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Aggregation versus Heterogeneity in Cross-Country Growth Empirics*

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Abstract:

The cross-country growth literature commonly uses aggregate economy datasets such as the Penn World Table (PWT) to estimate homogeneous production function or convergence regression models. Against the background of a dual economy framework this paper investigates the potential bias arising when aggregate economy data instead of sectoral data is adopted in macro production function regressions. Using a unique World Bank dataset we estimate production functions in agriculture and manufacturing for a panel of 41 developing and developed countries (1963-1992). We employ novel empirical methods which can accommodate technology heterogeneity, variable nonstationarity and the breakdown of the standard cross-section independence assumption. We then investigate the potential for biased estimates due to aggregation and empirical misspecification, relying on both theory and Monte Carlo simulations. We confirm substantial bias in the technology coefficients using data for a stylised aggregate economy made up of agricultural and manufacturing sectors and a matched PWT dataset.

Keywords: dual economy model; cross-country production function; aggregation bias; technology heterogeneity; common factor model; panel time series econometrics

JEL classification: C23, O47, O11

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1. INTRODUCTION

In the early literature on developing countries a distinction was made between the processes of economic development and of economic growth. Economic development was seen to be a process of structural transformation by which in Lewis' frequently cited phrase an economy which was "previously saving and investing 4 or 5 percent of its national income or less, converts itself into an economy where voluntary savings is running at about 12 to 15 percent of national income" (Lewis, 1954, p.155). An acceleration in the investment rate was only one part of this process of structural transformation; of equal importance was the process by which an economy moved from a dependence on subsistence agriculture to one where an industrial modern sector absorbed an increasing proportion of the labour force (e.g. Jorgensen, 1961; Kuznets, 1961; Ranis & Fei, 1961; Robinson, 1971). In contrast to these models of "development for backward economies" (Jorgensen, 1961, p.309), where duality between the modern and traditional sectors was a key feature of the model, was the analysis of economic growth in developed economies.[1] Here the processes of factor accumulation and technical progress occur in an economy which is already 'developed', in the sense that it has a modern industrial sector and agriculture has ceased to be a major part of the economy (e.g. Solow, 1956, 1957; Swan, 1956).

Much of the early growth modelling work proceeded without close connection to observed data. The models were in Solow's classic exposition of growth theory inspired by stylised 'Kaldor' facts (Kaldor, 1957). The dual economy models of structural transformation used case studies (e.g. Paauw & Fei, 1973) and facts at least as stylised as those in the Solow-Swan growth context. The key papers which brought modelling and data together were the contributions of Barro (1991) and Mankiw, Romer, and Weil (1992), which initiated a major revival in the Solow-Swan model and effectively merged the concerns of economic development with those of growth.

The literature begun in the early 1990s has yielded a large array of models in which there has been increasing interaction between the theory and the empirics (see discussion in Durlauf & Quah, 1999; Easterly, 2002; Durlauf, Johnson, & Temple, 2005). The latter continue to be dominated by an empirical version of the aggregate Solow-Swan model (Temple, 2005) with much of the empirical debate focusing on the roles of factor accumulation versus technical progress (Young, 1995; Klenow & Rodriguez-Clare, 1997a, 1997b; Easterly & Levine, 2001; Baier, Dwyer, & Tamura, 2006). While there is some new theoretical and empirical work using a dual economy model (e.g. Vollrath, 2009a, 2009b), this is largely absent from textbooks on economic growth and has not been the central focus of attention for most of the empirical analyses (Temple, 2005). A primary reason for the focus has been the availability of data. The Penn World Table (PWT) dataset (most recently, Heston, Summers, & Aten, 2009) and the Barro-Lee data on human capital (most recently, Barro & Lee, 2010) have supplied macro-data which ensure that the aggregate Solow-Swan model can be readily estimated. However, somewhat underappreciated by the applied empirical literature, a team at the World Bank has developed comparable sectoral data for agriculture and manufacturing (Crego, Larson, Butzer, & Mundlak, 1998) that enables a closer matching between a dual economy framework and the data, which we seek to exploit in this paper.

Cross-country growth regressions represent one of the most active fields of empirical analysis within applied development economics, however the viability of this empirical approach has been seriously questioned over the past decade and at present these methods are deeply unfashionable. We have argued elsewhere that much can be learned from cross-country empirics provided the empirical setup

[1] A note on nomenclature: we refer to 'duality' or 'dual economy models' as representing economies with two stylised sectors of production (agriculture and manufacturing). 'Production technology' and 'technology parameters' refer to the coefficients on capital and labour in the production function model (elasticities with respect to capital and labour), *not* Total Factor Productivity (TFP) or its growth rate (technical/technological progress).

allows for greater flexibility in the estimation equation and recognises the salient data properties of macro panel datasets (Eberhardt & Teal, 2010). Methods developed in the emerging panel time series literature (Bai & Ng, 2002, 2004; Coakley, Fuertes, & Smith, 2006; Pesaran, 2006; Bai, 2009) can go further in providing robust estimation and inference for nonstationary panel data where variable series may be correlated across countries and where common shocks are likely to impact all countries in the sample, albeit to a different extent.

This paper, providing empirical analysis of panel data for developing and developed economies, sets out to address three main objectives: (i) rather than using a calibrated dual economy model for quantitative analysis we provide empirical estimates for technology coefficients in sectoral production functions. (ii) We estimate a stylised aggregate production function model from agriculture and manufacturing data, and compare results with those from disaggregated regressions. This will allow us to judge whether neglecting a dual economy structure leads to bias in the empirical technology coefficients. (iii) We use theoretical arguments and evidence from Monte Carlo simulations to investigate the sources and manifestation of aggregation bias in cross-country growth analysis.

The remainder of the paper is organised as follows: Section 2 motivates technology heterogeneity across sectors and countries. In Section 3 we introduce an empirical specification of our dual economy framework, discuss the data and briefly review the empirical methods and estimators employed. Section 4 reports and discusses empirical findings at the sector-level. Section 5 then investigates the potential sources of bias in aggregate economy data employing Monte Carlo simulations to provide support and presents empirical findings from stylised and PWT aggregate data. Section 6 summarizes and concludes.

2. TECHNOLOGY HETEROGENEITY

2.1 Technology Heterogeneity across Sectors

From a technical point of view, an aggregate production function only offers an appropriate construct in cross-country analysis if the economies investigated do not display large differences in sectoral structure (Temple, 2005), since a single production function framework assumes common production technology across all 'firms' facing the same factor prices. Take two distinct sectors within this economy, assuming marginal labour product equalisation and capital homogeneity across sectors, and Cobb-Douglas-type production technology. Then if technology parameters differ between sectors, aggregated production technology cannot be of the (standard) Cobb-Douglas form (Theil, 1954; Stoker, 1993; Temple & Wößmann, 2006; Córdoba & Ripoll, 2009). Finding differential technology parameters in sectoral production function estimation thus is potentially a serious challenge to treating production in form of an aggregated function.

An alternative motivation for a focus on sector-level rather than aggregate growth across countries runs as follows: it is common practice to exclude oil-producing countries from any aggregate growth analysis, since "the bulk of recorded GDP for these countries represents the extraction of existing resources, not value added" (Mankiw et al., 1992, p.413). The underlying argument is that sectoral 'distortions', such as resource wealth, justify the exclusion of the country observations. By extension of the same argument, we could suggest that given the large share of agriculture in GDP for countries such as Malawi (25-50%), India (25-46%) or Malaysia (8-30%) over the period 1970-2000, these countries should be excluded from any *aggregate* growth analysis since a significant share of their *aggregate* GDP derives from a single resource, namely land.[2] Sector-level analysis, in contrast, does not face these difficulties, since sectors such as manufacturing or agriculture are defined closely enough to represent a reasonably homogeneous conceptual construct.

Having already indicated the importance of agriculture for GDP for a number of countries, we complete this section by providing some more data to highlight the importance and dynamics of agriculture in a wider set of countries.

`[Table I about here]`

As can be seen in Table I the shift away from agriculture has been most dramatic in the East Asia group, whereas the Sub-Saharan Africa has seen virtually no change over the same period.

2.2 Technology Heterogeneity across Countries

A theoretical justification for heterogeneous technology parameters *across countries* can be found in the 'new growth' literature. This strand of the theoretical growth literature argues that production functions differ across countries and seeks to determine the sources of this heterogeneity (Durlauf, Kourtellos, & Minkin, 2001). As Brock and Durlauf (2001, p.8/9) put it: "…the assumption of parameter homogeneity seems particularly inappropriate when one is studying complex heterogeneous objects such as countries …". The model by Azariadis and Drazen (1990) can be seen as the 'grandfather' for many of the theoretical attempts to allow for countries to possess different technologies from each other (and/or at different points in time). Further theoretical papers lead to multiple equilibria interpretable as factor parameter heterogeneity in the production function (e.g. Murphy, Shleifer, & Vishny, 1989; Durlauf, 1993; Banerjee & Newman, 1993). A simpler justification for heterogeneous production functions is offered by Durlauf et al. (2001, p.929): the Solow model was never intended to be valid in a homogeneous specification for *all* countries, but may still be a good way to investigate *each* country, i.e. if we allow for parameter differences *across* countries.

3. AN EMPIRICAL MODEL OF A DUAL ECONOMY

In seeking to understand processes of growth at the macro-level, empirical work has focused primarily on an aggregate production specification (see surveys in Barro & Sala-i-Martin, 1995; Temple, 1999; Aghion & Durlauf, 2005). While duality has featured prominently in theoretical developments there has been only a very limited matching of this theory to empirical models. This disjunction between theory and testing has reflected in large part the availability of data. In this paper we employ a large-scale cross-country dataset made publicly available by the World Bank in 2003 (henceforth Crego et al (1998), although the data is also described in detail in Larson, Butzer, Mundlak, & Crego, 2000) which allows us to specify manufacturing and agricultural production functions and thus provides a macro-model of a dual economy that can be compared with the single sector models dominating the empirical literature. In the following we first present a general empirical specification for our sector-specific analysis of agriculture and manufacturing. Next we review a number of empirical estimators, focusing in particular on those arising from the recent panel time series literature, before we briefly discuss the data.

[2] The quoted shares are from the World Development Indicators database (World Bank, 2008). For comparison, maximum share of oil revenue in GDP, computed as the difference between 'industry share in GDP' and 'manufacturing share in GDP' from the same database yields the following ranges for some of the countries omitted in Mankiw et al. (1992): Iran (12-51%), Kuwait (15-81%), Gabon (28-60%), Saudi Arabia (29-67%).

3.1 Empirical Specification

Our empirical setup adopts a common factor representation for a standard log-linearised Cobb-Douglas production function model. Each sector/level of aggregation (agriculture, manufacturing, aggregate(d) data) is modelled separately — for ease of notation we do not identify this multiplicity in our general model. Let

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{1}$$

$$x_{mit} = \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \rho_{1mi} f_{1mt} + \ldots + \rho_{nmi} f_{nmt} + v_{mit} \tag{2}$$

$$\boldsymbol{f}_t = \boldsymbol{\varrho}' \boldsymbol{f}_{t-1} + \boldsymbol{\omega}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t \tag{3}$$

for $i = 1, \ldots, N$, $t = 1, \ldots, T$ and $m = 1, \ldots, k$, where $\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$ and the error terms ε_{it}, v_{mit}, $\boldsymbol{\omega}_t$ and $\boldsymbol{\epsilon}_t$ are white noise. Equation (1) represents the production function model, with y as sectoral or aggregated value-added and $\boldsymbol{x}$ as a set of inputs: labour, physical capital stock, and a measure for natural capital stock (arable and permanent crop land) in the agriculture specification (all variables are in logs). We consider additional inputs (human capital, livestock, fertilizer) as robustness checks for our general findings (results available on request). The output elasticities associated with each input ($\boldsymbol{\beta}_i$) are allowed to differ across countries. For unobserved TFP we employ the combination of a country-specific TFP level (α_i) and a set of common factors ($\boldsymbol{f}_t$) with country-specific factor loadings $\boldsymbol{\lambda}_i$ — TFP is thus in the spirit of a 'measure of our ignorance' (Abramowitz, 1956) and operationalised via an unobserved common factor representation.[3] Equation (3) provides some structure for the unobserved common factors, which are modelled as simple AR(1) processes, where we do not exclude the possibility of unit root processes ($\boldsymbol{\varrho} = 1$, $\boldsymbol{\kappa} = 1$) leading to nonstationary observables and unobservables. Note that from this the potential for spurious regression results arises if the empirical equation is misspecified. Equation (2) details the evolution of the set of $m = 1, \ldots, k$ regressors; crucially, some of the common factors contained in the covariates are also assumed to be driving the unobservables in the production function equation (u_{it}). This setup leads to endogeneity whereby the regressors are correlated with the unobservables, making it difficult to identify $\boldsymbol{\beta}_i$ separately from $\boldsymbol{\lambda}_i$ and $\boldsymbol{\rho}_i$ (Kapetanios et al., 2009).

Our empirical specification allows for a large degree of flexibility with regard to the impact of observables and unobservables on output. Empirical implementation will necessarily lead to different degrees of restrictions on this flexibility, which will then be formally tested: the emphasis is on comparison of different empirical estimators allowing for or restricting the heterogeneity in observables and unobservables outlined above. A conceptual justification for the pervasive character of unobserved common factors is provided by the nature of macro-economic variables in a globalised world. In our mind latent forces drive all of the variables in our model, and their presence makes it difficult to argue for the validity of traditional approaches to causal interpretation of cross-country growth analyses. Instrumental variable estimation in standard cross-section growth regressions or Arellano and Bond (1991)-type lag-instrumentation in pooled panel models are both invalid in the face of common factors and/or heterogeneous equilibrium relationships (Pesaran & Smith, 1995; Lee, Pesaran, & Smith, 1997). In the next section we introduce a novel estimation approach developed by Pesaran (2006) which allows us to bypass these issues.

[3] The parameters $\boldsymbol{\beta}_i$ are unknown random coefficients with fixed means and finite variances. The same applies for the unknown factor loadings. The random coefficient assumption is for convenience and coefficients could alternatively be fixed but differing across countries — see Pesaran and Smith (1995, footnote 2, p.81) and Kapetanios, Pesaran, and Yamagata (2009, p.6).

3.2 Empirical Implementation

Our empirical approach emphasises the importance of parameter and factor loading heterogeneity across countries. The following 2×2 matrix indicates how the various estimators implemented below account for these matters.[4] Note that we confined results for the estimators marked with stars to the Technical Appendix to save space.

		Factor loadings: HOMOGENEOUS	*Factor loadings:* HETEROGENEOUS
Technology parameters:	HOMOGENEOUS	POLS, 2FE, FD, GMM*, PMG*	CCEP, CPMG*
	HETEROGENEOUS	MG, FDMG	CMG

We abstract from discussing the standard panel estimators here in great detail and refer to the overview articles by Coakley et al. (2006), as well as the articles by Bond and Eberhardt (2009) and Bond (2002) for more information. As a robustness check we also investigate the Pooled Mean Group (PMG) estimator by Pesaran et al. (1999); for a detailed discussion of this approach in the context of cross-country regressions refer to Arnold, Bassanini, and Scarpetta (2007). We further implement a simple extension to the PMG where we include cross-section averages of the dependent and independent variables, as suggested in Binder and Offermanns (2007).

The Common Correlated Effects estimators developed in Pesaran (2006) and extended to nonstationary variables in Kapetanios et al. (2009) augment the regression equation with cross-section averages of the dependent ($\bar{y}_t$) and independent variables ($\bar{\boldsymbol{x}}_t$) to account for the presence of unobserved common factors. For the Mean Group version (CMG), the individual country regression is specified as

$$y_{it} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + c_{0i}\bar{y}_t + \sum_{m=1}^{k} \boldsymbol{c}_{mi}\bar{x}_{mt} + e_{it} \tag{4}$$

for $m = 1, \ldots, k$ observed covariates and e_{it} white noise, whereupon the parameter estimates are averaged across countries akin to the Pesaran and Smith (1995) Mean Group estimator. The pooled version (CCEP) is specified as

$$y_{it} = a_i + \boldsymbol{b}' \boldsymbol{x}_{it} + \sum_{j=1}^{N} c_{0i}(\bar{y}_t D_j) + \sum_{m=1}^{k}\sum_{j=1}^{N} \boldsymbol{c}_{mi}(\bar{x}_{mt} D_j) + e_{it} \tag{5}$$

where the D_j represent country dummies. Thus in the MG version we have N individual country regressions with $2k + 2$ RHS variables and in the pooled version we have a single regression equation with $k + (k + 2)N$ RHS variables.

[4]Abbreviations: POLS — Pooled OLS, 2FE — 2-way Fixed Effects, FD — OLS with variables in first differences, GMM — Arellano and Bond (1991) Difference GMM and Blundell and Bond (1998) System GMM, MG — Pesaran and Smith (1995) Mean Group with linear country trend, FDMG — dto. but with variables in first difference and country drift, PMG — Pesaran, Shin, and Smith (1999) Pooled Mean Group estimator, CPMG — dto. but augmented with cross-section averages following Binder and Offermanns (2007), CCEP/CMG — Pesaran (2006) Common Correlated Effects estimators. Note that our POLS and FD models are augmented with $T - 1$ year dummies.

In order to get an insight into the workings of this approach, consider the cross-section average of our common factor model in equation (1): given $\bar{\varepsilon}_t = 0$

$$\bar{y}_t = \bar{\alpha} + \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t + \bar{\boldsymbol{\lambda}}'\bar{\boldsymbol{f}}_t \tag{6}$$

which can be expressed as

$$\bar{\boldsymbol{f}}_t = \bar{\lambda}^{-1}(\bar{y}_t - \bar{\alpha} - \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t) \tag{7}$$

Thus we can see that the unobserved common factors can be captured by the cross-sectional means of y and $\boldsymbol{x}$ provided $\bar{f}_t \xrightarrow{p} f_t$ as $N \to \infty$. Given the assumed heterogeneity in factor loadings across countries ($\boldsymbol{\lambda}_i$) the estimator is implemented in the fashion detailed above which allows for each country i to have different parameter estimates on $\bar{y}_t$ and the $\bar{\boldsymbol{x}}_t$. Simulation studies (Pesaran, 2006; Coakley et al., 2006; Kapetanios et al., 2009; Pesaran & Tosetti, 2010) have shown that this approach performs well even when the cross-section dimension N is small, when variables are nonstationary, cointegrated or not, subject to structural breaks and/or in the presence of 'weak' unobserved common factors (spatial spillovers) and global/local business cycles. In the present study we implement two variants of the CCE estimators in the sector-level regressions: a standard form as described above; and a variant which includes the cross-section averages of the input and output variables in the own *as well as* the other sector. The latter specification allows for cross-section dependence *across* sectors, albeit at the cost of a reduction in degrees of freedom.

A number of alternative nonstationary panel estimators for the case of homogeneous factor loadings are available in the literature (Pedroni, 2000, 2001), however given our emphasis on cross-section dependence we do not consider them in this work. Finally, we do not adopt any empirical methods accommodating unobserved factor via a two-step method where the number of significant factors in an equilibrium relationship is determined first (Bai & Ng, 2002) before estimates of the factors, loadings and slope parameters are determined jointly (Bai & Kao, 2006; Bai, Kao, & Ng, 2009). The reasons for this choice are: firstly, the reliance of these methods on the Bai and Ng (2002) method, which is suggested to overpredict the number of relevant factors (Pesaran, 2009); secondly, the failure of these methods to account for cross-section dependence of the 'weak' type, e.g. local spillovers (Chudik, Pesaran, & Tosetti, 2010); and thirdly, the difficulties arising from unbalancedness in the panel, in which case the CCE estimators are most straightforward to implement.[5]

3.3 Data

Descriptive statistics and a more detailed discussion of the data can be found in the Appendix. Briefly, we conduct all empirical analysis with four datasets:

(1) for the agricultural sector, building on the sectoral investment series developed by Crego et al. (1998) and output from the World Development Indicators (WDI; World Bank, 2008), as well as sectoral labour and land data from FAO (2007);
(2) for the manufacturing sector, building on the sectoral investment series developed by Crego et al. (1998), output data from the WDI and labour data from UNIDO (2004);
(3) for a stylised aggregate economy made up of the aggregated data for the agriculture and manufacturing sectors;[6]
(4) for the aggregate economy, building on data provided by the Penn World Table (PWT; we use version 6.2, Heston, Summers, & Aten, 2006).

[5]We do not account for missing observations in any way; recently Smith and Tasiran (2010) have investigated this issue in the context of the Swamy (1970) random coefficient model (RCM). The preferred empirical specifications presented below are based on heterogeneous parameter models, where arguably the unbalancedness (25% of observations in the balanced panel are missing) comes less to bear than in the homogeneous models due to the averaging of estimates.

[6]We sum the values for value-added, capital stock (both in per worker terms) and labour and then take the logarithms.

The capital stocks in the agriculture, manufacturing and PWT samples are constructed from investment series following the perpetual inventory method (see Klenow & Rodriguez-Clare, 1997b, for details), for the aggregated sample we simple added up the sectoral capital stocks. Comparison across sectors and with the stylised aggregate sector is possible due to the efforts by Crego et al. (1998) in providing sectoral investment data for agriculture and manufacturing. All monetary values in the sectoral and stylised aggregated datasets are transformed into US$ 1990 values (in the capital stock case this transformation is applied to the investment data), following the suggestions in Martin and Mitra (2002). Given concerns that the stylised aggregate economy data may not represent a sound representation of true aggregate economy data we have adopted the PWT data, which measures monetary values in International $ PPP, as a benchmark for comparison — despite a number of vocal critics (e.g. Johnson, Larson, Papageorgiou, & Subramanian, 2009) the latter is without doubt the most popular macro dataset for cross-country empirical analysis. We are of course aware that the difference in deflation between our sectoral and stylised aggregated data on the one hand and PWT on the other makes them conceptually very different measures of growth and development: the former emphasise tradable goods production whereas the latter puts equal emphasis on tradable and non-tradable goods and services. However, we believe that these differences are comparatively unimportant for estimation and inference in comparison to the distortions introduced by neglecting the sectoral makeup and technology heterogeneity of economies at different stages of economic development.

Our sample is an unbalanced panel for 1963 to 1992 made up of 41 developing and developed countries with a total of 928 observations (average $T = 22.6$) — our desired aim to compare estimates across the four datasets requires us to match the same sample, thus reducing the number of observations to the smallest common denominator. Only eight countries in our sample are in Africa, while around half are present-day ‘industrialised economies’ — these numbers are however deceiving if one recalls that structural change and development in many of the latter has been primarily achieved during our period of study. For instance, it bears reminding that prior to 1964, GDP per capita was higher in Ghana than in South Korea (Baptist & Teal, 2008). In 1970 the share of agricultural value-added in GDP for Finland, Ireland, Portugal and South Korea amounted to 13%, 16%, 31% and 26% respectively, while the 1992 figures are 5%, 8%, 7% and 8% — strong evidence of economies undergoing structural change. A detailed description of our sample is available in Table A-I, descriptive statistics are provided in Table A-II for each sample.

4. EMPIRICAL RESULTS

Preliminary data analysis (unit root and cross-section dependence tests) have been confined to the Technical Appendix of the paper. We adopt the Pesaran (2007) CIPS panel unit root test which assumes a single unobserved common factor. This is clearly restrictive, however given the data restrictions (unbalanced panel, relatively short T) we were unable to implement the more recent CIPSM version of this test (Pesaran, Smith, & Yamagata, 2009) which allows for multiple common factors. Results (see Table TA-1) strongly suggest that variables in levels for the agriculture and manufacturing data as well as the two aggregate economy representations are nonstationary.

A number of formal and informal procedures to investigate cross-section correlation in the data were carried out. Results (see Table TA-2) indicate very high average absolute correlation coefficients for the data in log levels, .6 to .95, and even in the data represented as growth rates (first difference of log levels), where the same measure is between .2 and .5. Formal tests for cross-section dependence (Pesaran, 2004; Moscone & Tosetti, 2009) reject cross-section independence in virtually all variable series tested.

In the following we discuss the empirical results from sectoral production function regressions for agriculture and manufacturing respectively, first assuming technology parameter homogeneity (Section 4.1) and then allowing for differential technology across countries (Section 4.2). For all regression models we report residual diagnostic tests including the Pesaran (2007) panel unit root test and the Pesaran (2004) CD test for cross-section independence.

4.1 Pooled Models

Table II presents the empirical results for agriculture and manufacturing, Panel (A) for unrestricted returns to scale and Panel (B) for the specification with CRS imposed. Beginning with agriculture, the empirical estimates for the models [1],[2] and [5] neglecting cross-section dependence are quite similar, with the capital coefficient around .63 and statistically significant *decreasing* returns to scale. The land coefficients are insignificant except in the 2FE model, where it carries a negative sign. Diagnostic tests indicate that the residuals in these models are cross-sectionally dependent, and that the levels models (POLS, 2FE) have nonstationary residuals and thus may represent spurious regressions. It is important to point out that in the presence of nonstationary residuals the t-statistics in the levels models are invalid (Kao, 1999) and have commonly been found to vastly overstate the precision of the estimates (Bond & Eberhardt, 2009). The two CCEP models yield stationary and cross-sectionally independent residuals, capital coefficients of around .5 and insignificant land coefficients. Imposition of CRS (Panel (B)) does not change these results substantially, with the exception of the 2FE estimates, where the land variable (previously negative and significant) is now insignificant and the capital coefficient has become further inflated.

In the manufacturing data the models [6], [7] and [10] ignoring cross-section dependence yield increasing returns to scale and capital coefficients in excess of .85 for POLS and 2FE, and .72 in the FD model. Residuals for the former two models again display nonstationarity but the CD tests now imply that they are cross-sectionally independent. FD residuals are I(0) but cross-sectionally correlated. Surprisingly the standard CCEP model in [8], with a capital coefficient of around .5 (like in agriculture) does not pass the cross-section correlation test. However, further accounting for cross-*sector* dependence in [9] yields favourable diagnostics and a similar capital coefficient. Following imposition of CRS *all* models reject cross-section independence, while parameter estimates are more or less identical to those in the unrestricted models. Based on these pooled regression results, the diagnostic tests seem to favour the CCEP results in [3] and [4] for the agriculture data, while in the manufacturing data the unrestricted CCEP model which accounts for cross-sectoral impact [9] emerges as preferred specification.

`[Table II about here]`

For the agriculture sample we conducted a number of robustness checks, including further covariates (livestock per worker, fertilizer per worker) in the pooled regression framework. Results (available on request) did not change from those presented above. We also conducted robustness checks including human capital in the estimation equation of both sectors (linear and squared terms)[7] — as a consequence a number of countries drop out of our sample leading to marginally reduced samples ($n = 860$ in manufacturing, $n = 830$ in agriculture). Results (see Table TA-IV in the Technical Appendix) for agriculture follow similar patterns to those in the unaugmented models, with the human capital proxies insignificant in the preferred CCEP specifications (unrestricted and CRS). For manufacturing the standard CCEP yields favourable diagnostics and significant human capital coefficients: returns to eduction follow a concave function (wrt years of schooling) and for the mean education value across

[7] We follow the convention and pick the average years of schooling in the population as a proxy for Human Capital stock. We assume that the aggregate economy data for schooling developed by Barro and Lee (2001), which is available in 5-year intervals, is a sound reflection of the manufacturing sector. Simple interpolation to obtain annual data is not ideal, however the evolution of this variable over time is commonly very stable (linear), s.t. we do not feel that linear interpolation creates additional problems or distortions.

countries are quite high in these models, around 8% and 11% per annum in the unrestricted and restricted models respectively. In either case residuals are stationary and cross-sectionally independent. The alternative CCEP may suffer from the large number of parameters to be estimated, yielding insignificant human capital coefficients (capital .45) and unfavourable diagnostics.

In summary, based on diagnostics testing the alternative CCEP estimator arises as the preferred estimator for both the agriculture and manufacturing samples — in the former case the imposition of CRS seems valid, whereas in the latter case this is rejected by the data. Alternative specifications incorporating a proxy for human capital did not yield any favourable results in the agriculture sector, while resulting in large and positive returns to education (evaluated at the sample mean) in the case of manufacturing. Essentially the results for the technology coefficients on land and capital qualitatively did not change compared with the standard production function results. Across preferred specifications it is notable that the mean capital coefficients for agriculture and manufacturing are quite similar, around .5. Our shift to heterogeneous technology models in the next section will allow us to judge whether these results are the outcome of empirical misspecification.

4.2 Averaged Country Regressions

Table III presents the robust means for each regressor across N country regressions for the unrestricted (Panel (A)) and CRS models (Panel (B)) respectively. We adopt robust means[8] as these are more reliable than unweighted means, which are subject to greater distortion by outliers. The t-statistics reported for each average estimate test whether the average parameter is statistically different from zero, following Pesaran and Smith (1995); we also provide test statistics for the 'panel t-statistic' following Pedroni (1999) — under the null both of these statistics are standard normal distributed.

`[Table III about here]`

Beginning with the unrestricted models in Panel (A), we can see that MG and FDMG suffer from high imprecision in both agriculture and manufacturing equations. This aside, in the agriculture model MG yields decreasing returns to scale that are nonsensical in magnitude. Monte Carlo simulations for nonstationary and cross-sectionally dependent data (Coakley et al., 2006; Bond & Eberhardt, 2009) frequently show that MG estimates are severely affected by their failure to account for cross-section dependence. As in the pooled models, the standard CMG estimator yields an insignificant land coefficient in agriculture and in both sectors results are generally very much in line with the CCEP results in Table II. All unrestricted models yield stationary residuals and cannot reject constant returns to scale; in agriculture the alternative CMG does not result in a significant capital coefficient, whereas in the manufacturing data this specification is preferable to the standard CMG, given that the latter suffers from cross-sectionally dependent residuals. Moving on to the models where CRS is imposed in Panel (B), we can see that MG and FDMG estimates are now somewhat more precise, while the standard and alternative CMG estimates in agriculture are now virtually the same. The residual diagnostics are sound in these two cases, but all of the manufacturing models suffer from cross-sectionally dependent residuals.

We further implemented an alternative specification for manufacturing which includes the level and squared human capital terms (average years of schooling in the adult population) as additional covariates (see Table TA-V in the Technical Appendix).[9] Results for the MG and FDMG mirror those in the unaugmented models presented above. In the unrestricted models these estimators yield very imprecise estimates, although if CRS is imposed the capital coefficients are estimated more precisely at

[8] We use robust regression to produce a robust estimate of the mean — see Hamilton (1992) for details.

[9] In the agriculture data augmentation with human capital did not lead to statistically significant results (available on request).

around .3; average estimates on the linear and quadratic eduction terms are insignificant and the implied returns to education are negative albeit insignificant in the robust regression approach adopted. For the standard CMG models we find capital coefficients somewhat below those in the unaugmented models, but still within each other's 95% confidence intervals.[10] Average education coefficients are significant and indicate rather high returns to eduction: 11% and 12% in the unrestricted and CRS model respectively.

The shift from homogeneous to heterogeneous parameter models brought seemingly little change to the estimated technology parameters in agriculture, where land remains insignificant, the capital coefficient is around .5 and CRS cannot be rejected. For manufacturing we note a shift toward a lower capital coefficient around .35, while the imposition of constant returns to scale leads to unfavourable diagnostics. Given the aim of our study, we do not want to focus narrowly on the best estimate what the 'true' sectoral technology coefficients could be, but instead want to highlight the discrepancy between the results in the present section and those we turn to when analysing aggregate economy data in the next section. Before we do so we discuss the issue of aggregation bias conceptually and introduce some tentative evidence from a Monte Carlo simulation exercise.

5. AGGREGATION BIAS

In this section we ask what the implications of the dual economy model are for aggregate cross-country growth analysis. First we discuss the econometric concerns arising from the aggregation of heterogeneous sectoral data created by separate technologies. We then formulate a number of production technologies for agriculture and manufacturing which reflect our insights into the effects of parameter heterogeneity, variable nonstationarity and cross-section dependence. The different technologies are investigated using Monte Carlo simulations of stylised aggregate data constructed from two sectors of production. We then investigate whether the assumption of an aggregate production function yields biased estimation results in our dataset (stylised aggregate data from agriculture and manufacturing). To the best of our knowledge this is the first paper to consider this issue empirically in a large number of economies. As a robustness check we compare our results with those for a matched sample of aggregate economy data from the Penn World Table.

5.1 Aggregation Bias — Conceptual Development

This section provides a brief insight into the problems for estimation arising from aggregation. Given that we use annual data in our analysis and in the interest of space we abstract from issues surrounding temporal aggregation, although we acknowledge their importance for empirical analysis (Rossana & Seater, 1992; Madsen, 2005). Much of the *theoretical literature* on 'cross-sectional' aggregation considers issues across a moderate to large number of 'individuals' or 'families', as is conceptually appropriate when investigating the micro-foundations of single aggregate/macro variables and the implications for forecasting arising in this process (Granger, 1987; Biørn, Skjerpen, & Wangen, 2006). In the *applied literature*, however, these concerns about aggregation bias and the 'correct' empirical specification for aggregate data are largely ignored (van Garderen, Lee, & Pesaran, 2000; Blundell & Stoker, 2005).

Perhaps most relevant for the present analysis of sectoral heterogeneity versus aggregation in a large number of economies are the studies by van Garderen et al. (2000) and Hsiao, Shen, and Fujiki (2005).

[10] The 'alternative CMG estimator' addressing cross-sectoral correlation leads to a considerable increase in covariates, resulting in a dimensionality problem where we have very few degrees of freedom in each country regression. As a result we decided not to implement this estimator in the human capital specifications.

The former derive expressions for the 'optimal aggregate specification' which in the case of log-linear equations for the underlying micro units (e.g. sector-level production functions) and parameter heterogeneity *across* these units include both the aggregated variables and their cross-product terms (all in logs). They illustrate their findings by estimating sectoral production functions for 8 UK industries (1954-1995) and providing estimates for various model specifications using the aggregated data, including the 'analogue form' which simply uses the aggregated variables in the same empirical specification.[11] Three of their findings are particularly noteworthy: firstly, the results for the aggregated data differ considerably depending on the inclusion of productivity dummies (indicating shocks such as the oil crisis, strikes and severe weather)[12] and/or the cross-product terms: labour coefficients range from .16 to .67. Secondly, the estimates from the aggregated models seem out of line with the sector-based ones, regardless of the inclusion or exclusion of the cross-product terms and productivity dummies. Thirdly, the cross-product terms included in two of their aggregate models, although having considerable impact on the technology parameter estimates, turn out statistically insignificant.

Hsiao et al. (2005, p.579) note that the use of aggregate versus disaggregate (prefecture-level) data to investigate money demand in Japan "can yield diametrically opposite results" if heterogeneity across 'micro units' is ignored. An interesting contribution of their paper is the discussion of nonstationarity and cointegration in the context of cross-section aggregation: if variable series are nonstationary and cointegrated at the micro unit level, then aggregation is only going to yield stable macro relations if either all technology parameters are the same across units or provided there is no change in their weighting to make up the aggregate economy series. With reference to our own empirical question of interest the latter would imply the absence of any structural change in the economy over time!

It is difficult to draw any conclusions from this literature for our present empirical problem. Although the discussion and empirical examples in van Garderen et al. (2000) and Hsiao et al. (2005) offer some useful insights, they analyse data within single countries (UK, Japan) rather than in a large panel of developing and developed economies. In terms of their theoretical contribution, it needs to be stressed that they do not consider the arguably crucial question of cross-section dependence.

5.2 Aggregation Bias — Monte Carlo Experiments

This section provides simulation results based on a sample of stylised aggregate economies made up of two heterogeneous sectors. We do not present all of the simulation results (see Table TA-3 in the Technical Appendix) but limit our discussion to four scenarios for which we illustrate results using box plots. Our data generating process (DGP), described in detail in Section A-2 of the Appendix, builds on log-linear Cobb-Douglas production functions for agriculture and manufacturing respectively. We limit our presentation to the dimensions $T = 30$, $N = 50$ so as to provide direct insights for the present empirical case. In each Monte Carlo iteration the two sectoral datasets are created, aggregated and estimated with the same estimators we employ throughout our study.[13]

[11]Given their primary interest in forecasting aggregate output the authors further provide prediction criteria and misspecification tests based on mean squared forecast errors. This is developed in more detail in Pesaran (2003). It is unclear how applicable these types of tests would be in a large panel of heterogeneous economies.

[12]Note that their formulation depends on detailed knowledge of sector-level productivity shocks — it is difficult to see how one would go about formulating these productivity shocks in the agricultural and manufacturing sectors across a large sample of economies. Our own empirical strategy encompasses this approach by the use of the common factor framework (Chudik et al., 2010).

[13]Due to the log-linear structure of the sectoral production function model aggregation is defined as

$$Y_{it} = \sum_j Y_{ijt} \qquad X_{it} = \sum_j X_{ijt} \qquad \text{where } Y_{ijt} = e^{y_{ijt}} \text{ and } X_{ijt} = e^{x_{ijt}} \tag{8}$$

We specify a single input with (initially) common slope coefficient across sectors. A number of heterogeneous trends drive the evolution of the single input and to begin with our DGP excludes any common factors. Although our first model has homogeneous β across countries, the first results we present (MODEL 4) already incorporate country-specific β_i. Sectoral TFP levels differ across countries and are systematically larger in manufacturing than in agriculture. Aggregation of the two sectors should not create any problems under this scenario given the technology homogeneity across sectors. In a second set of simulations we introduce common factors, first with homogeneous and then in MODEL 6 with heterogeneous factor loadings across countries; these common factor differ between y- and x-equations (no endogeneity) and across sectors. The heterogeneity introduced by the presence of common factors and the data dependencies created when such data-series are aggregated have not been previously studied in the literature. We then introduce endogeneity in the sectoral equation (same common factor in y- and x-equations) and slope heterogeneity across sectors, with MODEL 8 having parameters differ following $\beta_i^m = 1 - \beta_i^a$. Ignoring common factors the existing literature suggests that the 'analogue form' of an equation with aggregated data is now misspecified unless cross-terms of the variables are included. Finally, in MODEL 10 we investigate the effect of having the same common factors in input and output *within* but also *across* sectors. We further introduce independent slope parameters between agriculture (mean .5) and manufacturing (.3) in this model. Figure 1 presents boxplots for the slope coefficient distribution across 1,000 replications under the four scenarios discussed above.

[Figure 1 about here]

The solid line in the middle of each box plot is the median, the area marked by the 'box' is that from the 25th to the 75th percentile, and the 'whiskers' extend to the 1st and 99th percentile of the distribution. Here we exclude outliers from the graph to aid comparison across estimators. The first two box plots in each graph are for the CMG estimator applied to sectoral data. The third represents not an estimate but a weighted average computed from the 'true' sectoral slope coefficients, where the weights are the sectoral share in total output. All three of these are intended to act as benchmarks for the remaining estimates from the aggregated data, namely the pooled OLS, fixed effects, first difference OLS and CMG estimators — we include year dummies in all pooled models. The MG estimator with linear trend term is included in the simulation results but not in the box plots — the magnitude of its bias would impact the readability of the figure. In all box plots we have recentred the estimates around zero by subtracting the 'true' parameter mean.

As expected the aggregation of sectoral data in MODEL 4 does not create any bias in the estimates, given that technology is identical across sectors. The 2FE estimator picks up the TFP-level heterogeneity and yields the most precise estimates, whereas the heterogeneous estimators (CMG) both in the sectoral and aggregated data are less efficient. Once we introduce common factors in MODEL 6, all estimators for the aggregated data are biased downward. The introduction of cross-sector parameter heterogeneity in MODEL 8 increases imprecision of the estimates, but does so in the sectoral CMG estimates as well as in all of the estimates using aggregate data. Once technology parameter differ independently across sectors as in MODEL 10 and the same common factor drives both sectors the estimates do not provide evidence of additional bias due to these features.[14]

At face value, these results suggest that estimates for the slope parameters derived from aggregate data are biased, primarily due to the impact of unobserved common factors rather than that of cross-country and/or cross-sector technology heterogeneity. The difference between MODELS 5 and 6 (see TA-III in

Thus we cannot simply add up the y_{it}^a and y_{it}^m but have to transform these values first.

[14]Note that in this model the average manufacturing share in total output is around .55 and that in 95% of the 1,000 replications this share lies between .4 and .7. Thus we have further confirmation measure that the manufacturing sector does not dominate in each aggregate economy.

the Technical Appendix) indicates that although more pronounced in the heterogeneous factor loading case, this bias is already present when factors have the same impact across countries.

5.3 Aggregation Bias — Empirical Evidence

Our empirical results in Section 4 suggested fairly similar pooled and averaged capital coefficients for manufacturing and agriculture across the various empirical models. This might lead one to suggest that carrying out cross-country growth empirics may best be conducted taking the aggregate economy, and thus the Penn World Table (PWT) data, as the basic unit of analysis. Our empirical approach emphasised the importance of unobserved heterogeneity across countries, but did not test technology parameter differences *across sectors* with any formal methods — our justification is that in our most flexible specification (CMG) the individual country-estimates are not reliable (Pedroni, 2007) and should not be the basis for comparison. In this section we will instead provide practical evidence that the use of an aggregate production function will lead to seriously biased technology estimates, with the focus on the empirical capital coefficient. We carry out this analysis by creating a stylised 'aggregated economy' from our data on agriculture and manufacturing. Since it might be suggested that results could be severely distorted by the overly simplistic nature of our setup, we compare results with those from a matched sample of aggregate economy data from the PWT. Pre-estimation testing (panel unit root estimation and cross-section correlation analysis) revealed that both datasets employed in this section are made up of nonstationary series which are cross-sectionally correlated — see Tables TA-1 and TA-2 in the Technical Appendix for details.

We begin our discussion with the pooled models in Table IV. Across all specifications the estimated capital coefficients in the stylised aggregated data far exceed those derived from the respective agriculture and manufacturing samples in Table II. Furthermore, the patterns across estimators are replicated one-to-one in the PWT data, which also yields excessively high capital coefficients across all models. All models suffer from cross-sectional dependence in the residuals, while there are also indications that the residuals in the CCEP model for the aggregated data are nonstationary (those in the two other levels specifications are *always* nonstationary). We also investigated the impact of human capital (proxied via average years of schooling attained in the population over 15 years of age) in these aggregate economy data models, but as Table TA-VI in the Technical Appendix reveals the basic bias remains.

`[Table IV about here]`

In addition we estimated pooled dynamic models (introducing the PMG and CPMG estimators) in Table TA-VIII in the Technical Appendix — all of these results more or less confirm the patterns across sectoral and aggregated data described above.

`[Table V about here]`

Turning to the results from averaged country regressions in Table V: the MG and FDMG model point to some differences between the aggregated and PWT data, whereby the capital coefficients in the former are estimated very imprecisely but seem to centre around .3, whereas in the latter they are considerably higher at around .7 to .9. Results for the conceptually superior CMG, however, are again very consistent between the two samples and across unrestricted and CRS models, with capital coefficients around .7. Residual testing suggests that all specifications yield stationary residuals — this is somewhat surprising in the MG case, given the misspecification implicit in this equation. Cross-section correlation tests reject independence in all residual series tests — in case of the stylised aggregated data the CMG rejects marginally.

As a further robustness check we ran regressions where rather than aggregate the data we forced manufacturing and agriculture production to follow the same production technology, using a Seemingly Unrelated Regression (SUR) model. Results (available on request) for homogeneous and heterogeneous parameter models qualitatively did not differ from the aggregated results presented above. Thus across a large number of empirical specifications we have found there to be a systematic difference between results for the sectoral data on the one hand and those for the stylised aggregated and aggregate economy data on the other.

6. CONCLUDING REMARKS

In this paper we employed unique panel data for agriculture and manufacturing to estimate sector-level and aggregate production functions. Our empirical analysis emphasised the contribution of the recent panel time-series econometrics literature and in particular the concerns over cross-sectional dependence commonly found in macro panel data. In addition we took the nonstationarity of observable and unobservable factor inputs into account and emphasised the importance of parameter heterogeneity — across countries as well as sectors. To the best of our knowledge this is the first time that these matters are investigated empirically at this level of aggregation, with previous empirical work on the dual economy model dominated by calibration and accounting exercises. Our analysis was enabled by the unique data on agricultural and manufacturing investment compiled by Crego et al. (1998) — a dataset which deserves far greater attention than it presently receives.

We draw the following conclusions from our first, crude attempts at highlighting the importance of structural makeup and change in the empirical analysis of cross-country growth and development: firstly, empirical analysis of growth and development at the cross-country level — most commonly conducted using the Penn World Tables — gains considerably from the separate consideration of modern and traditional sectors that make up the economy. Our analysis of agriculture and manufacturing versus a stylised aggregated economy suggests that the latter yields severely distorted empirical results. Across multiple empirical specifications and estimators we could show that the capital coefficient for aggregated data far exceeds that obtained from separate sector regressions, with serious implications for estimates of TFP derived from aggregate analysis. Analysis of PWT data in parallel with the aggregated data suggested that this finding is not an artefact of our stylised empirical setup.

Secondly, our toy model Monte Carlo simulations seem to suggest that the source of distortion in the aggregate data is primarily the presence of unobserved common factors. Much of the mainstream growth empirics literature still assumes away the presence of global economic shocks and spillovers across country borders; arguably, with the experience of the recent global financial crisis it is now more evident than ever that economic performance in a globalised world is highly interconnected, that domestic markets cannot 'de-couple' from the global financial and goods markets and, in econometric terms, that latent forces drive *all* of the observable and unobservable variables and processes we are trying to model. One implication is that commonly applied instruments in cross-country growth regressions are invalid — a sentiment echoed in recent work by Clemens and Bazzi (2009). The cross-country growth empirics literature is deeply unfashionable in a time that sees randomised control trials and country-level growth diagnostics as providing the answers to many development questions. We argue that recent contributions to the panel time series literature allow us to develop a new type of cross-country empirics, which is more informative and more flexible in the problems that it can address than its critics have allowed.

Thirdly, we are aware of the serious data limitations for sectoral data from developing economies, in particular regarding the high data requirements of panel time series methods. For instance the analysis in the present paper is carried out for a mere 41 countries, of which around half could be seen as 'developed' in the present day, and for which the time series dimension of the data is relatively short. The Crego et al. (1998) dataset allowed us to make sectoral analysis directly comparable between manufacturing and agriculture, however for alternative research questions the use of data from *one or the other sector* may be sufficient. There are at least two existing data sources, namely FAO (2007) data for agriculture and UNIDO (2004) data for manufacturing, ideally suited to carry out this type of analysis at the sector-level, for a large number of countries and over a substantial time period. A recent example in this vein is the work on aid, Dutch Disease and manufacturing exports by Rajan and Subramanian (2010).

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Tables and Figures

Table I: Evolution of agricultural VA- and employment-share

Agricultural VA † (in % of GDP; Decadal Medians)					
	1960s	1970s	1980s	1990s	2000s
Canada & US		4.3	3.0	2.3	1.3
Europe (Euro area)		6.2	4.3	2.9	2.2
Latin America & Caribbean	14.0	12.8	10.2	7.5	6.6
Middle East & North Africa	21.7	15.2	15.2	15.2	12.4
Australia & New Zealand		9.0	6.7	5.3	4.0
East Asia & Pacific	37.8	32.0	27.6	19.0	13.2
Sub-Saharan Africa	26.2	21.5	20.1	19.4	17.5
South Asia	42.3	38.6	31.6	27.5	21.6

Employment in Agriculture ‡ (% of total employment; Means, Medians for 2000s ♯)					
	1960	1970	1980	1990	2000s
United States	6.6	4.3	3.5	2.8	2.6
Europe	31.0	21.1	15.9	12.2	4.8
Latin America & Caribbeans	49.0	42.0	34.2	25.4	16.8
Australia & New Zealand	11.9	8.7	7.3	6.3	6.0
Eastern Asia	76.8	70.9	66.9	64.8	45.4
Africa	79.6	75.8	68.7	62.8	

Notes: † World Bank (2008) World Development Indicators. ‡ ILO decadal estimates 1950-1990, 'economically active population in agriculture'. ♯ World Bank (2008) WDI; here: 'employment in agriculture' and Europe = Euro Area. 2000s includes the most recently available data, which differs somewhat by region but typically includes data up to 2006.

Table II: Pooled regression models for agriculture and manufacturing

Panel (A): Unrestricted returns to scale

	Agriculture					*Manufacturing*				
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **CCEP**$^\flat$	[5] **FD**	[6] **POLS**	[7] **2FE**	[8] **CCEP**	[9] **CCEP**$^\flat$	[10] **FD**
log labour	-0.059	-0.205	-0.203	-0.080	-0.113	0.043	0.069	0.089	0.022	0.125
	[7.06]**	[10.03]**	[1.73]	[0.40]	[3.13]**	[3.56]**	[3.68]**	[1.77]	[0.39]	[6.81]**
log capital pw	0.618	0.654	0.484	0.533	0.633	0.897	0.855	0.511	0.497	0.720
	[74.18]**	[42.29]**	[11.24]**	[6.88]**	[21.00]**	[55.53]**	[32.93]**	[8.90]**	[8.93]**	[23.95]**
log land pw	0.012	-0.151	-0.092	0.094	-0.001					
	[1.07]	[4.89]**	[0.64]	[0.45]	[0.01]					
Implied RS†	DRS	DRS	CRS	CRS	DRS	IRS	IRS	CRS	CRS	IRS
Implied $\beta_L{}^\ddagger$	0.323	0.346	0.516	0.467	0.254	0.146	0.214	0.489	0.503	0.405
$\hat{e}$ integrated$^\natural$	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)
CD test p-value$^\sharp$	0.00	0.00	0.57	0.38	0.00	0.44	0.55	0.00	0.59	0.00
R-squared	0.94	0.86	1.00	1.00	-	0.84	0.67	1.00	1.00	-
Observations	928	928	928	928	879	928	928	928	928	879

Panel (B): Constant returns to scale imposed

	Agriculture					*Manufacturing*				
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **CCEP**$^\flat$	[5] **FD**	[6] **POLS**	[7] **2FE**	[8] **CCEP**	[9] **CCEP**$^\flat$	[10] **FD**
log capital pw	0.644	0.724	0.493	0.514	0.660	0.920	0.865	0.510	0.499	0.767
	[85.54]**	[48.86]**	[11.84]**	[8.61]**	[22.70]**	[71.30]**	[34.11]**	[11.75]**	[11.22]**	[25.60]**
log land pw	0.009	-0.005	0.108	0.123	0.002					
	[0.70]	[0.15]	[1.57]	[1.15]	[0.02]					
Implied $\beta_L{}^\ddagger$	0.348	0.281	0.399	0.486	0.338	0.080	0.135	0.490	0.501	0.233
$\hat{e}$ integrated$^\natural$	I(1)	I(1)/I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)
CD test p-value$^\sharp$	0.00	0.00	0.71	0.58	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.94	0.85	1.00	1.00	-	0.84	0.66	1.00	1.00	-
Observations	928	928	928	928	879	928	928	928	928	879

Notes: Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the 2FE and FD equations. Estimators: POLS — pooled OLS, 2FE — 2-way Fixed Effects, CCEP — Common Correlated Effects Pooled version (see below), FD — pooled OLS with variables in first difference. We omit reporting the estimates on the intercept term. t-statistics reported in brackets are constructed using White heteroskedasticity-robust standard errors. *, ** indicate significance at 5% and 1% level respectively. $N = 41$, average $T = 22.6$ (21.4 for FD). Time dummies are included explicitly in [1], [5], [6] and [10] or implicitly in [2] and [7]. Cross-section average augmentation in [3],[4],[8] and [9]. $\flat$ The model includes cross-section average for *both* the agricultural and manufacturing sector variables respectively. $\dagger$ Returns to scale, based on significance of log labour estimate. $\ddagger$ Based on returns to scale result. $\natural$ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). $\sharp$ Pesaran (2004) CD-test (full results for this and other CSD tests available on request).

Table III: Heterogeneous parameter models (robust means)

PANEL (A): UNRESTRICTED RETURNS TO SCALE

	Agriculture				*Manufacturing*			
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **CMG**$^\flat$	[5] **MG**	[6] **FDMG**	[7] **CMG**	[8] **CMG**$^\flat$
log labour	-1.936	-0.414	-0.533	0.009	-0.125	-0.154	0.094	0.012
	[2.50]*	[0.48]	[0.91]	[0.01]	[0.90]	[1.36]	[1.12]	[0.14]
log capital pw	-0.053	0.135	0.526	0.292	0.214	0.139	0.545	0.341
	[0.28]	[0.61]	[2.76]**	[1.32]	[1.38]	[0.84]	[6.34]**	[4.30]**
log land pw	-0.334	-0.245	-0.352	-0.318				
	[1.09]	[0.85]	[1.12]	[1.01]				
country trend/drift	0.018	0.010			0.014	0.019		
	[1.81]	[1.22]			[2.54]*	[3.35]**		
Implied RS†	DRS	CRS	CRS	CRS	CRS	CRS	CRS	CRS
Implied β_L‡	n/a	n/a	0.474	0.708	n/a	n/a	0.455	0.659
reject CRS (10%)	27%	12%	20%	12%	44%	12%	39%	15%
panel-t Labour	-3.17**	-0.93	-1.02	-1.34	-2.98**	-2.92**	4.68**	1.24
panel-t Capital	0.89	0.95	8.10**	3.57**	4.14**	0.09	16.15**	6.64**
panel-t Land	-0.32	0.23	-0.02	0.95				
panel-t trend/drift	14.95**	5.41**			16.23**	8.35**		
sign. trends/drifts (10%)	20	7			19	10		
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
avg. abs. correl. coeff.	0.23	0.22	0.25	0.25	0.24	0.22	0.23	0.23
CD-test (p)$^\sharp$	0.00	0.00	0.51	0.63	0.00	0.00	0.01	0.09
Observations	928	879	928	928	928	879	928	928

PANEL (B): CONSTANT RETURNS TO SCALE IMPOSED

	Agriculture				*Manufacturing*			
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **CMG**$^\flat$	[5] **MG**	[6] **FDMG**	[7] **CMG**	[8] **CMG**$^\flat$
log capital pw	-0.012	0.297	0.547	0.578	0.320	0.388	0.550	0.424
	[0.07]	[2.14]*	[4.66]**	[3.00]**	[2.74]**	[4.02]**	[6.33]**	[6.43]**
log land pw	0.360	0.138	0.163	0.208				
	[1.30]	[0.71]	[0.90]	[1.04]				
country trend/drift	0.016	0.014			0.011	0.011		
	[2.89]**	[3.09]**			[2.63]*	[3.06]**		
Implied β_L‡	1.012	0.703	0.453	0.422	0.680	0.612	0.450	0.567
panel-t Capital	5.42**	2.65**	13.68**	9.05**	10.58**	6.36**	20.03**	13.58**
panel-t Land	6.74**	1.53	1.24	1.42				
panel-t trend/drift	14.87**	5.61**			22.65**	8.39**		
sign. trends/drifts (10%)	22	6			31	15		
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
avg. abs. correl. coeff.	0.23	0.22	0.26	0.26	0.29	0.22	0.26	0.23
CD-test (p)$^\sharp$	0.00	0.00	0.90	0.76	0.00	0.00	0.00	0.00
Observations	928	879	928	928	928	879	928	928

Notes: Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the FD equations. Estimators: MG — Mean Group, FDMG — MG with variables in first difference, CMG — Common Correlated Effects Mean Group version. We report robust means; estimates on intercept terms are not shown. t-statistics in brackets following Pesaran and Smith (1995). Panel-t statistic following Pedroni (2004). *, ** indicate significance at 5% and 1% level respectively. $N = 41$, average $T = 22.6$ (21.4 for FD). Estimates on cross-section averages in [3],[4],[7] and [8] not reported.
$\flat$ The model includes cross-section average for *both* the agricultural and manufacturing sector variables respectively. † Returns to scale, based on significance of log labour estimate. ‡ Based on returns to scale result. ♮ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). ♯ Based on Pesaran (2004) CD-test (full results for this and other CSD tests available on request).

Table IV: Pooled regression models for aggregated and PWT data

Panel (A): Unrestricted returns to scale

	Aggregated data				*Penn World Table data*			
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **FD**	[5] **POLS**	[6] **2FE**	[7] **CCEP**	[8] **FD**
log labour	0.011	-0.096	0.036	-0.013	0.034	-0.138	-0.201	0.019
	[1.50]	[4.49]**	[0.52]	[0.54]	[7.43]**	[4.74]**	[1.75]	[0.94]
log capital pw	0.829	0.792	0.655	0.820	0.742	0.700	0.684	0.729
	[108.41]**	[64.71]**	[21.71]**	[66.28]**	[114.77]**	[49.71]**	[16.90]**	[50.08]**
Implied RS†	CRS	DRS	CRS	CRS	IRS	DRS	CRS	CRS
Implied β_L‡	0.171	0.111	0.345	0.180	0.292	0.162	0.316	0.271
$\hat{e}$ integrated♮	I(1)	I(1)	I(1)/I(0)	I(0)	I(1)	I(1)	I(1)/I(0)	I(0)
CD test p-value♯	0.98	0.01	0.07	0.00	0.02	0.00	0.02	0.00
R-squared	0.96	0.88	1.00	-	0.96	0.82	1.00	
Observations	928	928	928	879	922	922	922	873

Panel (B): Constant returns to scale imposed

	Aggregated data				*Penn World Table data*			
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **FD**	[5] **POLS**	[6] **2FE**	[7] **CCEP**	[8] **FD**
log capital pw	0.825	0.823	0.672	0.821	0.730	0.745	0.656	0.726
	[120.85]**	[72.25]**	[23.14]**	[66.91]**	[130.53]**	[62.33]**	[20.61]**	[50.88]**
Implied β_L‡	0.175	0.177	0.328	0.179	0.270	0.256	0.344	0.274
$\hat{e}$ integrated♮	I(1)	I(1)	I(1)/I(0)	I(0)	I(1)	I(1)	I(0)	I(0)
CD test p-value♯	0.91	0.86	0.05	0.00	0.00	0.00	0.03	0.00
R-squared	0.96	0.88	1.00	-	0.96	0.81	1.00	
Observations	928	928	928	879	922	922	922	873

Notes: Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the 2FE and FD equations. Estimators: POLS — pooled OLS, 2FE — 2-way Fixed Effects, CCEP — Common Correlated Effects Pooled version, FD — pooled OLS with variables in first difference. We omit reporting the estimates for the intercept term. t-statistics reported in brackets are constructed using White heteroskedasticity-robust standard errors. Time dummies are included explicitly in [1], [4], [5] and [8] or implicitly in [2] and [6]. Cross-section average augmentation in [3] and [7]. *, ** indicate significance at 5% and 1% level respectively. $N = 41$, average $T = 22.6$ (21.4 for FD).
† Returns to scale, based on significance of log labour estimate. ‡ Based on returns to scale result. ♮ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). ♯ Pesaran (2004) CD-test (full results for this and other CSD tests available on request).

Table V: Heterogeneous parameter models (robust means)

Panel (A): Unrestricted returns to scale

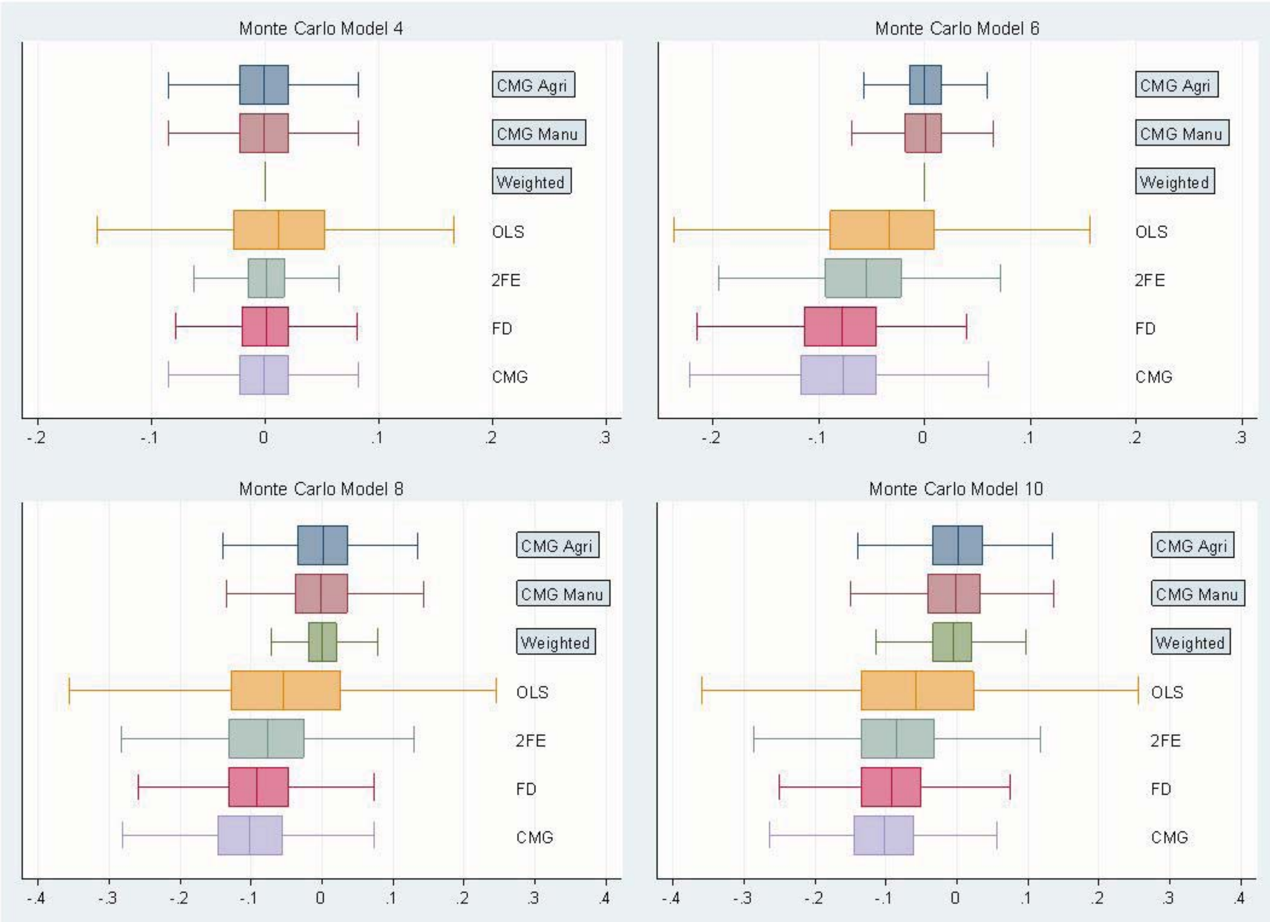
	Aggregated data			*Penn World Table data*		
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **MG**	[5] **FDMG**	[6] **CMG**
log labour	-0.233	-0.169	0.057	-0.442	-1.089	-0.172
	[0.55]	[0.51]	[0.31]	[0.74]	[2.35]*	[0.45]
log capital pw	0.233	0.289	0.651	0.625	0.976	0.715
	[1.28]	[1.71]	[7.00]**	[4.64]**	[6.40]**	[5.49]**
country trend/drift	0.026	0.022		0.011	-0.005	
	[2.93]**	[2.57]*		[1.12]	[0.83]	
Implied RS†	CRS	CRS	CRS	CRS	DRS	CRS
Implied β_L‡	n/a	n/a	0.349	0.375	n/a	0.285
reject CRS (10%)	56%	15%	29%	74%	26%	51%
panel-t Labour	-0.77	-0.16	4.12**	-0.65	-4.42**	-4.36**
panel-t Capital	5.97**	1.83	22.39**	24.66**	18.12**	26.16**
panel-t trend/drift	23.44**	9.31**		16.65**	7.41**	
sign. trends/drifts (10%)	27	13		30	12	
$\hat{e}$ integrated♮	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
abs correl.coeff.	0.24	0.23	0.23	0.25	0.19	0.24
CD-test (p)♯	0.00	0.00	0.00	0.00	0.00	0.00
Observations	928	928	879	922	922	873

Panel (B): Constant returns to scale imposed

	Aggregated data			*Penn World Table data*		
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **MG**	[5] **FDMG**	[6] **CMG**
log capital pw	0.324	0.222	0.745	0.681	0.892	0.785
	[2.12]*	[2.09]*	[11.78]**	[8.38]**	[7.47]**	[12.59]**
country trend/drift	0.013	0.018		0.001	-0.004	
	[2.69]*	[4.65]**		[0.23]	[1.24]	
Implied β_L‡	0.676	0.778	0.255	0.319	0.108	0.215
panel-t Capital	11.61**	2.68**	40.06**	34.32**	18.49**	51.35**
panel-t trend/drift	21.26**	8.72**		19.33**	8.75**	
sign. trends/drifts (10%)	25	11		27	12	
$\hat{e}$ integrated♮	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
abs correl.coeff.	0.29	0.23	0.26	0.32	0.23	0.30
CD-test (p)♯	0.00	0.00	0.07	0.00	0.00	0.00
Observations	928	928	879	922	922	873

Notes: Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the FD equations. Estimators: MG — Mean Group, FDMG — MG with variables in first difference, CMG — Common Correlated Effects Mean Group version. We report robust means; estimates for intercept terms are not shown. t-statistics in brackets following Pesaran and Smith (1995). Panel-t statistic following Pedroni (2004). *, ** indicate significance at 5% and 1% level respectively. $N = 41$, average $T = 22.6$ (21.4 for FDMG). Estimates on cross-section averages in [3] and [6] not reported.
† Returns to scale, based on significance of log labour estimate. ‡ Based on returns to scale result. ♮ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). ♯ Based on Pesaran (2004) CD-test (full results for this and other CSD tests available on request).

Figure 1: Box plots — Simulation results



Notes: We present box plots for the $M = 1,000$ estimates using various estimators under 4 DGP setups. In all cases the true coefficient is subtracted from the estimates, such that the plots are centred around zero.
The estimators are as follows: 'CMG Agri' and 'CMG Manu' — Pesaran (2006) CMG regressions on the *sector-level* data; Weighted — this is *not* an estimator but the weighted average $\beta^a s_i^a + \beta^m s_i^m$ with β^j the mean sectoral slope coefficient and s_j the sectoral share of total output; the remaining four estimators use the aggregated data: OLS — pooled OLS with $T-1$ year dummies; 2FE — OLS with country and time dummies; FD — OLS with variables in first differences (incl. time dummies); CMG — Pesaran (2006) CMG. We omit the results for the Pesaran and Smith (1995) MG estimator as these are very imprecise and would counter the readability of the graphs. The MC setups are described in detail in Section A-2 of the Appendix.

Appendix

A-1 Data construction and descriptives

We use a total of four datasets in our empirical analysis, comprising data for agriculture and manufacturing (Crego et al., 1998; UNIDO, 2004; FAO, 2007), an 'aggregated dataset' where the labour, output and capital stock values for the two sectors are added up, and finally a Penn World Table (PWT 6.2) dataset (Heston et al., 2006) for comparative purposes. It is important to stress that the former three datasets differ significantly in their construction from the latter, primarily in the choice of exchange rates and deflation: the former use international (US$-LCU) exchange rates for the year 1990, whereas the Penn World Table dataset comprises Purchasing Power Parity (PPP) adjusted International Dollars taking the year 2000 as the comparative base. The former thus put an emphasis on traded goods, whereas the latter are generally perceived to account better for non-tradables and service. Provided that all monetary values making up the variables used in each regression are comparable (across countries, times), and given that the comparison of sectoral and aggregated data with the PWT is for illustrative purposes, we do not feel there is an issue in presenting results from these two conceptually different datasets.

In all cases the results present are for matched observations across datasets: the four datasets are identical in terms of countries and time-periods — we prefer this arrangement for direct comparison despite the fact that more observations are available for individual data sources (e.g. the PWT are now available in the latest version 6.3, covering up to 188 countries for 1950 to 2007, see Heston et al., 2009), which may improve the robustness of empirical estimates. We provide details on the sample makeup in Table A-I. The next two subsections describe data construction. Descriptive statistics for all variables in the empirical analysis are presented in Table A-II.

Table A-I: Descriptive statistics: Sample makeup for all datasets

#	WBCODE	COUNTRY	OBS	#	WBCODE	COUNTRY	OBS
1	AUS	Australia	20	22	JPN	Japan	28
2	AUT	Austria	22	23	KEN	Kenya	29
3	BEL	Belgium-Luxembourg	22	24	KOR	South Korea	29
4	CAN	Canada	30	25	LKA	Sri Lanka	17
5	CHL	Chile	20	26	MDG	Madagascar	20
6	COL	Colombia	26	27	MLT	Malta	23
7	CRI	Costa Rica	10	28	MUS	Mauritius	16
8	CYP	Cyprus	18	29	MWI	Malawi	23
9	DNK	Denmark	26	30	NLD	Netherlands	23
10	EGY	Egypt	24	31	NOR	Norway	22
11	FIN	Finland	28	32	NZL	New Zealand	19
12	FRA	France	23	33	PAK	Pakistan	24
13	GBR	United Kingdom	22	34	PHL	Philippines	24
14	GRC	Greece	28	35	PRT	Portugal	20
15	GTM	Guatemala	19	36	SWE	Sweden	23
16	IDN	Indonesia	22	37	TUN	Tunisia	17
17	IND	India	29	38	USA	United States	23
18	IRL	Ireland	23	39	VEN	Venezuela	19
19	IRN	Iran	25	40	ZAF	South Africa	26
20	ISL	Iceland	20	41	ZWE	Zimbabwe	25
21	ITA	Italy	21			**Total**	**928**

Table A-II: Descriptive statistics

AGRICULTURE DATA

Panel (A): Variables in untransformed level terms

Variable	mean	median	std. dev.	min.	max.
Output	1.74E+10	5.91E+09	2.95E+10	3.54E+07	2.24E+11
Labour	9.51E+06	1.21E+06	3.45E+07	3.00E+03	2.33E+08
Capital	6.42E+10	1.01E+10	1.45E+11	2.90E+07	8.64E+11
Land	1.73E+07	3.50E+06	4.06E+07	6.00E+03	1.91E+08
in logarithms					
Output	22.369	22.500	1.737	17.382	26.134
Labour	13.984	14.006	2.011	8.006	19.267
Capital	22.933	23.037	2.276	17.183	27.485
Land	15.089	15.068	1.986	8.700	19.066
in growth rates					
Output	1.75%	1.94%	10.36%	-41.54%	53.86%
Labour	-0.63%	0.00%	3.00%	-28.77%	13.35%
Capital	1.89%	1.25%	3.61%	-5.13%	31.40%
Land	0.06%	0.00%	2.17%	-23.06%	13.57%

Panel (B): Variables in per worker terms

Variable	mean	median	std. dev.	min.	max.
Output	12,615.6	6,419.6	13,130.6	44.2	57,891.3
Capital	51,847.1	9,661.9	63,427.8	13.1	222,396.5
Land	9.57	2.94	20.25	0.29	110.00
in logarithms					
Output	8.385	8.767	1.817	3.788	10.966
Capital	8.950	9.176	2.694	2.573	12.312
Land	1.105	1.078	1.404	-1.244	4.701
in growth rates					
Output	2.33%	2.52%	10.49%	-43.67%	55.98%
Capital	2.47%	2.00%	4.17%	-7.83%	31.12%
Land	0.70%	0.50%	3.40%	-18.37%	28.77%

MANUFACTURING DATA

Variable	mean	median	std. dev.	min.	max.
Output	7.47E+10	8.31E+09	2.07E+11	7.20E+06	1.43E+12
Labour	1.73E+06	4.75E+05	3.42E+06	9.56E+03	1.97E+07
Capital	1.33E+11	1.91E+10	2.97E+11	1.41E+07	1.81E+12
Output	22.812	22.840	2.292	15.790	27.991
Labour	13.081	13.072	1.653	9.166	16.794
Capital	23.619	23.675	2.269	16.462	28.222
Output	4.45%	3.83%	10.09%	-40.91%	84.23%
Labour	1.96%	1.13%	6.83%	-38.84%	78.12%
Capital	4.84%	3.62%	4.97%	-5.10%	53.03%

Variable	mean	median	std. dev.	min.	max.
Output	26,898.2	20,212.6	22,071.3	753.0	101,933.8
Capital	63,080.3	42,543.9	64,355.0	1,475.5	449,763.4
Output	9.731	9.914	1.084	6.624	11.532
Capital	10.538	10.658	1.083	7.297	13.016
Output	2.51%	2.48%	9.00%	-66.95%	73.01%
Capital	2.90%	2.91%	6.59%	-71.65%	42.44%

AGGREGATED DATA

Panel (A): Variables in untransformed level terms

Variable	mean	median	std. dev.	min.	max.
Output	9.22E+10	1.69E+10	2.31E+11	1.14E+08	1.55E+12
Labour	1.12E+07	2.31E+06	3.55E+07	2.23E+04	2.40E+08
Capital	1.97E+11	2.79E+10	4.31E+11	1.02E+08	2.25E+12
in logarithms					
Output	23.470	23.553	2.016	18.552	28.069
Labour	14.640	14.653	1.736	10.011	19.297
Capital	24.078	24.052	2.213	18.438	28.442
in growth rates					
Output	3.17%	3.15%	7.37%	-33.87%	42.14%
Labour	0.19%	0.49%	2.56%	-11.39%	19.30%
Capital	3.57%	2.73%	3.62%	-5.00%	25.14%

Panel (B): Variables in per worker terms

Variable	mean	median	std. dev.	min.	max.
in levels					
Output	19,327.1	10,736.2	19,174.0	72.5	76,031.1
Capital	49,187.4	22,087.4	55,406.5	52.7	236,312.1
in logarithms					
Output	8.830	9.281	1.845	4.284	11.239
Capital	9.438	10.003	2.191	3.964	12.373
in growth rates					
Output	2.95%	3.30%	7.04%	-31.02%	44.49%
Capital	3.38%	3.14%	3.74%	-18.43%	22.16%

PENN WORLD TABLE DATA

Variable	mean	median	std. dev.	min.	max.
Output	4.24E+11	1.27E+11	1.01E+12	1.34E+09	7.98E+12
Labour	5.05E+07	1.30E+07	1.19E+08	2.12E+05	8.54E+08
Capital	1.21E+12	3.25E+11	2.93E+12	3.30E+09	2.27E+13
Output	25.423	25.564	1.716	21.018	29.708
Labour	16.469	16.380	1.627	12.266	20.565
Capital	26.359	26.506	1.801	21.918	30.753
Output	4.00%	4.00%	4.96%	-37.12%	26.63%
Labour	1.56%	1.43%	1.14%	-1.87%	4.82%
Capital	4.60%	4.19%	2.84%	-1.30%	16.43%

Variable	mean	median	std. dev.	min.	max.
Output	11,396.7	10,308.1	8,162.3	594.3	31,074.1
Capital	36,832.4	32,026.3	31,668.2	660.8	136,891.2
Output	8.945	9.241	1.016	6.387	10.344
Capital	9.868	10.374	1.365	6.493	11.827
Output	2.44%	2.57%	4.96%	-41.22%	23.19%
Capital	3.04%	2.77%	2.87%	-4.23%	14.26%

Notes: We report the descriptive statistics for value-added (in US$1990 or PPP I$2000), labour (headcount), capital stock (same monetary values as VA in each respective dataset) and land (in hectare) for the full regression sample ($n = 928$; $N = 41$).

A-1.1 Sectoral and aggregated data

Investment data Data for agricultural and manufacturing investment (`AgSEInv`, `MfgSEInv`) in constant 1990 LCU, the US$-LCU exchange rate (`Ex_Rate`, see comment below) as well as sector-specific deflators (`AgDef`, `TotDef`) were taken from Crego et al. (1998).[15] Note that Crego et al. (1998) also provide capital stock data, which they produced through their own calculations from the investment data. Following Martin and Mitra (2002) we believe the use of a single year exchange rate is preferrable to the use of annual ones in the construction of real output (see next paragraph) and capital stock (see below).

Output data For manufacturing we use data on aggregate GDP in current LCU and the share of GDP in manufacturing from the World Bank World Development Indicators (WDI) (World Bank, 2008). For agriculture we use agricultural value-added in current LCU from the same source. We prefer the latter over the share of GDP in agriculture for data coverage reasons (in theory coverage should be the same, but it is not). The two sectoral value-added series are then deflated using the Crego et al. (1998) sectoral deflator for agriculture and the total economy deflator for manufacturing, before we use the 1990 US$-LCU exchange rates to make them comparable across countries.

Note that the currencies used in the Crego et al. (1998) data differ from those applied in the WDI data for a number of European countries due to the adoption of the Euro: for the latter we therefore need to use an alternative 1990 US$-LCU exchange rate for these economies.[16]

Labour data For agriculture we adopt the variable 'economically active population in agriculture' from the FAO's PopSTAT (FAO, 2007). Manufacturing labour is taken from UNIDO's INDSTAT (UNIDO, 2004).

Additional data The land variable is taken from ResourceSTAT and represents arable and permanent crop land (originally in 1000 hectare) (FAO, 2007). For the robustness checks (results available on request): 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:

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

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. For human capital we employ years of schooling attained in the population aged 25 and above from Barro and Lee (2001).

Capital stock We construct capital stock in agriculture and manufacturing by applying the perpetual inventory method described in detail in Klenow and Rodriguez-Clare (1997b) using the investment data from Crego et al. (1998), which is transformed into US$ by application of the 1990 US$-LCU

[15] Data is available in excel format on the World Bank website at `http://go.worldbank.org/FS3FXW7461`. All data discussed in this appendix are linked at `http://sites.google.com/site/medevecon/devecondata`.

[16] In detail, we apply exchange rates of 1.210246384 for AUT, 1.207133927 for BEL, 1.55504706 for FIN, 1.204635181 for FRA, 2.149653527 for GRC, 1.302645017 for IRL, 1.616114954 for ITA, 1.210203555 for NLD and 1.406350856 for PRT. See Table A-I for country codes.

exchange rate. For the construction of sectoral base year capital stock we employ average sector value-added growth rates g_j (using the deflated sectoral value-added data), the average sectoral investment to value-added ratio $(I/Y)_j$ and an assumed depreciation rate of 5% to construct

$$\left(\frac{K}{Y}\right)_{0j} = \frac{IY_j}{g_j + 0.05}$$

for sector j. This ratio is then multiplied by sectoral value-added in the base year to yield K_{0j}. Note that the method deviates from that discussed in Klenow and Rodriguez-Clare (1997b) as they use *per capita* GDP in their computations and therefore need to account for population growth in the construction of the base year capital stock.

Aggregated data We combine the agriculture and manufacturing data to produce a stylised 'aggregate economy': for labour we simply add up the headcount, for the monetary representations of output and capital stock we can do so as well. We are afforded this ability to simply add up variables for the two sectors by the efforts of Crego et al. (1998), who have built the first large panel dataset providing data on investment in agriculture for a long timespan.

A-1.2 Penn World Table data

As a means of comparison we also provide production function estimates using data from PWT version 6.2. We adopt real per capita GDP in International $ Laspeyeres (`rgdpl`) as measure for output and construct capital stock using investment data (derived from the investment share in real GDP, `ki`, and the output variable, `rgdpl`) in the perpetual inventory method described above, adopting again 5% depreciation (this time we need to use the data on population from PWT, `pop`, to compute the average annual population growth rate).

A-2 Monte Carlo Simulations: Data Generating Process

We run $M = 1,000$ replications of the following DGP for $N = 50$ cross-section elements and $T = 30$ time periods. Our basic setup for the DGP closely follows that of Kapetanios et al. (2009), albeit with a single rather than two regressors. For notational simplicity we do not identify the different sectors (agriculture and manufacturing) in the following, but all processes and variables are created independently across sectors, unless otherwise indicated.

$$y_{it} = \beta_i x_{it} + u_{it} \qquad u_{it} = \alpha_i + \lambda^y_{i1} f_{1t} + \lambda^y_{i2} f_{2t} + \varepsilon_{it} \tag{9}$$
$$x_{it} = a_{i1} + a_{i2} d_t + \lambda^x_{i1} f_{1t} + \lambda^x_{i3} f_{3t} + \upsilon_{it} \tag{10}$$

for $i = 1, \ldots, N$ unless indicated below and $t = 1, \ldots, T$.
The common deterministic trend term (d_t) and individual-specific errors for the x-equation are zero-mean independent AR(1) processes defined as

$$d_t = 0.5 d_{t-1} + \upsilon_{dt} \qquad \upsilon_{dt} \sim N(0, 0.75) \qquad t = -48, \ldots, 1, \ldots, T \qquad d_{-49} = 0$$
$$\upsilon_{it} = \rho_{\upsilon i} \upsilon_{i,t-1} + \upsilon_{it} \qquad \upsilon_{it} \sim N(0, (1 - \rho^2_{\upsilon i})) \qquad t = -48, \ldots, 1, \ldots, T \qquad \upsilon_{i,-49} = 0$$

where $\rho_{\upsilon i} \sim U[0.05, 0.95]$. The common factors are nonstationary processes

$$f_{jt} = \mu_j + f_{j,t-1} + \upsilon_{ft} \qquad j = 1,2,3 \qquad \upsilon_{ft} \sim N(0,1) \qquad t = -49, \ldots, 1, \ldots, T \tag{11}$$
$$\mu^a_j = \{0.01, 0.008, 0.005\},\ \mu^m_j = \{0.015, 0.012, 0.01\} \qquad f_{j,-50} = 0$$

where we deviate from the Kapetanios et al. (2009) setup by including drift terms. Unless indicated the sets of common factors differ between sectors.
Innovations to y are generated as a mix of heterogeneous AR(1) and MA(1) errors

$$\begin{aligned}
\varepsilon_{it} &= \rho_{i\varepsilon}\varepsilon_{i,t-1} + \sigma_i\sqrt{1-\rho_{i\varepsilon}^2}\omega_{it} \qquad i = 1,\dots,N_1 \qquad t = -48,\dots,0,\dots,T \\
\varepsilon_{it} &= \frac{\sigma_i}{\sqrt{1+\theta_{i\varepsilon}^2}}(\omega_{it} + \theta_{i\varepsilon}\omega_{i,t-1}) \qquad i = N_1+1,\dots,N \qquad t = -48,\dots,0,\dots,T
\end{aligned}$$

where N_1 is the nearest integer to $N/2$ and $\omega_{it} \sim N(0,1)$, $\sigma_i^2 \sim U[0.5,1.5]$, $\rho_{i\varepsilon} \sim U[0.05,0.95]$, and $\theta_{i\varepsilon} \sim U[0,1]$. ρ_{vi}, $\rho_{i\varepsilon}$, $\theta_{i\varepsilon}$ and σ_i do not change across replications. Initial values are set to zero and the first 50 observations are discarded for all of the above.
Regarding parameter values, $\alpha_i \sim N(2,1)$ and a_{i1}, $a_{i2} \sim \text{iid}N(0.5,0.5)$ do not change across replications. To begin with TFP levels α_i are specified to be the same across sectors. The slope coefficient β can vary across countries and across sectors (see below). In case of cross-country heterogeneity we have $\beta_i = \beta + \eta_i$ with $\eta_i \sim N(0,0.04)$. If the mean of the slope coefficient β is the same across sectors we specify $\beta = 0.5$, otherwise $\beta^a = 0.5$ and $\beta^m = 0.3$ for agriculture and manufacturing respectively.
For the factor loadings may be heterogeneous and are distributed

$$\lambda_{i1}^x \sim N(0.5,0.5) \qquad \text{and} \qquad \lambda_{i3}^x \sim N(0.5,0.5) \tag{12}$$

$$\lambda_{i1}^y \sim N(1,0.2) \qquad \text{and} \qquad \lambda_{i2}^y \sim N(1,0.2) \tag{13}$$

The above represents our basis DGP for the simulations carried out. We investigate the following ten models (the focus of the main text is on those marked with stars):

(1) Cross-country homogeneity (β) and no factors. We set all λ_i to zero such that x and y are stationary and cross-sectionally independent; technology is the same across countries and sectors.

(2) As Model (1) but now we have heterogeneous β across countries.

(3) As Model (2) but with substantially larger heterogeneity in TFP levels across countries.

(4) ★ As Model (2) but with TFP levels in manufacturing are now 1.5 times those in agriculture. We keep this feature for the remainder of setups.

(5) This sees the introduction of common factors (f_{2t} and f_{3t}) albeit with homogeneous factor loadings across countries. Both factors and loadings are independent across sectors. The absence of f_{1t} means there is no endogeneity problem.

(6) ★ As Model (5) but now we have factor loading heterogeneity across countries.

(7) As Model (6) but with factor-overlap between x and y equations: f_{1t} is contained in both of these, inducing endogeneity in a sectoral regression.

(8) ★ As Model (7) but slope coefficients now differ across countries and sectors — for the latter we specify $\beta_i^m = 1 - \beta_i^a$.

(9) As Model (8) except we now have independent slope coefficients across sectors with means $\beta^m = 0.3$ and $\beta^a = 0.5$.

(10) ★ As Model (9) but we now have the same factor f_{1t} contained in y and x-equations of both sectors, although with differential (and independent) factor loadings.

Models (1) to (4) analyse a homogeneous parameter world without common factors, where aggregation should lead to no problems for estimation. Models (5) to (7) show what happens when factors are introduced. Models (8) and (9) introduce parameter heterogeneity across sectors and Model (10) adds factor-overlap between sectors (on top of overlap across variables within sector).

TECHNICAL APPENDIX

TA-1 Time-series properties of the data

Table TA-I: Second generation panel unit root tests

PANEL (A): AGRICULTURE DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
0	-0.662	(.25)	7.869	(1.00)	7.182	(1.00)	0	-16.230	(.00)	-2.829	(.00)	-1.550	(.06)
1	-0.326	(.37)	5.392	(1.00)	3.871	(1.00)	1	-9.960	(.00)	3.394	(1.00)	-0.359	(.36)
2	2.911	(1.00)	7.550	(1.00)	5.490	(1.00)	2	-4.970	(.00)	5.639	(1.00)	4.161	(1.00)
3	4.817	(1.00)	9.859	(1.00)	5.417	(1.00)	3	-1.474	(.07)	6.238	(1.00)	5.171	(1.00)

	Land pw			**Land pw**	
lags	Ztbar	(p)	lags	Ztbar	(p)
0	9.432	(1.00)	0	-9.704	(.00)
1	7.223	(1.00)	1	-3.433	(.00)
2	6.069	(1.00)	2	1.324	(.91)
3	3.266	(1.00)	3	3.132	(1.00)

PANEL (B): MANUFACTURING DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
0	0.903	(.82)	2.539	(.99)	1.668	(.95)	0	-18.029	(.00)	-11.824	(.00)	-9.259	(.00)
1	2.631	(1.00)	1.971	(.98)	0.667	(.75)	1	-8.603	(.00)	-6.586	(.00)	-4.928	(.00)
2	2.513	(.99)	4.240	(1.00)	2.060	(.98)	2	-3.585	(.00)	-3.700	(.00)	-2.263	(.01)
3	4.022	(1.00)	4.066	(1.00)	3.240	(1.00)	3	-1.059	(.14)	-0.176	(.43)	0.847	(.80)

PANEL (C): AGGREGATED DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
0	2.558	(.99)	6.950	(1.00)	5.920	(1.00)	0	-15.283	(.00)	-5.625	(.00)	-4.489	(.00)
1	3.112	(1.00)	4.292	(1.00)	3.668	(1.00)	1	-8.185	(.00)	-2.324	(.01)	-1.073	(.14)
2	5.190	(1.00)	4.906	(1.00)	4.177	(1.00)	2	-3.429	(.00)	0.035	(.51)	1.154	(.88)
3	5.361	(1.00)	5.131	(1.00)	4.307	(1.00)	3	-0.640	(.26)	2.637	(1.00)	3.472	(1.00)

PANEL (D): PENN WORLD TABLE DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)	lags	Ztbar	(p)	Ztbar	(p)	Ztbar	(p)
0	4.544	(1.00)	-1.069	(.14)	2.802	(1.00)	0	-14.287	(.00)	0.711	(.76)	-4.690	(.00)
1	6.126	(1.00)	7.647	(1.00)	6.097	(1.00)	1	-6.603	(.00)	-1.977	(.02)	-2.437	(.01)
2	6.581	(1.00)	7.215	(1.00)	7.215	(1.00)	2	-4.112	(.00)	1.784	(.96)	-1.801	(.04)
3	7.772	(1.00)	6.475	(1.00)	7.576	(1.00)	3	-1.050	(.15)	2.205	(.99)	-0.468	(.32)

Notes: We report test statistics and p-values for the Pesaran (2007) CIPS panel unit root test of the variables in our four datasets. In all cases we use $N = 41$, $n = 928$ for the levels data.

TA-2 Cross-section dependence in the data

Table TA-II: Cross-section correlation analysis

	Variables in levels				*Variables in first diff.*			
Agriculture data	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ
log VA pw	0.41	0.57	57.65	74.45	0.05	0.23	6.57	6.59
(p)			(.00)	(.00)			(.00)	(.00)
log Labour	-0.01	0.76	-1.10	0.45	0.12	0.52	14.50	22.60
(p)			(.27)	(.65)			(.00)	(.00)
log Cap pw	0.41	0.72	56.06	97.01	0.08	0.40	9.09	11.26
(p)			(.00)	(.00)			(.00)	(.00)
log Land pw	0.02	0.72	2.90	3.49	0.04	0.28	4.96	5.67
(p)			(.00)	(.00)			(.00)	(.00)
Manufacturing data	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ
log VA pw	0.43	0.63	66.34	84.24	0.05	0.21	6.27	6.49
(p)			(.00)	(.00)			(.00)	(.00)
log Labour	0.26	0.60	38.19	54.53	0.14	0.25	17.82	18.98
(p)			(.00)	(.00)			(.00)	(.00)
log Cap pw	0.61	0.77	86.11	136.03	0.07	0.22	8.22	9.04
(p)			(.00)	(.00)			(.00)	(.00)
Aggregated data	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ
log VA pw	0.61	0.69	83.57	118.17	0.08	0.23	10.65	11.23
(p)			(.00)	(.00)			(.00)	(.00)
log Labour	0.01	0.72	1.36	6.42	0.06	0.31	8.24	9.47
(p)			(.18)	(.00)			(.00)	(.00)
log Cap pw	0.76	0.85	97.16	188.46	0.07	0.29	7.99	9.81
(p)			(.00)	(.00)			(.00)	(.00)
Penn World Table data	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ	$\bar{\rho}$	$\lvert\bar{\rho}\rvert$	CD	CDZ
log VA pw	0.72	0.74	111.55	170.81	0.14	0.20	21.89	19.07
(p)			(.00)	(.00)			(.00)	(.00)
log Labour	0.95	0.95	149.58	298.19	0.11	0.38	16.80	17.57
(p)			(.00)	(.00)			(.00)	(.00)
log Cap pw	0.76	0.86	116.84	219.82	0.26	0.38	39.69	38.66
(p)			(.00)	(.00)			(.00)	(.00)

Notes: In all cases we use $N = 41$, $n = 928$ for the levels data. We report the average correlation coefficient across the $N(N-1)$ variable series $\bar{\rho}$, as well as the average absoulte correlation coefficient $|\bar{\rho}|$. CD and CDZ are formal cross-section correlation tests introduced by Pesaran (2004) and Moscone and Tosetti (2009). Under the H_0 of cross-section independence both statistics are asymptotically standard normal. We investigated two further tests introduced by Moscone and Tosetti (2009), namely $\mathrm{CD}_{\mathrm{LM}}$ and $\mathrm{CD}_{\mathrm{ABS}}$, which yield the same conclusions as the tests presented (detailed results available on request).

TA-3 Monte Carlo simulations: detailed results

Table TA-III: Simulation results

	Model 1					Model 2			
	mean	median	ste$^{\bullet}$	ste$^{\flat}$		mean	median	ste$^{\bullet}$	ste$^{\flat}$
CMG Agri	0.4999	0.4990	0.0318	0.0324	CMG Agri	0.5007	0.4996	0.0425	0.0424
CMG Manu	0.4999	0.4990	0.0318	0.0324	CMG Manu	0.5007	0.4996	0.0425	0.0424
Weighted	0.5000	0.5000	0.0000		Weighted	0.5007	0.4998	0.0289	
POLS	0.5054	0.5064	0.0462	0.0298	POLS	0.5058	0.5065	0.0572	0.0304
2FE	0.5002	0.5005	0.0248	0.0226	2FE	0.5014	0.5007	0.0392	0.0232
FD	0.5000	0.5007	0.0295	0.0257	FD	0.5014	0.5014	0.0441	0.0262
CCEP	0.4996	0.4997	0.0292	0.0271	CCEP	0.5008	0.5001	0.0424	0.0276
MG	0.4993	0.4987	0.0276	0.0283	MG	0.5001	0.4993	0.0389	0.0399
CMG	0.4999	0.4990	0.0318	0.0324	CMG	0.5007	0.4996	0.0425	0.0424
	Model 3					Model 4			
	mean	median	ste$^{\bullet}$	ste$^{\flat}$		mean	median	ste$^{\bullet}$	ste$^{\flat}$
CMG Agri	0.4999	0.4990	0.0318	0.0324	CMG Agri	0.4999	0.4990	0.0318	0.0324
CMG Manu	0.4999	0.4990	0.0318	0.0324	CMG Manu	0.4999	0.4990	0.0318	0.0324
Weighted	0.5000	0.5000	0.0000		Weighted	0.5000	0.5000	0.0000	
POLS	0.5310	0.5280	0.1968	0.1128	POLS	0.5119	0.5112	0.0593	0.0365
2FE	0.5002	0.5005	0.0248	0.0226	2FE	0.5002	0.5005	0.0248	0.0226
FD	0.5000	0.5007	0.0295	0.0257	FD	0.5000	0.5007	0.0295	0.0257
CCEP	0.4996	0.4997	0.0292	0.0271	CCEP	0.4996	0.4997	0.0292	0.0271
MG	0.4993	0.4987	0.0276	0.0283	MG	0.4993	0.4987	0.0276	0.0283
CMG	0.4999	0.4990	0.0318	0.0324	CMG	0.4999	0.4990	0.0318	0.0324
	Model 5					Model 6			
	mean	median	ste$^{\bullet}$	ste$^{\flat}$		mean	median	ste$^{\bullet}$	ste$^{\flat}$
CMG Agri	0.4993	0.4987	0.0299	0.0298	CMG Agri	0.5005	0.5002	0.0238	0.0233
CMG Manu	0.5000	0.5014	0.0311	0.0321	CMG Manu	0.4994	0.5004	0.0253	0.0246
Weighted	0.5000	0.5000	0.0000		Weighted	0.5000	0.5000	0.0000	
POLS	0.4936	0.4936	0.0753	0.0432	POLS	0.4558	0.4669	0.1059	0.0197
2FE	0.4563	0.4571	0.0331	0.0266	2FE	0.4382	0.4450	0.0588	0.0176
FD	0.4427	0.4416	0.0418	0.0268	FD	0.4181	0.4224	0.0517	0.0219
CCEP	0.4516	0.4502	0.0327	0.0278	CCEP	0.4231	0.4326	0.0522	0.0186
MG	0.4663	0.4687	0.3257	0.0369	MG	0.4305	0.4333	0.1816	0.0496
CMG	0.4498	0.4497	0.0362	0.0379	CMG	0.4161	0.4226	0.0516	0.0342
	Model 7					Model 8			
	mean	median	ste$^{\bullet}$	ste$^{\flat}$		mean	median	ste$^{\bullet}$	ste$^{\flat}$
CMG Agri	0.5000	0.4998	0.0448	0.0436	CMG Agri	0.5009	0.5020	0.0528	0.0520
CMG Manu	0.4979	0.4972	0.0454	0.0445	CMG Manu	0.4986	0.4978	0.0550	0.0528
Weighted	0.5000	0.5000	0.0000		Weighted	0.5007	0.4998	0.0289	
POLS	0.4405	0.4469	0.1212	0.0236	POLS	0.4459	0.4452	0.1299	0.0248
2FE	0.4143	0.4161	0.0700	0.0210	2FE	0.4217	0.4234	0.0807	0.0220
FD	0.4027	0.4011	0.0541	0.0238	FD	0.4106	0.4073	0.0635	0.0245
CCEP	0.3956	0.3987	0.0619	0.0227	CCEP	0.4040	0.4047	0.0702	0.0233
MG	0.6759	0.6585	0.2510	0.0782	MG	0.6826	0.6644	0.2532	0.0828
CMG	0.3897	0.3928	0.0584	0.0496	CMG	0.3985	0.3976	0.0650	0.0560
	Model 9					Model 10			
	mean	median	ste$^{\bullet}$	ste$^{\flat}$		mean	median	ste$^{\bullet}$	ste$^{\flat}$
CMG Agri	0.5009	0.5020	0.0528	0.0520	CMG Agri	0.5009	0.5020	0.0528	0.0520
CMG Manu	0.2961	0.2972	0.0543	0.0526	CMG Manu	0.2961	0.2972	0.0543	0.0526
Weighted	0.3924	0.3928	0.0391		Weighted	0.3939	0.3946	0.0391	
POLS	0.3383	0.3388	0.1324	0.0246	POLS	0.3400	0.3415	0.1322	0.0246
2FE	0.3151	0.3127	0.0814	0.0217	2FE	0.3163	0.3144	0.0816	0.0217
FD	0.3074	0.3053	0.0625	0.0242	FD	0.3086	0.3071	0.0626	0.0242
CCEP	0.2963	0.2973	0.0666	0.0229	CCEP	0.2976	0.2986	0.0667	0.0229
MG	0.5793	0.5562	0.2558	0.0814	MG	0.5796	0.5561	0.2558	0.0815
CMG	0.2956	0.2962	0.0625	0.0543	CMG	0.2970	0.2976	0.0627	0.0544

Notes: See Section A-2 in the Appendix for details on the estimators and the DGP in each of the experiments. ste$^{\bullet}$ marks the empirical standard error and ste$^{\flat}$ the mean standard error from 1,000 replications. 'CMG Agri' and 'CMG Manu' employ the sector-level data, 'Weighted' calculates the aggregate slope coefficient based on the size (output) and slope of the respective sector, the remaining six estimators use the aggregated data.

TA-4 Additional tables and figures

Table TA-IV: Pooled regression models (HC-augmented)

Panel (A): Unrestricted returns to scale

	Agriculture					*Manufacturing*				
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **CCEP**$^\flat$	[5] **FD**	[6] **POLS**	[7] **2FE**	[8] **CCEP**	[9] **CCEP**$^\flat$	[10] **FD**
log labour	-0.079	-0.151	-0.457	-0.557	-0.085	0.005	0.029	0.121	-0.048	0.162
	[11.71]**	[4.35]**	[1.54]	[1.46]	[1.46]	[0.62]	[0.88]	[1.91]	[0.47]	[4.62]**
log capital pw	0.471	0.671	0.554	0.676	0.595	0.692	0.851	0.533	0.446	0.654
	[61.84]**	[27.20]**	[4.51]**	[4.32]**	[12.60]**	[44.38]**	[22.14]**	[8.00]**	[4.52]**	[14.56]**
log land pw	0.018	-0.020	-0.154	-0.174	0.111					
	[1.17]	[0.48]	[0.56]	[0.50]	[1.14]					
Education	0.241	0.087	0.007	-0.068	0.101	0.226	-0.006	0.152	-0.017	0.095
	[9.95]**	[3.12]**	[0.07]	[0.40]	[1.30]	[11.91]**	[0.21]	[2.04]*	[0.16]	[1.53]
Educationˆ2	-0.010	-0.007	-0.003	0.005	-0.006	-0.009	0.002	-0.006	-0.004	-0.005
	[4.73]**	[4.15]**	[0.49]	[0.50]	[1.23]	[6.22]**	[1.39]	[1.32]	[0.66]	[1.10]
Implied RS†	CRS	CRS	CRS	CRS	IRS	CRS	CRS	CRS		IRS
Implied β_L‡	0.529	0.329	0.446	0.324	0.321	0.308	0.149	0.467		0.508
$\hat{e}$ integrated$^\natural$	I(1)	I(1)	I(0)	I(1)/I(0)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)
CD test p-value$^\sharp$	0.11	0.09	0.14	0.21	0.00	0.87	0.18	0.58	0.84	0.00
Mean Education	5.82	5.82	5.82	5.82	5.94	5.82	5.82	5.82	5.82	5.94
Returns to Edu	13.3%	0.7%	-2.9%	-0.7%	3.0%	12.3%	1.9%	8.5%	-6.6%	4.1%
[t-statistic]$^\flat$	[15.71]**	[0.50]	[0.68]	[0.11]	[0.78]	[19.88]**	[1.30]	[3.11]**	[1.56]	[1.54]
R-squared	0.91	0.57	1.00	1.00	-	0.91	0.57	1.00	1.00	-
Observations	830	830	830	775	793	860	860	860	775	817

Panel (B): Constant returns to scale imposed

	Agriculture					*Manufacturing*				
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **CCEP**$^\flat$	[5] **FD**	[6] **POLS**	[7] **2FE**	[8] **CCEP**	[9] **CCEP**$^\flat$	[10] **FD**
log capital pw	0.502	0.720	0.592	0.709	0.611	0.695	0.839	0.472	0.463	0.558
	[59.09]**	[33.18]**	[5.32]**	[5.08]**	[13.29]**	[49.18]**	[24.30]**	[8.87]**	[5.59]**	[13.85]**
log land pw	0.014	0.078	0.144	0.122	0.124					
	[0.71]	[2.23]*	[0.99]	[0.69]	[1.27]					
Education	0.278	0.069	-0.003	-0.031	0.107	0.226	0.014	0.234	0.036	0.220
	[11.54]**	[2.48]*	[0.03]	[0.23]	[1.38]	[11.80]**	[0.71]	[3.67]**	[0.38]	[3.91]**
Educationˆ2	-0.012	-0.005	0.000	0.002	-0.006	-0.009	0.001	-0.010	-0.007	-0.010
	[6.17]**	[3.19]**	[0.06]	[0.28]	[1.26]	[6.11]**	[0.98]	[2.55]*	[1.22]	[2.41]*
Implied β_L‡	0.498	0.202	0.408	0.291	0.389	0.305	0.162	0.528	0.537	0.443
Mean Education	5.82	5.82	5.82	5.82	5.94	5.82	5.82	5.82	5.82	5.94
Returns to Edu	13.9%	0.8%	-0.7%	-0.3%	3.4%	12.3%	2.7%	11.7%	-4.3%	10.5%
[t-statistic]$^\spadesuit$	[16.25]**	[0.52]	[0.18]	[0.07]	[0.90]	[20.20]**	[2.30]*	[5.25]**	[1.18]	[4.62]**
$\hat{e}$ integrated$^\natural$	I(1)	I(1)	I(0)	I(1)/I(0)	I(0)	I(1)	I(1)	I(0)	I(1)/I(0)	I(0)
CD test p-value$^\sharp$	0.29	0.23	0.07	0.23	0.00	0.88	0.04	0.08	0.02	0.00
R-squared	0.91	0.57	1.00	1.00	-	0.91	0.57	1.00	1.00	-
Observations	830	830	830	775	793	860	860	860	775	817

Notes: We include our proxy for education in levels and as a squared term. Returns to Education are computed from the sample mean ($\bar{E}$) as $\beta_E + 2\beta_{E2}\bar{E}$ where β_E and β_{E2} are the coefficients on the levels and squared education terms respectively. $\spadesuit$ computed via the delta-method. For more details see Notes of Table II of the main text.

Table TA-V: Heterogeneous Manufacturing models (HC-augmented)

	Panel (A): Unrestricted			Panel (B): CRS imposed		
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **MG**	[5] **FDMG**	[6] **CMG**
log labour	-0.305	-0.293	0.097			
	[1.20]	[1.50]	[0.62]			
log capital pw	0.059	0.144	0.426	0.352	0.347	0.386
	[0.22]	[0.74]	[3.73]**	[3.25]**	[3.66]**	[3.95]**
Education	-0.478	0.237	1.248	-0.228	0.085	0.668
	[1.02]	[0.81]	[2.66]*	[0.62]	[0.29]	[2.43]*
Education squared	0.050	0.011	-0.098	0.005	-0.019	-0.042
	[1.38]	[0.35]	[2.67]*	[0.13]	[0.67]	[1.95]
country trend/drift	0.016	0.020		0.008	0.013	
	[1.55]	[2.44]*		[1.16]	[2.23]*	
reject CRS (10%)	38%	8%	38%			
Implied β_L‡	n/a	0.857	0.574	0.648	0.653	0.614
Mean Education	5.82	5.91	5.82	5.87	5.94	5.87
Returns to Edu	-6.3%	-1.3%	10.9%	-6.2%	-2.1%	11.9%
[t-statistic]♭	[1.01]	[0.25]	[1.89]	[1.00]	[0.47]	[1.70]
panel-t Labour	4.49**	-2.51*	1.81			
panel-t Capital	0.30	-0.25	8.62**	7.52**	5.48**	10.19**
panel-t Edu	2.08*	0.93	3.58**	3.08**	0.88	3.38**
panel-t Edu^2	1.93	-0.91	3.31**	2.47*	0.97	2.67**
panel-t trend/drift	12.59**	6.41**		13.89	7.05	
sign. trends (10%)	15	9		17	7	
$\hat{e}$ integrated♮	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
abs correl. coeff.	0.21	0.22	0.22	0.22	0.22	0.22
CD-test (p)♯	0.00	0.00	0.71	0.00	0.00	0.27
Obs (N)	775 (37)	732 (37)	775 (37)	775 (37)	732 (37)	775 (37)

Notes: All averaged coefficients presented are robust means across i. ♭ The returns to education and associated t-statistics are based on a two-step procedure: first the country-specific mean education value ($\bar{E}_i$) is used to compute $\beta_{i,E} + 2\beta_{i,E2}\bar{E}_i$ to yield the country-specific returns to education. The reported value then represents the robust mean of these N country estimates, s.t. the t-statistic should be interpreted in the same fashion as that for the regressors, namely as a test whether the average parameter is statistically different from zero, following Pesaran et al. (2009). For other details see Notes for Tables III (main text) and TA-IV above.

Table TA-VI: Aggregate & PWT data: Pooled models (HC-augmented)

Panel (A): Unrestricted returns

	Aggregated data				*Penn World Table data*			
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **FD**	[5] **POLS**	[6] **2FE**	[7] **CCEP**	[8] **FD**
log labour	-0.001	-0.058	0.566	0.083	0.040	-0.064	-0.193	-0.032
	[0.14]	[1.97]*	[4.13]**	[2.50]*	[8.99]**	[3.27]**	[1.49]	[1.11]
log capital pw	0.662	0.782	0.677	0.766	0.725	0.680	0.601	0.676
	[97.95]**	[31.50]**	[7.25]**	[25.24]**	[72.79]**	[24.79]**	[9.12]**	[18.96]**
Education	0.243	-0.004	0.086	0.065	0.041	0.043	0.032	0.103
	[16.97]**	[0.15]	[1.24]	[1.22]	[3.42]**	[2.86]**	[0.80]	[3.41]**
Education squared	-0.010	0.003	-0.007	-0.003	-0.001	-0.002	-0.002	-0.006
	[8.05]**	[1.82]	[1.57]	[0.77]	[1.77]	[2.97]**	[0.83]	[2.94]**
Implied RS†	CRS	DRS	CRS	CRS	CRS	DRS	CRS	CRS
Implied β_L‡	0.337	0.160	0.890	0.318	0.315	0.256	0.206	0.292
Mean Education	5.824	5.824	5.824	5.885	5.822	5.822	5.822	5.883
Returns to Edu	12.9%	2.5%	1.0%	3.4%	2.4%	1.9%	0.9%	3.3%
[t-statistic]♭	[22.35]**	[1.68]	[0.37]	[1.40]	[6.82]**	[2.02]*	[0.56]	[2.26]*
$\hat{e}$ integrated♮	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	I(0)	I(1)/I(0)
CD test p-value♯	0.00	0.02	0.59	0.00	0.34	0.22	0.01	0.00
R-squared	0.98	0.87	1.00	-	0.97	0.78	1.00	-
Observations	775	775	775	732	769	769	769	726

Panel (B): Constant returns to scale imposed

	Aggregated data				*Penn World Table data*			
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **FD**	[5] **POLS**	[6] **2FE**	[7] **CCEP**	[8] **FD**
log capital pw	0.662	0.798	0.485	0.744	0.694	0.706	0.611	0.691
	[102.10]**	[35.45]**	[7.03]**	[25.48]**	[73.08]**	[27.73]**	[10.05]**	[21.13]**
Education	0.243	-0.016	0.210	0.111	0.043	0.037	0.016	0.092
	[16.98]**	[0.62]	[3.00]**	[2.21]*	[3.30]**	[2.44]*	[0.48]	[3.22]**
Education squared	-0.010	0.004	-0.013	-0.005	-0.001	-0.002	-0.002	-0.006
	[8.17]**	[2.75]**	[2.92]**	[1.37]	[0.97]	[2.12]*	[0.95]	[2.79]**
Constant	1.586				1.843			
	[21.62]**				[20.44]**			
Implied β_L‡	0.338	0.203	0.515	0.256	0.306	0.294	0.390	0.309
Mean Education	5.824	5.824	5.824	5.885	5.822	5.824	5.824	5.883
Returns to Edu	12.9%	2.6%	6.5%	5.8%	3.3%	2.0%	-0.6%	2.7%
[t-statistic]♭	[22.41]**	[1.68]	[2.56]**	[2.56]**	[8.62]**	[1.99]*	[0.42]	[1.98]*
$\hat{e}$ integrated♮	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)
CD test p-value♯	0.00	0.00	0.65	0.00	0.25	0.57	0.02	0.00
R-squared	0.98	0.86	1.00		0.97	0.78	1.00	
Observations	775	775	775	732	769	769	769	726

Notes: We include our proxy for education in levels and as a squared term. Returns to Education are computed from the sample mean ($\bar{E}$) as $\beta_E + 2\beta_{E2}\bar{E}$ where β_E and β_{E2} are the coefficients on the levels and squared education terms respectively. ♭ computed via the delta-method. For more details see Notes for Tables IV (in the main text) and (for the education variables) TA-IV above.

Table TA-VII: Aggregate & PWT data: Heterogeneous models with HC

	Panel (A): Unrestricted returns to scale					
	Aggregated data			*Penn World Table data*		
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **MG**	[5] **FDMG**	[6] **CMG**
log labour	-0.066	0.269	-0.428	-1.609	-2.478	-1.324
	[0.16]	[0.57]	[1.22]	[1.97]	[3.76]**	[2.79]**
log capital pw	-0.070	-0.021	0.453	0.963	1.245	1.122
	[0.26]	[0.07]	[2.47]*	[4.44]**	[5.99]**	[5.52]**
Education	0.601	0.637	0.489	0.123	0.004	-0.012
	[1.29]	[1.75]	[0.98]	[0.52]	[0.02]	[0.05]
Education squared	-0.089	-0.065	-0.063	-0.002	0.004	-0.001
	[1.76]	[1.70]	[1.48]	[0.11]	[0.25]	[0.03]
country trend/drift	0.005	0.005		0.021	0.008	
	[0.33]	[0.29]		[2.25]*	[0.77]	
Mean Education	5.72	5.84	5.72	5.72	5.84	5.72
Returns to edu	-7.1%	-3.2%	-11.1%	-4.5%	0.5%	1.3%
[t-statistic]$^\flat$	[1.33]	[0.65]	[1.24]	[1.33]	[0.18]	[0.43]
Implied RS†	CRS	CRS	CRS	CRS	DRS	DRS
Implied β_L‡	n/a	n/a	0.547	n/a	n/a	n/a
reject CRS (10%)	38%	3%	19%	38%	18%	33%
panel-t Labour	-1.77	0.16	-1.42	-6.37**	-5.60**	-7.30**
panel-t Capital	0.58	0.94	2.79**	15.62**	13.48**	14.39**
panel-t Edu	0.26	1.21	0.86	0.89	0.23	0.68
panel-t Edu ˆ2	-1.07	-1.87	-1.26	-1.55	-0.35	-0.72
panel-t trends	14.73**	10.93**		11.09**	5.83**	
# sign. trends	18	13		18	4	
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
abs correl.coeff.	0.24	0.24	0.22	0.23	0.24	0.22
CD-test (p)$^\sharp$	7.23(.00)	7.88(.00)	-0.50(.61)	7.59.00)	9.29.00)	0.98(.33)

	Panel (B): CRS imposed					
	Aggregated data			*Penn World Table data*		
	[1] **MG**	[2] **FDMG**	[3] **CMG**	[4] **MG**	[5] **FDMG**	[6] **CMG**
log capital pw	0.093	0.151	0.528	0.779	1.052	0.906
	[0.49]	[0.90]	[4.90]**	[5.75]**	[6.43]**	[5.86]**
Education	0.075	0.260	0.683	-0.215	-0.134	0.089
	[0.18]	[0.99]	[1.73]	[1.25]	[0.84]	[0.42]
Education squared	-0.023	-0.023	-0.075	0.013	0.014	-0.023
	[0.65]	[0.89]	[1.57]	[0.82]	[1.13]	[1.16]
country trend/drift	0.017	0.015		-0.001	-0.010	
	[1.96]	[1.33]		[0.21]	[2.08]*	
Implied β_L‡	n/a	n/a	0.472	0.221	n/a	0.094
Mean Education	5.79	5.84	5.79	5.79	5.84	5.79
Returns to edu	-9.3%	-4.0%	3.2%	-1.4%	0.3%	-0.2%
[t-statistic]$^\flat$	-1.34	-0.88	0.50	0.50	0.16	0.05
panel-t Capital	2.96**	1.84	7.63**	16.24**	11.99**	15.70**
panel-t Edu	-2.05*	1.97*	3.78**	-1.80	-1.23	0.74
panel-t Edu ˆ2	0.79	-2.77**	-3.83**	1.20	0.96	-1.11
panel-t trends	15.65**	12.21**		11.57**	7.84**	
# sign. trends	15	13		15	14	
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
abs correl.coeff.	0.24	0.24	0.23	0.26	0.24	0.22
CD-test (p)$^\sharp$	8.05(.00)	8.59(.00)	0.11(.92)	9.75(.00)	10.84(.00)	3.12(.00)

Notes: All averaged coefficients presented are robust means across i. $\flat$ The returns to education and associated t-statistics are based on a two-step procedure: first the country-specific mean education value ($\bar{E}_i$) is used to compute $\beta_{i,E} + 2\beta_{i,E2}\bar{E}_i$ to yield the country-specific returns to education. The reported value then represents the robust mean of these N country estimates, s.t. the t-statistic should be interpreted in the same fashion as that for the regressors, namely as a test whether the average parameter is statistically different from zero, following Pesaran et al. (2009). For other details see Notes for Tables III (in the main text) and TA-V above.

Table TA-VIII: Alternative dynamic panel estimators

Panel (A): Agriculture

	Dynamic FE			**PMG**				**CPMG***			**DGMM**	**SGMM**
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EC [y_{t-1}]	-0.293	-0.312	-0.300	-0.460	-0.459	-0.624	-0.466	-0.482	-0.503	-0.455	-1.087	-0.432
	[11.80]**	[12.43]**	[11.91]**	[10.63]**	[9.34]**	[14.29]**	[10.44]**	[10.06]**	[9.74]**	[9.34]**	[2.60]**	[5.38]**
capital pw	0.672	0.684	0.582	0.652	0.714	0.036	0.132	0.501	0.464	0.530	1.135	0.776
	[12.47]**	[12.69]**	[7.50]**	[20.16]**	[18.52]**	[0.57]	[3.01]**	[10.78]**	[11.05]**	[10.83]**	[2.85]**	[12.59]**
land pw	0.124	0.121	0.135	0.136	0.367	0.867	0.361	0.247	0.494	0.228	0.083	-0.247
	[1.30]	[1.29]	[1.45]	[2.90]**	[6.43]**	[8.27]**	[8.05]**	[5.03]**	[8.95]**	[4.73]**	[0.35]	[1.17]
trend(s)†			0.001			0.008	0.012					
			[1.59]			[3.36]**	[12.26]**					
Constant	0.667	0.679	0.896	1.072	0.644	4.273	3.084	1.545	1.402	1.298		0.714
	[5.03]**	[4.75]**	[4.58]**	[10.48]**	[7.53]**	[13.11]**	[10.27]**	[10.38]**	[9.69]**	[9.94]**		[4.21]**
lags [trends]‡	1	2	1 [l-r]	1	2	1 [s-r]	1 [l-r]	1	2	1	i: 2-3	i: 2-3
impl. labour	0.328	0.316	0.418	0.212	-0.081	0.098	0.507	0.253	0.042	0.242	-0.135	0.224
obs	894	857	894	894	857	894	894	894	857	872	857	894

Panel (B): Manufacturing

	Dynamic FE			**PMG**				**CPMG***			**DGMM**	**SGMM**
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EC [y_{t-1}]	-0.196	-0.195	-0.195	-0.219	-0.181	-0.543	-0.214	-0.245	-0.194	-0.272	-2.196	-0.041
	[9.40]**	[9.16]**	[9.31]**	[6.59]**	[5.97]**	[4.04]**	[4.13]**	[7.16]**	[6.45]**	[7.33]**	[0.72]	[0.65]
capital pw	0.711	0.708	0.637	1.016	1.044	0.298	1.379	0.598	1.264	0.505	1.866	-1.515
	[12.96]**	[12.34]**	[6.85]**	[29.64]**	[33.09]**	[5.34]**	[26.80]**	[11.58]**	[22.28]**	[9.47]**	[3.25]**	[0.40]
trend(s)†			0.001			0.001	-0.010					
			[1.00]			[0.24]	[6.77]**					
Constant	0.452	0.456	0.588	-0.212	-0.228	3.493	-0.977	0.225	-0.434	0.372		1.042
	[3.87]**	[3.73]**	[3.29]**	[5.43]**	[4.95]**	[3.87]**	[4.18]**	[5.68]**	[5.77]**	[6.48]**		[1.80]
lags [trends]‡	1	2	1 [l-r]	1	2	1 [s-r]	1 [l-r]	1	2	1	i: 2-3	i: 2-3
impl. labour	0.289	0.292	0.363	-0.016	-0.044	0.702	-0.379	0.402	-0.264	0.495	-0.866	2.515
obs	902	880	902	902	880	902	902	902	880	879	880	902

Panel (C): Aggregated data

	Dynamic FE			**PMG**				**CPMG***			**DGMM**	**SGMM**
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EC [y_{t-1}]	-0.172	-0.176	-0.173	-0.279	-0.277	-0.429	-0.284	-0.292	-0.294	-0.317	-0.380	-0.243
	[8.59]**	[8.39]**	[8.59]**	[6.89]**	[7.25]**	[9.55]**	[6.72]**	[6.98]**	[7.38]**	[7.48]**	[0.71]	[4.21]**
capital pw	0.705	0.709	0.668	0.974	1.015	0.128	0.899	0.891	0.949	0.905	0.271	0.896
	[15.25]**	[14.65]**	[8.17]**	[36.86]**	[37.38]**	[1.90]	[21.11]**	[24.84]**	[24.92]**	[27.54]**	[0.27]	[22.80]**
trend(s)†			0.000			0.011	0.004					
			[0.54]			[6.07]**	[2.42]*					
Constant	0.390	0.393	0.446	-0.100	-0.200	3.061	0.082	-0.062	-0.169	-0.145		0.120
	[4.96]**	[4.62]**	[3.42]**	[3.73]**	[5.18]**	[9.30]**	[4.20]**	[2.53]*	[4.97]**	[4.58]**		[1.44]
lags [trends]‡	1	2	1 [l-r]	1	2	1 [s-r]	1 [l-r]	1	2	1	i: 2-3	i: 2-3
impl. labour	0.295	0.292	0.332	0.026	-0.015	0.872	0.102	0.109	0.051	0.095	0.729	0.104
obs	879	836	879	879	836	879	879	879	836	879	836	879

Panel (D): Penn World Table data

	Dynamic FE			**PMG**				**CPMG***			**DGMM**	**SGMM**
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EC [y_{t-1}]	-0.098	-0.101	-0.107	-0.333	-0.138	-0.567	-0.392	-0.338	-0.081	-0.347	0.835	0.031
	[5.82]**	[6.01]**	[6.22]**	[6.70]**	[4.37]**	[12.63]**	[7.88]**	[6.63]**	[2.56]*	[8.24]**	[1.07]	[0.49]
capital pw	0.538	0.553	0.356	0.923	0.916	0.698	0.652	0.903	-0.125	0.731	0.604	0.863
	[8.14]**	[8.66]**	[3.44]**	[130.34]**	[71.72]**	[65.10]**	[67.96]**	[52.90]**	[1.81]	[86.83]**	[0.60]	[1.88]
trend(s)†			0.001			0.002	0.006					
			[2.44]*			[2.57]*	[19.84]**					
Constant	0.363	0.360	0.567	-0.122	-0.020	1.085	0.935	-0.071	0.456	0.504		0.010
	[5.38]**	[5.29]**	[5.28]**	[4.44]**	[1.63]	[13.05]**	[7.79]**	[3.47]**	[2.99]**	[8.29]**		[0.07]
lags [trends]‡	1	2	1 [l-r]	1	2	1 [s-r]	1 [l-r]	1	2	1	i: 2-3	i: 2-3
impl. labour	0.462	0.447	0.645	0.077	0.084	0.302	0.349	0.097	1.125	0.270	0.396	0.137
obs	914	904	914	914	904	914		914	904	873	904	914

Notes: We report the long-run coefficients on capital per worker (and in the agriculture equations also land per worker). EC [y_{t-1}] refers to the Error-Correction term (speed of adjustment parameter) with the exception of Models [11] and [12], where we report the coefficient on y_{t-1} — conceptually, these are the same, however in the latter we do not impose common factor restrictions like in all of the former models. Note that in the PMG and CPMG models the ECM term is heterogeneous across countries, while in the Dynamic FE and GMM models these are common across i. † In model [6] we include *heterogeneous* trend terms, whereas in [7] a *common* trend is assumed (i.e. linear TFP is part of cointegrating vector). ‡ 'lags' indicates the lag-length of first differenced RHS variables included, with the exception of Models [11] and [12]: here 'i:' refers to the lags (levels in [11], levels and differences in [12] used as instruments. ⋆ In the models in [8] and [9] the cross-section averages are only included for the long-run variables, whereas in the model in [10] cross-section averages for the first-differenced dependent and independent variables (short-run) are also included. Note that in the agriculture equation for Model [10] we drop CRI ($n = 7$) as otherwise no convergence would occur.