Structural Change and Cross-Country Growth Empirics*

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Abstract: One of the most striking features of economic growth is the process of structural change whereby the share of agriculture in GDP falls as countries develop. The cross-country growth literature typically estimates aggregate homogeneous production function or convergence regression models which abstract from this process of structural change. In this paper we investigate how much the aggregation and homogeneity assumptions matter for inferences regarding the nature of technology differences across countries. Using a unique World Bank dataset we estimate production functions for agriculture and manufacturing in a panel of 40 developing and developed countries (1963-1992). In doing so we empirically model dimensions of heterogeneity across countries, allowing for different choices of technology within both sectors. We argue that heterogeneity is important within sectors across countries, implying that aggregation will not produce useful measures of either the nature of the technology or productivity. We show that many of the puzzling elements in aggregate cross-country empirics can be explained by the combination of inappropriate aggregation across heterogeneous sectors.

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

JEL classification: O47, O11, C23

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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 Arthur 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; 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; Swan, 1956).

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 (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; Lin, 2011; McMillan & Rodrik, 2011; Page, 2012), 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, 2011) and the Barro-Lee data on human capital (most recently, Barro & Lee, 2010) have supplied macro-data which ensure that the aggregate human capital-augmented 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.

We estimate production functions for both manufacturing and agriculture and use the result to create a 'stylised' aggregate production function. We compare the results from this exercise with the standard approach in the literature, which is to use the PWT data to estimate aggregate functions ignoring both aggregation and heterogeneity issues at the sectoral level. Our findings indicate that technological differences across countries and within sectors are both important and that aggregate specifications are likely to lead to very misleading inferences regarding TFP.

The remainder of the paper is organised as follows: Section I motivates technology heterogeneity across sectors and countries. In Section II we introduce an empirical specification of our dual

[1] We refer to 'dual economy models' as representing economies with two stylised sectors of production (agriculture and manufacturing). '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).

economy framework, discuss the data and briefly review the empirical methods and estimators employed. Section III reports and discusses empirical findings at the sector-level. Section IV presents empirical findings from stylised and PWT aggregate data as well as evidence for technology heterogeneity. Section V summarizes and concludes.

I. Technology Heterogeneity

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 (Stoker, 1993; Temple & Wößmann, 2006). 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, Romer, & Weil, 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 mitigates this problem as manufacturing or agriculture are clearly more homogeneous than any aggregate construct, although our analysis shows that heterogeneity within these sectors is an important aspect of the data.

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

[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 dropped in Mankiw et al. (1992): Iran (12-51%), Kuwait (15-81%), Gabon (28-60%), Saudi Arabia (29-67%).

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). Other 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). Further challenge to the assumption of common technology is provided by the 'appropriate technology' literature, which argues that different technologies are appropriate to different factor endowments (see Basu & Weil, 1998). Under this explanation, global R&D leaders develop productivity-enhancing technologies that are suitable for their own capital-labour ratios and cannot be used effectively by poorer countries, so the latter do not develop. Empirical evidence which lends some support to this hypothesis can be found, among others, in Clark (2007) and Jerzmanowski (2007). 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.

Further, more formal insights for empirical modelling can be gained from the micro production framework introduced in Mundlak (1988) and taken to the macro (agriculture) data in Mundlak, Larson, and Butzer (1999) and Mundlak, Butzer, and Larson (forthcoming). Here the technology of production available to individual firms is a collection of possible techniques, each with its own production function, with optimal output over implemented techniques defined as

$$Y^* \equiv F(X^*, s) = \varphi(s) \tag{1}$$

where X^* and Y^* represent (optimal) inputs and output aggregated over implemented techniques and s is a vector of state variables determining both optimal input choice X^* and implemented technique $F(\cdot)$.[3] In each period[4] firms thus face the economic problem of choosing inputs as well as the appropriate production technique. This joint determination of inputs and technique makes it difficult to identify parameter coefficients in an empirical equivalent of equation (1) unless additional structure is imposed on the problem. Adopting a number of simplifying assumptions Mundlak et al. (forthcoming) provide the following approximation for their empirical model of output and inputs (i.e. production/supply and factor demand functions), explicitly including the exogenous state variables s

$$\begin{aligned} y_{it} &= x_{it}\beta(s) + s_{it}\gamma + m_{0it} + u_{0it} \qquad (2)\\ x_{jit} &= s_{it}\gamma + m_{0it} + \varepsilon_{jit} \qquad (3) \end{aligned}$$

where subscript j refers to the specific observed input to production x and y is observed output.[5] m_{0it} represents a firm-specific productivity shock at time t which is observed by the firm, thus influencing its input choice, but unknown to the econometrician. A large microeconometric literature (for a recent survey see Eberhardt & Helmers, 2010) has attempted to address the resulting 'transmission bias' first highlighted by Marschak and Andrews (1944). Mundlak et al. (forthcoming) simplify this productivity shock by requiring that it be decomposable into firm- and time-specific effects, $m_{0it} = m_{0i} + m_{0t}$ (similarly for the input equations). The setup further highlights two 'tech-

[3]Crucially, *all* changes in X^* are instigated by the state variables and with the exception of error it is deemed 'meaningless' to think of any other factors driving inputs (Mundlak et al., 1999).

[4]For simplicity the exposition in Mundlak et al. (forthcoming) is limited to a static model.

[5]u_{0it} and ε_{jit} are white noise.

nology shifters': firstly, the state variables affect output directly and indirectly through the selection of inputs, thus acting as input/output shifters; secondly, the state variables further directly influence the technology parameters β. Here, the state variables act as technology shifters in the sense that conditional on s (i) different countries will have different β coefficients, and/or (ii) at different points in time the same country may have different β coefficients. The presence of the state variables in the equations for *y and x* prevents the straightforward application of instrumental variables.[6]

Following some simplifying assumptions regarding aggregation (see Mundlak, 1988) the above framework is extended to apply at the country level. Empirical testing in the case of the cross-country production function for agriculture is carried out with a set of state variables including proxies for human capital, level of development, institutions, peak agricultural yield and a number of indicators for prices and price variability.[7] Using the simplifying assumption that $\beta(s) = \beta$, where they refer to the latter as a 'sample-dependent constant', the model is estimated using OLS following a within-country-time transformation of the variables, i.e. applying the two-way fixed effects estimator — the authors refer to the results from this regression as 'core technology'.[8] Further analysis in the paper and a related study by one of the co-authors (Butzer, 2011) investigate parameter constancy over time and parameter heterogeneity across countries by splitting the data into two periods and two country groups, respectively. Our own empirical implementation builds on the model by Mundlak et al. (forthcoming) as will become clear in the following discussion.

II. An Empirical Model of A Dual Economy

In the following we first present a general empirical specification for our sector-specific analysis of agriculture and manufacturing which shows how recent developments in the econometric modelling of production functions link with the framework set out by Mundlak. Next we review a number of empirical estimators, focusing on those arising from the recent panel time series literature, before we briefly discuss the data.

Empirical Specification

Our empirical framework 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

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{4}$$

$$x_{mit} = \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \phi_{1mi} f_{1mt} + \ldots + \phi_{nmi} f_{nmt} + v_{mit} \tag{5}$$

$$\boldsymbol{f}_t = \boldsymbol{\rho}' \boldsymbol{f}_{t-1} + \boldsymbol{\omega}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t \tag{6}$$

for $i = 1, \ldots, N$ countries, $t = 1, \ldots, T$ time periods and $m = 1, \ldots, k$ inputs.[9] Equation (4) represents the *production function*, with y as sectoral or aggregated value-added and $\boldsymbol{x}$ as a set of inputs: labour,

[6]Mundlak et al. (forthcoming) refer to the presence of state variables in both equations as technology 'heterogeneity'. Note that our use of the term differs in that we refer to $\beta_i \neq \beta$ as technology heterogeneity.

[7]The between country regressions further include time-invariant proxies for countries' physical environment.

[8]Between-time and between-country estimates are also provided but the 2FE results are the focus of attention.

[9]Further, $\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$ and the error terms ε_{it}, v_{mit}, $\boldsymbol{\omega}_t$ and $\boldsymbol{\epsilon}_t$ are white noise.

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 (see Supplemental Appendix S4). The output elasticities associated with each input ($\boldsymbol{\beta}_i$) are allowed to differ across countries.[10]

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), driven by some 'latent' processes that are either difficult to measure or truly unobservable. Equation (6) provides some structure for these unobserved common processes, which are modelled as simple AR(1) processes, where we do not exclude the possibility of unit root processes ($\boldsymbol{\rho} = 1$, $\boldsymbol{\kappa} = 1$), leading to nonstationary observables and unobservables. Note that from this the potential for spurious regression results arises if the empirical equation is misspecified.

Equation (5) details the evolution of the set of inputs, the *input demand functions*; crucially, some of the same processes determining the evolution of inputs are also assumed to be driving TFP in the production function equation.[11] Economically, this implies that the processes that make up TFP (e.g. knowledge, innovation, absorptive capacity) are affecting choices over inputs, i.e. the accumulation of capital stock, the evolution of the labour force and (in the agriculture equation) the area of land under cultivation, while at the same time affecting the production of output directly. Simply put, technical progress affects both production and the choice of productive inputs. Econometrically, 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 $\boldsymbol{\phi}_i$ (Kapetanios, Pesaran, & Yamagata, 2011). A conceptual justification for the pervasive character of unobserved common factors is provided by the nature of macro-economic variables in a globalised world, where economies are strongly connected to each other and latent forces drive all of the outcomes. The presence of such latent factors makes it difficult to argue for the validity of traditional approaches to causal interpretation of cross-country empirical analyses. Instrumental variable estimation in 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).

This model can be viewed as an empirical version of the theoretical model of Mundlak et al. (forthcoming) developed above: equations (4) and (5) capture the jointness property, which in the former's empirical model is made explicit by inclusion of a set of 'state variables' that impact inputs and output in an identical fashion — γ in equations (2) and (3). Instead, our framework allows for underlying unobserved factors to affect inputs and output differentially via the factor loadings.[12] These factors are conceptually similar to the state variables in the Mundlak model in that they represent any variable which may affect both factor choice and underlying TFP. The empirical implementation of our model differs from that of Mundlak in that we allow the data to seek to identify the different choices for the β coefficients. The evolution of the factors is fairly general, including nonstationarity, and the setup provides for globally common effects (strong factors) as well as local spillovers (weak factors). Similarly to Mundlak et al. (forthcoming) the productivity shock term m_{0it}

[10]Heterogeneity over time will be addressed in Section IV.

[11]Others, namely $\boldsymbol{g}_t$, are specific to the input evolution.

[12]A detailed review of the important contribution of factor models to empirical macroeconometrics is beyond the scope of this study — see Stock and Watson (2002), Bai and Ng (2008) and Onatski (2009) for more details.

is accounted for by a fixed effect α_i (m_{0i}) and the common factor structure ($m_{0t} = \lambda f_t$).[13] Finally, we allow for technology heterogeneity $\boldsymbol{\beta}_i$ across countries and test parameter constancy over time ($\boldsymbol{\beta}_{it} = \boldsymbol{\beta}_i$). The latter will further provide insights into the 'core technology' by highlighting whether technology parameters are likely to be functions of unobservables (in our case $\boldsymbol{f}_t$, in the Mundlak et al. (forthcoming) notation s). Our empirical implementation is focused on recent panel time series estimators which address nonstationarity, parameter heterogeneity and cross-section dependence. The following section introduces these methods in some more detail.

Empirical Implementation

Our empirical setup incorporates a large degree of flexibility with regard to the impact of observable and unobservable inputs 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. The following 2×2 matrix indicates the assumptions implicit in the various estimators implemented below.[14] We confine results for the estimators marked with stars to the Supplemental Appendix to save space.[15]

		Impact of Unobservables:	
		COMMON	IDIOSYNCRATIC
Production Technology:	COMMON	POLS, 2FE, GMM⋆, PMG⋆	CCEP, CPMG⋆
	IDIOSYNCRATIC	MG, FDMG	CMG

The panel time series econometric approach is given particular attention in this study for a number of reasons (for a detailed discussion see Eberhardt & Teal, 2011a). *Firstly*, we know that many macro variables are potentially nonstationary (Nelson & Plosser, 1982; Granger, 1997; Pedroni, 2007), which is confirmed for the variables in our data (see Supplemental Appendix, S1). When variables are nonstationary, standard regression output has to be treated with extreme caution, since results are potentially spurious. Provided variables are cointegrated we can nevertheless establish long-run equilibrium relationships in the data. The practical indication of cointegration is when regressions yield stationary residuals, whereas nonstationary residuals indicate a potentially spurious regression. Panel time series estimators can address the concern over spurious regression and we investigate the residuals of each empirical model using panel unit root tests. *Secondly*, panel time series methods allow for parameter heterogeneity across countries, which as motivated above is the central interest in our analysis. *Thirdly*, panel time series methods can address the problems

[13]The shock can never be truly idiosyncratic, i.e. m_{0it}, differing for each country i at each point in time t. We feel this is a reasonable assumption given the interconnectedness of economies.

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

[15]GMM, PMG and CPMG estimation were based on an error correction model specification, see Pesaran et al. (1999) for details. Further discussion of the empirical setup and results are available on request.

arising from cross-section correlation. Whether this is the result of common economic shocks or local spillover effects, cross-section correlation can potentially induce serious bias in the estimates, since the impact assigned to an observed covariate in reality confounds its impact with that of the unobservable processes. Although the panel time series approach does not allow us to quantify their impact, common shocks and local spillovers can be accommodated in the empirical analysis to obtain unbiased technology coefficients for the observable inputs. We will employ diagnostic tests to analyse each model's residuals for the presence/absence of cross-section dependence.

In the following we introduce the Common Correlated Effects (CCE) estimators developed in Pesaran (2006) and extended to nonstationary variables in Kapetanios et al. (2011) since there are at present relatively few applied studies which employ them (examples include Holly, Pesaran, & Yamagata, 2010; Moscone & Tosetti, 2010; Cavalcanti, Mohaddes, & Raissi, 2011; Eberhardt, Helmers, & Strauss, forthcoming).[16]

The CCE estimators 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 with heterogeneous impact. For the Mean Group version (CMG), the individual country regression is specified as

$$y_{it} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + c_{0i}\bar{y}_t + \sum_{m=1}^{k} \boldsymbol{c}_{mi}\bar{x}_{mt} + e_{it} \tag{7}$$

whereupon the parameter estimates $\hat{\boldsymbol{b}}_i$ are averaged across countries akin to the Pesaran and Smith (1995) Mean Group estimator.[17] The pooled version (CCEP) is specified as

$$y_{it} = a_i + \boldsymbol{b}' \boldsymbol{x}_{it} + \sum_{j=1}^{N} c_{0i}(\bar{y}_t D_j) + \sum_{m=1}^{k}\sum_{j=1}^{N} \boldsymbol{c}_{mi}(\bar{x}_{mt} D_j) + e_{it} \tag{8}$$

where the D_j represent country dummies.[18] The former is thus a simple extension to the Pesaran and Smith (1995) MG estimator based on on country-specific OLS regressions, whereas the latter is a standard fixed effects estimator augmented with additional regression terms.

In order to get an insight into the workings of this approach, consider the cross-section average of our model in equation (4): as the cross-section dimension N increases, given $\bar{\varepsilon}_t = 0$, we get

$$\bar{y}_t = \bar{\alpha} + \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t + \bar{\boldsymbol{\lambda}}'\boldsymbol{f}_t \qquad \Leftrightarrow \qquad \boldsymbol{f}_t = \bar{\boldsymbol{\lambda}}^{-1}(\bar{y}_t - \bar{\alpha} - \bar{\boldsymbol{\beta}}'\bar{\boldsymbol{x}}_t) \tag{9}$$

This simple derivation provides a powerful insight: working with cross-sectional means of y and $\boldsymbol{x}$ can account for the impact of unobserved common factors (TFP) in the production process.[19] Given the assumed heterogeneity in the impact of unobserved factors across countries ($\boldsymbol{\lambda}_i$) the estimator is implemented in the fashion detailed above, which allows for each country i to have different

[16] We abstract from discussing the standard panel estimators here in great detail and refer to the articles by Coakley, Fuertes, and Smith (2006), Bond and Eberhardt (2009) and Bond (2002) for more information. We also investigate the Pooled Mean Group (PMG) estimator by Pesaran et al. (1999) as well as a simple extension to the PMG where we include cross-section averages of the dependent and independent variables (CPMG), as suggested in Binder and Offermanns (2007).

[17] Although $\bar{y}_t$ and e_{it} are not independent their correlation goes to zero as N becomes large.

[18] Thus in the MG version we have N individual country regressions with $2k + 2$ RHS variables and in the pooled version a single regression equation with $k + (k + 2)N$ RHS variables.

[19] Most conservatively the CCE estimators require $\bar{\boldsymbol{\lambda}} \neq 0$, i.e. that the impact of each factor is on average non-zero (Coakley et al., 2006). Alternative scenarios (see Pesaran, 2006; Kapetanios et al., 2011) allow for this assumption to be dropped in certain situations but for the sake of generality we maintain it here.

parameter estimates on $\bar{y}_t$ and the $\bar{x}_t$, and thus implicitly on $\boldsymbol{f}_t$. Simulation studies (Pesaran, 2006; Coakley et al., 2006; Kapetanios et al., 2011; Pesaran & Tosetti, 2011) 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 local spillovers and global/local business cycles.[20] In the present study we implement two versions 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. It is conceivable that the evolution of the agricultural sector of developing countries influences that of the wider economy in general and the manufacturing sector in particular, such that this extension is sensible in the dual economy context.

This completes our discussion of the empirical implementation within each sector/level of aggregation. There is a direct link from the problems these estimators seek to address and the issue raised in the previous section regarding the problems posed in identifying the technology parameters of interest. Heterogeneity in the impact of observables and unobservables across countries can be directly interpreted as differences in the production technology and differential TFP evolution across countries. The above discussion suggests that from an economic theory standpoint there are reasons to prefer a more flexible approach, however we do not impose this on the data. Instead we use established econometric diagnostics (tests for residual stationarity and cross-section independence) to identify the models that are rejected and those that are supported by the data.

Data

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

(i) 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);
(ii) 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);
(iii) for a stylised aggregate economy made up of the aggregated data for the agriculture and manufacturing sectors;[21]
(iv) for the aggregate economy, building on data provided by the Penn World Table (PWT; we use version 6.2, Heston, Summers, & Aten, 2006).

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.

[20] An alternative approach to empirically implement equation (4) is to estimate factors, factor loadings and slope coefficients jointly, as in the Bai and Kao (2006) and Bai, Kao, and Ng (2009) estimators. Computational complexity aside, two recent theoretical contributions speak in favour of the Pesaran (2006) approach adopted in this study: theoretical work by Westerlund and Urbain (2011, p.17f) compares the former and latter approaches and concludes that "one is unlikely to do better than when using the relatively simple CA [cross-sectional average augmentation] approach.". Similarly, a study by Bailey, Kapetanios, and Pesaran (2012, p.25) concludes that the methods to determine the number of strong factors the former approach is reliant on are "invalid and will select the wrong number of factors, even asymptotically".

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

(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.[22]

Our sample is an unbalanced panel[23] for 1963 to 1992 made up of 40 developing and developed countries with a total of 918 observations (average $T = 23$) — 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. 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.

III. Empirical Results

Panel unit root and cross-section dependence tests have been confined to the Supplemental Appendix (S1, S2) of the paper. We adopt the Pesaran (2007) CIPS panel unit root test to analyse the time series properties of each variable series. Results 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 Supplemental Appendix, S2) indicate high average absolute correlation coefficients for the data in log levels and even in the data represented as growth rates. 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) and then allowing for differential technology across countries (Section). For all re-

[22]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.

[23]We do not account for missing observations in any way. 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.

gression models we report residual diagnostic tests including the Pesaran (2007) panel unit root test (we summarise results using I(0) for stationary, I(1) for nonstationary residuals, with I(1)/I(0) indicating ambiguous results) and the Pesaran (2004) CD test (H_0: cross-section independence), which we take to build our judgement for a preferred empirical model. Residual nonstationarity invalidates the inferential tools (e.g. t-statistics) employed (Kao, 1999) and indicates that regression results are potentially spurious. Just like serial dependence may point to dynamic misspecification, residual cross-section dependence violates the iid assumption for the error terms and indicates that the present model fails to adequately address the correlation of inputs and output across different countries, induced by for instance common shocks or local spillover effects.[24]

Note that the empirical model implemented expresses all variables in per worker terms (in logs). The inclusion of the log labour variable then indicates/tests the deviation from constant returns to scale (i.e. $\hat{\beta}_L + \hat{\beta}_K\,(+\hat{\beta}_N) - 1$): a positive (negative) significant coefficient on log labour points to increasing (decreasing) returns, an insignificant one to constant returns. The coefficient on labour in the regression is *not* the output elasticitiy with respect to labour, which we also report in a lower panel of each table ('Implied $\hat{\beta}_L$'),[25] along with the returns to scale ('Implied RS'). This setup allows for an easy imposition of constant returns by dropping the log labour variable from the model. In each table Panel (A) shows results with no restrictions on returns to scale, whereas Panel (B) imposes CRS.

Pooled Models

Table 1 presents the empirical results for agriculture and manufacturing. Beginning with *agriculture*, the empirical estimates for the models [1] and [2] neglecting cross-section dependence are quite similar, with the capital coefficient around .63 and statistically significant decreasing returns to scale. The land coefficient is 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. 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. Land is still insignificant, but at least in models [3] and [4] it has a plausible coefficient estimate.

In the *manufacturing* data the models [5] and [6] ignoring cross-section dependence yield increasing returns to scale and capital coefficients in excess of .85. Residuals again display nonstationarity but the CD tests now imply that they are cross-sectionally independent. Surprisingly the standard CCEP model in [7], 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 [8] yields favourable diagnostics and a similar capital coefficient. Following imposition of CRS all models

[24]If the correlation is caused by the same factors as those present in the inputs the situation is altogether more serious than mere efficiency concerns as β may be unidentified. Residual diagnostics and their importance for empirical modelling are discussed in more detail in Eberhardt and Teal (2011a).

[25]This computation is based on statistically significant parameters only: $\hat{\beta}_L = 1 - (\hat{\beta}_K + \hat{\beta}_N) + \hat{\beta}_{RS}$ where the latter is the log labour coefficient discussed above. If any of $\hat{\beta}_K, \hat{\beta}_N$ or $\hat{\beta}_{RS}$ is insignificant it is omitted from this calculation; if all are insignificant we report 'not applicable' (n/a).

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 (stationary and cross-section independent residuals) favour the CRS 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 [8] emerges as preferred specification. All other results cannot be readily interpreted in the standard fashion due to the presence of nonstationary and/or correlated residuals.[26]

In summary, based on diagnostic 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. Across preferred specifications it is notable that the mean capital coefficients are quite similar for agriculture and manufacturing, around .5. Our shift to heterogeneous technology models in the next section will allow us to judge whether these results are representative of the underlying technology: although the CCEP imposes common technology coefficients, theory and simulations (Pesaran, 2006) have shown that results nevertheless reflect the *mean* coefficient across countries; outliers may however exert undue influence on this mean and our heterogeneous parameter models therefore account for this possibility and reports outlier-robust average coefficients.[27]

Averaged Country Regressions

Table 2 presents the robust means for each regressor across N country regressions for the unrestricted (Panel (A)) and CRS models (Panel (B)) respectively. The t-statistics reported for each average estimate test whether the average parameter is statistically different from zero, following Pesaran and Smith (1995). In addition we report the share of countries for which the country results rejected CRS as well as the share of countries for which linear country trends are statistically significant (at the 10% level, respectively).

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 — simulations for nonstationary and cross-sectionally dependent data (Coakley et al., 2006; Bond & Eberhardt, 2009) show that MG estimates are severely affected by their failure to account for cross-section dependence and this is likely the cause for the results. Standard CMG in agriculture and manufacturing yields a similar capital coefficient of around .5, while the alternative CMG results (recall that these allow for agriculture sectors to influence manufacturing ones and vice-versa) provide somewhat lower estimates, around .3. Diagnostics are sound in case of the two CMG results in agriculture, but only for the alternative CMG estimator in manufacturing (cross-sectionally dependent residuals in model [7]). Panel (B) shows how imposition of constant returns affects the results: MG and FDMG in both sectors are generally more sensible, however the diagnostic tests indicate cross-section correlation which may indicate serious misspecification. The CMG estimates for agriculture are now very similar; land coefficients are still insignificant but positive. Manufacturing results for

[26] The implication here is that these empirical results are potentially spurious. We conduct a number of robustness checks, including further covariates in the agriculture equations (livestock per worker, fertilizer per worker) in the pooled regression framework. Results (available on request) did not change from those presented above. We also conduct robustness checks including human capital in the estimation equation of both sectors (linear and squared terms) — results are confined to the Supplemental Appendix, S4 (see also discussion below).

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

standard CMG are virtually unchanged from the unrestricted model, but this includes the rejection of cross-sectionally independent residuals. The same caveat applies to the alternative CMG for manufacturing.

In summary, the diagnostic tests point to the CRS versions of the CMG estimators in the agricultural data and the unrestricted returns to scale version of the 'alternative' CMG estimator in the manufacturing data. These preferred models suggest that average technology differs across sectors, with the manufacturing capital coefficient around .3 and the agriculture one around .5.[28]

Two brief comments on the land coefficient: our preferred estimates indicate a positive albeit statistically insignificant average coefficient. Given the relative persistence of area under cultivation the short time-series dimension of the data may be responsible for this outcome. It is important to note that any form of quality adjustment of land would require time-varying information on land quality, which is difficult to obtain at an annual rate over a long time horizon.[29] Time-invariant adjustments would be accounted for by the country-specific intercepts.

Given the aim of our study, we do not want to focus narrowly on the best estimate for the 'true' sectoral technology coefficients, 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.

IV. Aggregation versus Heterogeneity

Aggregation Bias — Empirical Evidence

In this section we provide practical evidence that the use of an aggregate production function will lead to seriously biased technology estimates. 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 revealed that both datasets employed in this section are made up of nonstationary series which are cross-sectionally correlated — results are provided in the Supplemental Appendix (S1, S2).[30]

[28]We further implemented alternative specifications for both sectors which include the level and squared human capital terms (average years of schooling in the adult population) as additional covariates (see Supplemental Appendix). In the agriculture data augmentation with human capital did not lead to statistically significant results (available on request). Manufacturing results for the MG and FDMG mirror those in the unaugmented models presented above. 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 (we do not estimate the 'alternative CMG estimator' with human capital since we encounter a dimensionality problem due to the large number of covariates). Average education coefficients are significant and indicate high returns to eduction in manufacturing: 11% and 12% in the unrestricted and CRS model respectively.

[29]It can be argued that the CCE approach accounts for the induced bias for systematic distortion of the land variable: in Eberhardt et al. (forthcoming) we suggest that similar 'mismeasurement' of R&D investments leading to 'expensing' and 'double-counting' bias can be addressed in a common factor approach to the Griliches knowledge production function.

[30]The Supplemental Appendix also contains details of an extensive simulation exercise, where we formulate a number of production technologies for agriculture and manufacturing reflecting our insights into the effects of parameter heterogeneity, variable nonstationarity and cross-section dependence and analyse stylised aggregate data constructed from these two sectors. This exercise suggests that more than any other feature the introduction of common factors (even different ones across sectors) creates the biggest problems in the aggregate empirical results.

We begin our discussion with the pooled models in Table 3. 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 1. 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 results in the Supplemental Appendix (S4) reveal the basic bias remains.

Turning to the results from averaged country regressions in Table 4: the MG and FDMG models 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. Cross-section correlation tests reject independence in all but the PWT data unrestricted CMG residual series.

For ease of comparison, Table 5 provides an overview of the preferred empirical results at the sectoral and aggregate data level, assuming common technology (top panel) or technology differences across countries (bottom panel).[31] 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. Theoretical work by Hsiao, Shen, and Fujiki (2005) provides some insights as to the potential causes of this phenomenon. They find that if variable series are nonstationary and cointegrated at the 'micro unit' level (in their empirical illustration Japanese prefectures), 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.

Technology heterogeneity

Our empirical analysis has been based on the theoretical model first developed in Mundlak (1988) and like the empirical implementation in Mundlak et al. (1999) and Mundlak et al. (forthcoming) we have had to make simplifying assumption to take this model to the data. By assuming parameter constancy over time we have imposed the same restriction on the parameter coefficients with regard to the time series dimension as the latter studies. Where our empirical model has allowed for *more* flexibility is in the cross-section dimension, where we have allowed for parameter heterogeneity across countries within each of the sectors. We first discuss our insights into technology

[31] As a further robustness check we ran regressions where rather than aggregate the data we forced manufacturing and agriculture production to follow the same technology. Results (available on request) did not differ qualitatively from the aggregated results presented above. In addition we estimated dynamic pooled models, introducing the PMG and CPMG estimators (for results see Supplemental Appendix) — all of these results more or less confirm the patterns across sectoral and aggregated data described above.

heterogeneity across countries and then provide some evidence for parameter constancy.

As is evident from the empirical results in Table 1 all pooled specifications except for the CCEP estimators yield residual series which are nonstationary and therefore we cannot rule out that the estimated coefficients are spurious. In addition the unrestricted POLS and 2FE models for agriculture as well as all POLS and 2FE models where the constant returns to scale restriction has been imposed (in all these cases the data rejects constant returns) result in cross-sectionally dependent residual series. In contrast, the preferred heterogeneous parameter models for agriculture and manufacturing in Table 5 do not suffer from nonstationary and/or cross-sectionally correlated residuals. In conclusion, it appears that the data for either sector rejects the crucial assumptions underlying a pooled regression model (well-behaved residuals) and cannot reject those underlying a heterogeneous one. We interpret this evidence for misspecification in the pooled models as an indication for heterogeneous production technology within each sector of production.[32]

Given this finding of heterogeneity one would naturally want to investigate the patterns of parameter heterogeneity across countries. With the specific data at our disposal (unbalanced panel, average $T = 23$) a closer analysis of whether we can identify any discernable patterns must be interpreted with caution and we view them as merely indicative. Previous empirical analysis averaging over individual country regressions has frequently found that while country estimates were widely dispersed and at times economically implausible, averages represented very plausible estimates (Boyd & Smith, 2002; Baltagi, Bresson, Griffin, & Pirotte, 2003). Pedroni (2007, p.440) calls for caution when interpreting the estimates for any individual country since the "long-run signals contained in [limited] years of data may be relatively weak", whereas the cross-section averages will amplify the signal patterns sufficiently. Abstracting from the presence of common factors Smith and Fuertes (2010) discuss this somewhat more formally, arguing for omitted variable bias in the country regression: assume a simple DGP

$$y_{it} = \beta_i x_{it} + w_{it} + u_{it} \tag{10}$$

where w represents all variables omitted from the empirical model. w is assumed to be correlated with the included regressor x in a particular country i and over a particular period of time T, indicated by the parameter subscript iT:

$$w_{it} = b_{iT} x_{it} + v_{it} \tag{11}$$

In a single country regression of y on x we obtain

$$\mathbb{E}[\hat{\beta}_i] = \beta_i + b_{iT} \tag{12}$$

If the w_{it} are structural, operating in all time periods and countries, this would cause a systematic bias in the cross-country average estimate ($\hat{\beta}^{MG}$).[33] If they are not structural but just happen to be correlated in a particular sub-sample then they will lead to bias in these countries' estimates of β_i. However, averaging *across countries* in this case yields $\mathbb{E}[b_{iT}] = 0$ such that the biases cancel out in the average estimate $\hat{\beta}^{MG}$. The same principle applies to the CCEMG estimators in the presence of unobserved common factors.

[32]The importance of correctly specified technology heterogeneity in the presence of nonstationary processes is discussed in detail in Eberhardt and Teal (2011a, p.139f).

[33]This is akin to ignoring common factors when these drive both y and x — see Eberhardt and Teal (2011a, p.137f).

In the following we carry out basic analysis to obtain some insights into the patterns of technology heterogeneity across countries. We begin by plotting the country-specific capital coefficients from the preferred agriculture and manufacturing models in Table 5 against country mean aggregate income per capita (from PWT, in logs). Figure 1 presents individual country estimates and linear regression lines, together with 90% confidence intervals, for the two sectors.[34] Although the capital coefficients in agriculture appear to rise with income, whereas those in manufacturing appear to fall, the confidence intervals indicate that neither relationship is very precise from a statistical standpoint and (full-sample) robust regressions of the two equations yield statistically insignificant slope coefficients.[35]

Figure 2 is somewhat less ambitious than the previous analysis and provides density and distribution plots to highlight the differential distribution of capital coefficients in the agriculture and manufacturing equations. In the density plots on the left, manufacturing coefficients (dashed line) are notably distributed over a much narrower range than the agriculture coefficients. In other work on the cross-country production function in agriculture (Eberhardt & Teal, 2011b) we have argued that this heterogeneity[36] may in part be due to the difference in output structure (wheat *vs.* rice *vs.* livestock) and in the commercialisation of agriculture (subsistence *vs.* industrialised farming), both of which are functions of the level of development and productive specialisation across countries. Manufacturing production in comparison represents a comparatively more homogeneous undertaking, such that here the heterogeneity may be less pronounced. As the cumulative distribution plots on the right of Figure 2 indicate the robust means we report in our regression results do not distort the underlying relative relationship, namely that most agriculture coefficients are further to the right and thus larger than those for manufacturing.

The graphs in Figure 3 address the question of slope parameter constancy over time by estimating each model with an increasing number of observations and plotting the resulting estimates.[37] We plot the estimates for the CCEP (first and second row) and CCEMG (third row) capital coefficient $\hat{\beta}_K$ from the preferred agriculture, manufacturing and aggregated data models, corresponding to the models presented in columns [1]-[3] of Table 5, Panels (A) and (B) for pooled and heterogeneous parameter models respectively. In each plot the number of observations increases as we move to the right: in the left plots all regressions include data from 1963-1979, the graphs then shows the parameter estimates when we add one year of data at a time *at the end of the sample period* until we reach 1992; in the right plots all regressions include data from 1976-1992, the graphs then shows the parameter estimates when we add one year at a time *at the beginning of the sample period*, until we reach 1963. In each case we begin (on the left of the plot) with a reduced sample where $T_i^{min} = 11$ and $T_i^{max} = 18$, corresponding to $n = 473$ ($n = 623$ for the right plot) from $N = 34$ ($N = 38$) countries. The solid grey line indicates the results for the aggregated data, solid and dashed black lines are for agriculture and manufacturing respectively. In the CCEP plots

[34]We exclude the most extreme outliers from this plot using the following rule: we run a robust regression of the capital coefficients on mean income pc (in logs), reported in the notes to Figure 1, further computing the weights assigned to each observation by the algorithm. Countries with weights below 0.5 are then excluded (5 countries in the agriculture and 1 country in the manufacturing sample).

[35]Following Pedroni (2007) we also replaced the mean income variable in this analysis with a number of proxies for institutions and 'social capital', provided and investigated by Hall and Jones (1999). The patterns and significance levels for the correlations between sectoral capital coefficients and these alternative variables were very similar to those for the income correlations presented above.

[36]Note that whether this refers to true technology heterogeneity or simply bigger bias in the country regression for agriculture cannot be determined in this context.

[37]Following the example in our main results we use robust means for the heterogeneous parameter models.

in the second row we indicate the 90% confidence intervals for the agriculture (grey area) and manufacturing (area between the dashed lines) estimates; here the estimates for the aggregated data are omitted to improve illustration. In the CCEMG plots squares indicate coefficients which are statistically insignificant at the 10% level.

We use these graphs to provide some insights into two specific questions: (i) From an econometric point of view, are the $\hat{\beta}_K$ coefficients *on average* constant over time? (ii) In line with the suggestion in Mundlak et al. (forthcoming), if the β_K parameters were functions of common factors (or in their terminology: state variable) which would imply that any estimated coefficient is a constant associated with the specific sample under analysis ($\hat{\beta}_K(S)$), we would expect differing results over time (given different samples). Do our recursive plots provide any evidence for sample dependence in the estimated β_K coefficients? Naturally, the answer to (i) will be based on evidence for (ii) and vice-versa, since these are in effect one and the same question but motivated from econometric and economic theory respectively.

In the pooled models, where the preferred CCEP models yield relatively similar capital coefficients around .5 in the full samples, the recursive regressions suggest that the agriculture (manufacturing) capital coefficient decreases (increases) over time as we add more years of data. Since the same pattern results whether we add years at the beginning or the end of the sample it would seem that this pattern is driven by small sample bias: as more observations become available in each country the results become more precise. The associated confidence intervals included in the plots in the second row of the figure support this hypothesis: coefficient estimates in the extreme left of each plot (reduced sample) are contained within the 90% confidence interval of the coefficient estimates at the extreme right of each plot (full sample). Turning to the heterogenous parameter model estimates in the bottom row of Figure 3 it is important to reiterate that the robust mean coefficients marked with a square are statistically insignificantly different from zero. If we eliminate these from the graphs we find remarkably stable recursive estimates for both the manufacturing and agriculture capital coefficients. The answer to the above question (i) on parameter constancy is thus a tentative 'yes'. The answer to the question (ii) on sample dependence a tentative 'no'. The former suggests that the assumption $\beta_{it} = \beta_i$ is valid and the latter implies that we find no evidence for a systematic relationship between technology coefficients and unobserved time-varying factors (or state variables) since otherwise we would not have observed such stability in the estimation results.

V. 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 importance of parameter heterogeneity — across countries as well as sectors. In addition we took the nonstationarity of observable and unobservable factor inputs into account and addressed concerns over cross-sectional dependence commonly found in macro panel data.

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*, duality matters. Empirical analysis of growth and development across countries gains considerably from the 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 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, focusing on technology and TFP within each sector, we found the data rejected empirical specifications that impose common technology, TFP evolution and independence of shocks and evolution of observables and unobservables across countries. That is to say a standard assumption in existing work on the dual economy model using growth accounting methods, namely that of common technology within a sector across countries, is not in line with the data. If these restrictions were correct we should be able to find pooled technology models satisfying the most basic assumptions of stationary and cross-sectionally independent residuals — in practice, however, we find results much more in line with the notion of differential technology across countries, for which we have provided support from economic theory.

Thirdly, the presence of unobserved common factors, both as latent processes driving all observables and as a conceptual framework for TFP, has been shown to have a substantial impact on empirical results. Much of the cross-country empirical 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 important implication is that commonly applied instruments in cross-country growth regressions are invalid — a sentiment echoed in recent work by Clemens and Bazzi (2009). We argue that panel time series methods 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.

Fourthly, 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. 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 data for agriculture and UNIDO data for manufacturing, which are ideally suited to inform this type of analysis at the sector-level, for a large number of countries and over a substantial period of time.

Cross-country panel data plays a crucial role in policy analysis for development. The present work is only a first step in establishing an empirical version of a dual economy model to inform this literature. From the perspective of dual economy theory, we have only analysed one aspect of the canon, namely technology heterogeneity between traditional and modern sectors of production. In future work we will implement empirical tests to investigate the suggested sources of growth arising from this literature, including marginal factor product differences as well as heterogeneous TFP levels or growth across sectors.

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Tables and Figures

Table 1: Pooled regression models for agriculture and manufacturing

Panel (A): Unrestricted Returns to Scale

	Agriculture				*Manufacturing*			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	POLS	**2FE**	**CCEP**	**CCEP**$^{\flat}$	**POLS**	**2FE**	**CCEP**	**CCEP**$^{\flat}$
log labour	-0.060	-0.199	-0.266	-0.142	0.043	0.081	0.082	0.002
$\hat{\beta}_L + \hat{\beta}_K\,(+\hat{\beta}_N) - 1$	[7.20]**	[9.60]**	[2.13]*	[0.55]	[3.53]**	[4.35]**	[1.53]	[0.03]
log capital pw	0.618	0.661	0.480	0.531	0.897	0.845	0.472	0.469
$\hat{\beta}_K$	[73.80]**	[43.62]**	[9.87]**	[5.92]**	[55.38]**	[32.69]**	[7.62]**	[5.34]**
log land pw	0.011	-0.160	-0.165	0.052				
$\hat{\beta}_N$	[1.02]	[4.93]**	[0.98]	[0.20]				
Implied RS†	DRS	DRS	DRS	CRS	IRS	IRS	CRS	CRS
Implied $\hat{\beta}_L$‡	0.322	0.300	0.254	0.469	0.146	0.236	0.528	0.532
$\hat{e}$ integrated$^{\natural}$	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)
CD test p-value$^{\sharp}$	0.00	0.00	0.45	0.38	0.19	0.34	0.00	0.93
R-squared	0.94	0.86	1.00	1.00	0.84	0.67	1.00	1.00
RMSE	0.446	0.127	0.095	0.086	0.439	0.128	0.090	0.066

Panel (B): Constant Returns to Scale Imposed

	Agriculture				*Manufacturing*			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	POLS	**2FE**	**CCEP**	**CCEP**$^{\flat}$	**POLS**	**2FE**	**CCEP**	**CCEP**$^{\flat}$
log capital pw	0.644	0.725	0.496	0.526	0.919	0.860	0.490	0.500
$\hat{\beta}_K$	[85.46]**	[48.87]**	[11.22]**	[6.70]**	[70.80]**	[34.01]**	[13.55]**	[8.38]**
log land pw	0.008	-0.007	0.092	0.126				
$\hat{\beta}_N$	[0.66]	[0.20]	[1.24]	[1.02]				
Implied $\hat{\beta}_L$‡	0.356	0.275	0.504	0.474	0.081	0.140	0.510	0.500
$\hat{e}$ integrated$^{\natural}$	I(1)	I(0)/I(1)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)
CD test p-value$^{\sharp}$	0.00	0.00	0.87	0.52	0.02	0.00	0.00	0.00
R-squared	0.94	0.85	1.00	1.00	0.84	0.66	1.00	1.00
RMSE	0.457	0.132	0.098	0.089	0.444	0.129	0.094	0.074

Notes: $N = 40$ countries, 918 observations, average $T = 23$. Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the 2FE equation. Estimators: POLS — pooled OLS, 2FE — 2-way Fixed Effects, CCEP — Common Correlated Effects Pooled version (see below). We omit reporting the estimates on the intercept term. Absolute t-statistics reported in brackets are constructed using White heteroskedasticity-robust standard errors. For CCEP in [3],[4],[7] and [8] we report results based on bootstrapped standard errors (100 replications). *, ** indicate significance at 5% and 1% level respectively. Time dummies are included explicitly in [1] and [5] or implicitly in [2] and [6]. Cross-section average augmentation in [3],[4],[7] and [8]. $\flat$ 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 and significant parameter estimates — see main text. $\natural$ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request), H_0: nonstationary residuals. $\sharp$ Pesaran (2004) CD-test (full results available on request), H_0: cross-sectionally independent residuals. RMSE: root mean squared error.

Table 2: 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	-1.935	-0.474	-0.682	-0.068	-0.132	-0.127	0.069	0.003
$\hat{\beta}_L + \hat{\beta}_K\,(+\hat{\beta}_N) - 1$	[2.43]*	[0.53]	[1.05]	[0.08]	[0.92]	[1.15]	[0.78]	[0.03]
log capital pw	-0.084	0.133	0.496	0.360	0.195	0.179	0.525	0.284
$\hat{\beta}_K$	[0.42]	[0.58]	[2.25]*	[1.37]	[1.32]	[1.12]	[6.46]**	[3.35]**
log land pw	-0.430	-0.269	-0.445	-0.129				
$\hat{\beta}_N$	[1.46]	[0.96]	[1.44]	[0.50]				
country trend/drift	0.015	0.010			0.015	0.018		
	[1.55]	[1.06]			[2.70]**	[3.31]**		
Implied RS†	DRS	CRS	CRS	CRS	CRS	CRS	CRS	CRS
Implied $\hat{\beta}_L$‡	-0.935	n/a	0.504	n/a	n/a	n/a	0.475	0.717
reject CRS (10%)	38%	20%	23%	23%	50%	13%	38%	25%
sign. trends/drifts (10%)	40%	18%			40%	20%		
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD-test (p)$^\sharp$	0.00	0.00	0.49	0.75	0.00	0.00	0.02	0.18
RMSE	0.081	0.094	0.069	0.059	0.080	0.077	0.068	0.047
Observations	918	872	918	918	918	872	918	918

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	-0.050	0.300	0.538	0.620	0.291	0.346	0.509	0.413
$\hat{\beta}_K$	[0.29]	[2.22]*	[4.55]**	[2.98]**	[2.60]**	[3.64]**	[6.19]**	[6.37]**
log land pw	0.260	0.031	0.082	0.073				
$\hat{\beta}_N$	[1.03]	[0.20]	[0.47]	[0.38]				
country trend/drift	0.016	0.014			0.012	0.013		
	[2.71]**	[3.09]**			[2.72]**	[3.61]**		
Implied $\hat{\beta}_L$‡	n/a	0.700	0.462	0.380	0.709	0.654	0.491	0.588
sign. trends/drifts (10%)	45%	13%			55%	23%		
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD-test (p)$^\sharp$	0.00	0.00	0.93	0.73	0.00	0.00	0.00	0.00
RMSE	0.087	0.096	0.076	0.068	0.088	0.078	0.080	0.059
Observations	918	872	918	918	918	872	918	918

Notes: $N = 40$ countries, average $T = 23$ (21.8 for FDMG). 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 outlier-robust means; estimates on intercept terms are not shown. Absolute t-statistics in brackets following Pesaran and Smith (1995). *, ** indicate significance at 5% and 1% level respectively. 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 and significant parameter estimates — see main text. 'reject CRS' and 'sign. trends/drifts' reports the percentage of countries where CRS is rejected and where country trends/drifts are statistically significant (10% level). $\natural$ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request), H_0: nonstationary residuals. $\sharp$ Pesaran (2004) CD-test (full results available on request), H_0: cross-sectionally independent residuals. RMSE: root mean squared error.

Table 3: 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] **POLS**	[5] **2FE**	[6] **CCEP**
log labour	0.010	-0.082	-0.054	0.035	-0.131	-0.097
$\hat{\beta}_L + \hat{\beta}_K - 1$	[1.32]	[3.75]**	[0.78]	[7.57]**	[4.57]**	[0.76]
log capital pw	0.828	0.798	0.657	0.742	0.704	0.631
$\hat{\beta}_K$	[107.55]**	[66.20]**	[19.77]**	[113.76]**	[51.43]**	[13.71]**
Implied RS†	CRS	DRS	CRS	IRS	DRS	CRS
Implied $\hat{\beta}_L{}^{\ddagger}$	0.172	0.120	0.343	0.293	0.165	0.369
$\hat{e}$ integrated$^{\natural}$	I(1)	I(1)	I(0)/I(1)	I(1)	I(1)	I(0)
CD test p-value$^{\sharp}$	0.40	0.00	0.04	0.10	0.00	0.00
R-squared	0.96	0.89	1.00	0.96	0.82	1.00
RMSE	0.358	0.109	0.078	0.195	0.095	0.061
Observations	918	918	918	912	912	912

Panel (B): Constant Returns to Scale Imposed

	Aggregated data			*Penn World Table data*		
	[1] **POLS**	[2] **2FE**	[3] **CCEP**	[4] **POLS**	[5] **2FE**	[6] **CCEP**
log capital pw	0.825	0.824	0.666	0.730	0.745	0.651
$\hat{\beta}_K$	[120.48]**	[73.01]**	[20.85]**	[130.30]**	[63.41]**	[19.33]**
Implied $\hat{\beta}_L{}^{\ddagger}$	0.175	0.176	0.334	0.270	0.255	0.349
$\hat{e}$ integrated$^{\natural}$	I(1)	I(1)	I(0)/I(1)	I(1)	I(1)	I(0)
CD test p-value$^{\sharp}$	0.31	0.30	0.06	0.00	0.00	0.00
R-squared	0.96	0.88	1.00	0.96	0.82	1.00
RMSE	0.358	0.109	0.086	0.202	0.097	0.069
Observations	918	918	918	912	912	912

Notes: $N = 40$ countries, average $T = 23$. Dependent variable: value-added per worker (in logs). All variables are suitably transformed in the 2FE equations. Estimators: POLS — pooled OLS, 2FE — 2-way Fixed Effects, CCEP — Common Correlated Effects Pooled version. We omit reporting the estimates for the intercept term. Absolute t-statistics reported in brackets are constructed using White heteroskedasticity-robust standard errors. For CCEP in [3] and [6] we report results based on bootstrapped standard errors (100 replications). Time dummies are included explicitly in [1] and [4] or implicitly in [3] and [5]. Cross-section average augmentation in [3] and [6]. *, ** indicate significance at 5% and 1% level respectively. † Returns to scale, based on significance of log labour estimate. ‡ Based on returns to scale and significant parameter estimates — see main text. ♮ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request), H_0: nonstationary residuals. ♯ Pesaran (2004) CD-test, H_0: cross-sectionally independent residuals. RMSE: root mean squared error.

Table 4: 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	-0.154	-0.079	0.117	-1.152	-1.681	-0.389
$\hat{\beta}_L + \hat{\beta}_K - 1$	[0.36]	[0.25]	[0.62]	[1.23]	[2.28]*	[1.03]
log capital pw	0.220	0.297	0.609	0.655	1.004	0.753
$\hat{\beta}_K$	[1.17]	[1.66]	[6.11]**	[4.22]**	[5.38]**	[5.26]**
country trend/drift	0.025	0.020		0.010	-0.010	
	[2.73]**	[2.42]*		[0.90]	[1.88]	
Implied RS†	CRS	CRS	CRS	CRS	DRS	CRS
Implied $\hat{\beta}_L$‡	n/a	n/a	0.391	0.345	-1.685	0.247
reject CRS (10%)	60%	23%	38%	68%	33%	53%
sign. trends/drifts (10%)	55%	33%		43%	18%	
$\hat{e}$ integrated$^{\natural}$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD-test $(p)^{\sharp}$	0.00	0.00	0.00	0.00	0.00	0.16
RMSE	0.061	0.062	0.051	0.047	0.042	0.041
Observations	918	872	918	918	866	918

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	0.293	0.202	0.725	0.619	0.923	0.811
$\hat{\beta}_K$	[1.92]	[1.90]	[10.95]**	[6.36]**	[6.01]**	[12.09]**
country trend/drift	0.014			0.002	-0.007	
	[2.93]**			[0.50]	[1.97]*	
Implied $\hat{\beta}_L$‡	n/a	n/a	0.275	0.381	0.077	0.189
sign. trends/drifts (10%)	48%	28%		48%	25%	
$\hat{e}$ integrated$^{\natural}$	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD-test $(p)^{\sharp}$	0.00	0.00	0.05	0.00	0.00	0.00
RMSE	0.074	0.064	0.067	0.061	0.044	0.059
Observations	918	872	918	912	866	912

Notes: $N = 40$, average $T = 23$ (21.8 for FDMG). 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 outlier-robust means; estimates for intercept terms are not shown. Absolute t-statistics in brackets following Pesaran and Smith (1995). *, ** indicate significance at 5% and 1% level respectively. 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 and significant parameter estimates — see main text. ♮ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). ♯ Pesaran (2004) CD-test, H_0: cross-sectionally independent residuals.

Table 5: Comparison of preferred models

PANEL (A): HOMOGENEOUS TECHNOLOGY

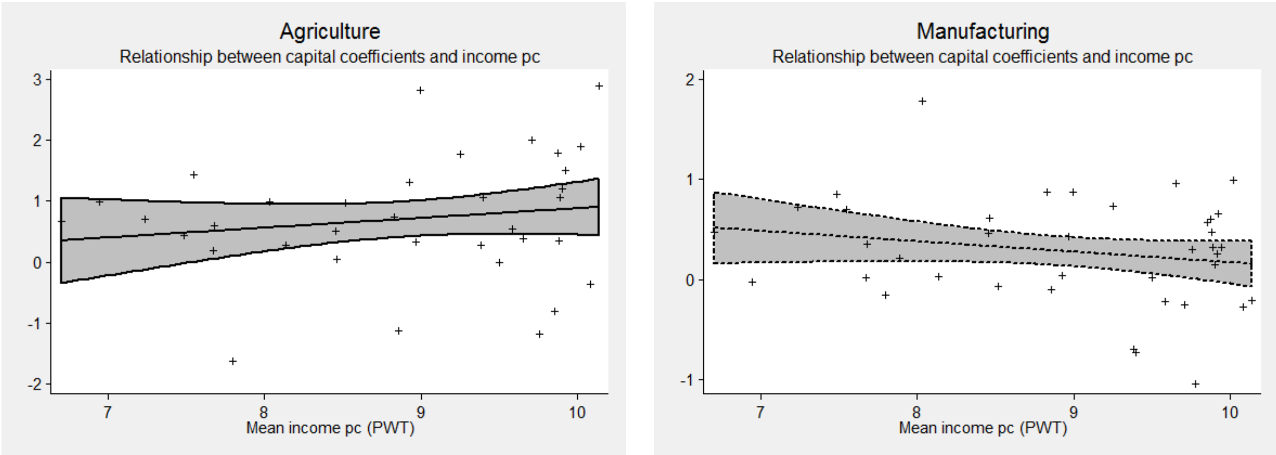
	Sectoral data		*Aggregate data*	
	Agri	Manu	Stylised	PWT
	[1]	[2]	[3]	[4]
	CCEP$^\flat$	**CCEP**$^\flat$	**CCEP**	**CCEP**
log labour		0.002		-0.097
$\hat{\beta}_L + \hat{\beta}_K\,(+\hat{\beta}_N) - 1$		[0.03]		[0.76]
log capital pw	0.526	0.469	0.666	0.631
$\hat{\beta}_K$	[6.70]**	[5.34]**	[20.85]**	[13.71]**
log land pw	0.126			
$\hat{\beta}_N$	[1.02]			
Implied β_L‡	0.474	0.532	0.334	0.369
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)/I(1)	I(0)
CD test p-value$^\sharp$	0.52	0.93	0.06	0.00
RMSE	0.089	0.066	0.086	0.061
Observations	918	918	918	912

PANEL (B): HETEROGENEOUS TECHNOLOGY

	Sectoral data		*Aggregate data*	
	Agri	Manu	Stylised	PWT
	[1]	[2]	[3]	[4]
	CMG$^\flat$	**CMG**$^\flat$	**CMG**	**CMG**
log labour		0.003		-0.389
$\hat{\beta}_L + \hat{\beta}_K\,(+\hat{\beta}_N) - 1$		[0.03]		[1.03]
log capital pw	0.620	0.284	0.725	0.753
$\hat{\beta}_K$	[2.98]**	[3.35]**	[10.95]**	[5.26]**
log land pw	0.073			
$\hat{\beta}_N$	[0.38]			
Implied β_L‡	0.380	0.717	0.275	0.247
$\hat{e}$ integrated$^\natural$	I(0)	I(0)	I(0)	I(0)
CD-test (p)$^\sharp$	0.73	0.18	0.05	0.16
RMSE	0.068	0.047	0.067	0.041
Observations	918	918	918	918

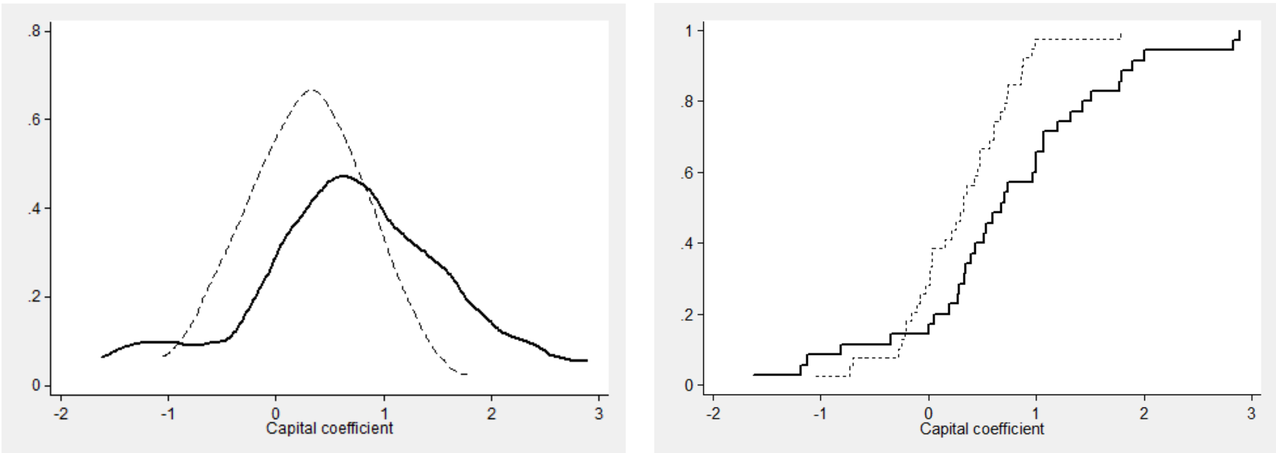
Notes: Panel (A) of this table combines regression results from (from left to right) Table 1 Panel (B) column [4] and Panel (A) column [8], Table 3 Panel (B) column [3] and Panel (A) column [6]. Panel (B) combines results from (from left to right) Table 2 Panel (B) column [4] and Panel (A) column [8] and Table 4 Panel (B) column [3] and Panel (A) column [6]. In the agricultural regressions where the CCEP and CCEP$^\natural$ both had sound diagnostics (and very similar coefficient estimates) we report the latter since it allows for greater flexibility. Results for CCEP models based on bootstrapped standard errors (100 replications). *, ** indicate significance at 5% and 1% level respectively. $\flat$ 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 and significant parameter estimates — see main text. $\natural$ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). $\sharp$ Pesaran (2004) CD-test, H_0: cross-sectionally independent residuals.

Figure 1: Investigating technology heterogeneity and income



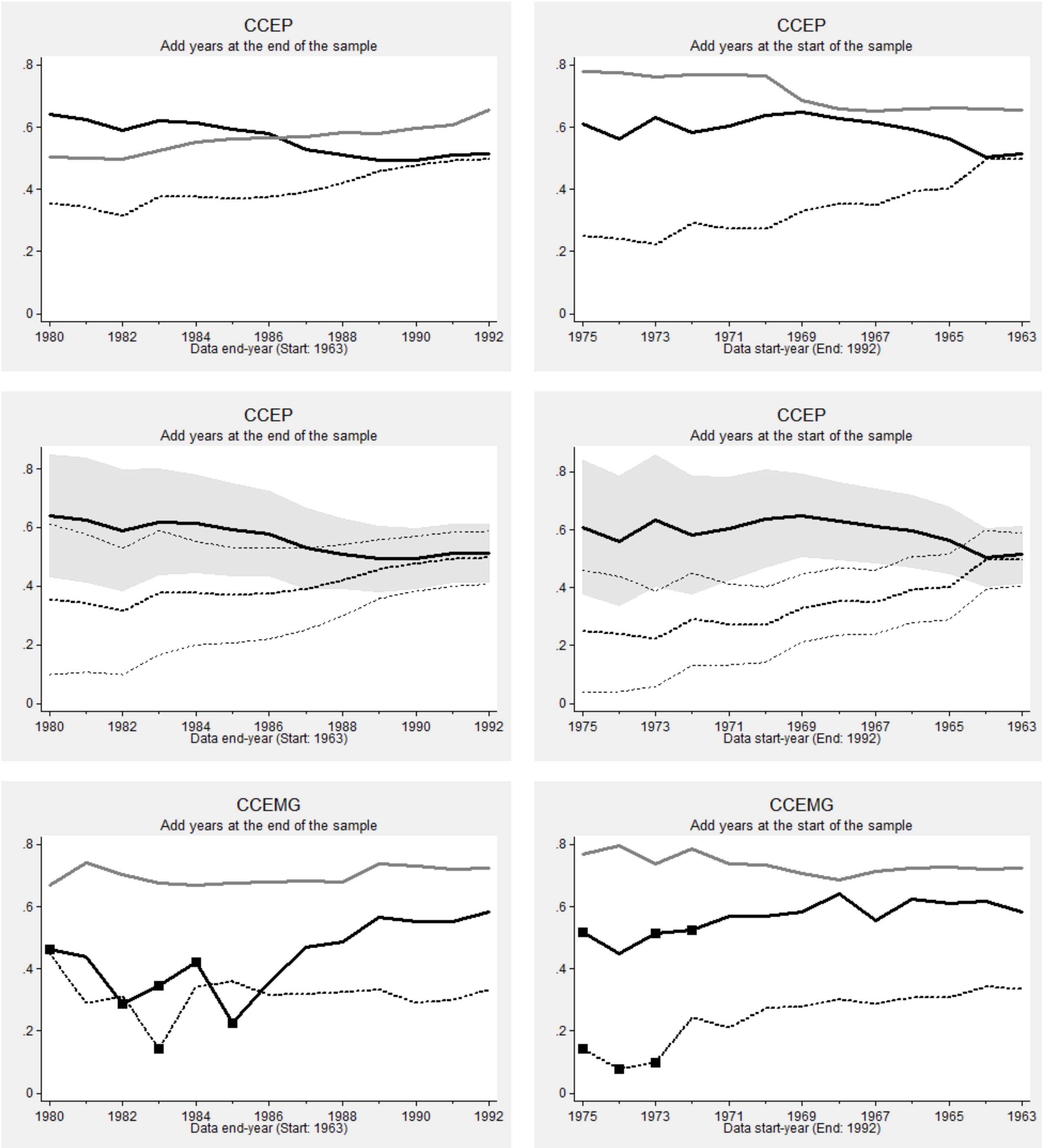
Notes: These graphs investigate the issue of slope heterogeneity across countries. We plot the country estimates for the CCEMG capital coefficient $\hat{\beta}_K$ from the preferred heterogeneous agriculture and manufacturing models, corresponding to the models presented in columns [1]-[2] of Table 5, Panel (B). The shaded areas represent 90% confidence intervals of a linear regression of the respective capital coefficients on mean income per capita, where means are computed from aggregate PWT data over the entire 1963-1992 time horizon. Robust regression of these relationships yield the following (statistically insignificant) slope parameters (standard errors in square brackets): .108 [.217], -.079 [.087] for agriculture and manufacturing respectively. Note that for both plots we exclude outliers based on weights computed from these robust regressions: any coefficient with a weight less than .5 is excluded from the graph (for agriculture: 5 countries; for manufacturing: 1 country).

Figure 2: Investigating technology heterogeneity across sectors



Notes: These graphs investigate the issue of slope heterogeneity across sectors. In the density plots on the left we estimate separate Epanechnikov kernels (using common bandwidth .34) for the agriculture (solid line) and manufacturing (dashed line) capital coefficients from Table 5, Panel (B); the right plots chart the cumulative distribution functions of the respective sector coefficients. For both sets of plots we follow the same strategy as in Figure 1 to exclude extreme outliers.

Figure 3: Investigating technology constancy — recursive estimates



Notes: These graphs investigate the issue of slope parameter constancy over time by estimating each model with an increasing number of observations and plotting the resulting estimates. We plot the robust estimates for the CCEP (rows 1 and 2) and CCEMG (row 3) capital coefficients from the preferred agriculture, manufacturing and aggregated data models, corresponding to the results presented in columns [1]-[3] of Table 5, Panels (A) and (B) for pooled and heterogeneous parameter models respectively.
In each plot the number of observations increases as we move to the right: in the left plots all regressions include data from 1963-1979, the graphs then shows the parameter estimates when we add one year of data at a time *at the end of the sample period* until we reach 1992; in the right plots all regressions include data from 1976-1992, the graphs then shows the parameter estimates when we add one year at a time *at the beginning of the sample period*, until we reach 1963. In each case we begin (on the left of the plot) with a reduced sample where $T_i^{min} = 11$ and $T_i^{max} = 18$, corresponding to $n = 473$ (623 for the right plot) observations from $N = 34$ (38) countries.
In each plot: grey solid line — aggregated data; black solid line — agriculture data; black dashed line — manufacturing data. In the CCEP plots in the second row we indicate the 90% confidence intervals for the agriculture (grey area) and manufacturing (area between the dashed lines) estimates; here the estimates for the aggregated data are omitted to improve illustration. In the CCEMG plots squares indicate coefficients which are statistically *insignificant* at the 10% level.

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 presented 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, which may improve the robustness of empirical estimates. We provide details on the sample makeup in Table A-I. The next two subsections describe the 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	KEN	Kenya	29
2	AUT	Austria	22	23	KOR	South Korea	29
3	BEL	Belgium-Luxembourg	22	24	LKA	Sri Lanka	17
4	CAN	Canada	30	25	MDG	Madagascar	20
5	CHL	Chile	20	26	MLT	Malta	23
6	COL	Colombia	26	27	MUS	Mauritius	16
7	CYP	Cyprus	18	28	MWI	Malawi	23
8	DNK	Denmark	26	29	NLD	Netherlands	23
9	EGY	Egypt	24	30	NOR	Norway	22
10	FIN	Finland	28	31	NZL	New Zealand	19
11	FRA	France	23	32	PAK	Pakistan	24
12	GBR	United Kingdom	22	33	PHL	Philippines	24
13	GRC	Greece	28	34	PRT	Portugal	20
14	GTM	Guatemala	19	35	SWE	Sweden	23
15	IDN	Indonesia	22	36	TUN	Tunisia	17
16	IND	India	29	37	USA	United States	23
17	IRL	Ireland	23	38	VEN	Venezuela	19
18	IRN	Iran	25	39	ZAF	South Africa	26
19	ISL	Iceland	20	40	ZWE	Zimbabwe	25
20	ITA	Italy	21				
21	JPN	Japan	28			**Total**	**918**

Table A-II: Descriptive statistics

AGRICULTURE DATA / MANUFACTURING DATA

Panel (A): Variables in untransformed level terms

Variable	mean	median	std. dev.	min.	max.	Variable	mean	median	std. dev.	min.	max.
Output	1.8E10	6.0E09	3.0E10	3.5E07	2.2E11	Output	7.6E10	8.8E09	2.1E11	7.2E06	1.4E12
Labour	9.6E06	1.3E06	3.5E07	3.0E03	2.3E08	Labour	1.7E06	4.8E05	3.4E06	9.6E03	2.0E07
Capital	6.5E10	1.1E10	1.5E11	2.9E07	8.6E11	Capital	1.3E11	2.0E10	3.0E11	1.4E07	1.8E12
Land	1.8E07	3.5E06	4.1E07	6.0E03	1.9E08						
in logarithms											
Output	22.39	22.51	1.73	17.38	26.13	Output	22.84	22.89	2.29	15.79	27.99
Labour	14.00	14.04	2.02	8.01	19.27	Labour	13.10	13.08	1.65	9.17	16.79
Capital	22.96	23.07	2.28	17.18	27.48	Capital	23.64	23.74	2.27	16.46	28.22
Land	15.11	15.07	1.99	8.70	19.07						
in growth rates											
Output	1.7%	1.9%	10.4%	-41.5%	53.9%	Output	4.4%	3.9%	10.1%	-40.9%	84.2%
Labour	-0.6%	0.0%	3.0%	-28.8%	13.4%	Labour	1.9%	1.1%	6.8%	-38.8%	78.1%
Capital	1.9%	1.2%	3.6%	-5.1%	31.4%	Capital	4.8%	3.6%	5.0%	-5.1%	53.0%
Land	0.1%	0.0%	2.2%	-23.1%	13.6%						

Panel (B): Variables in per worker terms

Variable	mean	median	std. dev.	min.	max.	Variable	mean	median	std. dev.	min.	max.
Output	12,724	6,644	13,161	44.18	57,891	Output	27,093	20,475	22,111	753	101,934
Capital	52,367	9,925	63,576	13.10	222,397	Capital	63,533	43,577	64,557	1,475	449,763
Land	9.66	3.00	20.34	0.29	110						
in logarithms											
Output	8.39	8.80	1.83	3.79	10.97	Output	9.74	9.93	1.09	6.62	11.53
Capital	8.96	9.20	2.71	2.57	12.31	Capital	10.54	10.68	1.09	7.30	13.02
Land	1.11	1.10	1.41	-1.24	4.70						
in growth rates											
Output	2.3%	2.5%	10.5%	-43.7%	56.0%	Output	2.5%	2.5%	9.0%	-67.0%	73.0%
Capital	2.5%	2.0%	4.2%	-7.8%	31.1%	Capital	2.9%	2.9%	6.6%	-71.7%	42.4%
Land	0.7%	0.5%	3.4%	-18.4%	28.8%						

AGGREGATED DATA / PENN WORLD TABLE DATA

Panel (A): Variables in untransformed level terms

Variable	mean	median	std. dev.	min.	max.	Variable	mean	median	std. dev.	min.	max.
Output	9.3E10	1.7E10	2.3E11	1.1E08	1.6E12	Output	4.3E11	1.3E11	1.0E12	1.3E09	8.0E12
Labour	1.1E07	2.4E06	3.6E07	2.2E04	2.4E08	Labour	5.1E07	1.3E07	1.2E08	2.1E05	8.5E08
Capital	2.0E11	2.9E10	4.3E11	1.0E08	2.3E12	Capital	1.2E12	3.3E11	2.9E12	3.3E09	2.3E13
in logarithms											
Output	23.50	23.58	2.01	18.55	28.07	Output	25.44	25.58	1.71	21.02	29.71
Labour	14.66	14.67	1.74	10.01	19.30	Labour	16.49	16.41	1.63	12.27	20.57
Capital	24.10	24.08	2.21	18.44	28.44	Capital	26.38	26.52	1.80	21.92	30.75
in growth rates											
Output	3.1%	3.1%	7.4%	-33.9%	42.1%	Output	4.0%	4.0%	5.0%	-37.1%	26.6%
Labour	0.2%	0.4%	2.6%	-11.4%	19.3%	Labour	1.5%	1.4%	1.1%	-1.9%	4.8%
Capital	3.6%	2.7%	3.6%	-5.0%	25.1%	Capital	4.6%	4.2%	2.9%	-1.3%	16.4%

Panel (B): Variables in per worker terms

Variable	mean	median	std. dev.	min.	max.	Variable	mean	median	std. dev.	min.	max.
Output	19,493	11,197	19,212	72	76,031	Output	11,445	10,630	8,193	594	31,074
Capital	49,634	23,140	55,541	53	236,312	Capital	37,059	32,981	31,765	661	136,891
in logarithms											
Output	8.84	9.32	1.85	4.28	11.24	Output	8.95	9.27	1.02	6.39	10.34
Capital	9.44	10.05	2.20	3.96	12.37	Capital	9.87	10.40	1.37	6.49	11.83
in growth rates											
Output	3.0%	3.3%	7.0%	-31.0%	44.5%	Output	2.5%	2.6%	5.0%	-41.2%	23.2%
Capital	3.4%	3.2%	3.8%	-18.4%	22.2%	Capital	3.1%	2.8%	2.9%	-4.2%	14.3%

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 regression sample ($n = 918$; $N = 40$).

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).[38] 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: we therefore need to use an alternative 1990 US$-LCU exchange rate for these economies.[39]

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 (in 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).

[38] 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`. Stata code for empirical estimators and tests is available from SSC: `pescadf`, `xtmg`, `xtcd`.

[39] 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.

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 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).