00	202.25	.99
1	264.64	.34	523.52	.00	2373.71	.00	289.99	.07	764.06	.00	187.07	1.00
2	274.14	.21	403.42	.00	2180.19	.00	280.98	.14	815.30	.00	179.45	1.00
3	281.71	.13	344.04	.00	2100.88	.00	279.59	.15	858.99	.00	181.16	1.00
4	288.05	.08	311.81	.01	2063.62	.00	279.96	.15	899.75	.00	180.85	1.00
5	298.86	.03	294.77	.05	2089.83	.00	283.25	.12	946.55	.00	183.07	1.00
6	308.91	.01	287.25	.09	2013.23	.00	285.65	.10	983.57	.00	184.63	1.00
Variables in levels: ADF equation contains intercept & trend												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	473.86	.00	205.02	.99	916.00	.00	272.79	.22	411.14	.00	160.72	1.00
1	459.81	.00	136.91	1.00	803.17	.00	267.51	.30	408.40	.00	167.54	1.00
2	463.28	.00	120.88	1.00	759.12	.00	260.85	.40	411.18	.00	174.00	1.00
3	468.30	.00	117.74	1.00	762.21	.00	258.26	.45	412.02	.00	180.44	1.00
4	472.24	.00	119.26	1.00	775.59	.00	254.96	.51	411.84	.00	183.58	1.00
5	475.65	.00	121.56	1.00	819.31	.00	251.47	.57	411.58	.00	184.72	1.00
6	478.72	.00	123.13	1.00	883.30	.00	246.73	.65	410.36	.00	184.77	1.00
Variables in first differences: ADF equation contains drift												
variable ‡	**Δly**		**ΔlL**		**Δltr**		**Δllive**		**Δlf**		**Δln**	
lags	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
0	5893.19	.00	513.12	.00	2092.88	.00	2780.22	.00	5138.24	.00	2408.11	.00
1	5958.33	.00	517.81	.00	2103.97	.00	2763.12	.00	5179.80	.00	2390.08	.00
2	6140.51	.00	548.19	.00	2108.97	.00	2759.40	.00	5284.52	.00	2410.07	.00
3	6261.04	.00	571.63	.00	2106.40	.00	2768.50	.00	5357.08	.00	2438.08	.00
4	6369.17	.00	571.18	.00	2111.24	.00	2774.13	.00	5418.36	.00	2463.51	.00
5	6487.63	.00	566.35	.00	2121.16	.00	2782.00	.00	5469.27	.00	2484.50	.00
6	6592.92	.00	565.60	.00	2135.74	.00	2798.47	.00	5520.19	.00	2499.74	.00

Notes: †Output per worker (lo), labour (lL), tractors per worker (ltr), livestock per worker (llive), fertilizer per worker (lf) and land per worker (ln) — all in logs. ‡The Δ symbolise the growth rates for the above variables (first differences of the variables in logs).
The null is nonstationarity in all countries' variable series, the alternative stationarity in *all* countries' variable series.

Table B-3: Second generation panel unit root tests

Im, Pesaran & Shin (2003) unit root test for heterogeneous panels with cross-section dependence												
Variables in levels: ADF equation contains intercept												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*
0	0.70	.76	28.08	1.00	-20.32	.00	9.65	1.00	-7.03	.00	15.85	1.00
1	2.71	1.00	13.00	1.00	-3.05	.00	6.37	1.00	-3.84	.00	11.00	1.00
2	3.37	1.00	11.58	1.00	-1.32	.09	5.11	1.00	-3.21	.00	9.28	1.00
3	2.77	1.00	11.43	1.00	-2.11	.02	4.51	1.00	-1.68	.05	8.35	1.00
4	2.35	.99	12.44	1.00	-3.19	.00	4.47	1.00	-2.00	.02	7.16	1.00
5	2.70	1.00	13.47	1.00	-4.60	.00	4.33	1.00	-1.50	.07	7.10	1.00
6	2.80	1.00	14.24	1.00	-1.71	.04	3.74	1.00	-3.11	.00	7.89	1.00
Variables in levels: ADF equation contains intercept & trend												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*
0	-4.59	.00	16.98	1.00	-9.05	.00	6.63	1.00	-9.30	.00	10.28	1.00
1	0.13	.55	-0.02	.49	-0.53	.30	1.87	.97	-3.66	.00	1.69	.95
2	2.53	.99	0.08	.53	-0.61	.27	0.52	.70	-2.54	.01	1.65	.95
3	2.46	.99	2.02	.98	-1.99	.02	0.75	.77	-0.27	.39	0.30	.62
4	1.56	.94	1.46	.93	-1.07	.14	1.19	.88	-1.00	.16	-0.28	.39
5	2.50	.99	1.75	.96	-2.96	.00	0.45	.67	-0.01	.50	-1.01	.16
6	2.27	.99	3.53	1.00	0.15	.56	1.39	.92	-3.77	.00	-0.85	.20
Variables in first differences: ADF equation contains drift												
variable ‡	**Δly**		**ΔlL**		**Δltr**		**Δllive**		**Δlf**		**Δln**	
lags	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*	Wtbar	*p*
0	-77.80	.00	-10.40	.00	-42.24	.00	-46.39	.00	-69.35	.00	-39.20	.00
1	-47.05	.00	-6.55	.00	-28.17	.00	-28.74	.00	-39.86	.00	-23.90	.00
2	-29.98	.00	-6.85	.00	-18.86	.00	-20.97	.00	-29.20	.00	-15.43	.00
3	-21.77	.00	-5.17	.00	-15.16	.00	-17.02	.00	-21.12	.00	-11.75	.00
4	-16.67	.00	-4.88	.00	-11.55	.00	-12.87	.00	-16.44	.00	-8.77	.00
5	-12.57	.00	-5.75	.00	-10.40	.00	-10.83	.00	-13.12	.00	-7.89	.00
6	-9.57	.00	-3.90	.00	-8.52	.00	-7.83	.00	-12.38	.00	-7.58	.00

Pesaran (2007) unit root test (CIPS) for heterogeneous panels with cross-section dependence												
Variables in levels: CADF equation contains intercept												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*
0	-7.19	.00	14.77	1.00	-0.38	.35	2.56	.99	-9.53	.00	12.13	1.00
1	-2.55	.01	11.70	1.00	-3.17	.00	-1.37	.08	-5.23	.00	7.95	1.00
2	-0.78	.22	13.78	1.00	-2.16	.02	-0.96	.17	-2.51	.01	7.94	1.00
3	-0.34	.37	16.22	1.00	-3.37	.00	0.14	.55	0.54	.71	6.33	1.00
4	0.29	.61	17.63	1.00	0.08	.53	3.06	1.00	1.54	.94	7.89	1.00
Variables in levels: CADF equation contains intercept & trend												
variable †	**ly**		**lL**		**ltr**		**llive**		**lf**		**ln**	
lags	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*
0	-2.31	.01	7.90	1.00	3.26	1.00	6.68	1.00	-9.31	.00	9.69	1.00
1	2.94	1.00	-0.82	.20	-1.09	.14	1.80	.96	-5.61	.00	1.70	.96
2	5.85	1.00	5.24	1.00	-0.59	.28	2.74	1.00	-2.33	.01	0.71	.76
3	7.15	1.00	8.98	1.00	-0.17	.43	4.51	1.00	0.63	.74	-0.07	.47
4	7.38	1.00	10.17	1.00	0.42	.66	6.97	1.00	1.90	.97	0.59	.72
Variables in first differences: CADF equation contains drift												
variable ‡	**Δly**		**ΔlL**		**Δltr**		**Δllive**		**Δlf**		**Δln**	
lags	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*	Ztbar	*p*
0	-48.44	.00	-1.37	.09	-32.95	.00	-33.72	.00	-48.55	.00	-28.58	.00
1	-33.63	.00	-0.84	.20	-20.81	.00	-21.62	.00	-35.92	.00	-15.30	.00
2	-20.34	.00	-0.52	.30	-14.15	.00	-13.72	.00	-25.44	.00	-7.51	.00
3	-14.30	.00	1.84	.97	-8.11	.00	-8.41	.00	-16.36	.00	-4.64	.00
4	-7.54	.00	3.41	1.00	-4.26	.00	-4.01	.00	-10.44	.00	-0.92	.18

Notes: †Output per worker (ly), labour (lL), tractors per worker (ltr), livestock per worker (llive), fertilizer per worker (lf) and land per worker (ln) — all in logs. ‡The Δ symbolise the growth rates for the above variables (first differences of the variables in logs).
The null is nonstationarity in all countries' variable series, the alternative stationarity in *some* countries' variable series.

C Cross-section dependence in the data

In this section we investigate the potential for cross-section dependence in the data. We initially focus on the full sample 'global' data ($N = 128$, average $T = 40.3$ for the variables in levels). Table C-1 details the share of the variance accounted for by the first two principal components (PCs) to indicate the factor structure of the data, as suggested by Coakley et al. (2006). In principal component analysis (PCA) the eigenvalues (ordered by magnitude) over the cumulated eigenvalues give an indication of the variance in the standardized data explained by the different 'principal components'. The latter are linear combinations of the $N(N-1)$ data time-series to account for the maximum variation in the overall dataset. In Panel [a] we apply this method to the variables in levels (log) and find that the first two principal components account for 76-93% of the variance. We also investigate whether the residuals from pooled OLS ($\hat{e}^{POLS^*}$) and 2-way Fixed Effects ($\hat{e}^{2FE^*}$) regressions[15] show signs of factor structures. Again the share of the first two PCs is very high, around 65% in both cases. In Panel [b] we carry out the same analysis for the variables in first differences (for the residuals the production function OLS and 2FE regressions are run with variables in first differences); the explained variance is now considerably lower, although labour force growth (dlL) and growth in tractors per worker (dltr) still exhibit strong underlying factor structures.

Table C-1: 'Global' Cross-section Dependence (i)

Principal Component Analysis Share of variance (in %) accounted for by the first two Principal Components								
Panel [a]	**Variables in levels**†						**Residuals**‡	
	ly	lL	ltr	llive	lf*	ln	$\hat{e}^{POLS^*}$	$\hat{e}^{2FE^*}$
%V Comp1	66.8	83.2	75.0	59.4	62.8	67.5	48.3	44.5
%V Comp2	11.5	9.5	15.0	17.0	13.8	16.0	16.8	20.3
sum	78.4	92.7	90.0	76.3	76.7	83.5	65.1	64.8
Panel [b]	**Variables in first differences**†						**Residuals**‡	
	dly*	dlL*	dltr*	dllive*	dlf*	dln*	$\hat{e}^{FD-OLS^*}$	$\hat{e}^{FD2FE^*}$
%V Comp1	12.03	28.6	29.7	10.7	15.4	13.8	12.5	12.3
%V Comp2	5.97	22.3	11.9	7.4	8.9	10.5	6.1	7.6
sum	18.0	50.9	41.6	18.0	24.3	24.2	18.6	19.9
N	127	127	127	126	128	126	128	128
excluded	FIN	FIN	FIN	BLX,FIN	-	BLX,FIN	-	-

†Output per worker (ly), labour (lL), tractors per worker (ltr), livestock per worker (llive), fertilizer per worker (lf) and land per worker (ln) — all in logs. The prefix d- identifies data in first differences.
‡These are the residuals from a pooled OLS regression with $T-1$ year dummies (POLS), the 2-way Fixed Effects regression (2FE), the pooled OLS regression with variables (and year dummies) in first differences (FD-OLS) and the 2-way Fixed Effects regression with variables in first differences (FD2FE).
*This indicates that the variable had to be interpolated since there were not enough common years of data across all countries to carry out PCA. Otherwise we excluded some countries from the analysis as indicated.

In Table C-2 we report the means for the $N(N-1)$ correlation coefficients for variable series or regression residuals, as well as the Pesaran (2004) Cross-Section Dependence (CD) test statistics. The former represents the simple average of the pairwise correlation coefficients between all country series ($\hat{\rho}_{ij}$) or the average of their absolute values ($|\hat{\rho}_{ij}|$). The CD test statistic is also based on the mean pairwise correlation coefficients. In the unbalanced panel case it is defined as

$$CD = \sqrt{\left(\frac{2}{N(N-1)}\right)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}}\hat{\rho}_{ij}\right)$$

were T_{ij} is the number of observations used to estimate the correlation coefficient between the series in country i and j and $CD \sim N(0,1)$ for $T_{ij} > 3$ and sufficiently large N under the null

[15]These are production function regressions as outlined in the main section of this paper.

of cross-section independence. This test is robust to the presence of nonstationary processes, parameter heterogeneity or structural breaks, and was shown to perform well even in small samples.

Table C-2: 'Global' Cross-section Dependence (ii)

Mean Correlation Coefficients and Pesaran (2004) CD test♯ Global cross-section dependence in the data; $N = 128$, $n = 16,256$								
Panel [a]	**Variables in levels**†						**Residuals**‡	
	ly	lL	ltr	llive	lf	ln	$\hat{e}^{POLS}$	$\hat{e}^{2FE}$
$(N(N-1))^{-1}\sum_i\sum_j \hat{\rho}_{ij}$	0.372	0.100	0.532	0.125	0.458	-0.007	-0.005	0.015
$(N(N-1))^{-1}\sum_i\sum_j \lvert\hat{\rho}_{ij}\rvert$	0.611	0.799	0.699	0.561	0.544	0.645	0.424	0.408
Pesaran CD Statistic							-2.49	9.64
Panel [b]	**Variables in first differences**†						**Residuals**‡	
	dly	dlL	dltr	dllive	dlf	dln	$\hat{e}^{FD-OLS}$	$\hat{e}^{FD2FE}$
$(N(N-1))^{-1}\sum_i\sum_j \hat{\rho}_{ij}$	0.021	0.053	0.210	0.020	0.051	0.008	0.000	0.023
$(N(N-1))^{-1}\sum_i\sum_j \lvert\hat{\rho}_{ij}\rvert$	0.141	0.351	0.276	0.144	0.147	0.172	0.145	0.149
Pesaran CD Statistic							0.04	12.84
Panel [c]	**AR regression residuals**♮						**Residuals**‡	
	$\hat{e}^{ly}$	$\hat{e}^{lL}$	$\hat{e}^{ltr}$	$\hat{e}^{llive}$	$\hat{e}^{lf}$	$\hat{e}^{ln}$	$\hat{e}^{MG}$	$\hat{e}^{CCEMG}$
$(N(N-1))^{-1}\sum_i\sum_j \hat{\rho}_{ij}$	0.020	0.075	0.012	0.013	0.025	0.008	0.017	0.001
$(N(N-1))^{-1}\sum_i\sum_j \lvert\hat{\rho}_{ij}\rvert$	0.137	0.301	0.143	0.134	0.143	0.141	0.147	0.150
Pesaran CD Statistic	11.52	42.23	7.02	7.47	14.63	4.36	9.16	0.21

†Variables as defined in Table C-2. ‡These are the residuals from a pooled OLS regression with $T-1$ year dummies (POLS), the 2-way Fixed Effects regression (2FE), individual country regressions with intercept and linear trend (MG) and from the Pesaran (2006) Common Correlated Effects MG estimator (CCEMG).
♮ Each of the variables in levels is entered into a regression $z_{it} = \pi_{1,i}z_{i,t-1} + \pi_{2,i}z_{i,t-2} + \pi_{t,i}t + \pi_{0,i}$, conducted separately for each country i. The correlations and cross-section dependence statistic are then based on the residuals from these AR regressions.
♯ $\hat{\rho}_{ij}$ where $i \neq j$ refers to the correlation coefficient for the variable/residuals in question between countries i and j. $|\hat{\rho}_{ij}|$ is the absolute value of the same statistic. The CD Test Statistic (for unbalanced panels) is

$$CD = \sqrt{\left(\frac{2}{N(N-1)}\right)}\left(\sum_i \sum_j \sqrt{T_{ij}}\hat{\rho}_{ij}\right)$$

where $i = 1, \ldots, N-1$ and $j = i+1, \ldots, N$ and T_{ij} is the number of observations for each pairwise correlation. In our case $N = 128$ and average $T = 38.8$. Note that we adjusted the residual series for each i by subtracting their mean for the period T_{ij} since they may not sum to zero otherwise (Pesaran, 2004, p.17). For $N \to \infty$ the CD statistic is distributed standard normal under the null of cross-section independence.

Panel [a] of Table C-2 again investigates the variable series in levels and residuals from the pooled OLS and 2FE regressions. Average correlation varies considerably across the variables, from .53 in the case of tractors per worker (ltr) to virtually no correlation in land per worker (ln). Average correlation is low for the regression residuals, however the CD statistic rejects the null of cross-section independence at $p < .01$ in both cases. This result emphasises the importance of parameter heterogeneity (in the presence of nonstationarity): if production function parameters and the influence of the unobserved common factor(s) were *identical* across countries the $2FE$ transformation should be able to eliminate all the cross-section dependence in the data (Coakley et al., 2006). This is seemingly not the case here.

Panel [b] shows the average correlations for the data in first differences and the CD statistic for residuals from OLS and 2FE regressions with the data in first differences. A similar pattern to the PCA results emerges, in that the average correlations are considerably lower than in the levels case in panel [a]. The CD test cannot reject cross-section independence for the FD-OLS residuals (CD=0.04) — recall that this regression includes $T-1$ year dummies which seem to capture the average impact of the unobserved common factor(s) across countries. In contrast the residuals from the 2FE regression with data in first differences (*after* the 2FE transformation) display cross-section dependence.

Finally, we follow Pesaran (2004) and run autoregressions for each variable in each country. Panel [c] reports CD statistics and the mean correlations across countries for the residuals ($\hat{e}_{it}$) from an AR(2) regression defined $z_{it} = \pi_{1,i} z_{i,t-1} + \pi_{2,i} z_{i,t-2} + \pi_{t,i} t + \pi_{0,i} + e_{it}$. We also report these statistics for the residuals from individual country regressions ($\hat{e}^{MG}$) and the Pesaran (2006) Common Correlated Effects country regressions ($\hat{e}^{CCEMG}$) — again, these are the production functions discussed in the main section. The AR regression and country regression residual series fail the test for cross-section independence since these regressions do not account for the impact of unobserved common factors. In contrast we cannot reject cross-section independence for the CCEMG residuals (CD=0.21).

In summary, the investigation of the full sample ('global' data) offers strong evidence of cross-section dependence in the variable series studied. The basic assumption of the standard panel estimators that data is cross-sectionally independent is therefore violated. We can see this in our analysis of the regression residuals from the pooled OLS and 2-way Fixed Effects estimators, as well as the individual country regressions (MG). Crucially, residuals from the pooled OLS estimator with variables in first differences (FD-OLS) and the Pesaran (2006) CCEMG estimator, the latter specifically developed to deal with heterogeneous and cross-sectionally dependent panels, both pass the test for cross-section independence.

Having investigated the full sample case, we now turn to analyse unobserved common factors in various spatial groupings. We begin with an investigation of the within-group correlations in a number of 'geo-historical' categories, where we distinguish countries from East Asia (EA), Latin America & the Caribbean (LAC), Middle East & North Africa (MENA), South Asia (SA), Sub-Saharan Africa (SSA) and Europe & other Western Industrialised Countries (EU). The latter category includes the United States, Canada, New Zealand and Australia, pointing to the general makeup of each category not just based on geography, but also cultural characteristics and historical grounds.

Table C-3: Regional Cross-section Dependence (i)

Mean Absolute Correlation Coefficients Regional cross-section dependence									
Panel [a]		**Variables**†						**Residuals**‡	
	obs	ly	lL	ltr	llive	lf	ln	$\hat{e}^{POLS}$	$\hat{e}^{2FE}$
Mean absolute correlations: $(N(N-1))^{-1}\sum_i\sum_j\lvert\hat{\rho}_{ij}\rvert$									
East Asia	182	0.727	0.740	0.617	0.461	0.600	0.554	0.407	0.516
Europe & other WIC	756	0.893	0.870	0.848	0.732	0.726	0.843	0.682	0.479
Latin America & Caribbean	552	0.610	0.661	0.657	0.465	0.566	0.544	0.365	0.445
MENA	272	0.697	0.643	0.871	0.640	0.725	0.531	0.320	0.331
South Asia	30	0.497	0.914	0.740	0.680	0.733	0.871	0.781	0.313
SSA	1482	0.427	0.914	0.631	0.520	0.385	0.634	0.367	0.350
Panel [b]		**AR regression residuals**♮						**Residuals**‡	
	obs	$\hat{e}^{ly}$	$\hat{e}^{lL}$	$\hat{e}^{ltr}$	$\hat{e}^{llive}$	$\hat{e}^{lf}$	$\hat{e}^{ln}$	$\hat{e}^{MG}$	$\hat{e}^{CCEMG}$
Mean absolute correlations: $(N(N-1))^{-1}\sum_i\sum_j\lvert\hat{\rho}_{ij}\rvert$									
East Asia	182	0.132	0.409	0.170	0.142	0.164	0.136	0.139	0.159
Europe & other WIC	756	0.155	0.420	0.163	0.154	0.176	0.155	0.149	0.156
Latin America & Caribbean	552	0.139	0.347	0.146	0.131	0.135	0.140	0.154	0.154
MENA	272	0.156	0.321	0.131	0.133	0.156	0.151	0.154	0.171
South Asia	30	0.108	0.388	0.125	0.138	0.169	0.142	0.137	0.126
SSA	1482	0.131	0.232	0.151	0.133	0.149	0.135	0.152	0.157

See Table C-2 for notes and descriptions. Country groupings are described in Table ?? ("other WIC" refers to other Western industrialised countries, namely the US, Canada, New Zealand and Australia).

Table C-3 presents variable (and residual) mean absolute correlations (we omit the mean standard correlations to save space) within each of these country groupings. The number of observations ranges from 30 in South Asia ($N = 6$) to 1,482 in Sub-Saharan Africa ($N = 39$). In panel [a] we report results for the variables in levels and the regression residuals from OLS and 2FE regressions. All variables are uniformly highly correlated within country groupings. For the regression residuals in particular the members of the Europe & WIC and East Asia groups show high levels of correlation.[16] In panel [b] we investigate residuals from the autoregressions outlined above as well as the country regressions and CCE country regressions. All of these show significantly lower levels of correlation. Average correlation (not reported) shows a much higher range of correlation coefficients across the groups, in the case of land from -.06 in East Asia to .58 in Europe & WIC and .87 in South Asia. In the latter analysis regression residuals from POLS and 2FE remain high in the Europe & WIC case (.41 and .28 respectively), but are virtually insignificant in the MG and CCEMG case (.05 and .02).

In Table C-4 we present the results for the CD test statistic within and across regions applied to various regression residuals. Panels [a] to [e] are for the pooled OLS (POLS), 2-way Fixed Effects (2FE), OLS in first differences (FD-OLS), country regression and CCE country regression residuals respectively. Panel [f] shows the number of observations (pairwise correlations) for each test. We marked the test statistics which indicate rejection of the null of cross-section independence in bold.

Focusing first on the *within-group* CD test statistics (on the diagonals), we can see that these commonly reject cross-section independence across all estimation strategies, although less so in the country and CCEMG regression cases. With regard to *cross-group* dependence tests, it can be seen that residuals from the pooled regression in levels and the pooled 2FE regression display a high level of common factor structure, leading to the rejection of the null of cross-section independence in almost all cases. For the pooled regression with variables in first differences 10 out of 15 cross-group tests cannot reject the null of cross-section independence, whereas for country regressions 12 tests cannot reject. For CCEMG all 15 tests cannot reject independence across groups. The results in panel [e] for CCEMG residuals suggests that this estimation approach cannot entirely wipe out the cross-section dependence in the data if viewed from a group-perspective. It is no longer the case that the number of observations is systematically linked to the test statistic, suggesting that the results are not driven by small sample size.

In Table C-5 we apply an alternative 'spatial' grouping, whereby the share of arable land in one of three eco-climatic zones determines group membership. We use data from Matthews (1983), reported in Gallup et al. (1999), on this variable and group countries into equatorial (EQ), arid (AR) or temperate & cold (TEMP) climate zones if they have 40% or more arable land share in the respective climatic zone. We provide details on the countries that drop out of the sample as a result of this categorisation and the treatment of those countries that enter more than one category in the table footnote. Panels [a] to [e] again provide CD test statistics for regression residuals, panel [f] shows the number of observations for each climate-zone combination. Again the pooled and standard country regression estimators fail most or all tests for residual independence within and across groups, although for 2FE only the temperate & cold zone shows high levels of dependence. The CCEMG residuals now cannot reject independence in any of the tests.

[16]Note that the South Asian group is made up of 6 countries only, so that the CD test statistics are likely to be highly distorted. We nevertheless kept these countries separate due to their distinct geographical and climatic characteristics.

Table C-4: Regional Cross-section Dependence (ii)

Pesaran CD statistic — within and across regions Regional cross-section dependence						
Panel [a]	***Residuals from pooled OLS regression***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	0.42					
Europe & other WIC (EU)	**-11.31**	**50.77**				
Latin America & Caribbean (LAC)	0.64	**7.11**	**3.45**			
Middle East & N Africa (MENA)	**-4.33**	**9.72**	**-2.37**	1.06		
South Asia (SA)	**4.84**	**-21.47**	**-4.20**	**-2.85**	**7.07**	
Sub-Saharan Africa (SSA)	**5.41**	**-26.89**	**-4.85**	**-5.97**	**11.73**	**10.42**
Panel [b]	***Residuals from 2-way FE regression***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	0.59					
Europe & other WIC (EU)	**10.00**	**34.51**				
Latin America & Caribbean (LAC)	**4.00**	**13.46**	**3.69**			
Middle East & N Africa (MENA)	**3.54**	**12.20**	**2.07**	**11.62**		
South Asia (SA)	0.36	**-3.44**	**-2.11**	**6.14**	**3.80**	
Sub-Saharan Africa (SSA)	**-5.14**	**-15.29**	**-4.93**	**-13.44**	**-5.07**	**10.82**
Panel [c]	***Residuals from FD-OLS regression***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	**2.15**					
Europe & other WIC (EU)	**2.04**	**3.17**				
Latin America & Caribbean (LAC)	**2.32**	0.60	**2.45**			
Middle East & N Africa (MENA)	-1.82	0.16	**-2.04**	0.11		
South Asia (SA)	1.63	-0.04	0.83	-0.99	**2.71**	
Sub-Saharan Africa (SSA)	-0.10	**-2.20**	-1.11	**-2.07**	0.24	0.96
Panel [d]	***Residuals from country regressions***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	0.83					
Europe & other WIC (EU)	**3.00**	**6.21**				
Latin America & Caribbean (LAC)	0.58	0.02	1.86			
Middle East & N Africa (MENA)	0.29	**2.77**	0.18	0.32		
South Asia (SA)	0.87	1.65	0.73	-0.15	1.87	
Sub-Saharan Africa (SSA)	0.05	1.92	**2.04**	1.03	1.31	**5.92**
Panel [e]	***Residuals from CCE country regressions***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	**2.14**					
Europe & other WIC (EU)	1.35	**2.36**				
Latin America & Caribbean (LAC)	0.13	-1.92	1.58			
Middle East & N Africa (MENA)	0.27	0.40	-0.94	1.29		
South Asia (SA)	0.94	-0.26	0.34	-0.10	**2.43**	
Sub-Saharan Africa (SSA)	-0.47	-1.91	0.53	-0.48	-0.37	1.29

Panel [f]	***Number of observations***					
	EA	EU	LAC	MENA	SA	SSA
East Asia (EA)	182					
Europe & other WIC (EU)	392	756				
Latin America & Caribbean (LAC)	336	672	552			
Middle East & N Africa (MENA)	238	476	408	272		
South Asia (SA)	84	168	144	102	30	
Sub-Saharan Africa (SSA)	546	1092	936	663	234	1482

See Table C-2 for notes and descriptions. Country groupings are described in Table **??** ("other WIC" refers to other Western industrialised countries, namely the US, Canada, New Zealand and Australia).
The test statistics in bold are statistically significant at the 5% level and thus reject the null of cross-section independence.
Note that the 'own-correlation' coefficients ($\hat{\rho}_{ii} = 1$) are excluded from the analysis, such that they do not interfere with the within-group dependence statistic on the diagonal.
Panel [f] reports the number of individual correlation estimates ($N(N-1)$) used in the construction of the CD statistic.

Table C-5: Climate-zone Cross-section Dependence

Pesaran CD statistics — within and across climate zones We take 40% of arable land in each climate-zone as cut-off							
Panel [a] **POLS residuals**	EQ	AR	TEMP	**Panel [b]** **2FE residuals**	EQ	AR	TEMP
Equatorial (EQ)	**2.29**			Equatorial (EQ)	-0.09		
Arid (AR)	2.00	-0.59		Arid (AR)	-1.18	-1.78	
Temperate & Cold (TEMP)	**-11.71**	**-9.36**	**31.28**	Temperate & Cold (TEMP)	-0.89	1.38	**32.79**
Panel [c] **FD-OLS**	EQ	AR	TEMP	**Panel [d]** **MG residuals**	EQ	AR	TEMP
quatorial (EQ)	**4.10**			Equatorial (EQ)	**2.50**		
Arid (AR)	**-3.02**	0.68		Arid (AR)	**3.47**	**3.90**	
Temperate & Cold (TEMP)	0.39	**-2.74**	0.20	Temperate & Cold (TEMP)	**2.64**	**3.47**	**6.67**
Panel [e] **CCEMG residuals**	EQ	AR	TEMP	**Panel [f]** **Observations**	EQ	AR	TEMP
Equatorial (EQ)	1.93			Equatorial (EQ)	2652		
Arid (AR)	0.29	1.31		Arid (AR)	987	342	
Temperate & Cold (TEMP)	-0.78	-1.78	1.39	Temperate & Cold (TEMP)	2650	966	2550

We divide countries into climatic zones based on the share of their arable land within the (a) equatorial, (b) arid, or (c) temperate & cold climate zones, based on the data provided in Gallup et al. (1999). The cut-off is 40%; for instance a country is grouped as equatorial if 40% or more of its arable land is in the equatorial climate zone. The following 12 countries are excluded from the analysis since they do not have 40% of more in either of the three categories: AFG, ARE, ECU, ETH, IND, IRN, KEN, KWT, MEX, OMN, QAT, YEM. Note that half of these 12 countries have 59% or more land in the 'highland' climatic zone. Further, the following 6 countries are contained in more than one climatic zone: AUS, BEN, LAO, VNM, ZAF, ZWE; since the own-correlation coefficients ($\hat{\rho}_{ii} = 1$) are excluded from the analysis, this does not affect the CD statistics. The test statistics in bold are statistically significant at the 5% level and thus reject cross-section independence.

D Additional tables and figures

Table D-1: Dynamic specification — Pooled regressions (CRS imposed)

Pooled regressions dependent variable: [1],[2] & [4]-[7] log output per worker, [3] dto. in 2FE transformation♮, [8] Δlog output per worker, [9] dto. in 2FE transformation♮						
	[1] **POLS**◇	[2] **2FE**♮	[3] **CCEP**	[4] **CCEP**	[5] **CCEP**	[6] **CCEP**
weight matrix‡			none	neighbour	distance	agro-climate
lagged levels						
output pw $(t-1)$	-0.0189	-0.1764	-0.6072	-0.4024	-0.4959	-0.5699
	[5.71]**	[22.80]**	[22.54]**	[19.87]**	[21.44]**	[22.80]**
tractors pw $(t-1)$	0.0022	0.0134	0.0678	0.0454	0.0429	0.0493
	[1.85]	[5.47]**	[7.02]**	[7.51]**	[5.90]**	[5.76]**
livestock pw $(t-1)$	0.0042	0.0709	0.2045	0.1064	0.1850	0.2298
	[2.49]*	[10.07]**	[9.67]**	[5.89]**	[9.31]**	[10.32]**
fertilizer pw $(t-1)$	0.0061	0.0147	0.0258	0.0360	0.0243	0.0237
	[5.86]**	[7.76]**	[5.79]**	[8.45]**	[4.10]**	[5.64]**
land pw $(t-1)$	0.0045	0.0554	0.1959	0.1097	0.1980	0.1837
	[2.28]*	[7.28]**	[5.35]**	[4.46]**	[6.38]**	[5.77]**
growth rates						
Δtractors pw	0.0555	0.0970	0.0828	0.0591	0.0558	0.0771
	[4.12]**	[8.49]**	[4.37]**	[3.55]**	[4.61]**	[4.82]**
Δlivestock pw	0.3153	0.3307	0.3097	0.2899	0.3175	0.2726
	[7.57]**	[17.31]**	[9.43]**	[8.82]**	[10.65]**	[8.21]**
Δfertilizer pw	0.0123	0.0172	0.0132	0.0196	0.0171	0.0152
	[3.48]**	[5.63]**	[3.27]**	[4.79]**	[3.67]**	[3.99]**
Δland pw	0.3010	0.3290	0.3249	0.3272	0.3404	0.3170
	[4.38]**	[11.67]**	[4.86]**	[5.88]**	[7.42]**	[6.42]**
Constant	0.0485		2.6725	1.7939	0.0141	3.5301
	[5.34]**		[0.35]	[1.75]	[0.01]	[1.85]
Observations	5,013	5,013	5,013	5,013	5,013	5,013
R-squared	0.12	0.20	0.54	0.54	0.81	0.60
Estimated long-run coefficients♭						
tractors pw	0.118	0.076	0.112	0.113	0.087	0.087
	[2.09]*	[5.58]**	[7.21]**	[7.73]**	[6.33]**	[5.80]**
livestock pw	0.224	0.402	0.337	0.264	0.373	0.403
	[2.77]**	[11.30]**	[10.51]**	[6.30]**	[10.40]**	[11.27]**
fertilizer pw	0.322	0.083	0.042	0.089	0.049	0.042
	[5.07]**	[8.09]**	[5.85]**	[8.67]**	[4.16]**	[5.80]**
land pw	0.238	0.314	0.323	0.273	0.399	0.322
	[2.56]*	[7.95]**	[5.34]**	[4.50]**	[6.69]**	[5.93]**
Implied β_L	0.098	0.125	0.186	0.261	0.092	0.146
Arellano-Bond Serial Correlation Test — H_0: no serial correlation in the residuals						
AR(1) (p)	-9.69 (.00)	-14.95 (.00)	-3.30 (.00)	-6.46 (.00)	-4.71 (.00)	-3.88 (.00)
AR(2) (p)	-0.41 (.68)	3.15 (.00)	-1.28 (.20)	1.43 (.15)	-3.36 (.00)	0.06 (.95)
AR(3) (p)	0.60 (.55)	4.12 (.00)	-1.68 (.09)	0.39 (.70)	-0.82 (.41)	-1.98 (.05)
Nonstationarity: Pesaran (2007) CIPS test applied to residuals♯ — H_0: residuals are I(1)						
lags	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)	Ztbar (p)
none	-48.93 (.00)	-44.51 (.00)	-45.04 (.00)	-47.06 (.00)	-45.84 (.00)	-44.61 (.00)
1 lag	-38.33 (.00)	-29.68 (.00)	-32.18 (.00)	-32.43 (.00)	-32.08 (.00)	-31.67 (.00)
2 lags	-23.23 (.00)	-16.08 (.00)	-20.66 (.00)	-21.58 (.00)	-22.27 (.00)	-20.41 (.00)
3 lags	-15.77 (.00)	-8.30 (.00)	-16.05 (.00)	-14.15 (.00)	-16.51 (.00)	-15.44 (.00)
CSD: Mean Correlation coefficient & Pesaran (2004) CD test — H_0: no CSD						
Mean ρ_{ij}	0.00	0.01	0.00	0.00	0.10	0.00
Mean $\lvert\rho_{ij}\rvert$	0.14	0.15	0.17	0.14	0.16	0.15
CD (p)	-0.08 (.94)	2.66 (.00)	-0.47 (.64)	1.31 (.19)	26.34 (.00)	-0.62 (.53)
Further residual diagnostic tests⋆ — H_0: no heteroskedasticity, regular skewness/kurtosis						
(A) Joint test χ^2 (p)	1019.7 (.00)	943.6 (.00)	623.4 (.00)	551.0 (.00)	559.4 (.00)	566.1 (.00)
(B) Joint test χ^2 (p)	1463.7 (.00)	1166.1 (.00)	-	-	-	-

Notes: See Table 6 for details.
◇ We include $T-1$ year dummies in equation [1].