CSAE WPS/2009-07

Econometrics for Grumblers: A New Look at the Literature on Cross-Country Growth Empirics

Markus Eberhardt* Francis Teal

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

12th June 2009

Abstract:

Since the seminal contribution of Gregory Mankiw, David Romer and David Weil (1992), the growth empirics literature has used increasingly sophisticated methods to select relevant growth determinants in estimating cross-section growth regressions. The vast majority of empirical approaches however limit cross-country heterogeneity in production technology to the specification of Total Factor Productivity, the 'measure of our ignorance' (Abramowitz, 1956). The central theme of this survey is an investigation of this choice of specification against the background of pertinent data properties when the units of observations are countries or regions and the time-series dimension of the data becomes substantial. We present two general empirical frameworks for cross-country productivity analysis and demonstrate that they encompass the approaches in the growth empirics literature of the past two decades. We then develop our central argument, that cross-country heterogeneity in the impact of observables and unobservables on output is important for reliable empirical analysis. This idea is developed against the background of the pertinent time-series and cross-section properties of macro panel data.

Keywords: Cross-Country Empirical Analysis; Nonstationary Panel Econometrics; Parameter Heterogeneity; Common Factor Model; Cross-section Dependence
JEL classification: O11, O47, C32

*Correspondence: Centre for the Study of African Economies (CSAE), Department of Economics, Manor Road Building, Oxford OX1 3UQ, UK; Email: markus.eberhardt@economics.ox.ac.uk

"One model is supposed to apply everywhere and always. Each country is just a point on a cross-section regression, or one among several essentially identical regressions, leaving only grumblers to worry about what is exogenous and what is endogenous, and whether simple parameterizations do justice to real differences in the way the economic mechanism functions in one place or another."
Solow (1986, p.S23)

"As a careful reading of Solow (1956, 1970) makes clear, the stylized facts for which this model was developed were not interpreted as universal properties for every country in the world. In contrast, the current literature imposes very strong homogeneity assumptions on the cross-country growth process as each country is assumed to have an identical ... aggregate production function."
Durlauf, Kourtellos, and Minkin (2001, p.929)

Robert Solow's criticism of empirical cross-country growth analysis rings as true today as it did in 1986, despite the explosion of empirical papers on the topic in the 1990s following the seminal contributions by Barro (1991) and Mankiw, Romer, and Weil (1992). In essence, as Durlauf et al. (2001) comment, one model of *common* technology parameters[1] — the coefficients on labour, capital and material inputs — and (in the original representation) *common* Total Factor Productivity (TFP) is supposed to apply everywhere and always, one aggregate model is assumed to correctly summarise a sample of economies at very different stages of industrial development and made up of diverse industrial sectors. Later variations on the theme have introduced limited forms of heterogeneity in TFP, using intercepts and trends for heterogeneous TFP levels and constant TFP growth rates, but at the same time cross-country regression models have *for the most part* held on to the common technology specification.

We believe that there are a number of important reasons why one might want to side with Solow and reject the standard cross-country growth regression framework and its panel cousins. Rather than to simply 'grumble' about parameter heterogeneity in the observables and unobservables, we show that this property has very important implications for estimation and inference once the pertinent time-series properties of the data (nonstationarity, cointegration, cross-country correlation) are recognised. Intuitively, the heterogeneity in production technology could be taken to mean that countries can chose an 'appropriate' production technology from a menu of feasible options. The cross-country heterogeneity in unobservables (TFP) relates to both differences in the underlying processes that make up TFP and in the impact of these processes on output.

The majority of regression approaches following the standard empirical models tend to yield implied technology coefficients considerably out of line with macro evidence on factor income shares. Following Mankiw et al. (1992) most empirical studies put this down to the failure to account for forms of intangible capital (human capital, 'social capital') in the regression model. This belief has led to a growth empirics literature that for the most parts neglects technology-parameter heterogeneity across countries as well as dynamics. Instead, the *mainstream* literature favours ever more sophisticated statistical devices — most recently Bayesian Model Averaging and 'general-to-specific' automatic model selection algorithms — to pick out the 'relevant' variables in an augmented Solow regression model with time-averaged variables, so-called 'Barro-regressions'. At the last count no fewer than 145 variables have been investigated in their impact on growth (Durlauf, Johnson, & Temple, 2005) *and most were found to matter.*

A small number of papers however question this paradigm and have integrated considerations of parameter heterogeneity and variable nonstationarity into their cross-country empirics. Their regression results are encouraging and further diagnostic tests for variable nonstationarity and parameter heterogeneity confirm both of these properties in a formal manner (Pedroni, 2007; Canning & Pedroni, 2008). Our approach in this paper is in the same spirit and further highlights the importance of cross-section dependence in macro productivity analysis (Eberhardt & Teal, 2008; Costantini & Destefanis, 2009; Eberhardt & Teal, 2009). We will make use of recent developments in the panel time-series literature which have relaxed the standard assumption of cross-section independence. This has led to the development of analytical methods robust to the impact of correlation across panel units (Bai & Ng, 2004; Pesaran, 2006, 2007; Kapetanios, Pesaran, & Yamagata, 2008; Bai, Kao, & Ng, 2009). In the context of cross-country growth and development analysis, the potential for this type of data dependency is particularly salient, given the interconnectedness of countries through history, geography and trade-relations.

Nonstationarity, TFP heterogeneity (including the potential for cross-section dependence), and technology heterogeneity — these three themes thus form the framework for this survey. The issues surrounding the time-series and cross-section correlation properties of macro panel data in their impact on model specification have previously not been considered in great detail in the *empirical* growth literature (Temple, 1999; Durlauf et al., 2005), but have solid foundations in the *theoretical* literatures on growth and econometrics respectively. As our discussion will develop, we believe that they should be recognised as integral parts of the growth empirics canon. Existing empirical work instead has worried about the potential endogeneity of regressors in the empirical framework, an issue which is given considerably more attention in the literature than the potential misspecification of the empirical regression model.

We believe that our review of the cross-country growth empirics literature is particularly timely, as over the recent years empirical development economics has witnessed the emergence of two powerful analytical tools which explicitly or implicitly question the validity of cross-country regressions and signal nothing less than a paradigm shift in the field. The first of these new tools is the increased use of 'randomised experiments' in economics (see Banerjee & Duflo, 2008), which have been brought to great prominence by Abhijit Banerjee, Esther Duflo and collaborators at the Abdul Latif Jameel Poverty Action Lab (J-PAL), MIT. The work by these authors frequently refers to 'hard evidence' of causal links between economic and social processes and implies that cross-country growth regression results certainly do not attain this status. The second approach is that of 'growth diagnostics' (see Hausmann, Rodrik, & Velasco, 2006), developed by a group of economists at the Kennedy School of Government, Harvard University, including Dani Rodrik, Ricardo Hausmann and Lant Pritchett. Their method calls for country-specific analysis by development experts to identify the most important binding constraints to growth and development. Both of these approaches are in agreement that cross-country growth regressions are uninformative as to the causes of growth and this empirical approach is now deeply unfashionable. The fact that we have not learnt the causes of growth from cross-country regressions does not mean we have learnt nothing and — as this survey will seek to demonstrate — it does not mean that we cannot learn more by using appropriate methods.

The remainder of this paper is organised as follows: the next section presents and motivates two general empirical frameworks for cross-country production analysis, one for the production function approach, a second for the convergence regression equation. These are shown to encompass a wide variety of modelling approaches representing the full evolution of growth empirics over the past two decades. Our aim here is not to provide an exhaustive review of the empirical growth literature, but to highlight the gradual relaxation of assumptions over the course of this period. In Sections 2, 3 and 4 we discuss the central issues of parameter heterogeneity, variable nonstationarity and cross-section dependence in great detail and show how their interplay leads to the breakdown of standard assumptions in the empirical estimators commonly applied in the literature. A brief conclusion summarises the arguments.

1 A general empirical framework for production analysis with cross-country panel data

This section sets out two general empirical framework for a macro production function and the implied convergence equation from the canonical Solow model based on the standard Cobb-Douglas specification.[2] It motivates their specification and shows that they encompass the most important models of the empirical growth literature in the past two decades. We set out the general production function and convergence equation models below as a means to build an encompassing framework for the literature which affords maximum flexibility with regard to specification. Our focus in this survey is on cross-country *macro* data. The question whether the empirical specification is most appropriately applied to data at the aggregate economy or at the sectoral level, although in our view of great importance, is not central to the discussion. This aside, the question as to *how to empirically implement these general models* is a separate issue and we refer to recent contributions to the nonstationary panel econometric literature for suggestions (Bai & Ng, 2004; Coakley, Fuertes, & Smith, 2006; Pesaran, 2006; Kapetanios et al., 2008). In our review of the growth empirics literature we discuss the restrictions made by each of the seminal contributions on the general model and set out their implications for estimation and inference.

1.1 An encompassing framework

We assume panel data for N countries, with a substantial time-series dimension T which may vary across countries (unbalanced panel). For the empirical production function let

$$O_{it} = \alpha_i\, L_{it} + \beta_i\, K_{it} + \gamma_i\, M_{it} + u_{it} \qquad u_{it} = A_{0,i} + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{1}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. We can think of the this framework as representing N country equations, or a single pooled equation. O represents gross output, L labour force, K capital stock and M material inputs (all in logarithms). These represent the observable variables of the model. For TFP we employ the combination of a country-specific TFP level $A_{0,i}$ and a set of common factors $\boldsymbol{f}_t$ with country-specific factor loadings $\boldsymbol{\lambda}_i$ — TFP is unobserved. We introduce common factor models in detail in Section 3; for the time being we highlight this specification of unobservables as a flexible way to allow for each country to be influenced differentially.

Much of the micro-econometric literature on production functions adopts gross-output based models, but at the macro level, a specification using value-added (Y in logs) as dependent variable is more common:

$$Y_{it} = \alpha_i^{va} L_{it} + \beta_i^{va} K_{it} + u_{it} \qquad u_{it} = A_{0,i}^{va} + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{2}$$

Our notation in (2) indicates that parameter values and interpretation will differ between a value-added based and gross-output based empirical specification, but under certain assumptions we can transform results to make them directly comparable.[3]

We maintain the following assumptions for the general output-based production function model and the data it is applied to (similarly for the VA-variants):

A.1 The parameters α_i, β_i and γ_i are unknown random coefficients with fixed means and finite variances. Similarly for the unknown factor loadings, i.e. $\boldsymbol{\lambda}_i = \boldsymbol{\lambda} + \boldsymbol{\eta}_i$ where $\boldsymbol{\eta}_i \sim \text{iid}(0, \Omega_\eta)$.[4]

A.2 Error terms $\varepsilon_{it} \sim N(0, \sigma^2)$, where σ^2 is finite.

A.3 The unobserved TFP evolution, captured by $\boldsymbol{\lambda}_i' \boldsymbol{f}_t$, can contain elements which are common across countries as well as elements which are country-specific.

A.4 Observable inputs $\mathbf{x}_{it} = \{L_{it},\, K_{it},\, M_{it}\}$ and output O_{it}, as well as the unobserved common factors $\boldsymbol{f}_t$ are <u>not</u> *a priori* assumed to be stationary variables/processes.

A.5 The observable inputs $\boldsymbol{x}_{it}$ may be functions of some of the unobserved common factors $\boldsymbol{f}_t$ driving output. This would lead to correlation between regressors and unobservables u_{it}, creating difficulties for the identification of the technology parameters $\alpha_i, \beta_i, \gamma_i$.

The majority of the growth empirics literature does not estimate production functions, but focuses on versions of the 'convergence regression equation' (Mankiw et al., 1992), which is exclusively estimated for aggregate economy data. In its simplest form — without human capital augmentation — this links country i's per capita GDP (y_i in logs) to a proxy for its savings rate (s_i^k in logs). For the most general, 'unrestricted' form of this equation let

$$\begin{aligned} y_{i,t_2} - y_{i,t_1} &= -\left\{1 - e^{-\xi_i \tau}\right\} \left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right) (\delta + \bar{n}_{i\tau} + \mu^\star) \qquad (3) \\ &\quad + \left\{1 - e^{-\xi_i \tau}\right\} \left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right) \bar{s}_{i\tau}^k - \left\{1 - e^{-\xi_i \tau}\right\} y_{i,t_1} + u_{i\tau} \\ u_{i\tau} &= \left\{1 - e^{-\xi_i \tau}\right\} A_{0,i}^{va} + \left\{1 - e^{-\xi_i \tau}\right\} \boldsymbol{\lambda}_i' \boldsymbol{f}_\tau + \varepsilon_{i\tau} \qquad (4) \end{aligned}$$

where $\tau = t_2 - t_1$ (more on this notation below). $\bar{n}$ is the average population growth rate over period τ and $\bar{s}^k$ is the average savings rate over the same period. δ is the depreciation rate for physical capital and ξ indicates the speed of convergence (per annum) to either a common or country-specific steady-state equilibrium, depending on specification.

$\bar{n}$, $\bar{s}^k$ and y are the observable variables in this framework, whereas TFP ($A_{0,i}^{va}$ and $\boldsymbol{\lambda}_i' \boldsymbol{f}_\tau$) is unobserved. This framework allows for TFP evolution to differ across time and countries. Note that there is an additional parameter which also refers to TFP growth, namely $\mu^\star$: this is the outcome of Solow's steady-state equation for income, where capital stock per effective worker k^* is a function of both the savings rate s^k and as well as population growth, TFP growth and capital depreciation $(\delta + n + \mu^\star)$. We adopt this notation to highlight that empirical work using this type of framework has commonly neglected $\mu^\star$, which together with depreciation δ is simply assumed to equal a constant 5% per annum in all countries.[5]

Following estimation, the coefficients on the observables in this model can be transformed to yield the 'implied' capital coefficient β_i^{va}. As in the production function framework, this β_i^{va} is the technology parameter in a Cobb-Douglas production function that frames the production analysis. Although the literature refers to equations like (3) as 'growth regressions', this is essentially a levels regression where y_{i,t_1} has been subtracted from both sides to investigate out-of-steady-state behaviour.[6] The convergence regression model can be rewritten as an equivalent dynamic panel equation with variables in levels *on both* sides (see Islam, 1995; Bond, 2002) to underline this point.

This framework provides us with a panel of T/τ equations for N countries. We briefly illustrate the implications of adopting different values for τ: at one extreme, if $\tau = T$, we have a single cross-section regression equation with N observations. Let $t_2 = 1985$ and $t_1 = 1960$, thus $\tau = 26$, then (3) transforms into

$$\begin{aligned} y_{i,1985} - y_{i,1960} &= -\left\{1 - e^{-\xi_i \tau}\right\}\left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right)(\delta + \bar{n}_i + \mu^\star) \\ &\quad + \left\{1 - e^{-\xi_i \tau}\right\}\left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right)\bar{s}_i^k - \left\{1 - e^{-\xi_i \tau}\right\} y_{i,1960} + \left\{1 - e^{-\xi_i \tau}\right\} a^{va} + \varepsilon_i \end{aligned} \tag{5}$$

where TFP levels $A_{i,0}^{va}$ and evolution $\boldsymbol{\lambda}_i' \boldsymbol{f}_\tau$ have been subsumed into a single intercept term a^{va}. Since the steady-state equation is valid at any point in time (provided the economy is close to the steady state), this intercept term a^{va} represents initial TFP level A_0^{va} *as well as* the constant for TFP evolution $\boldsymbol{\lambda}_i \boldsymbol{f}_t$. Our discussion in section 1.3 will highlight the important assumptions implicit in this specification of TFP.

At the other extreme, if $\tau = t$ we have a panel of dimension $T \times N$

$$\begin{aligned} \Delta y_{it} &= -\left\{1 - e^{-\xi_i}\right\}\left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right)(\delta + n_{it} + \mu^\star) \\ &\quad + \left\{1 - e^{-\xi_i}\right\}\left(\frac{\beta_i^{va}}{1-\beta_i^{va}}\right) s_{it}^k - \left\{1 - e^{-\xi_i}\right\} y_{i,t-1} + u_{it} \end{aligned} \tag{6}$$

$$u_{it} = \left\{1 - e^{-\xi_i}\right\} A_{i,0}^{va} + \left\{1 - e^{-\xi_i}\right\} \boldsymbol{\lambda}_i' \boldsymbol{f}_\tau + \varepsilon_{it} \tag{7}$$

where we have $A_{i,0}^{va}$ and $\boldsymbol{\lambda}_i \boldsymbol{f}_t$, to capture the unobservables.

The two examples indicate that the choice of τ has considerable impact on empirical implementation, as will become clearer when we discuss the applied literature below. We maintain the following assumptions for the general convergence model in (3) and the data:

B.1 The parameters β_i^{va}, ξ_i are unknown random coefficients with individual means and finite variances. Similarly for the unknown factor loadings $\boldsymbol{\lambda}_i$.

B.2 Error terms $\varepsilon_{i\tau} \sim N(0, \sigma^2)$, where σ^2 is finite.

B.3 The specification of TFP levels and their evolution paths is equivalent to an unobserved common factor model which allows for common and idiosyncratic elements of TFP.

B.4 We allow for the possibility that the observed inputs ($s^k_{i\tau}$, $n_{i\tau}$), per capita GDP (y_{i,t_1}) and the unobserved factors driving TFP evolution ($\boldsymbol{f}_t$) may be nonstationary. The consequences of this property will be investigated.

B.5 The observable inputs $\boldsymbol{x}_{it}$ may contain some of the unobserved common factors $\boldsymbol{f}_t$ driving output. This would lead to correlation between regressors and unobservables u_{it}, making the technology parameters difficult to identify.

In *econometric* terms, the setup in the general empirical production function and convergence equation frameworks allows for parameter heterogeneity across countries in the impact of observables (factor-inputs) and unobservables (TFP) on output. The common factor model specification for the production function errors u_{it}, equation (1), operationalises cross-section dependence in the panel, whereby unobserved processes are correlated across countries. Note that this specification encompasses the case of serial correlation in the u_{it}, which can be thought of as arising from persistence in one or more of the common factors, i.e. $\boldsymbol{f}_t = \mu + \boldsymbol{\rho}\boldsymbol{f}_{t-1} + e_t$ where μ is a drift term and $0 < \boldsymbol{\rho} \leq 1$. The impact of processes driving TFP evolution can be heterogeneous ($\boldsymbol{\lambda}_i$) or homogeneous ($\boldsymbol{\lambda}_i \equiv \boldsymbol{\lambda}\,\forall i$) across countries, or a mixture of both. Furthermore, since observable inputs may be driven by (some of) the same unobserved factors as output we encounter variable endogeneity, which makes it difficult to identify the technology parameters separately from the factor loadings $\boldsymbol{\lambda}_i$. Factor-input variables and output, as well as unobserved factors may be nonstationary. This allows for a number of potential cases: *firstly*, factor-inputs and output are nonstationary and cointegrated; *secondly* factor-inputs, output and (some) common factors are nonstationary and cointegrated; and thirdly, neither of the above (noncointegration). Whether cointegrating vectors are homogeneous or heterogeneous across countries depends on the nature of the factor-input parameters (α_i, β_i, γ_i). Thus our empirical frameworks provides maximum flexibility with regards to the time-series and cross-section properties of the variable series and unobserved processes analysed. Similarly for the VA production function and the general convergence equation in (3).

Note that our discussion thus far has focused on 'structural regression models': in a structural regression equation the specification arises out of the steady-state solutions of a theory model, as exemplified by the human capital augmented Solow-model of Mankiw et al. (1992). In a structural model the regressors are assumed exogeneous by theoretical construction. Many empirical papers have however entered additional covariates into the convergence specification of Mankiw et al. (1992) without deriving their impact in the solution to an economic theory model. These 'reduced form' regressions are also referred to as 'Barro regressions', following the seminal contribution by Robert Barro (1991). Typically a range of instrumentation strategies are employed for Barro regressions to deal with potential variable endogeneity. Note that our common factor model setup allows for variable endogeneity which will need to be addressed in the estimation approach.

In *economic* terms, the above frameworks in (1), (2) and (3) are *as general as possible*, allowing for individual countries to possess idiosyncratic production technologies with regard to factor-input parameters, TFP levels and TFP evolution. We briefly motivate this in the following paragraphs.

A theoretical justification for *heterogeneous technology parameters* 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 et al., 2001). As Brock and Durlauf (2001, p.8/9) put it:

> *"... the assumption of parameter homogeneity seems particularly inappropriate when one is studying complex heterogeneous objects such as countries ..."*

The model by Azariadis and Drazen (1990) can be seen as the 'grandfather' for many of the theoretical attempts to allow for countries to possess different technologies from each other (and/or at different points in time). Their model incorporates a qualitative change in the production function, whereby upon reaching a critical 'threshold' of human capital, economies will jump to a higher steady-state equilibrium growth path represented by a different production function. Further theoretical papers lead to multiple equilibria interpretable as factor parameters heterogeneity in the production function (e.g. Murphy, Shleifer, & Vishny, 1989; Durlauf, 1993; Banerjee & Newman, 1993). A simpler justification for heterogeneous production functions is offered by Durlauf et al. (2001), as quoted at the beginning of this paper: 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.

The empirical implementation of parameter heterogeneity is largely dominated by the empirical convergence literature.[7] Originally technology parameters were assumed group-specific rather than fully heterogeneous, e.g. Durlauf and Johnson (1995), Caselli, Esquivel, and Lefort (1996) or Liu and Stengos (1999). Durlauf et al. (2001) then allowed for parameters to vary *by country* as a function of initial per capita income in a simple cross-section regression model, referred to as 'local' Solow growth model. Thus the 'new growth theory' literature provides the foundations for the assumption of heterogeneous technology parameters in production. Existing empirical implementations have provided some indicative evidence for this and we therefore adopt this flexible approach for our general empirical frameworks.

Many empirical growth models in the applied literature assume common technology parameters in a framework allowing for *differential TFP* across countries — a specification derived from further extension of the empirical version of a neoclassical Solow-Swan model by Mankiw et al. (1992). Mankiw et al. (1992) include human capital in their theory model and derive an empirical equivalent using secondary education as a proxy for human capital. In alternative theoretical models determinants such as institutional environment, good governance or geographical features are deemed equally important for the production process. However, identifying good proxy variables in these cases proved more cumbersome, especially if the empirics were conducted allowing for dynamics, rather than in a single cross-section regression. In a black-box approach to the specification of an underlying production function, empirical models therefore allowed for heterogeneity in TFP levels and growth rates across countries: since including all non-standard growth determinants (i.e. those other than labour, capital and materials) in the model is difficult, it is assumed that a flexible TFP specification can empirically 'mop up' the excess variation in the data as displayed in standard neoclassical growth models with homogeneous technology parameters. At the same time, any notion of common TFP evolution as implicitly assumed by Solow (1956)[8] and implemented empirically by Mankiw et al. (1992) has been dropped.

In our general empirical model above we emphasise a view of TFP as a 'measure of ignorance' (Abramowitz, 1956), which is in contrast to the the notion of TFP as an efficiency index in the microeconometric literature on production analysis. Furthermore, we allow for the possibility that TFP is in parts common to all countries, e.g. representing the global dissemination of non-rival scientific knowledge. These considerations lead to the adoption of a TFP structure which allows for common and/or country-specific evolution as implemented via the common factor model approach. Finally, we do not impose restrictions on the individual evolution paths of these unobservables.

The following sections will show that our framework encompasses empirical specifications in the literature of the past two decades. In our presentation we highlight technology parameter estimates reported in different studies and to put these estimates into context, we briefly discuss parameter values and their consistency with macro data on factor-input shares.

1.2 A note on factor shares and production function parameters

Conducting empirical growth analysis with *aggregate* economy data has an advantage over many other empirical exercises, in that we already know parts of the answers we are seeking: the values for α^{va} and β^{va} in the above value-added based production function (2), and implied β^{va} in the convergence equation (3) should be equal to the labour and capital shares in aggregate income. Macroeconomic data for labour are available through the aggregate data on wages and welfare payments to labour. From this it can be deduced that the labour share in income is roughly two thirds, with capital's share around one third (Mankiw et al., 1992, p.415).[9] It has been pointed out that whilst country data shows high persistence over time, there is considerable variation in the factor shares *across* countries, with labour share ranging from 5% to 80% of aggregate value-added (from UN (2004) national accounts data). Gollin (2002) attributes this to the mismeasurement of labour income in small firms, which is particularly the case in Less Developed Countries (LDCs), and concludes that adjusted labour shares are in a range of 65% to 80% in the majority of countries. As Islam (2003) and Pedroni (2007) point out, the majority of empirical approaches tend to produce capital coefficients far in excess of .3 and this paper points to empirical misspecification (heterogeneity of observables and unobservables) and the neglect of time-series and cross-section dependence properties of the data as potential explanations for this 'empirical puzzle'.

1.3 Complete parameter homogeneity

The canonical Mankiw et al. (1992) single cross-section regression model is explicitly derived from the Solow-Swan model (Solow, 1956, 1957; Swan, 1956), where the steady-state solutions are given empirical equivalents. We simplify their notation to

$$y_{i,1985} = -\left(\frac{\beta^{va}}{1-\beta^{va}}\right)(\delta + \bar{n}_i + \mu^\star) + \left(\frac{\beta^{va}}{1-\beta^{va}}\right)\bar{s}_i^k + a^{va} + \varepsilon_i \tag{8}$$

The regression applies *end of period level* of per capita GDP and *total period averages* for population growth ($\bar{n}$) and the savings rates for physical capital ($\bar{s}^k$) — this is never motivated, but reduction of measurement error and boosting the robustness of results (in the presence of business cycles and/or changes in capacity utilization over time) might be plausible reasons for this choice. The a term is said to include not only 'technology', but also resource endowment, geography, climate, institutions, etc. thus in the spirit of a 'measure of ignorance'.

In a first step, Mankiw et al. (1992) estimate the above equation by OLS using Penn World Table (PWT) data — in the following we concentrate on results for the samples including both developed and developing economies in each paper discussed. Imposing parameter homogeneity Mankiw et al. (1992) find coefficients on the two input terms considerably above the magnitudes suggested by theory (.5), although of correct (opposite) signs. The implied income elasticity for capital ($\hat{\beta}^{va}$) is .60, s.t. 60% of income are attributed to capital — double the value observed in macro data for capital share in income. The author's first important empirical result derives from the theory-driven inclusion of human capital[10] into this model, which yields implied income elasticities for physical and human capital of .31 and .28 respectively. This 'augmented Solow model' explains around 80% of the variation in the data.

The second part of the Mankiw et al. (1992) analysis concerns the *out-of-steady-state* behaviour of the augmented Solow model, thus addressing the convergence argument, which has found huge interest in the empirical literature: convergence refers to "the tendency of differences between countries [in income terms] to disappear over time" (Durlauf & Johnson, 2008). Via approximation around the steady state and minor transformation, they derive a convergence regression as represented in equation (5) above, with 1985 as end of period and 1960 as base year, imposing parameter homogeneity ($\beta_i^{va} = \beta^{va} \, \forall \, i$, dto. for the convergence term ξ). Again using OLS they find that the conditional convergence rate in the model augmented with human capital is statistically significant and higher than in the unaugmented case: around 1.4% per annum — this is the second result in this paper which had a strong impact on the literature. The implied income elasticities for physical capital are now .82 and .48 in the unaugmented and human capital-augmented case respectively[11] — thus considerably different from the steady state model results. The implied human capital coefficient in the augmented model is .23, thus very similar to the estimate of .28 in the cross-section regression.

The paper received most criticism for its assumption of random cross-country differences in TFP levels, which allow for the empirical representation $A_{i,0} = a + \epsilon_i$ by assuming error term exogeneity such that $\epsilon_i \perp n$, s^k, s^h (Islam, 1995; Caselli et al., 1996; Temple, 1999). In words, this assumption implies that the probability of Malawi having a higher initial TFP level than the US is the same as the probability of the reverse (Comment by Steven Durlauf). Furthermore, if the underlying unobserved factors drive both regressors and TFP growth contained in the error terms then regression parameters on the observables are unidentified, as will be shown in Section 3 below.

Later papers also pointed out that in using OLS the convergence specification *by construction* induces downward bias in the convergence rate (Knight, Loayza, & Villanueva, 1993; Islam, 1995; Caselli et al., 1996): the presence of the initial income variable on the RHS induces non-zero correlation between $y_{i,1960}$ and the regression error, as both contain the omitted country-specific effect ϵ_i from $A_{0,i} = a + \epsilon_i$. The parameter estimate on $y_{i,1960}$ is biased toward zero, with the implication of a reduced convergence rate ξ. Nevertheless, this specification forms the basis for the popular reduced form or 'Barro regressions' where the convergence equation is expanded by any variable deemed a relevant growth determinant. The inclusion of additional variables in the model can be viewed as relaxing the assumption of *random* TFP level differences (Durlauf et al., 2005, p.579), but the problems raised above remain.

Given the static, cross-section nature of this empirical framework, the time-series properties of the underlying data (potential nonstationarity) would seem not to have any bearing on consistent estimation. There is a limited theoretical literature on the identification of cointegrating vectors in cross-sections when the underlying data is characterised as nonstationary (Madsen, 2005). For our present purposes we assert that single convergence regressions are free from the impact of time-series properties of the underlying data series. Cross-section dependence induced by the presence of unobserved common factors leads to non-randomness in the regression errors if TFP growth differs across countries; the absence of endogeneity between the regressors and the error terms for identification is also questionable.

The Mankiw et al. (1992) convergence regression model in (5) is nested within our more general model, under the assumption of

(i) common technology parameters across countries ($\beta_i^{va} \equiv \beta^{va}$), or no bias from imposition of a common parameter on heterogeneous country coefficients, i.e. the resulting estimate is the unweighted mean of underlying 'micro-parameters';
(ii) roughly constant savings rates s^k and population growth rates n for each country over the *full* period of observation;
(iii) common and constant TFP evolution across countries, equivalent to common factor loadings on unobserved common factors which themselves are linear in evolution;
(iv) random differences in TFP levels across countries; and
(v) cross-section independence.

The essence of the Mankiw et al. (1992) empirics is that if we assume all countries are in *steady state* and can be represented by the same underlying production function, then the augmentation of an empirical Solow model with a proxy for human capital yields sensible values for implied physical capital, and can account for a large share of the variation in the data. The same cannot be said for the *out-of-steady-state* version of their model (convergence equation), where the implied capital coefficient in the human capital augmented model changes considerably. This aside, the assumption of error term exogeneity required for the specification of $A_{i,0} = a + \varepsilon_i$ is econometrically useful but conceptually questionable, while the convergence equation setup induces downward bias in the estimate for ξ by construction.

1.4 Heterogeneous TFP levels

Given the availability of longer time-series data, the application of panel data methods to investigate the growth and development process was a natural next step, notably the contributions by Knight et al. (1993), Loayza (1994) and Islam (1995). The latter tackles the critical assumption of error term exogeneity in the Mankiw et al. (1992) convergence framework by transforming the single convergence equation into a dynamic panel model in levels with non-overlapping panels of 5-year averages and then introducing country fixed effects

$$y_{i,\tau} = -\left\{-e^{-\xi_i \tau}\right\}\left(\frac{\beta^{va}}{1-\beta^{va}}\right)(\delta + \bar{n}_{i\tau} + \mu^\star) + \left\{-e^{-\xi_i \tau}\right\}\left(\frac{\beta^{va}}{1-\beta^{va}}\right)\bar{s}^k_{i\tau} \qquad (9)$$

$$- \left\{ -e^{-\xi_i \tau} \right\} y_{i,\tau-1} + \left\{ -e^{-\xi_i \tau} \right\} A^{va}_{0,i} + \left\{ -e^{-\xi_i \tau} \right\} \sum_{\tau=2}^{T} \mu_\tau D_\tau + u_{i\tau}$$

where due to the change in dependent variable the interpretation of estimated coefficients changes slightly,[12] but the implied technology coefficient β^{va} is equivalent to that in our general model in equation (3) with $\tau = 5$.[13] The crucial innovation over Mankiw et al. (1992) is the introduction of country fixed effects (operationalised using the 'within-groups' transformation), which allow for differential TFP levels across countries. Islam further uses period dummies (the sum of Ds with parameter coefficients μ in (9)) to account for common TFP evolution — this specification imposes no assumption about linearity (or stationarity) on the underlying common TFP evolution, although time-averaging arguably diminishes the model's ability to capture TFP dynamics (Lee, Pesaran, & Smith, 1997). Islam also uses the PWT dataset with sample and variable construction close to that in Mankiw et al. (1992).

Following some OLS estimations to show that a pooled convergence regression of five-year averages yields next to identical results to the single convergence regression, the above panel model is estimated *without* the human capital variable but accounting for country fixed effects. The implied convergence rate is much higher than in Mankiw et al. (1992), around 5% per annum, while the implied income elasticity for capital is .44 — it is thus suggested that individual country effects (TFP levels) play an important role in the development process.[14] Inclusion of the human capital variable slightly lowers the convergence rate but the implied capital coefficient at .52 is quite similar to the regression without augmentation.

The major criticism leveled at Islam's and other panel approaches was to highlight the potential endogeneity issues in the empirical model. Although the within-groups transformation wipes out the country fixed effects, Nickell (1981) has shown that in the presence of a lagged dependent variable this approach requires sizeable T for consistency, which is not given in the averaged panel case. The estimate on y_{i,t_1} is therefore likely to be biased *downward* (in absolute terms, i.e. smaller negative value in a model with $y_{i,t_2} - y_{i,t_1}$ on the LHS, smaller positive value in a model like Islam's with y_{i,t_2} on the LHS). Islam (1995) remarks that his own Monte Carlo experiments indicate that this bias is likely to be small. Potential bias due to the dynamic setup aside, Caselli et al. (1996) argue that violation of the exogeneity assumption with regard to the input variables renders Islam's results, as well as those from similar panel fixed effects models, inconsistent. Lee et al. (1997, p.321) highlight that the validity of Islam's estimates depend critically on the assumption of *common* TFP evolution for all countries — if this is violated, country-errors will contain a term which is serially correlated with unit coefficient, causing *upward* bias in the convergence rate estimate. Variable endogeneity due to the presence of common factors (see Section 3) is also a matter for concern.

The model in (9) is nested within our more general model in (3), under the assumption of

(i) common technology parameters across countries ($\beta^{va}_i \equiv \beta^{va}$), or no bias from imposition of a common parameter on heterogeneous country coefficients;
(ii) roughly constant population growth rates n and savings rates s^k over the 5-year intervals;
(iii) common TFP evolution across countries, equivalent to common factor loadings on the unobserved common factors;
(iv) heterogeneous TFP levels across countries;
(v) stationary input and output variable series;

(vi) cross-section independence; and
(vii) no dynamic misspecification through period averaging.

The last point merits further comment. The Islam (1995) framework of short period-averaged panels has become a standard alternative to the single convergence regression model and both are commonly implemented without any concern for the time-series properties of the data. If we were to apply the period-averaged panel approach to the most recent PWT data (Heston, Summers, & Aten, 2006) we would obtain $T = 9$; given that averages constructed from nonstationary variables are nonstationary themselves (Granger, 1988; Granger & Siklos, 1995; Marcellino, 1999), the use of longer T eventually faces the same issues as annual data, outlined in detail in section 2. As our discussion of Caselli et al. (1996) below indicates, high levels of persistence in the data (with unit roots the extreme case) in general can have a serious impact on estimation and inference. In defense of Islam (1995), his approach successfully challenges single convergence regressions by providing evidence of the significance of fixed effects in a panel setup.

A variant on the above panel estimation approach is presented by Caselli et al. (1996). Instead of fixed effects estimation they apply dynamic panel GMM estimation techniques (Arellano & Bond, 1991), which eliminate heterogeneous TFP levels by differencing and overcome endogeneity issues by instrumentation making use of the panel structure (for a detailed discussion of the estimation approach see Bond, 2002). Their model setup and assumptions are identical to those in Islam (1995) described above — the difference between the approaches is in the empirical estimator, which is argued to deal with variable endogeneity in a short-T dynamic panel data model. Throughout their empirics the authors use variables in deviation from the cross-section mean to account for common TFP evolution, a practice which is valid if technology parameters are homogeneous across countries (as is assumed here), but otherwise introduces misspecification bias (Pedroni, 2000). TFP evolution is thus assumed identical across countries.

In their estimation without human capital the authors find an implausibly low income elasticity for capital of .10, with convergence very high at 13% per annum. In the human capital-augmented regression the income elasticities for physical and human capitals are .50 and -.26 respectively, with convergence around 6.8% per annum. The implied physical capital parameter is relatively close to the result in Islam (1995), while implied human capital parameter is negative significant and the convergence rate λ is almost doubled. Since the Islam results in turn have lower implied capital coefficients but roughly double the convergence rate of the Mankiw et al. (1992) convergence regression, Caselli et al. (1996) argue that the step-wise 'improvement' in the estimate for conditional convergence from Mankiw et al. (1992) to panel approaches like Islam (1995) and further to their own results is the outcome of appropriate accounting for country fixed effects and endogeneity respectively. They interpret the low capital estimate in their unaugmented model as a rejection of the empirical Solow model, and embark on more general 'Barro-type' regressions to analyse convergence using the same Difference GMM estimation method. Their model is thus no longer 'structural', but instead 'reduced form'. Augmentation is carried out using variables such as government consumption, male and female education, and black market premium. Results suggest consistently high convergence rates of up to 10% pa.

The 'Difference GMM' estimator used in the analysis by Caselli et al. (1996) was found to be liable to considerable small sample bias for highly persistent variable series (Blundell & Bond, 1998, 1999).[15] Furthermore, if technology parameters are heterogeneous across countries, "there exists no consistent instrumental variables estimator" (Lee et al., 1997, p.367).[16] Implied capital coefficients estimated by Caselli et al. (1996) are vastly different from the expected 30% share in value-added — a finding which led them to reject the empirical Solow model, but which may be attributable to misspecification and weak instrument bias.

Note that both Islam (1995) and Caselli et al. (1996) favour a dynamic empirical specification but in the form of a 'partial adjustment model' (PAM) ($Y_t = f(Y_{t-1}, X_t)$), which in turn is a (Kroyck) transformation of a distributed lag model with infinite lag structure ($Y_t = f(X_t, X_{t-1}, X_{t-2}, \ldots)$) and a geometric rate of decline in the impact of lagged values of X on Y. This structure emerges in the panel from the convergence equation by Mankiw et al. (1992), as is shown in Islam (1995, p.1135). A more general dynamic specification is the Autoregressive Distributed Lag (ARDL) model ($Y_t = f(Y_{t-1}, X_t, X_{t-1})$), for which "virtually every type of single equation model in empirical time-series econometrics is a special case" (Hendry, 1995, p.212), including the Error Correction Model (ECM). Although the PAM has "respectable pedigree in economic analysis" (Hendry, 1995, p.256) it nevertheless somewhat awkwardly imposes a zero-coefficient on X_{t-1} and a more general ARDL specification of dynamics may therefore be commendable.

1.5 Heterogeneous TFP levels and growth rates

A further variant on the stationary panel estimation approach is presented by Martin and Mitra (2002), who estimate sectoral production functions for agriculture and manufacturing using Crego, Larson, Butzer, and Mundlak (1998) data for 1967 to 1992 ($T = 26$) — to our knowledge this is the only paper in the literature specifying separate production functions at this level of aggregation in a sample including developed and developing countries. In a further contrast to the previous papers, the authors allow for differential TFP levels *and* growth rates across countries, modeled via country-specific intercepts and linear trend terms in a pooled panel estimation using *annual data* for around 50 countries. We adjust their notation for consistency

$$y^j_{it} = \beta^{j,va}\, k^j_{it} \, \left\{+\theta^{j,va}\, n_{it}\right\} + u_{it} \qquad u_{it} = A^{j,va}_{0,i} + \mu^j_i t + \varepsilon_{it} \qquad j = a,\, m \tag{10}$$

where the superscript j distinguishes the two sectors (*a*griculture and *m*anufacturing) and the additional factor-input refers to land per worker (in logarithms, as are sectoral value-added per worker, y, and capital stock per worker, k) which is only included in the agricultural production function. TFP growth is captured by the country trends and thus assumed to be constant over time and heterogeneous across countries (and sectors).

As indicated Martin and Mitra (2002) impose constant returns to scale (CRS) on this model and estimate it separately for agriculture and manufacturing data using LSDV.[17] Their results indicate considerable variation in TFP growth rates between sectors and across countries, with TFP growth rates in agriculture commonly *in excess* of those in manufacturing. The capital coefficient in the Cobb-Douglas estimation of the manufacturing data is estimated at .69; the authors highlight the magnitude of this coefficient in comparison to macro data on factor share and point to the omission of human capital from the model as a likely explanation. For agriculture, where arable land per worker is included as additional regressor (coefficient .24), the estimated capital elasticity is .12. As in many other studies which obtain country-specific TFP levels or growth rates via production function regressions, the validity of the TFP estimates in the face of possibly *biased* factor parameters is not questioned. The empirical approach furthermore assumes cross-section independence.

The sector-level Martin and Mitra (2002) regression model is nested within the value-added version of our general production function model in (2), under assumption of

(i) common technology parameters (within sector j) across countries ($\beta_i^j \equiv \beta^j$);
(ii) heterogeneous TFP growth across countries, constant over time, implying stationarity;
(iii) heterogeneous TFP levels across countries;
(iv) cross-section independence; and
(v) stationary input, output and TFP.

Martin and Mitra (2002) thus address the issue of heterogeneity in TFP levels and growth rates in a static pooled fixed effects model using annual data which imposes common technology parameters across countries. TFP growth rates (constant by construction) are found to be higher in agriculture than manufacturing.[18] Time-series and cross-section dependence properties of their data are not formally investigated. The estimation equations for agriculture and manufacturing are static and no investigation of error correlation is undertaken to justify this choice.

1.6 Full parameter heterogeneity in a stationary variable model

Inspired by the 'new growth theory' literature, Durlauf et al. (2001) test a 'local' Solow growth model which specifies all parameters in the Mankiw et al. (1992) convergence regression as functions $\psi(\cdot)$ of some 'development index' z_i (here: initial period GDP per capita), thus modeling parameter heterogeneity explicitly:

$$\begin{aligned} y_{i,1985} - y_{i,1960} &= \boldsymbol{\psi}(z_i)'\mathfrak{X}_i + u_i \qquad (11) \\ \mathfrak{X}_i &\equiv \left\{a^{va},\, (\delta + \bar{n}_i + \mu),\, \bar{s}_i^k,\, \bar{s}_i^h,\, y_{i,1960}\right\} \end{aligned}$$

where $\bar{s}^h$ is their measure for human capital and $\boldsymbol{\psi}(z_i)' \equiv \{\psi_0(z_i), \ldots, \psi_4(z_i)\}$. The notion underlying this specification is that a single Solow model was never intended to apply to *all* countries, but may still be a good representation for the production process in *each* country individually (Durlauf et al., 2001, p.929). In essence, all observables and the TFP levels are allowed to differ across countries but are constrained by the development index z_i; the empirical specification does not allow for TFP growth rates to differ from the constant 5% pa for depreciation plus TFP growth ($\delta + \mu$).

The authors use the same sample and variable definitions as Mankiw et al. (1992) so as to obtain directly comparable results, employing a two-step semi-parametric method for estimation. They find strong evidence for parameter heterogeneity in the impact of all regressors, and note that there is no monotonic relationship between initial income (z_i) and the country-specific capital coefficient estimates. They introduce a local goodness-of-fit measure, a generalisation of the conventional R^2, which indicates that vis-à-vis a homogeneous parameter model the fit is improved for countries with higher base-year income $y_{i,1960}$.

The Durlauf et al. (2001) model is nested within our more general convergence equation model in (3), under the assumption of

(i) heterogeneous technology parameters across countries, which are functions of initial income ($\beta_i \equiv \beta(z_i)$);

(ii) common and constant TFP growth across countries, implying its stationarity;
(iii) heterogeneous TFP levels across countries; and
(iv) cross-section independence.

Their paper concludes that substantial parameter heterogeneity seems to exists across countries, and that "empirical exercises which fail to incorporate parameter heterogeneity are likely to produce misleading results." (Durlauf et al., 2001, p.935).

1.7 Full parameter heterogeneity in a model with nonstationary inputs

In the mainstream growth literature it is argued that attempting to identify and quantify 'deep parameters' of a structural model for production is overly ambitious if one were to accept parameter heterogeneity (Durlauf et al., 2005, p.616). There is however a small number of papers explicitly contemplating the implications of nonstationarity and cointegration in a cross-country empirical production function which allows for heterogeneity in technology parameters and TFP evolution, most notably Pedroni (2007) and Canning and Pedroni (2008).

Of these, the most encompassing framework for a nonstationary panel analysis of growth is presented by Pedroni (2007). The author exploits the time-series properties of the data to argue for a simple heterogeneous, cointegrated panel specification

$$y_{it} = c_i + \mu_i t + \theta_i \, s^k_{it} + u_{it} \tag{12}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where s^k is the (log) investment share in GDP and y is (log) GDP per capita. The model setup and data transformations however allow for a much richer underlying framework, taking account of time-invariant and near time-invariant (unmeasured) variables such as social capital/institutions or other types of 'intangible capital' H, with savings rate s^h. The general specification can be written as

$$\begin{aligned} \Rightarrow y_{it} &= -\left(\frac{\beta^{va}_i \{+\varphi_i\}}{1-\beta^{va}_i \{-\varphi_i\}}\right)(\delta + n_{it} + \mu^\star) + \left(\frac{\beta^{va}_i \{+\varphi_i\}}{1-\beta^{va}_i \{-\varphi_i\}}\right) s^k_{it} \qquad (13) \\ &\quad \left\{+\left(\frac{\varphi_i}{(1-\beta^{va}_i - \varphi_i)}\right) s^h_{it}\right\} + u_{it} \\ u_{it} &= A^{va}_{i0} + \mu_i t + \varepsilon_{it} \qquad (14) \end{aligned}$$

where $A_{i,0}$ and μ_i are country-specific TFP levels (in logs) and constant growth rates respectively. The terms in curly brackets only come to bear if H is accumulated using a share of income Y, in which case s^h_{it} is the country-specific savings rate for this type of investment at time t. Otherwise, the term in brackets is subsumed into the intercept term and/or the linear trend term in (12). Thus the interpretation of θ_i in (12), as well as that of the deterministic fixed effect and trend terms varies depending on how the unmeasured intangible capital stocks are accumulated — with or without use of a share of aggregate income.[19] For the purpose of this exposition we limit discussion to the case where all forms of intangible capital H are accumulated *without* using a share of aggregate income. In this case, this intangible capital stock is absorbed into the fixed effect and trend terms in the estimation equation (12). Similarly for the population growth term $(\delta + n_{it} + \mu^\star)$. Under these assumptions, the slope coefficient for measured physical capital θ_i is simply a function of the production function share parameter for 'tangible' capital, i.e. $\hat{\theta}_i = \hat{\beta}_i(1-\hat{\beta}_i)^{-1}$ just like in the previous models presented.

Given that the nonstationary panel estimation approach extracts the long-run relationship $\hat{\beta}_i$ (via the cointegrating vector $\hat{\theta}_i$) *without* the requirement of proximity to the steady-state, there is no need to specify a lagged dependent variable term as in the standard convergence equation or any other dynamics: if savings rate and per capita GDP are nonstationary and cointegrated, then their long-run relationship will be extracted via the nonstationary panel econometric method applied, regardless of any short-run dynamics (Pedroni, 2007).

The model in (12) is estimated using the aggregate PWT data (version 5.6, 1950-1992). The nonstationary panel approach depends on a reasonably long time-series dimension, nonstationarity of the variables series and cointegration between savings rate and per capita GDP. Unit root and cointegration tests therefore form an *integral part* of the sample selection process in Pedroni (2007), reducing the sample from 152 to 51 (full time series, $T = 43$), and finally 29 countries (nonstationary series, cointegrated). With regard to variable stationarity, it is important to note that Pedroni does not postulate that the savings rate proxy is nonstationary *indefinitely* ('global' property). Instead, he suggests that unit root evolution is merely a 'local' behaviour of the series *within-sample*, which is commonly found in macro data (Jones, 1995). Estimation is carried out using the Phillips and Hansen (1990) time-series Fully Modified OLS (FMOLS) in each country and then averaging the results (this method is referred to as Group Mean FM-OLS — Pedroni, 2000). The FMOLS procedure modifies OLS to account for serial correlation in the errors and the endogeneity in the regressors resulting from the existence of a cointegrating relationship (Phillips, 1995): it exploits the fact that under cointegration the bias created by variable endogeneity is of second order, and the first differenced regressors can serve as instruments for this bias to construct bias-adjusted variables (Pedroni, 2007). The approach does away with a great deal of assumptions required in stationary empirics, most notably the proximity to steady state and the strict exogeneity of the regressors.[20]

The resulting cross-country mean for the capital coefficient is .27 — Pedroni (2007) interprets the proximity of this value to macro data on factor shares as vindication of his estimation approach. This value is surprisingly robust to the inclusion of countries previously dropped in the sample selection process: .25 for the sample of 51 countries. This average however falls to around .2 in either sample if data is cross-sectionally demeaned prior to estimation, a method adopted to eliminate *common* TFP. Interestingly, the cross-sectional demeaning of variables was identified as inappropriate in the presence of heterogeneous factor parameters by the same author (Pedroni, 2000). The adoption of the Pesaran (2006) Common Correlated Effects estimator (CCEMG) (see below) similarly leads to an average implied capital coefficient of around .2.

Essentially, Pedroni (2007) extracts structural parameters by 'blending out' unobservable features of the data through the use of country-specific trends and intercepts. The apparent heterogeneity in country parameter estimates $\hat{\theta}_i$ (and thus $\hat{\beta}_i$) is argued not to be due to sampling variation and the relatively short time-series of the country regressions: a combination of formal tests strongly reject factor parameter homogeneity in the sample of 29 countries.

The Pedroni (2007) model can be nested within our general model in (3) assuming

(i) heterogeneous technology parameters across countries (β_i^{va});
(ii) heterogeneous TFP levels and growth rates across countries, the latter constant over time and thus stationary;
(iii) cross-section independence;

(iv) nonstationary input and output variable series within-sample (required and confirmed); and

(v) cointegration between the savings rate and GDP per capita within-sample (required and confirmed).

The empirical implementation by Pedroni (2007) requires sample countries to satisfy strict data requirements (*full* 43 years of data, nonstationarity, cointegration), which in effect excludes the vast majority of LDCs from the analysis. His preferred regression approach precludes the possibility of a common, nonstationary TFP evolution; once this assumption is relaxed the implied mean capital coefficient drops to around .2. One explanation for this finding may be that following dual economy arguments (Temple, 2005) aggregate economy data represents the wrong basic unit of analysis for growth empirics, which should be based on sector-level analysis of agriculture, manufacturing and services.

1.8 Common technology parameters in a nonstationary panel model with cross-section dependence

As will be detailed in Section 3 the study of cross-section correlation has only very recently begun to concern panel time-series econometricians, such that the number of empirical papers which apply the insights of this new field of research to macro-production function estimation is still limited. Bai et al. (2009) raise the estimation and inference problems created by unobserved common factors in a production function framework as one of the motivations for their novel 'continuously updated' (CUP) estimators, which are applied by Costantini and Destefanis (2009) in a sectoral study of Italian regions (although the aggregate economy model is also estimated).

The latter's empirical model is a homogeneous technology human capital-augmented production function with a common factor structure. We adjust their notation for consistency

$$Y_{it}^{j} = A_{i,0}^{j} + \alpha^{j,va} L_{it}^{j} h_{it}^{j} + \beta^{j,va} K_{it}^{j} + u_{it} \qquad u_{it} = \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{15}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where the superscript j indicates different industrial sectors (or the aggregate economy) and Y^j, L^j and K^j are (sector-specific) value-added, labour force and capital stock respectively (all in logarithm). h^j is a transformation of the educational attainment of each labour unit in sector j following Hall and Jones (1999), based on the returns to education coefficients from Mincerian wage equations for Italy and the average years of education for the male and female population. The sectors investigated separately in this study are the construction, services, industry and agricultural sectors.

Prior to estimation the authors carry out three sets of testing procedures: firstly, they test all variables in their regression model for correlation across regions by applying the Pesaran (2004) CD test, which firmly rejects cross-section independence in all sectors and the aggregate economy data. Secondly, they carry out panel unit root tests for all variables following Bai and Ng (2004) — the latter's PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common components) stationarity tests allow for the presence of common factors, the number of which is determined by a method detailed in Bai and Ng (2002). These tests cannot reject nonstationarity of input and output variables in all sectors and the aggregate economy data. Furthermore, the authors establish that the nonstationarity of the observable variables derives both from common factors as well as idiosyncratic components. Finally, they defactor the data (i.e. remove the impact of unobserved common factors from the input and output variables) and apply cointegration tests following Pedroni (1999, 2004a). This approach follows a suggestion by Gengenbach, Palm, and Urbain (2006) and is appropriate since the nonstationarity of input and output variables was not merely due to the presence of common factors. The panel cointegration tests reject the null hypothesis of 'no cointegration' between value-added, capital stock and human capital-augmented labour in all sectors and the aggregate economy data in favour of homogeneous cointegration — this alternative is imposed on the data by the estimation approach favoured by the authors.

Using annual data for 20 Italian regions from 1970-2003 the authors estimate the above empirical model by sector, comparing results for the Pedroni (2000) Group Mean FM-OLS and Bai et al. (2009) continuous-updated fully modified (CUP-FM) estimators, imposing technology parameter homogeneity. Their CUP-FM results indicate relatively similar empirical capital coefficients across sectors (ranging from .24 in construction to .31 in services), although returns to scale differ substantially: agriculture, construction and in particular the services sector are characterised by decreasing returns, while the 'industrial' sector (manufacturing and utilities) displays increasing returns (all results statistically significant at the 5% level). It is particularly interesting to note that their results for aggregate economy data display a comparatively inflated capital coefficient of .40 which also rejects constant returns to scale in favour of the decreasing returns alternative. While empirical results for the Pedroni (2000) Group Mean FM-OLS estimator do not systematically bias capital coefficients upward or downward, they yield considerably higher labour coefficients in all sectors and the aggregate data, implying increasing returns across *all* models tested.

The Costantini and Destefanis (2009) model can be nested within our general production function model in (2) assuming

(i) homogeneous technology parameters (within sector j or the aggregate economy) across Italian regions ($\alpha_i^{j,va} \equiv \alpha^{j,va}$, $\beta_i^{j,va} \equiv \beta^{j,va}$);
(ii) heterogeneous TFP levels and growth rates across regions, with TFP evolution not required to be stationary;
(iii) cross-section dependence (confirmed);
(iv) nonstationary input and output variable series within-sample (required and confirmed); and
(v) cointegration between (sectoral) value-added, human capital-augmented labour and capital stocks within-sample (required and confirmed).

In comparing and contrasting the empirical estimates and returns to scale implications for nonstationary panel methods which neglect and account for cross-section dependence the authors highlight the importance of variable correlation between geographical regions for unbiased empirical estimation.

1.9 Parameter heterogeneity in a model with nonstationary inputs and cross-section dependence

Given the relatively recent emergence of cross-section correlation issues in macro panels only a small number of empirical papers combine cross-section correlation in macro panel data with heterogeneous production technology, including work by Bhattacharjee, Castro, and Jensen-Butler (2009) and Fleisher, Li, and Zhao (2009) on production in Danish regions and Chinese provinces respectively. This aside, we noted above that Pedroni (2007) adopts the Pesaran

(2006) CCEMG estimator as a robustness check in his analysis of Penn World Table data from 29 countries. In our own work (Eberhardt & Teal, 2008, 2009) we analysed cross-country macro data for the manufacturing (48 countries, 1970-2002) and agricultural (128 countries, 1961-2002) sectors respectively. In the following we present the results from the latter study, since it builds on the seminal contribution by Pesaran (2006) and extends this approach by aiming to identify the structure of the unobserved common correlation driving the data.

In Eberhardt and Teal (2009) we adopt the following empirical framework to study cross-country production in agriculture: for $i = 1, \dots, N$ and $t = 1, \dots, T$

$$\begin{aligned} y_{it} &= \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} && (16) \\ x_{mit} &= \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \rho_{1mi} f_{1mt} + \dots + \rho_{nmi} f_{nmt} + v_{mit} && (17) \\ & \quad \text{where} \qquad m = 1, \dots, k \qquad \text{and} \qquad \boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t \\ & \quad \boldsymbol{f}_t = \boldsymbol{\varrho}' \boldsymbol{f}_{t-1} + \boldsymbol{e}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t && (18) \end{aligned}$$

We assume a production function with observed net output (y_{it}) and observed inputs ($\boldsymbol{x}_{it}$) labour, agricultural capital stock, livestock, fertilizer and land under cultivation (all in logarithms). Unobserved agricultural TFP is represented by a combination of country-specific TFP levels α_i and a set of common factors $\boldsymbol{f}_t$ with factor loadings that can differ across countries ($\boldsymbol{\lambda}_i'$). We also introduce an empirical representation of the observed inputs in equation (17) in order to indicate the possibility for endogeneity: the input variables $\boldsymbol{x}_{it}$ are driven by a set of common factors $\boldsymbol{g}_{mt}$ as well as an additional set of factors $\boldsymbol{f}_{\cdot mt}$, whereby the latter as indicated represent a subset of the factors driving output in equation (16). The intuition is that some unobserved factors driving agricultural production are likely to similarly drive the evolution of the inputs (at least in parts). Equation (18) indicates that the factors are persistent over time, which allows for the setup to accommodate nonstationarity in the factors ($\boldsymbol{\varrho} = 1$, $\boldsymbol{\kappa} = 1$) and thus the observables. It further allows for various combinations of cointegration: between output y and inputs $\boldsymbol{x}$, and between output $\boldsymbol{y}$, inputs $\boldsymbol{x}$ and (some of) the unobserved factors $\boldsymbol{f}_t$.

We estimate the above empirical model using a number of standard and novel panel estimators, including the Pesaran (2006) Common Correlated Effects (CCE) estimators. Rather than obtaining explicit estimates for the unobserved common factors $\boldsymbol{f}_t$ as in Bai and Ng (2004) or Bai et al. (2009), the CCE estimators account for their presence implicitly by adding cross-section averages (average across all panel units in period t) for the dependent and independent variables to the regression equation. In the pooled variant (CCEP) each of these cross-section averages is interacted with a country dummy, whereas in the Mean Group alternative (CCEMG) they are simply added to the country regression — in either case the specification assures that coefficients on the implied common factors are allowed to differ across countries (equivalent to $\boldsymbol{\lambda}_i$ differing across i). The Pesaran (2006) estimators yield consistent and efficient estimates of the technology parameters by treating the unobservables (common factors with heterogeneous factor loadings) as nuisance parameters and are robust to structural breaks in the data. Crucially, no prior knowledge of the cointegrating properties of the observables and/or the unobservables is required, since the method is robust in all scenarios studied (Kapetanios et al., 2008).

Our extension to the CCE estimators in the agricultural production case investigates a number of alternative structures for the nature of cross-section correlation in the data, by applying different weight matrices before the period averages are computed. These alternative structures represent a neighbourhood effect (only countries sharing a common border affect each other), a distance effect (distance between countries is inversely related to strength of correlation) and an agro-climatic distance effect (similarity of countries in terms of their agro-climatic makeup, measured using data on the share of each country's arable land in different climatic zones (Matthews, 1983), determines the strength of correlation).

Prior to estimation our empirical tests are unable to reject nonstationarity and cross-section dependence in the data (FAO, 2007, data from 128 countries for 1961-2002). Our regression results support the specification of a common factor model in intercountry production analysis, highlight the rejection of constant returns to scale in pooled models as an artefact of empirical misspecification and suggest that agro-climatic environment, rather than neighbourhood or distance, drives similarity in TFP evolution across countries. The latter finding provides a possible explanation for the observed failure of technology transfer from advanced countries of the temperate 'North' to arid and/or equatorial developing countries of the 'South'.

The Eberhardt and Teal (2009) model can be nested within our general production function model in (2) assuming

(i) heterogeneous technology parameters in agricultural production across countries;
(ii) heterogeneous TFP levels and growth rates across countries, with TFP evolution not required to be stationary;
(iii) cross-section dependence (confirmed); and
(iv) nonstationary input and output variable series within-sample (confirmed).

This concludes our selective discussion of the growth empirics literature. We have shown that our general frameworks encompass the models employed in the growth empirics literature of the past two decades. The evolution we charted is one away from single cross-section regressions imposing common technology parameters and toward models allowing for parameter heterogeneity in the impact of observables and unobservables and the explicit treatment of variable time-series properties. We indicated on a number of occasions under which circumstances model assumptions in the literature are likely to be violated. We now provide a more detailed discussion of these concerns, beginning with variable time-series properties in the next section and subsequently discussing cross-section dependence and parameter heterogeneity.

2 Accounting for time-series properties in macro panel data

> *"In some panel data sets like the Penn-World Table, the time series components have strongly evident nonstationarity, a feature which received virtually no attention in traditional panel regression analysis."*
> Phillips and Moon (2000, p.264)

Since the seminal empirical papers on cross-country growth by Barro (1991) and Mankiw et al. (1992) the theory of panel data econometrics has progressed rapidly. First, in its analysis of the dynamic specification and estimation of stationary panel data (Arellano & Bond, 1991; Blundell & Bond, 1998), and more recently in its treatment of nonstationarity and cointegration in a panel setup (Pedroni, 1995, 1999, 2000; Kao, 1999; Phillips & Moon, 1999). The latter development has thus far found limited attention in the *mainstream* literature on empirical growth modeling[21] — for instance the chapter on growth econometrics in the recent *Handbook of Economic Growth* by Durlauf et al. (2005) contains only limited discussion of nonstationarity and cointegration with respect to panel data regression. In the following paragraphs we discuss important time-series properties some macro data series are likely to possess and highlight the implications for estimation — our focus is on annual data in the production function framework.

In the long-run, variable series such as gross output or capital stock often display high levels of persistence, such that it is not unreasonable to suggest for these series to be 'nonstationary' processes in *some* countries (Nelson & Plosser, 1982; Granger, 1997; Lee et al., 1997; Rapach, 2002; Bai & Ng, 2004; Pedroni, 2007; Canning & Pedroni, 2008). Nonstationarity is a property that can be viewed in simple terms as an extreme form of variable persistence over time. If we have a stationary variable, adding more observations (e.g. when more years of data become available) allows us to get a better understanding of the mean, variance, i.e. the distribution (probability density function) of the underlying process of which our variable is a realisation. In case of a nonstationary variable, adding more observations does not help us to get an idea of what the distribution looks like as mean, variance, etc. do not settle at ('converge' to) certain values.

If the first difference of a variable series transforms it into a stationary process, then the untransformed series is said to be 'integrated of order one' or I(1). The order of integration indicates how many times a variable series needs to be differenced to be stationary, which implies that a series which is stationary to start with is referred to as I(0). Although economic time-series in practice are usually not precisely integrated of any given order, it is for our purposes sufficient to assume that nominal and real value series typically behave as I(2) and I(1) respectively (Hendry, 1995, p.44) — note that this is a judgement derived from analysing data in a *developed country* context, but that less-developed countries may not submit to this generalisation. Further, as was pointed out in previous sections, Pedroni has suggested that variable (non)stationarity (in his case for the savings rate) should not be seen as a 'global' property, valid for all times, but as a "feature which describes local behaviour of the series within sample" (Pedroni, 2007, p.432). As we shall see, variable nonstationarity has important implications for estimation and inference.

In the context of the empirical literature on growth and development it is important to note here that the stationarity/nonstationarity property is invariant to time-averaging of variables (Granger, 1988; Granger & Siklos, 1995; Marcellino, 1999). Given that data for educational attainment is only available at five-year intervals (Barro & Lee, 1993, 1996, 2001) many empirical implementations using 'human capital' variables are based on short panels of five-year averages in levels. The above statement confirms that if the underlying variable series are nonstationary, this common practice of using 5-year averages does *not* render the resulting series of averages stationary I(0) and/or may introduce data dependencies which lead to violation of the standard assumptions of the ordinary least squares regression framework.

In conclusion, any macro production function is likely to contain at least some countries with nonstationary input and output variables, and these time-series properties will need to be taken into account in the empirical approach to avoid bias and/or inefficiency.

Unfortunately, empirical testing of variable (non)stationarity is fraught with difficulty in panels of moderate dimension[22] and for diverse sets of countries, such as the PWT or alternative annual production data at the country or regional level (e.g. UNIDO, 2004; FAO, 2007). Single time-series unit root tests, applied to each country variable series, suffer from low power while their panel cousins are difficult to interpret (Maddala, 1999; Smith & Fuertes, 2007): a Fisher-type test of unit roots in a panel (Maddala & Wu, 1999), for instance, investigates the null of *all* country series containing unit roots against the alternative that *at least one* series is stationary.[23] Thus while panel unit root tests have improved power over time-series unit root tests (Im, Pesaran, & Shin, 2003; Baltagi, 2005; Choi, 2007), the matter of their interpretation hinders a straightforward application to the data, with ultimately time-series unit root tests of individual country series providing the 'most relevant information' (Maddala, 1999). A second generation of panel unit root tests has been introduced to account for cross-section dependence in the data (e.g. Bai & Ng, 2004; Pesaran, 2007) — an additional data property which was shown to matter greatly in the macro panel context. We will introduce this topic in detail below.

In a single time-series setup, regressing nonstationary output on nonstationary input variables in a linear model is an appropriate estimation strategy *if and only if* the regression error terms turn out to be stationary I(0), i.e. in the presence of what is termed a 'cointegrating relationship' between inputs and output. If this is not the case, we encounter a 'spurious regression': even if the variables in question were entirely unrelated, our regression results may indicate a highly significant relationship, since the standard tests for significance and goodness of fit in this case are invalid.[24] In contrast, when processes are indeed cointegrated, they define a 'long-run equilibrium trajectory' for the economy. At times the observed evolution will deviate from this path, but short-run 'error corrections' in the system will assure a return to this long-run path (Hendry, 1995).

One could suggest that the macro production process is representative of a cointegrating relationship between output and 'some set of inputs' in the context of nonstationary variable series (Pedroni, 2007; Canning & Pedroni, 2008). This relationship could apply to all countries in the world *in the same way*, implying that all countries had the same long-run equilibrium trajectory (homogeneous cointegration). This means that the 'true' coefficients determining how inputs affect output (referred to as the Data Generating Process or DGP) would be the same for all countries. Alternatively, each country could follow a *different* long-run trajectory (heterogeneous cointegration), such that the DGP differed across countries. Naturally, if (some) country variable series are stationary the problem of noncointegration and potential for spurious regression does not arise (for these countries).

Formulating the correct hypotheses to empirically test for cointegration in a panel dataset involves severe conceptual difficulties and test results are often inconclusive, especially so in moderate T, N samples (Baltagi & Kao, 2000; Coakley, Fuertes, & Smith, 2001; Pedroni, 2007).[25] In addition, it is unclear how the cointegration tests perform if variable series are nonstationary in some countries but stationary in others. Further, the theoretical literature on panel cointegration testing has only recently entered the second generation of tests (Westerlund & Edgerton, 2008) which account for cross-section dependence. These tests however still show comparatively low power for $T = 100$. Thus formally testing variable series for cointegration in a diverse panel of moderate T dimension may leave many questions unanswered.

A conclusion to be drawn from this discussion is that while formal testing for nonstationarity and cointegration may be a frustrating endeavour in a relatively short macro panel of diverse countries, we should nevertheless consider variable series in levels for *some* countries as possessing the nonstationary property and adjust our estimation strategy accordingly (Pedroni, 2007). There are two implications: *firstly*, running separate country regressions in levels for the 'nonstationary countries' will only yield valid estimates if all elements of the underlying cointegrating relationship have been included correctly in the empirical model; any nonstationary elements left out will enter the error terms and thus lead to the breakdown of the cointegrating relationship and potentially spurious regression results. *Secondly*, some countries will have stationary variable series, in which case this problem of noncointegration does not arise.

Thus far we have focused on time-series properties of observables (inputs, output), but the issue is also prevalent with regard to TFP, our 'measure of ignorance'. A number of empirical papers report (or assume without conceptual justification) that their measures of TFP display nonstationarity, whether analysed at the economy level (Coe & Helpman, 1995; Coe, Helpman, & Hoffmaister, 1997; Kao, Chiang, & Chen, 1999; Engelbrecht, 2002; Bond, Leblebicioglu, & Schiantarelli, 2004; Coakley et al., 2006) or the sectoral level (Bernard & Jones, 1996b; Funk & Strauss, 2003). A recent paper by Abdih and Joutz (2006) forms a conceptual link between TFP evolution and a 'knowledge production function', in the spirit of R&D-based endogenous growth models (Romer, 1990; Grossman & Helpman, 1991; Aghion & Howitt, 1998). They model knowledge (proxied as in Jones (1995) by 'measured' TFP[26]) as a function of patent stock, and the flow of new patents as a function of patent stock and R&D activity. Their analysis of aggregate US data from 1948 to 1997 confirms that "inputs and output of the knowledge production function can be plausibly characterised as nonstationary and integrated of order one" (Abdih & Joutz, 2006, p.243). Thus the nonstationarity of TFP/nonfactor inputs is given a theoretical explanation by highlighting the link to R&D as postulated by parts of the endogenous growth literature. Palm and Pfann (1995, p.691) explain the nonstationarity of TFP as "reflecting the impact of common persistent innovations on TFP... [or] the impact of frequent but radical shocks".

Misspecification of the dynamic evolution of TFP in the estimation equation leads to nonstationary errors, just like in the case of misspecification of factor parameter heterogeneity. A single time-series regression limited to T observations does not allow for the dynamic TFP process to be specified using an unrestricted set of $(T-1)$ year dummies (Bond et al., 2004), and a linear trend may not be flexible enough to capture the idiosyncracies of nonstationary TFP evolution. The evolution of TFP in a nonstationary fashion implies that TFP becomes part of the cointegrating relationship.

We noted above that temporal aggregation of time-series data — e.g. taking five-year averages — does not change the stationarity properties. The use of five-year averages of variable series in empirical growth regressions or production functions is still a common practice in the literature, with only a small number of empirical papers using annual data (Lee et al., 1997; Martin & Mitra, 2002; Pedroni, 2007; Canning & Pedroni, 2008). The typical justification for the use of period-averaged data is that annual data will contain business cycle factors and/or changes in capacity utilization irrelevant for long-run income movements, whereas long-run averages are said to enable identification of long-run growth effects (Brock & Durlauf, 2001). In contrast, Lee et al. (1997, p.359) note that both the cross-section regressions exemplified by Mankiw et al. (1992) and the panel regressions using period-averaged data (Islam, 1995; Caselli et al., 1996) make it "impossible to consider either the complex dynamic adjustments involved in the countries' [income] processes or the heterogeneity of [TFP] growth rates across countries.". Our general models are therefore intended for empirical application using annual data, forcing the econometrician to deal with time-series properties explicitly.

3 Cross-section dependence in macro panel data

> *When studying macroeconomic and financial data ..., cross-sectional dependencies are likely to be the rule rather than the exception, because of strong inter-economy linkages."*
> Westerlund and Edgerton (2008, p.666)

Panel data econometrics over the recent years has seen a rising interest in models with unobserved time-varying heterogeneity induced by unobserved common shocks that affect all units (in our present interest: countries), but perhaps to a different degree (Coakley et al., 2006). This type of heterogeneity introduces cross-section correlation or dependence between the regression error terms, which can lead to inconsistency and incorrect inference in standard panel econometric approaches (Phillips & Sul, 2003; Pesaran, 2006; Pesaran & Tosetti, 2007). The latter typically assume 'cross-section independence', not necessarily because this feature is particularly intuitive given real-world circumstances, but "in part because of the difficulties characterizing and modelling cross-section dependence" (Phillips & Moon, 1999, p.1092). In the context of cross-country productivity analysis, the presence of correlation between macro variable series across countries seems particularly salient. As an empirical illustration for his CD test statistic of cross-section dependence, Pesaran (2004, p.23) even uses GDP series from the Penn World Table, concluding that "results clearly show significant evidence of cross section dependence in output innovations, that ought to be taken into account in cross country growth analysis." Further, Durlauf and Quah (1999) discuss the possibility of cross-section dependence in a Lucas (1993) growth model with human capital spillovers. These spillovers markedly change the dynamics of convergence and the authors call for the modelling of cross-country interactions in empirical covergence analysis (Shepotylo, 2008).

Cross-section dependence can be addressed in empirical specification in at least three ways (Pesaran & Tosetti, 2007): *firstly*, if particular drivers of the correlation are known, the dependence can be modelled explicitly. This is standard practice in spatial econometric models, where the strength of the correlation is determined by the location and distance of units in relation to each other. Models in *Empirical Regional Science* and *Analytical Geography* for instance often define spatial distance in terms of geographical proximity, but both in theory and practice distance can also be defined in terms of other variables, such as common colonial history, cultural affinity or bilateral trade volumes. To illustrate this approach, we can think of a 'spatial weight matrix', a pre-specified set of rules governing the spatial correlation, which assigns a unity value to a country pair which share a common border, and a zero otherwise (Pesaran, 2004). This weight matrix is then applied to a spatial error component or spatially lagged dependent variable in the empirical model. In practice, application of most of this work is restricted by the enforced time-invariance of the spatial correlation (distance does not change over time) with much of the work thus limited to the single cross-section framework. It is important to distinguish this impact of 'geography' on growth from that commonly discussed in the literature: the latter, most prominently the work by Jeffrey Sachs (Sachs & Warner, 1995, 2001; Sachs, 2003), argues that geographical features such as proximity to the equator or the 'disease environment' have considerable power in explaining cross-country income patterns. Spatial correlation, in contrast, suggests that neighbourhood (or distance) introduces cross-section correlation which induces bias in standard OLS approaches. Its aim is to account for this dependence and yield unbiased estimates on the other covariates. Naturally, there is a link between these two ideas since countries in close proximity will have similar disease environment and proximity to the equator, however the empirical implementation (and interpretation) are clearly different.

Secondly, we can use fixed effects and year dummies to account for time-invariant and time-variant correlation across units. However, this assumes that the impact of the cross-section dependence is identical across all countries, which in our general model equates to identical $\boldsymbol{\lambda}_i$ across countries. The same applies to using data in deviation from the cross-section mean (Pedroni, 1999; Coakley et al., 2006). In either case, violation of the homogeneity assumption leads to dependence in the error terms across countries and thus cannot solve the problem.

A *third* alternative and altogether more promising approach is the adoption of a multi-factor error structure, where cross-section dependence is modelled to arise from 'unobserved common factors' which need to be appropriately accounted for in order to obtain unbiased estimates of the parameters on the observed regressors. We can replace our general specification in (1) with a simple factor model for illustrative purposes

$$y_{it} = \beta_i x_{it} + u_{it} \qquad u_{it} = \alpha_i + \lambda_i f_t + \varepsilon_{it} \tag{19}$$

$$x_{it} = \phi_i f_t + \psi_i g_t + e_{it} \tag{20}$$

where x is a single observed input, y is output, f_t and g_t are unobserved common factors with heterogeneous factor loadings ϕ_i and ψ_i respectively, and ε_{it}, e_{it} are white noise. Note that we introduce g_t such that x is further driven by factors other than those driving y. The definition of x as being driven by the same factor f as y, albeit with a different factor loading introduces endogeneity into the y-equation.

If we assume stationary factors f_t and g_t, the consistency of standard panel estimators such as a pooled fixed effect regression or a Pesaran and Smith (1995) Mean Group regression with country-specific intercepts rests on the parameter values (factor loadings) of the unobserved common factors: if their averages are jointly non-zero ($\bar{\lambda}_i \neq 0$ *and* $\bar{\phi}_i \neq 0$) a regression of y on x and N intercepts (in the pooled fixed effects regression case) will be subject to the omitted variable problem and hence misspecified, since regression error terms will be correlated with the regressor, leading to biased estimates and incorrect inference (Coakley et al., 2006; Pesaran, 2006). In the case of nonstationary factors the consistency issues in the same setup is altogether more complex and will depend on the exact overall specification of the model (Kapetanios et al., 2008). However, the latter scenario in any case will not yield an estimate of β or the mean of the β_i, as is easily shown by solving equation (20) for f_t and plugging this into equation (19)

$$y_{it} = \alpha_i + \beta_i x_{it} + \lambda_i f_t + \varepsilon_{it} \tag{21}$$

$$= \alpha_i + \beta_i x_{it} + \lambda_i \phi_i^{-1}(x_{it} - \psi_i g_t - e_{it}) + \varepsilon_{it} \tag{22}$$

$$= \alpha_i + \underbrace{(\beta_i + \lambda_i \phi_i^{-1})}_{\varrho_i} x_{it} \underbrace{-\lambda_i \phi_i^{-1} \psi_i g_t - \lambda_i \phi_i^{-1} e_{it} + \varepsilon_{it}}_{\varsigma_{it}} \tag{23}$$

$$= \alpha_i + \varrho_i x_{it} + \varsigma_{it} \tag{24}$$

From equation (24) it is clear that with standard panel estimators we can only obtain a consistent estimator of $\varrho_i = \beta_i + \lambda_i \phi_i^{-1}$ or its mean and not of β_i or its mean (Kapetanios et al., 2008) — β_i

is unidentified. Under the specification described, a standard pooled fixed effects or Pesaran and Smith (1995) Mean Group estimator will therefore likely yield an inconsistent estimator (due to residual nonstationarity) of a parameter we are not interested in (due to the identification problem).

4 Parameter heterogeneity in the face of variable nonstationarity

> *"What do Thailand, the Dominican Republic, Zimbabwe, Greece, and Bolivia have in common that merits their being put in the same regression?"*
> Harberger (1987, p.256)
>
> *"The lesson for applied work is that if large T panels are available, the individual micro-relations should be estimated separately and the averages of the estimated micro-parameters and their standard errors calculated explicitly ... The hypothesis of homogeneity, common slope coefficients, can then be tested. Our experience is that it is almost always rejected ... "*
> Pesaran and Smith (1995, p.102)

It is a common practice in the literature to pursue 'TFP extraction' using an empirical specification characterised by homogeneous factor parameters, coupled with heterogeneous TFP levels and evolution (Parente & Prescott, 1994, 1999; Klenow & Rodriguez-Clare, 1997; Caselli & Coleman II, 2006; Acemoglu, Antras, & Helpman, 2007; Aiyar & Dalgaard, 2008). As the comments by Harberger (1987) above and Brock and Durlauf (2001) quoted earlier indicate, there is considerable unease about the standard empirical specification imposing *common* technology parameters and we have already provided a number of conceptual arguments for the heterogeneity of production technology and TFP across countries. Our general empirical specification has gone to great lengths to be as flexible as possible regarding heterogeneity in the impact of observables (technology parameters) and unobservables (factor loadings) on output. Why this emphasis on parameter heterogeneity? Misspecification of technology parameter heterogeneity *in itself* may not be regarded as a serious problem for estimation: if slope parameters vary randomly across countries and are orthogonal to included regressors and the error terms, the pooled regression coefficient represents an unbiased estimate of the mean of the parameter across countries (Durlauf et al., 2005, p.617). Note that these are very strong assumptions, which are likely to be violated in the data (Caselli et al., 1996). Nevertheless, it has been argued that variable omission and parameter heterogeneity may be interpreted as examples of deviations of empirical growth models from a statistical 'ideal', allowing for the kind of inferences a researcher would wish to make in the growth context (Brock & Durlauf, 2001). This viewpoint derives much of its justification from the assumption that variable series entering the empirical model are *stationary*.

Neglecting potential technology parameter heterogeneity and TFP heterogeneity in the empirical analysis however has more serious implications if observable and/or unobservable variables are *nonstationary*, namely the breakdown of the cointegrating relationship between inputs and output. We can illustrate this point quite easily: a pooled estimation equation in levels imposes *common* technology parameters on all countries and thus creates nonstationary errors if 'true' technology parameters are heterogeneous and input variables are nonstationary. With reference to our general model in equation (1) pooled error terms may contain one or more of

$$(\alpha_i - \pi_L)\, L_{it} \qquad (\beta_i - \pi_K)\, K_{it} \qquad (\gamma_i - \pi_M)\, M_{it} \tag{25}$$

where π_L, π_K, π_M are the *common* regression coefficients for labour (L), capital stock (K) and material inputs (M) respectively, while α_i, β_i, γ_i are the 'true' country-specific technology parameters. Each of the three terms in equation (25) is a linear combination of a nonstationary variable/process and thus will itself be nonstationary. The failure to account for technology parameter heterogeneity leads to the breakdown of the cointegrating relationship between inputs and output and thus produces potentially spurious results (Smith & Fuertes, 2007). Even if observed inputs and output cointegrate in each country equation (heterogeneous cointegration), the pooled equation does not and pooled estimation will not yield the mean of the cointegrating parameters across countries.

Similarly, a pooled estimation equation in levels augmented with $T-1$ year dummies imposes *common* TFP evolution on all countries and thus creates nonstationary errors if 'true' TFP is heterogeneous and nonstationary. In our general notation

$$(\boldsymbol{\lambda}_i' \boldsymbol{f}_t - \pi_{TFP}) \tag{26}$$

where $\boldsymbol{\lambda}_i \boldsymbol{f}_t$ represents the 'true' country-specific TFP process (nonstationary) and π_{TFP} the estimated TFP evolution specified via the set of common year dummies. Note that if the 'true' TFP process is nonstationary, country-by-country regressions with linear trend terms can capture technology parameter heterogeneity but lead to a misspecified TFP evolution (stationary linear trend instead of nonstationary evolvement) and thus result in nonstationary country-regression errors (Bai et al., 2009). Similarly in a pooled regression equation with linear country trends.

A recent development in econometric theory implies that the spurious regression conclusion may need qualification. Phillips and Moon (1999, p.1091) suggest that *pooled* regressions of level equations with I(1) errors will yield *consistent* estimates of "interesting long-run relations" between observable input variables and output *provided N and T are large enough* (see also Kao, 1999; Phillips & Moon, 2000; Smith & Fuertes, 2007). This implies that regardless of whether we have homogeneous cointegration, heterogeneous cointegration or noncointegration, the pooled fixed effects estimator in levels can provide a consistent point estimate of some average long-run correlation between inputs and output. The joint limit theorem of the paper however requires $N/T \to 0$, which limits the applicability of this result for cross-country growth analysis using macro data. This aside, the asymptotic result builds on the assumption of cross-section independence, which as was discussed above is seemingly unjustified in the macro panel data context. Monte Carlo simulations by Coakley et al. (2006) however show that the mere presence of heterogeneous cross-section dependence (unobserved common factors with different factor loadings across countries) does not change the Phillips and Moon (1999) result: the pooled fixed effects estimator is unbiased even in small samples but is rather inefficient. However, if unobserved factors drive both the input(s) and output variables, the Phillips and Moon (1999) results breaks down.

In Section 2 above we have shown that there is a general consensus that macro data series such as output, GDP or capital stock should not *a priori* be considered as stationary processes for all countries analysed. We also provided arguments to suggest that TFP evolution may be best represented as a nonstationary process. In Section 3 we then argued that unobserved TFP processes can be conceptualised using common factor models, which allow for cross-country heterogeneity in factor loadings. In the light of the discussion in this section, the assumption of parameter homogeneity, commonly adopted in the mainstream literature on growth empirics, is shown to have much more serious implications in the nonstationary than in the stationary context: any deviation from the homogeneity assumption no longer simply affects the precision of our estimate of the parameter 'mean', but will lead to the breakdown of cointegration and thus potentially spurious results. With regards to the specification of TFP evolution, we can state that the use of a linear trend may not capture the (potentially) nonstationary evolution and may thus equally lead to a breakdown in the cointegrating relationship, even if factor parameters were modelled correctly (Bai et al., 2009).

5 Concluding remarks

In his stimulating book *The Elusive Quest for Growth* Bill Easterly (2002) argues that after many decades of empirical work economists are still none the wiser as to what causes growth. In seeking a source for this failure many would see empirical growth regressions as the most likely guilty party. For the defense we would argue that while not blameless, much has been learnt from cross-country regressions and the lesson of incomplete success is not to abandon the 'quest' but to seek to understand why success has been so limited. We noted in the introduction that the 'growth regression approach' has been under attack from both those who think randomised experiments or country-based studies are the way forward. One of the themes of Easterly's book is that development economics has been dominated by fads and each new fad has been hailed as the solution to past problems. This survey has sought to show that one past fad, 'growth regressions', may have life left in it. That is not to say it is the *only* approach, it may well in the long term turn out not to be the best one, but as we have argued, it is more informative and more flexible in the problems that it can address than its critics have allowed.

In this paper we have provided two general empirical frameworks for cross-country growth and production analysis which encompass the various regression specifications favoured both in the mainstream as well as the emerging nonstationary panel literature over the past two decades. A selective review of this literature highlighted how parameter heterogeneity of the impact of observables and unobservables can be accommodated within our general modelling framework.

By placing the literature in this general framework we have been able to highlight two factors that may hold the key to some of the failures of growth regressions. The first is how central the assumption of homogeneity, of both technology and TFP, is to the results that have been derived. New econometric techniques allow us to relax these dimensions of homogeneity and the new evidence from these techniques certainly suggests that heterogeneity in both technology and TFP matter . . . a lot. The second factor to which we have drawn attention is the assumptions empirical models make about the time-series properties of the data. The standard empirical estimators (e.g. Fixed Effects, Difference and System GMM) not only impose homogeneous production technology, they implicitly assume stationary, cross-sectionally independent, variables. If we recognise the implications of these data properties for the estimators then we may well be able to reduce the gap between our models and the data they seek to explain — this, rather than banishment from the development discourse, is in our view the right verdict on growth regressions.

Acknowledgements

We are grateful to Stephen Bond and Hashem Pesaran for helpful comments and suggestions. Parts of this paper were presented at the Gorman Student Research Workshop and the Productivity Workshop, Department of Economics, University of Oxford (February 2008), at the Nordic Conference for Development Economics in Stockholm (June 2008), at the Economic & Social Research Council (ESRC) Development Economics conference in Brighton (September 2008) and at the International Conference for Factor Structures for Panel and Multivariate Time Series Data in Maastricht (September 2008). All remaining errors are our own. The first author gratefully acknowledges financial support during his doctoral studies from the ESRC, Award PTA-031-2004-00345.

Notes

[1]Here and in the remainder of the paper we refer to heterogeneity in 'technology parameters' to indicate differential production function parameters on observable factor-inputs across countries.

[2]A number of recent papers replace the Cobb-Douglas representation with a more general CES production representation or the Christensen, Jorgenson, and Lau (1973) translog production representation (Bernard & Jones, 1996a; Duffy & Papageorgiou, 2000; Temple & Wößmann, 2006). We confine the discussion to the Cobb-Douglas form as this allows us to show the importance of the econometric issues we highlight in the context of the most important results in the emprical literature.

[3]If we assume constancy of the material-output ratio, then results are directly comparable (Söderbom & Teal, 2004). In our notation: $\beta_i^{va} = \beta_i/(1-\gamma_i)$ and in analogy for α_i^{va}.

[4]The assumption of random coefficients is for convenience. Based on the findings by Pesaran and Smith (1995, footnote 2, p.81) the coefficients could alternatively be fixed but differing across groups. See also Kapetanios et al. (2008, p.6).

[5]The inherent contradiction that TFP growth on the one hand is allowed to differ across countries while on the other it is defined as common *within the same empirical equation* is lost on most commentators (Islam, 1995).

[6]The convergence argument suggests that due to diminishing returns to capital in the Solow model, countries with low levels of per capita capital stock will have higher marginal product of capital, and thus (for similar savings rates) will grow faster than countries with an already high stock of per capita capital (Islam, 1995). The steady-state income equation in levels is defined as

$$y_t = \left(1 - e^{-\xi_i \tau}\right) y^* + e^{-\xi_i \tau} y_0$$

where y_t is GDP at time t, y_0 is the same at some original point in time 0 and y^* is steady state level of income (all in logarithms of 'effective workers'). In the simple cross-section regressions of Mankiw et al. (1992) the substitute for the steady-state solution y^* and then subtract y_0 from both sides to yield equation 3.

[7]This is despite the problem that full parameter heterogeneity renders conventional notions of 'β-convergence' across countries a somewhat meaningless concept as countries converge to their own steady-state equilibrium paths (Lee, Pesaran, & Smith, 1998).

[8]One should note that Solow never claimed for his model to be applied to cross-country analysis: his focus was on explaining the growth experience of the United States (Durlauf et al., 2001).

[9]Data from the Federal Reserve Bank of Cleveland, for instance, shows an average labour share of 71.7% of value-added from 1970 to 2002 for the United States (Gomme & Rupert, 2004).

[10]Mankiw et al. (1992) use the share of adult population in secondary education, thus a 'flow' variable, to proxy for human capital. Later implementations shifted to 'stock' variables such as the population average of total years of education, readily available from Barro and Lee (1993, 1996, 2001)

[11]Mankiw et al. (1992) do not report results for the restricted case of the convergence regression without human capital. We therefore report implied $\hat{\beta}^{va}$ for the unrestricted case computed from result in Table IV of their paper. The imposition of the restriction has a second order effect on this estimate in all other regressions they present. Further, Islam (1995) reports the implied $\hat{\beta}^{va}$ for a slightly different sample, obtaining .83.

[12]The coefficient on y_{i,t_1} (the lagged dependent variable) is now $-e^{-\xi_i \tau}$, rather than $1 - e^{-\xi_i \tau}$, which needs to be accounted for in the computation of $\hat{\beta}^{va}$.

[13]The factor variables n and s^k are 5-year averages, starting with 1960-1964; if the output variable is $y_{i,1965}$ for y_{i,t_2}, then y_{i,t_1} is $y_{i,1960}$ and so on.

[14]Islam does not directly estimate the TFP levels which are subjected to a great deal of comparison and analysis in the literature. Instead he 'backs them out' using predictions from his 'within-groups' regression. As a consequence he does not carry out any formal test of statistically significant differences across the $A_{0,i}^{va}$.

[15]The parameter on the lagged dependent variable is biased downward (in absolute terms), implying higher rate of convergence (Bond, Hoeffler, & Temple, 2001; Durlauf et al., 2005).

[16]This result is due to Pesaran and Smith (1995, p.84). The reason for this is that $E[y_{i,t_1} u_{i\tau}] \neq 0$ as the error contains $[(-e^{-\xi\tau}) - (-e^{-\xi_i\tau})]y_{i,t_1}$. For more details refer to Section 4. All variables that are correlated with the lagged dependent variable will also be correlated with $u_{i\tau}$. If variables exist that are not correlated with the error, they are not informative and thus cannot act instruments.

[17]They also estimate a more general translog model but results are qualitatively the same.

[18]While this result is not investigated for statistical significance at the individual country level, they construct a number of test statistics which reject the null that agricultural TFP growth is the same as manufacturing TFP growth in favour of the alternative that the former is larger.

[19]See Pedroni (2007, p.435/6) for details. The working paper (Pedroni, 2004b) expands on this.

[20]The FMOLS estimates are superconsistent in a cointegrated framework of nonstationary variables. If the nonstationarity assumption is violated, the FMOLS transformation results in 'overdifferencing', which introduces noise while the endogeneity problems remain.

[21]This is surprising given that in their important contribution to the nonstationary panel literature, Phillips and Moon (1999, p.1057) mention the Penn World Tables in their opening paragraph and the same dataset is also highlighted in the opening paragraphs of review chapters on nonstationary panel econometrics by Kao and Chiang (2000), Smith and Fuertes (2007) and Baltagi (2005).

[22]The term 'moderate' here is to be interpreted from a time-series econometrics standpoint. Data for 50 years may not be sufficient to detect the time-series properties appropriately, and most macro datasets including observations from LDCs are considerably shorter.

[23]Panel-based tests that provide explicit information on which country series are I(1) and which I(0) (Breuer, McNown, & Wallace, 2001) were found to be highly sensitive to sample selection (Ford, Jackson, & Kline, 2006).

[24]Granger and Newbold (1974) illustrated this in a simulation using two independent random walks.

[25]Note that cointegration is invariant to temporal aggregation (Granger, 1988; Marcellino, 1999).

[26]This is obtained from the US Bureau of Labor Statistics. From the parsimonious description it has to be assumed that TFP is constructed via an accounting exercise.

References

Abdih, Y., & Joutz, F. (2006). Relating the Knowledge Production Function to Total Factor Productivity: An Endogenous Growth Puzzle. *IMF Staff Papers*, *53*(2), 242-271.

Abramowitz, M. (1956). Resource and output trend in the United States since 1870. *American Economic Review*, *46*(2), 5-23.

Acemoglu, D., Antras, P., & Helpman, E. (2007). Contracts and technology adoption. *American Economic Review*, *97*(3), 916-943.

Aghion, P., & Howitt, P. (1998). *Endogenous Growth Theory.* Cambridge, Mass.: MIT Press.

Aiyar, S., & Dalgaard, C.-J. (2008). Dual Economies and International Total Factor Productivity Differences: Channeling the Impact from Institutions, Trade, and Geography. *Economica*, *75*(300), 629-661.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data. *Review of Economic Studies*, *58*(2), 277-297.

Azariadis, C., & Drazen, A. (1990). Threshold externalities in economic development. *Quarterly Journal of Economics*, *105*(2), 501-26.

Bai, J., Kao, C., & Ng, S. (2009). Panel cointegration with global stochastic trends. *Journal of Econometrics*, *149*(1), 82-99.

Bai, J., & Ng, S. (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica*, *70*(1), 191-221.

Bai, J., & Ng, S. (2004). A PANIC attack on unit roots and cointegration. *Econometrica*, *72*, 191-221.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data*. New York: John Wiley and Sons.

Baltagi, B. H., & Kao, C. (2000). Nonstationary panels, cointegration in panels and dynamic panels. In B. H. Baltagi (Ed.), *Nonstationary panels, cointegration in panels and dynamic panels: A survey.* Amsterdam: Elsevier.

Banerjee, A. V., & Duflo, E. (2008). *The Experimental Approach to Development Economics* (NBER Working Papers No. 14467). National Bureau of Economic Research, Inc.

Banerjee, A. V., & Newman, A. F. (1993). Occupational Choice and the Process of Development. *Journal of Political Economy*, *101*(2), 274-98.

Barro, R. J. (1991). Economic growth in a cross-section of countries. *Quarterly Journal of Economics*, *106*(2), 407-443.

Barro, R. J., & Lee, J.-W. (1993). International comparisons of educational attainment. *Journal of Monetary Economics*, *32*(3), 363-394.

Barro, R. J., & Lee, J. W. (1996). International measures of schooling years and schooling quality. *American Economic Review*, *86*(2), 218-23.

Barro, R. J., & Lee, J.-W. (2001). International data on educational attainment: Updates and implications. *Oxford Economic Papers*, *53*(3), 541-63.

Bernard, A. B., & Jones, C. I. (1996a). Comparing apples to oranges: Productivity convergence and measurement across industries and countries. *American Economic Review*, *86*(5), 1216-38.

Bernard, A. B., & Jones, C. I. (1996b). Productivity across industries and countries: Time series theory and evidence. *The Review of Economics and Statistics*, *78*(1), 135-46.

Bhattacharjee, A., Castro, E., & Jensen-Butler, C. (2009). Regional variation in productivity: a study of the Danish economy. *Journal of Productivity Analysis*, *31*(3), 195-212.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115-143.

Blundell, R., & Bond, S. (1999). *GMM estimation with persistent panel data: an application to production functions* (IFS Working Papers No. W99/04). Institute for Fiscal Studies.

Bond, S. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal*, *1*(2), 141-162.

Bond, S., Hoeffler, A., & Temple, J. (2001). *GMM estimation of empirical growth models* (Discussion Paper No. 3048). C.E.P.R.

Bond, S., Leblebicioglu, A., & Schiantarelli, F. (2004). *Capital Accumulation and Growth: A New Look at the Empirical Evidence* (Economics Papers No. 2004-W08). Economics Group, Nuffield College, University of Oxford.

Breuer, J. B., McNown, R., & Wallace, M. S. (2001). Misleading Inferences from Panel Unit-Root Tests with an Illustration from Purchasing Power Parity. *Review of International Economics*, *9*(3), 482-93.

Brock, W., & Durlauf, S. (2001). Growth economics and reality. *World Bank Economic Review*, *15*(2), 229-272.

Canning, D., & Pedroni, P. (2008). Infrastructure, Long-Run Economic Growth And Causality Tests For Cointegrated Panels. *Manchester School*, *76*(5), 504-527.

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth*, *1*(3), 363-89.

Caselli, F., & Coleman II, W. J. (2006). The world technology frontier. *American Economic Review*, *96*(3), 499-522.

Choi, I. (2007). Nonstationary Panels. In T. C. Mills & K. Patterson (Eds.), *Palgrave Handbook of Econometrics* (Vol. 1). Basingstoke: Palgrave Macmillan.

Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The Review of Economics and Statistics*, *55*(1), 28-45.

Coakley, J., Fuertes, A., & Smith, R. (2001). *Small sample properties of panel time-series estimators with I(1) errors.* (unpublished working paper)

Coakley, J., Fuertes, A. M., & Smith, R. (2006). Unobserved heterogeneity in panel time series models. *Computational Statistics & Data Analysis*, *50*(9), 2361-2380.

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, *39*(5), 859-887.
Coe, D. T., Helpman, E., & Hoffmaister, A. W. (1997). North-South R&D spillovers. *Economic Journal*, *107*(440), 134-49.
Costantini, M., & Destefanis, S. (2009). Cointegration analysis for cross-sectionally dependent panels: The case of regional production functions. *Economic Modelling*, *26*(2), 320-327.
Crego, A., Larson, D., Butzer, R., & Mundlak, Y. (1998). *A new database on investment and capital for agriculture and manufacturing* (Policy Research Working Paper Series No. 2013). The World Bank.
Duffy, J., & Papageorgiou, C. (2000). A cross-country empirical investigation of the aggregate production function specification. *Journal of Economic Growth*, *5*(1), 87-120.
Durlauf, S. N. (1993). Nonergodic economic growth. *Review of Economic Studies*, *60*(2), 349-66.
Durlauf, S. N., & Johnson, P. A. (1995). Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics*, *10*(4), 365-84.
Durlauf, S. N., & Johnson, P. A. (2008). Convergence. In S. N. Durlauf & L. E. Blume (Eds.), *The New Palgrave Dictionary of Economics Online* (Second Edition ed.). Palgrave Macmillan. (Accessed March 2009)
Durlauf, S. N., Johnson, P. A., & Temple, J. R. (2005). Growth econometrics. In P. Aghion & S. Durlauf (Eds.), *Handbook of Economic Growth* (Vol. 1, p. 555-677). Elsevier.
Durlauf, S. N., Kourtellos, A., & Minkin, A. (2001). The local Solow growth model. *European Economic Review*, *45*(4-6), 928-940.
Durlauf, S. N., & Quah, D. T. (1999). The new empirics of economic growth. In J. B. Taylor & M. Woodford (Eds.), *Handbook of Macroeconomics* (Vol. 1, p. 235-308). Elsevier.
Easterly, W. (2002). *The Elusive Quest for Growth - Economists' Adventures and Misadventures in the Tropics.* Cambridge, Mass.: MIT Press.
Eberhardt, M., & Teal, F. (2008). *Modeling Technology and Technological Change in Manufacturing: How do Countries Differ?* (CSAE Working Paper, WPS/2008-12). Centre for the Study of African Economies, Department of Economics, University of Oxford.
Eberhardt, M., & Teal, F. (2009). *A Common Factor Approach to Spatial Heterogeneity in Agricultural Productivity Analysis* (CSAE Working Paper, WPS/2009-05). Centre for the Study of African Economies, Department of Economics, University of Oxford.
Engelbrecht, H.-J. (2002). Human Capital and International Knowledge Spillovers in TFP Growth of a Sample of Developing Countries: An Exploration of Alternative Approaches. *Applied Economics*, *34*(7), 831-41.
FAO. (2007). *FAOSTAT* (Online database, Rome: FAO). United Nations Food and Agriculture Organisation. (Accessed July 2007)
Fleisher, B., Li, H., & Zhao, M. Q. (2009). Human capital, economic growth, and regional inequality in china. *Journal of Development Economics*.
Ford, G. S., Jackson, J. D., & Kline, A. D. (2006). Misleading Inferences from Panel Unit Root Tests: a Comment. *Review of International Economics*, *14*(3), 508-511.
Funk, M., & Strauss, J. (2003). Panel tests of stochastic convergence: TFP transmission within manufacturing industries. *Economics Letters*, *78*(3), 365-371.
Gengenbach, C., Palm, F. C., & Urbain, J.-P. (2006). Cointegration Testing in Panels with Common Factors. *Oxford Bulletin of Economics and Statistics*, *68*(s1), 683-719.
Gollin, D. (2002). Getting income shares right. *Journal of Political Economy*, *110*(2), 458-474.
Gomme, P., & Rupert, P. (2004). *Measuring labor's share of income* (Policy Discussion Paper). Federal Reserve Bank of Cleveland. (November)
Granger, C. W. J. (1988). *Aggregation of time series variables: a survey* (Discussion Paper/Institute for Empirical Macroeconomics No. 1). Federal Reserve Bank of Minneapolis.
Granger, C. W. J. (1997). On modelling the long run in applied economics. *Economic Journal*, *107*(440), 169-77.
Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111-120.
Granger, C. W. J., & Siklos, P. L. (1995). Systematic sampling, temporal aggregation, seasonal adjustment, and cointegration theory and evidence. *Journal of Econometrics*, *66*(1-2), 357-369.
Grossman, G. M., & Helpman, E. (1991). *Innovation and growth in the global economy.* Cambridge, Mass: MIT Press.
Hall, R. E., & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics*, *114*(1), 83-116.
Harberger, A. (1987). Comment. In S. Fischer (Ed.), *NBER Macroeconomics Annual* (p. 255-258). Cambridge/Mass.: MIT Press.
Hausmann, R., Rodrik, D., & Velasco, A. (2006). The washington consensus reconsidered: Towards a new global governance. In J. Stiglitz & N. Serra (Eds.), (chap. Growth Diagnostics). Oxford University Press, New York.
Hendry, D. (1995). *Dynamic Econometrics.* Oxford University Press.

Heston, A., Summers, R., & Aten, B. (2006). *Penn World Table version 6.2.* (Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania)
Im, K., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74.
Islam, N. (1995). Growth empirics: A panel data approach. *Quarterly Journal of Economics*, *110*(4), 1127-70.
Islam, N. (2003). What have we learnt from the convergence debate? *Journal of Economic Surveys*, *17*(3), 309-362.
Jones, C. I. (1995). Time series tests of endogenous growth models. *Quarterly Journal of Economics*, *110*(2), 495-525.
Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, *65*(1), 9-15.
Kao, C., & Chiang, M. (2000). Nonstationary panels, cointegration in panels and dynamic panels. In B. H. Baltagi (Ed.), *On the estimation and inference of a cointegrated regression in panel data.* Amsterdam: Elsevier.
Kao, C., Chiang, M., & Chen, B. (1999). International R&D spillovers: An application of estimation and inference in panel cointegration. *Oxford Bulletin of Economics and Statistics*, *61*(Special Issue), 691-709.
Kapetanios, G., Pesaran, M. H., & Yamagata, T. (2008). *Panels with nonstationary multifactor error structures* (Tech. Rep.). (unpublished working paper, updated version of IZA Discussion Paper #2243)
Klenow, P. J., & Rodriguez-Clare, A. (1997). Economic growth: A review essay. *Journal of Monetary Economics*, *40*(3), 597-617.
Knight, M., Loayza, N., & Villanueva, D. (1993). Testing the Neoclassical Theory of Economic Growth: A Panel Data Approach. *IMF Staff Papers*, *40*(3), 512-541.
Lee, K., Pesaran, M. H., & Smith, R. (1997). Growth and convergence in a multi-country empirical stochastic Solow model. *Journal of Applied Econometrics*, *12*(4), 357-92.
Lee, K., Pesaran, M. H., & Smith, R. (1998). Growth empirics: A panel data approach — a comment. *Quarterly Journal of Economics*, *113*(1), 319-323.
Liu, Z., & Stengos, T. (1999). Non-linearities in Cross-Country Growth Regressions: A Semiparametric Approach. *Journal of Applied Econometrics*, *14*(5), 527-38.
Loayza, N. (1994). *A test of the international convergence hypothesis using panel data* (Policy Research Working Paper Series No. 1333). The World Bank.
Lucas, J., Robert E. (1993). Making a Miracle. *Econometrica*, *61*(2), 251-72.
Maddala, G. S. (1999). On the use of panel data methods with cross-country data. *Annales D'Économie et de Statistique*, *55/56*, 429-449.
Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(Special Issue), 631-652.
Madsen, E. (2005). Estimating cointegrating relations from a cross section. *Econometrics Journal*, *8*(3), 380-405.
Mankiw, G., Romer, D., & Weil, D. N. (1992). A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics*, *107*(2), 407-437.
Marcellino, M. (1999). Some consequences of temporal aggregation in empirical analysis. *Journal of Business & Economic Statistics*, *17*(1), 129-36.
Martin, W., & Mitra, D. (2002). Productivity Growth and Convergence in Agriculture versus Manufacturing. *Economic Development and Cultural Change*, *49*(2), 403-422.
Matthews, E. (1983). Global Vegetation and Land Use: New High Resolution Databases for Climate Studies. *Journal of Climate and Applied Meteorology*, *22*, 474-487.
Murphy, K. M., Shleifer, A., & Vishny, R. W. (1989). Industrialization and the Big Push. *Journal of Political Economy*, *97*(5), 1003-26.
Nelson, C. R., & Plosser, C. (1982). Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of Monetary Economics*, *10*(2), 139-162.
Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417-1426.
Palm, F. C., & Pfann, G. A. (1995). Unraveling Trend and Stationary Components of Total Factor Productivity. *Annales D'Economie et de Statistique*, *39*, 67-92.
Parente, S. L., & Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, *102*(2), 298-321.
Parente, S. L., & Prescott, E. C. (1999). Monopoly rights: A barrier to riches. *American Economic Review*, *89*(5), 1216-1233.
Pedroni, P. (1995). *Panel cointegration: asymptotic and finite sample properties of pooled time-series tests with application to the PPP hypothesis.* (Indiana Working Papers in Economics No. 95-013)
Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, *61*(Special Issue), 653-670.
Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. In B. H. Baltagi (Ed.), *Nonstationary panels, cointegration in panels and dynamic panels.* Amsterdam: Elsevier.

Pedroni, P. (2004a). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Econometric Theory*, *20*(3), 597-625.
Pedroni, P. (2004b). *Social capital, barriers to production and capital shares: implications for the importance of parameter heterogeneity from a nonstationary panel approach.* (Working paper, Williams College, June 2004)
Pedroni, P. (2007). Social capital, barriers to production and capital shares: implications for the importance of parameter heterogeneity from a nonstationary panel approach. *Journal of Applied Econometrics*, *22*(2), 429-451.
Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels.* (IZA Discussion Paper No. 1240 and CESifo Working Paper No. 1229)
Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, *74*(4), 967-1012.
Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265-312.
Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, *68*(1), 79-113.
Pesaran, M. H., & Tosetti, E. (2007). *Large panels with common factors and spatial correlations.* (IZA Discussion Papers No. 3032)
Phillips, P. C. B. (1995). Fully Modified Least Squares and Vector Autoregression. *Econometrica*, *63*(5), 1023–1078.
Phillips, P. C. B., & Hansen, B. E. (1990). Statistical Inference in Instrumental Variables Regression with I(1) Processes. *Review of Economic Studies*, *57*(1), 99-125.
Phillips, P. C. B., & Moon, H. R. (1999). Linear regression limit theory for nonstationary panel data. *Econometrica*, *67*(5), 1057-1112.
Phillips, P. C. B., & Moon, H. R. (2000). Nonstationary panel data analysis: An overview of some recent developments. *Econometric Reviews*, *19*(3), 263-286.
Phillips, P. C. B., & Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. *Econometrics Journal*, *6*(1), 217-259.
Rapach, D. E. (2002). Are real GDP levels nonstationary? Evidence from panel data tests. *Southern Economic Journal*, *68*(3), 473-495.
Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71-102.
Sachs, J. D. (2003). *Institutions Don't Rule: Direct Effects of Geography on Per Capita Income* (NBER Working Papers No. 9490). National Bureau of Economic Research,.
Sachs, J. D., & Warner, A. (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity*, *1*, 1-118.
Sachs, J. D., & Warner, A. M. (2001). The curse of natural resources. *European Economic Review*, *45*(4-6), 827-838.
Shepotylo, O. (2008). *Spatial HAC Estimator: Analysis of Convergence of European Regions.* (National University of Kyiv-Mohyla Academy, Kyiv School of Economics (KSE), December 2008)
Smith, R. P., & Fuertes, A.-M. (2007). *Panel Time Series.* (Centre for Microdata Methods and Practice (cemmap) mimeo, April 2007.)
Söderbom, M., & Teal, F. (2004). Size and efficiency in African manufacturing firms: evidence from firm-level panel data. *Journal of Development Economics*, *73*(1), 369-394.
Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*(1), 65-94.
Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, *39*(3), 312-20.
Solow, R. M. (1970). *Growth theory: an exposition.* Oxford: Oxford University Press.
Solow, R. M. (1986). Unemployment: Getting the questions right. *Economica*, *53*(210), S23-34.
Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, *32*(2), 334-61.
Temple, J. (1999). The new growth evidence. *Journal of Economic Literature*, *37*(1), 112-156.
Temple, J. (2005). Dual economy models: A primer for growth economists. *The Manchester School*, *73*(4), 435-478.
Temple, J., & Wößmann, L. (2006). Dualism and cross-country growth regressions. *Journal of Economic Growth*, *11*(3), 187-228.
UN. (2004). *National accounts statistics: Main aggregates and detailed tables, 1992* (New York: UN Publications Division). United Nations.
UNIDO. (2004). *UNIDO Industrial Statistics 2004* (Online database, Vienna: UNIDO). United Nations Industrial Development Organisation.
Westerlund, J., & Edgerton, D. L. (2008). A Simple Test for Cointegration in Dependent Panels with Structural Breaks. *Oxford Bulletin of Economics and Statistics*, *70*(5), 665-704.