CSAE WPS/2008-12

Modeling Technology and Technological Change in Manufacturing: How do Countries Differ?*

Markus EBERHARDT[a,b†] Francis TEAL[b]

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

April 2008

Abstract:

In this paper we ask how technological differences in manufacturing across countries can best be modeled when using a standard production function approach. We show that it is important to allow for differences in technology as measured by differences in parameters. Of similar importance are time-series properties of the data and the role of dynamic processes, which can be thought of as aspects of technological change. Regarding the latter we identify both an element that is common across all countries and a part which is country-specific. The estimator we develop, which we term the Augmented Mean Group estimator (AMG), is closely related to the Mean Group version of the Pesaran (2006) Common Correlated Effects estimator. Once we allow for parameter heterogeneity and the underlying time-series properties of the data we are able to show that the parameter estimates from the production function are consistent with information on factor shares.

JEL classification: C23, O14, O47
Keywords: Manufacturing Production; Parameter Heterogeneity; Nonstationary Panel Econometrics

*We are grateful to Stephen Bond for helpful comments and suggestions. Previous versions of this paper have been presented at the Gorman Student Research Workshop and the Productivity Workshop, Department of Economics, University of Oxford. All remaining errors are our own. The first author gratefully acknowledges financial support from the Economic & Social Research Council (ESRC).

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

Introduction

> *"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)

> *"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)

Why do we observe such dramatic differences in productivity across countries in the macro data? This question has been central to the empirical investigation of growth over the past twenty years. As the above quotes indicate the importance of parameter heterogeneity and variable nonstationarity have not been major concerns in this empirical investigation. In this paper we argue that many of the puzzles that have been thrown up by the use of econometric techniques that ignore these issues can be resolved once we allow for the relevance of both factors in datasets where the time-series dimension is of importance.

The possibility that technology differences across countries may be an important part of the growth process has been recognised in both the theoretical and empirical literature. There is a strand of the 'new growth' literature which argues that production functions differ across countries and seeks to determine the sources of this heterogeneity (Durlauf et al., 2001). 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).[1] The empirical implementation of parameter heterogeneity has primarily occurred in the empirical convergence literature, with factor parameters initially assumed group-specific (e.g. Durlauf & Johnson, 1995; Caselli, Esquivel, & Lefort, 1996; Liu & Stengos, 1999) and more recently country-specific (Durlauf et al., 2001).

In the long-run, macro 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* (Nelson & Plosser, 1982; Granger, 1997; Lee, Pesaran, & Smith, 1997; Canning & Pedroni, 2004; Pedroni, 2007).[2] In addition, a number of empirical papers report nonstationary evolvement of Total Factor Productivity, whether analysed at the economy (Coe & Helpman, 1995; Kao, Chiang, & Chen, 1999; Bond, Leblebicioglu, & Schiantarelli, 2004) or the sectoral level (Bernard & Jones, 1996; Funk & Strauss, 2003).

[1] Further examples of theoretical papers on factor parameter heterogeneity in the production function are Murphy, Shleifer, and Vishny (1989), Durlauf (1993) and Banerjee and Newman (1993).

[2] Although economic time-series in practice are usually not precisely integrated of any given order, it is for our purposes sufficient to assume that real value series typically behave as I(1) (Hendry, 1995).

As a result, any macro production function is likely to contain data for at least some countries with nonstationary observables and/or TFP processes. In a time-series model, regressing nonstationary output on nonstationary input variables and processes in a linear model is a valid estimation strategy *if and only if* the regression error terms turn out to be stationary I(0), i.e. in the presence of a *cointegrating relationship* between inputs and output. If this is not the case, regression estimates will be spurious (Granger & Newbold, 1974). For the macro production function to make econometric sense in the context of nonstationary variables it must be seen as representing a cointegrating relationship between output and 'some set of inputs' (Canning & Pedroni, 2004; Pedroni, 2007). This relationship could apply to all countries in the *same* way, implying that all economies had the same long-run equilibrium trajectory and thus production technology. Alternatively, each country could follow a *different* long-run trajectory, equivalent to factor parameter heterogeneity across countries. If country variable series are stationary the problem of noncointegration and spurious results does not arise. In practice, we are likely to be confronted with a mixture of countries in terms of the time-series properties of their variable series, and the empirical implementation will need to recognise this.

In the *next section* we set out a model which is sufficiently general to encompass both these concerns. *Section two* discusses the empirical implementation of this general framework, presenting a number of standard and novel estimation strategies. In *section three* we apply our model to an unbalanced panel dataset for manufacturing (UNIDO, 2004) to estimate production functions for 38 countries over the period from 1970 to 2002. We have chosen a sectoral data set as once we can show that parameter heterogeneity matters at this level of aggregation the expectation is that these issues will matter even more for aggregate economy analysis. *Section four* concludes.

1 A general empirical framework for cross-country production analysis

This section introduces a general empirical specification and comments on the insights gained from macro factor income share data for production function parameter estimates. We assume panel data for N countries, with a time-series dimension T which may vary across countries (unbalanced panel). For the empirical production function let

$$O_{it} = \alpha_i L_{it} + \beta_i K_{it} + \gamma_i M_{it} + A_{0,i} + \mu_{it} + u_{it} \quad (1)$$

$$u_{it} = \rho_i u_{i,t-1} + \varepsilon_{it} \quad (2)$$

for $i = 1, \ldots, N$; $t = 1, \ldots, T$. 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, while country-specific TFP level $A_{0,i}$ and its evolvement μ_{it} are not observed. This framework can represent N country equations, or a single pooled equation.
Much of the microeconometric literature on production functions adopts gross-output based models (Basu & Fernald, 1995), but at the macro level, specification using value-added (Y in logs) as dependent variable are more common:

$$Y_{it} = \alpha_i^{va} L_{it} + \beta_i^{va} K_{it} + A_{0,i}^{va} + \mu_{it}^{va} + u_{it} \quad (3)$$

The error structure remains as in equation (2). Our notation in (3) 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 production function model and the data it is applied to:

A.1 The parameters α_i, β_i, γ_i, ρ_i are random coefficients (scalar), μ_{it} is a random vector (dto. for the equivalents in the VA specification). All of them have individual means and finite variances. Most generally, we can specify TFP evolvement μ_{it} to have a country-specific as well as a common element: $\mu_{it} \equiv [\mu_{it}^1 + \mu_t^2]$.

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

A.3 Observable inputs $\mathbf{X}_{it} = \{L_{it}, K_{it}, M_{it}\}$, output O_{it} (Y_{it}) and μ_{it} are <u>not</u> *a priori* assumed to be stationary I(0) variables/processes.

In *econometric* terms, this allows for factor parameter heterogeneity across countries, country fixed effects ($A_{0,i}$), and dynamic evolvement (TFP 'growth') which is either country-specific (μ_{it}) or globally common ($\mu_{it} \equiv \mu_t \,\forall\, i$) or both ($\mu_{it} \equiv [\mu_{it}^1 + \mu_t^2] \,\forall\, i$). This evolvement is not constrained to linearity, and may be nonstationary. The error specification in (2) allows for two cases, $\rho_i < 1$ and $\rho_i = 1$. If variable series are nonstationary,

[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}.

these correspond to equation (1) cointegrating and not cointegrating for each country i, respectively. Similarly for the VA production function in (3). Thus our empirical framework provides maximum flexibility with regards to time-series properties of the variable series investigated.

In *economic* terms, the above frameworks in (1) and (3) are *as general as possible*, allowing for individual countries to possess idiosyncratic production technologies with regard to factor parameters, TFP levels and TFP evolvement. This specification allows for common and/or country-specific evolvement ($\mu_{it} \equiv [\mu_{it}^1 + \mu_t^2]$).

Conducting empirical growth analysis 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 (3) should be equal to the labour and capital shares in income. Macroeconomic data for labour are available through the aggregate data on wages and welfare payments to labour. 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. Thus, while we would expect some variation in factor shares in income across countries, *cross-country average capital shares should be around .3 and labour shares around .7 of value-added.* These averages will act as benchmarks of comparison for the consistency of our technology estimates with factor shares.

2 Empirical implementation of a cross-country macro production function model

We assume an unbalanced panel dataset where some countries display nonstationary processes in inputs and output while others do not. First we discuss the investigation of variable time-series properties; the following sections present various empirical implementations in the pooled regression and averaged country-regression case respectively. We focus on the gross-output specification to save space — the exposition applies equally to the value-added framework.

2.1 Investigation of variable time-series properties

A panel where the time-series dimension T is reasonably long opens up the opportunity to use both country-specific tests from the time-series literature as well as panel-based tests.[4] Time series unit root and cointegration tests can suffer from weak power given short T,

[4] See Choi (2007), Breitung and Pesaran (2005) or Smith and Fuertes (2004, 2007) for a discussion of the latter.

while panel tests cannot shake off an inherent difficulty of interpretation (Maddala, 1999), whereby the null of nonstationarity for *all* countries is contrasted with an alternative that *at least one* country is stationary. Further, test results are often highly sensitive to the number of lags (of the differenced dependent variable) included.
We adopt estimation methods which are robust to the potential for nonstationarity and cointegration within some, but not all, countries in the panel. This approach is less dependent on crucial assumptions about the data which are difficult to test.

2.2 Pooled estimation approach

2.2.1 Pooled estimators in levels

A standard starting point for empirical analysis are the pooled *OLS* $\hat{\Theta}_{POLS}$ and *Fixed Effects* $\hat{\Theta}_{FE}$ estimators.[5] The latter can be implemented either via LSDV or variables in deviations from countries' period means ($\tilde{X}_{it} = X_{it} - T^{-1}\sum_t X_{it}$, henceforth: mean-deviations). Under the assumption of variable stationarity this provides estimates of parameter averages across countries, the average of country-specific TFP evolvements over time, and (in the Fixed Effects case) country-specific TFP levels. The regression equation for these two approaches is

$$O_{it} = \pi_L\, L_{it} + \pi_K\, K_{it} + \pi_M\, M_{it} + \pi_0 \left\{ + \sum_{i=2}^{N} \pi_{0,i} \right\} + \sum_{t=2}^{T} \pi_t D_t \tag{4}$$

where we have homogeneous factor parameters π_L, π_K, π_M corresponding to the factors labour, capital and materials (L, K, M respectively, all in logs), a vector of $(T-1)$ year dummies D with corresponding parameters π_t, and in the FE case N intercepts $\pi_{0,i}$.[6]

Building on the principal component analysis approach adopted in Coakley, Fuertes, and Smith (2002), the *Common Correlated Effects* estimator $\hat{\Theta}_{CCE}$ developed by Pesaran (2006) accounts for a common dynamic process and cross-sectional dependence in the panel by including cross-section averages of *all* observable variables in the regression equation. An extension by Kapetanios, Pesaran, and Yamagata (2006) shows that this approach is robust to the unobserved common factor(s) being nonstationary I(1).
The pooled *OLS* and *Fixed Effects* versions of the estimator, $\hat{\Theta}_{CCEP}$ and $\hat{\Theta}_{CCEFE}$, are easily adapted from equation (4) using cross-section averages (denoted by bars)

$$\begin{aligned} O_{it} &= \pi_L\, L_{it} + \pi_K\, K_{it} + \pi_M\, M_{it} + \pi_0 \left\{ + \sum_{i=2}^{N} \pi_{0,i} \right\} \\ &\quad + \pi_{\bar{O}}\, \bar{O}_t + \pi_{\bar{L}}\, \bar{L}_t + \pi_{\bar{K}}\, \bar{K}_t + \pi_{\bar{M}}\, \bar{M}_t \end{aligned} \tag{5}$$

where in the CCEP case we have a single intercept $\pi_0 \,\forall\, i$, whereas in the CCEPFE case we have N intercepts $\pi_{0,i}$. The second line represents the cross-section averages at time t

[5] In the following we use $\Theta = \{\alpha,\, \beta,\, \gamma,\, \ldots\}$ to represent all model parameters.
[6] For POLS there is a single intercept $\pi_0 \,\forall\, i$.

for each of the variables ($\bar{X}_t = N^{-1} \sum_i X_{it}$).[7] Regression estimates for π_L, π_K, π_M from these two estimators are identical to those from a pooled OLS and FE estimations with $(T-1)$ year dummies, respectively.

Either of these approaches using a pooled specification in levels neglects any influence of variable time-series properties on the consistency of the estimates. Once (some) variable series are nonstationary and factor parameters differ across countries the pooled regression *by construction* leads to nonstationary error terms if the factor inputs are nonstationary, since they contain (one or more of)

$$(\alpha_i - \pi_L)\, L_{it} \qquad (\beta_i - \pi_K)\, K_{it} \qquad (\gamma_i - \pi_M)\, M_{it} \qquad (\mu_{it} - \pi_t) \tag{6}$$

where α_i, β_i, γ_i and μ_{it} are the 'true' country-specific parameters. Each of the four terms in equation (6) is a linear combination of a (potentially) nonstationary variable/process and thus will (potentially) be nonstationary itself. Under standard assumptions the nonstationarity in the error terms leads to the breakdown of the cointegrating relationship and manifests itself in spurious regression results, regardless of the number of time-series observations (Engle & Granger, 1987). Given the breakdown of cointegration in the presence of nonstationary error terms, we would expect *any* pooled panel estimation to yield spurious results if variables were nonstationary and parameters heterogeneous across countries.[8]

We have thus shown that in the presence of nonstationarity in the variable series for some countries, pooling across countries with heterogeneous production technology leads to spurious regression results.

2.2.2 Pooled estimators in first differences

The guiding principle for this approach is expressed by Smith and Fuertes (2004, p.40, change of notation for consistency):

> "*... if it is known that $\rho_i = 1$* [errors are I(1)] *in most cases the sensible procedure would be to use first differenced data which will produce $\sqrt{T}$-consistent (individual OLS) estimates of Θ_i and $\sqrt{NT}$-consistent (pooled OLS) estimates of a common Θ or mean of Θ_i.*"

As we showed above the pooled model(s) in (4) have nonstationary error terms by construction if the regressors are nonstationary and the production process differs across countries. *Simply differencing the model equation renders all elements stationary*, such

[7] Note that if we include one (OLS) or N (FE) intercepts, it is necessary to set the cross-section averages for the base year to zero. In an unbalanced panel, with different base years across countries it may be preferable to transform all variables into mean-deviations.

[8] A recent development in econometric theory implies that this conclusion needs qualification. Phillips and Moon (1999, p.1091) show that *pooled* regressions of level equations with I(1) errors will yield *consistent* estimates of "interesting long-run relations" between input variables and output provided N, T are large enough and $N/T \to 0$ (see also Kao, 1999; Phillips & Moon, 2000; Smith & Fuertes, 2004). When the latter condition is violated, the spurious regression bias can dominate and the pooled regression results remain distorted. Arguably, in the context of cross-country development analysis, the condition $N/T \to 0$ is hardly ever likely to hold, such that the Phillips and Moon (1999) result does not affect the bias in the pooled production function regression.

that we can apply OLS to compute $\hat{\Theta}_{\Delta OLS}$, an estimate of the unweighted mean of the country cointegrating coefficients (Smith & Fuertes, 2004). If sample country variables represent a mix of stationary and nonstationary series, then using first differences OLS represents a loss of information for those level series already stationary. However, this situation contrasts with much more serious problems if variable series remain in levels but actually evolve in a nonstationary fashion.

Common TFP evolvement can be implemented in the first difference equation via a set of $(T-1)$ year dummies. The underlying TFP evolvement in levels can be either stationary or nonstationary. At the same time, the set of year dummies also captures *country-specific* TFP evolvement, be it stationary or nonstationary. The pooled regression equation in first difference is

$$\Delta O_{it} = \pi_L \, \Delta L_{it} + \pi_K \, \Delta K_{it} + \pi_M \, \Delta M_{it} + \sum_{t=2}^{T} \pi_t \, \Delta \, D_t \tag{7}$$

where we have $(T-1)$ year dummies D in *first difference*[9] with corresponding parameter vector π_t, and factor parameters π_L, π_K, π_M. The emphasis of this estimation approach is by design on common or average TFP growth across countries. Note that the inclusion of year dummies is widespread in the econometric analysis of micro-panels, whereas in macro-panels researchers prefer to take the data in deviation from cross-section means to account for common processes. The latter transformation is however only equivalent if variables are stationary and technology is homogeneous across countries (Pedroni, 1999, 2000; Smith & Fuertes, 2007).

In practice the estimator in equation (7) yields identical results to the first difference CCEP estimator $\hat{\Theta}_{\Delta CCEP}$, which we develop a in analogy to the Pesaran (2006) CCEP estimators in levels:

$$\begin{aligned} \Delta \, O_{it} \;\; &= \;\; \pi_L \, \Delta L_{it} + \pi_K \, \Delta K_{it} + \pi_M \, \Delta M_{it} \\ &\quad\; + \pi_{\bar{O}} \, \bar{O}_t + \pi_{\bar{L}} \, \bar{L}_t + \pi_{\bar{K}} \, \bar{K}_t + \pi_{\bar{M}} \, \bar{M}_t \end{aligned} \tag{8}$$

where the second line represents the cross-section averages at time t for each of the variables in first difference ($\bar{X}_t = N^{-1} \sum_i \Delta X_{it}$). The estimates for π_L, π_K, π_M will be the same as those from the first difference approach with year dummies, which suggests that the inclusion of year dummies in equation (7) relaxes the assumption of cross-sectional independence of the variables in standard panel estimation.

[9] The advantage of using *first differenced* dummies is that the associated parameter vector π_t describes a *level* evolvement over time t, whereas parameter estimates on standard *level* dummies in a growth regression provide a vector of year-on-year growth rates.

2.3 Averaging of country-specific estimates

2.3.1 The Mean Group and Swamy RCM estimators in levels

Pesaran and Smith (1995) introduce the *Mean Group* (MG) estimator $\hat{\Theta}_{MG}$ for the study of stationary panels. This constructs simple mean estimates ($\hat{\Theta}_{MG} = N^{-1}\sum_i \hat{\Theta}_i$) across the respective parameter estimates derived from N separate country regressions

$$O_{it} = \pi_{L,i}L_{it} + \pi_{K,i}K_{it} + \pi_{M,i}M_{it} + \pi_{0,i} + \pi_i t \tag{9}$$

where $\pi_{0,i}$ and π_i represent country-specific TFP level and growth rate, and the subscript i indicates that *all* parameters can vary across countries by construction.

In a nonstationary panel this estimator represents an unweighted average of estimated cointegrating coefficients and thus requires the existence of a cointegrating relationship within each country (Phillips & Moon, 2000). In the case of heterogeneous cointegration, the individual Θ_i is estimated consistently in the time-series regression as $T \to \infty$. Subsequent averaging over N provides a $T\sqrt{N}$-consistent estimate of the mean of the cointegrating relations across countries (Smith & Fuertes, 2007).
The validity of this statement hinges on each country regression correctly specifying the cointegrating relationship. With reference to cross-country production function estimation, we need to stress that correct specification of the TFP evolvement in each country regression is a crucial requirement for the MG estimator to provide an unbiased mean estimate: since TFP evolvement is potentially nonstationary (Lee et al., 1997; Bond et al., 2004), its misspecification will lead to noncointegration in the individual country regression, and thus to biased MG estimates.
The most general estimation approach would be the inclusion of sets of year dummies in each country regression, thus allowing for idiosyncratic nonlinear TFP evolution. Given the dimensionality problem in the individual country regression, this is of course not possible. The inclusion of a linear trend in each country regression to capture TFP evolvement saves on degrees of freedom, but leads to noncointegration if the 'true' TFP process is nonstationary.[10]

Thus the MG estimator can only provide a consistent estimate of the average cointegrating relationship across countries if the (idiosyncratic and/or common) TFP evolvement is modeled correctly and countries cointegrate heterogeneously. If TFP evolvement is nonstationary and *common* to all countries, we cannot detect it using country regressions. In this case the country regression is misspecified and contains nonstationary errors, thus leading to noncointegration and biased MG estimates.

[10] The transformation of variables into deviations from the cross-section mean at time t (henceforth: 'demeaning') is sometimes raised as equivalent to year dummies in accounting for common dynamic processes, with particular reference to the MG estimator (Lee et al., 1997). This transformation is however only equivalent to year dummies if all parameter coefficients are homogeneous across countries Pedroni (2000) — otherwise, using data in deviations from the cross-sectional mean adds new (nonstationary) error terms in a pooled regression (Coakley, Fuertes, & Smith, 2006).

A closely related estimator which provides a variation on the averaging of country estimates is the *Swamy Random Coefficients Model* (RCM) estimator $\hat{\Theta}_{RCM}$. This represents a feasible GLS estimator, which is equivalent to using a weighted average of the individual OLS country estimates (Swamy, 1970) — the weights are measures of precision of the individual county estimate. The conditions for the MG estimator to produce consistent results also apply to the Swamy RCM estimator.

2.3.2 The Mean Group and Swamy RCM estimators in first differences

We can provide a variation on the Mean Group estimator by transforming the levels model in equation (9) into a model in first differences. This yields N regression equations

$$\Delta\, O_{it} = \pi_{L,i}\Delta\, L_{it} + \pi_{K,i}\Delta\, K_{it} + \pi_{M,i}\Delta\, M_{it} + \pi_i \tag{10}$$

where π_i is a country-specific drift term and the subscript i indicates that *all* parameters can vary across countries by construction. The *First Difference Mean Group* estimator $\hat{\Theta}_{\Delta MG}$ is a simple average of the country estimates, like in the levels case.

In contrast to the specification in levels in (9) we do not require the cointegrating relationship to be correctly specified in this model: since all variables and processes are in first differences, the error terms will be stationary by construction. Like in the levels model, this approach views each country i in isolation, neglecting any common dynamic effects across countries (common 'TFP') and/or cross-sectional dependence. Further, it discards information about the long-run which is contained in the levels series and reduces the precision of country estimates if variable series in levels are already stationary — as can be assumed for some countries in a 'diverse' panel from developing and developed countries. The argument extends to the *First Difference Swamy* estimator $\hat{\Theta}_{\Delta RCM}$.

2.3.3 Accounting for common effects in the levels specification

In the presence of nonstationary variables, it is crucial for both the MG and Swamy RCM estimators that individual country equations cointegrate. We propose that by making use of an earlier result from the pooled regression in first differences we can include additional information in the country regression: the TFP evolvement across all countries obtained from the year dummies (henceforth: 'common dynamic process') can be argued to represent an average of the country-specific nonstationary processes omitted from the estimation model. An alternative justification for the inclusion of the common dynamic process in each country regression is the assumption that some TFP evolvement may be common to all countries (e.g. non-rival knowledge). In the following we remain agnostic about the true nature of this process. The assumptions of this approach imply that the common dynamic process is part of the cointegrating relationship (Pedroni, 2007).
In addition, we can account for any stationary variables omitted from the country regression by including a linear trend term: if omitted variables evolve relatively smoothly over time, the trend term will pick up this evolution. If any omitted variables are constant over time, their impact will be captured by the intercept term. This implies that

our *Augmented Mean Group* (AMG) estimator $\hat{\Theta}_{AMG}$ is suited for use in panels with a mixture of countries with stationary and nonstationary variable series. It allows for country-specific TFP levels and flexible TFP evolution over time and across countries.[11]

Formally, stage one is as described in equation (7) — the vector of year dummy estimates π_t represents the common dynamic process (henceforth: $\hat{\mu}_t^\bullet$). For the second stage regression we have two options: we can include $\hat{\mu}_t^\bullet$ as an additional regressor in the country regression, or we can subtract the common dynamic process from the dependent variable, which imposes the common process on each country with a unit coefficient.[12] Here we specify N country regressions in which we adopted the latter implementation

$$\{O_{it} - \hat{\mu}_t^\bullet\} = \pi_{L,i}\, L_{it} + \pi_{K,i}\, K_{it} + \pi_{M,i}\, M_{it} + \pi_{0,i} + \pi_i t \qquad (11)$$

where $\pi_{0,i}$ is the country intercept and π_i is the country-specific parameter on a linear trend t. Subsequently we average across the N country estimates as in the MG case. If the panel is made up of a mixture of some countries with stationary and others with nonstationary variable series, the AMG estimator arguably will yield unbiased country estimates since the augmented country equations are seen as cointegrating relations of nonstationary variables or as relations of stationary variables. The argument extends to the *Augmented Swamy RCM* estimator $\hat{\Theta}_{ARCM}$.

The *Mean Group* version of the *Common Correlated Effects* (CCEMG) estimator $\hat{\Theta}_{CCEMG}$ similarly accounts for one or more unobserved common factor(s) and cross-sectional dependence in the panel by including cross-section averages of *all* variables in the individual country regression. Resulting country parameter estimates are then averaged across the sample as in the standard MG case. The omitted common 'factor(s)' (in a principal component analysis sense) can be nonstationary processes, and can have *differential* impact on individual countries. The N CCE country regression equations in levels are

$$\begin{aligned} O_{it} &= \pi_{L,i}\, L_{it} + \pi_{K,i}\, K_{it} + \pi_{M,i}\, M_{it} + \pi_{0,i} + \pi_i t \\ &\quad + \pi_{\bar{O},i}\, \bar{O}_t + \pi_{\bar{L},i}\, \bar{L}_t + \pi_{\bar{K},i}\, \bar{K}_t + \pi_{\bar{M},i}\, \bar{M}_t \end{aligned} \qquad (12)$$

where the second line represents the cross-section averages at time t for each variable ($\bar{X}_t = N^{-1} \sum_i X_{it}$). Averaging across country coefficients yields the CCEMG estimates.

[11] An alternative econometric approach by Pedroni (2000), as applied in Pedroni (2007), makes use of the nonstationarity and cointegration properties of the data and averages country regressions estimated using Fully-Modified OLS (FMOLS). This procedure requires that *all* country variable series are nonstationary and cointegrated. The empirical strategy is thus to select a sample to suit the requirements of the estimation method since otherwise the desirable properties of the Pedroni (2000) estimator (prime amongst these superconsistency) cannot be assumed to hold. This is in contrast to the approach taken in the AMG, ARCM and CCEMG estimators, which are hypothesised to apply to 'mixed' panels of country data where some, but not all, countries display variable nonstationarity. The latter estimators also allow for cross-section dependence in the panel and a common TFP evolvement to impact country production.

[12] The former implies $\hat{\mu}_t^\bullet$ represents common TFP evolvement available to, but not necessarily adopted by each country, or a proxy for nonstationary variable(s) omitted from the model. The latter implies the existence of a global TFP process (e.g. non-rival knowledge) which affects all countries equally.

In comparison to the AMG approach, the CCEMG estimator is relatively data-intensive, since the inclusion of the averages in each country regression reduces the number of degrees of freedom considerably. In relatively short country time-series this could lead to loss of precision in the country estimates.

In the context of nonstationary country variable series, each country equation in the models in (11) and (12) cointegrates if the unobserved common TFP evolvement is part of the cointegrating vector (Pedroni, 2007). We have added a country-specific linear trend to capture stationary processes omitted from the regression specification. If some omitted variables evolve relatively smoothly over time, the trend term π_i will pick up this evolution. The AMG, ARCM and CCEMG estimators further allow for cross-sectional dependence in the panel.
With reference to the general empirical framework we introduced in equation (1), the $\hat{\Theta}_{AMG}$, $\hat{\Theta}_{ARCM}$ and $\hat{\Theta}_{CCEMG}$ estimators augmented with a country trend allow for

(i) heterogeneous factor parameters,
(ii) TFP evolution which is common and/or country-specific,
(iii) nonstationary evolvement of all variables and processes, and
(iv) cross-section dependence in the panel.

2.3.4 Accounting for common effects in the specification in first differences

Similar to applying $\hat{\mu}_t^{\bullet}$ in the country equations in levels, we can use $\Delta\hat{\mu}_t^{\bullet}$ in the country equations in first difference. For the option where we impose this common process with a unit coefficient we get N country equations

$$\{\Delta O_{it} - \Delta\hat{\mu}_t^{\bullet}\} = \pi_{L,i}\,\Delta L_{it} + \pi_{K,i}\,\Delta K_{it} + \pi_{M,i}\,\Delta M_{it} + \pi_i \tag{13}$$

where π_i is a country-specific drift term to capture other omitted variables. All variables and processes, including $\Delta\hat{\mu}_t^{\bullet}$, are stationary by construction. The simple average of the country coefficients yields the *First Difference AMG* estimator $\hat{\Theta}_{\Delta AMG}$. Similarly for the *First Difference Augmented Swamy RCM* estimator $\hat{\Theta}_{\Delta ARCM}$.
In analogy to the treatment in levels, we can construct the N CCE country regressions in first difference for the $\hat{\Theta}_{\Delta CCEMG}$ estimator

$$\begin{aligned}\Delta O_{it} \;&=\; \pi_{L,i}\,\Delta L_{it} + \pi_{K,i}\,\Delta K_{it} + \pi_{M,i}\,\Delta M_{it} + \pi_i \\ &\quad + \pi_{\bar{O},i}\,\bar{O}_t + \pi_{\bar{L},i}\,\bar{L}_t + \pi_{\bar{K},i}\,\bar{K}_t + \pi_{\bar{M},i}\,\bar{M}_t\end{aligned} \tag{14}$$

where $\bar{X}_t = N^{-1}\sum_i \Delta X_{it}$. These averages capture cross-section dependence in the panel as well as common factors, whereas π_i captures country-specific omitted variables. All variables are stationary by construction.

These estimators allow for parameter heterogeneity as well as common and country-specific TFP processes, while addressing the nonstationarity issue. Differencing however discards long-run information, which may impact the precision of their estimates.

3 Empirical results

3.1 Data

For our empirical analysis we use aggregate sectoral data for manufacturing from developed and developing countries for 1970 to 2002 (UNIDO, 2004). Following data construction and cleaning our sample represents an unbalanced panel of 38 countries with an average of 23 time-series observations (n=872 observations).[13] For a detailed discussion and descriptive statistics see Appendix A. Note that *all* of the results presented are robust to the use of the data constructed without application of the cleaning rules — this 'raw' sample has almost 1,200 observations for 48 countries.

3.2 Time-series properties of the data

We carry out a number of unit root tests, including simple AR(1) regressions, country-specific time-series tests (ADF, KPSS) and panel unit root tests of the first and second generation (Breitung & Pesaran, 2005) — see section B in the appendix. Ultimately, in case of the present data dimensions and characteristics, and given all the problems and caveats of individual country unit root tests as well as panel unit root tests, we can conclude *most conservatively* that nonstationarity cannot be ruled out in this dataset. Investigation of the time-series properties of the data was not intended to select a subset of countries which we can be reasonably certain display nonstationary variable series as in Pedroni (2007); instead, our aim was to indicate that the sample is likely to be made up of a mixture of some countries with stationary and and others with nonstationary variable series.

3.3 Pooled regressions

We estimate pooled models with variables in levels or first difference, including $(T-1)$ year dummies or period-averages as in Pesaran (2006) to identify what we term the common dynamic process. The slope coefficients on the factor inputs and the year dummies are restricted to be identical across all countries.
Our results presented in Table 1 are for the following estimators: for the data in levels [**1**] the pooled OLS estimator (POLS), and [**2**] the Pesaran (2006) common correlated effects estimator in its pooled version (CCEP). For both models we also estimate versions allowing for country fixed effects: [**3**] FE and [**4**] CCEPFE. For the data in first difference we run [**5**] OLS (ΔOLS), and [**6**] the equivalent CCE estimator (ΔCCEP).
The POLS results in column [1] indicate that leaving out country-specific intercepts yields severely biased results. Implied capital coefficients in the FE model in [3] are surprisingly even further inflated. The fixed effects are highly significant ($F(37, 799) = 133.3$, $p = .00$), which confirms heterogeneous TFP levels. Residual tests following Arellano and Bond (1991) show autocorrelation *or* unit roots in the errors for both sets of estimates.

[13] Empirical analysis is carried out using `STATA` versions 9 and 10.

The OLS estimation in first difference in column [5] implies a VA-equivalent capital coefficient of around .3, thus in line with the observed macro data on factor share in income. The AR(1) test indicates first order serial correlation, which is to be expected given that errors are now in first differences, but no higher order autocorrelation. The first difference model in [5] does not reject constant returns to scale, contrary to *all* models in levels.

Table 1: Pooled regressions (unrestricted returns to scale)

Pooled regression specification$^\natural$ dependent variable: log output (lO) in [1]-[4], Δlog output in [5] & [6]						
regressors†	[1] **POLS**	[2] **CCEP***	[3] **FE****	[4] **CCEPFE**	[5] **ΔOLS**	[6] **ΔCCEP**
log labour ($\hat{\alpha}$)	.0169	.0169	.0957	.0957	.1498	.1498
t-stat	(2.70)	(2.74)	(8.44)	(8.58)	(3.43)	(3.49)
log capital ($\hat{\beta}$)	.0333	.0333	.2074	.2074	.0603	.0603
t-stat	(2.96)	(3.01)	(17.27)	(17.56)	(1.77)	(1.80)
log materials ($\hat{\gamma}$)	.9566	.9566	.7377	.7377	.8074	.8074
t-stat	(69.45)	(70.61)	(55.81)	(56.73)	(26.52)	(26.99)
intercept	.4565					
t-stat	(8.86)					
period-average lO		1.000		1.000		1.000
t-stat		(3.07)		(5.77)		(6.41)
period-average lL		-.0169		-.0957		-.1498
t-stat		(0.31)		(1.84)		(2.23)
period-average lK		-.0333		-.2074		-.0603
t-stat		(0.36)		(3.77)		(1.09)
period-average lM		-.9566		-.7377		-.8074
t-stat		(3.14)		(6.02)		(6.67)
sum of coeff.	1.01	1.01	1.04	1.04	1.02	1.02
F-Test for CRS (p)	6.5 (.02)	6.7 (.01)	34.3 (.00)	34.5 (.00)	0.4 (.53)	0.4 (.53)
labour coeff. (VA)‡	.390	.390	.365	.365	.778	.778
t-stat	(3.15)	(3.20)	(9.45)	(9.60)	(4.51)	(4.59)
capital coeff. (VA)‡	.767	.767	.791	.791	.313	.313
t-stat	(9.17)	(9.32)	(29.24)	(29.72)	(1.68)	(1.71)
obs (countries)	872 (38)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)
Arellano-Bond Serial Correlation Test, H_0: no serial correlation in the residuals						
AR(1) (p)	16.0 (.00)	16.0 (.00)	11.2 (.00)	11.3 (.00)	-3.8 (.00)	-3.8 (.00)
AR(2) (p)	16.0 (.00)	16.0 (.00)	7.6 (.00)	7.6 (.00)	-0.8 (.42)	-0.8 (.42)

♮ Values in parentheses are absolute t-statistics. [1], [3], and [5] include $(T-1)$ year dummies.
† For columns [5] & [6] all variables are in first differences. The CCE estimators include cross-section period averages of output (lO), labour (lL), capital stock (lK) and materials (lM), all in logs.
* Note the missing intercept term: we can include this if we set the cross-section averages for the base year 1970 to zero. In either case the factor parameters are identical to those in column [1].
** Implemented via manual 'within' transformation and a *full* set of year dummies (Bond et al., 2004).
‡ These are derived as $\alpha^{va} = \alpha/(1-\gamma)$ for labour, in analogy for capital (Söderbom & Teal, 2004). In practice we computed them using the `nlcom` command in `STATA`.

The Pesaran (2006) CCEP estimator provides for some interesting insights: firstly, as expected the coefficients in columns [2], [4] and [6] are *identical* to the corresponding pooled regressions with year dummies. Secondly, the coefficients on the cross-section averages of variables follow a particular pattern, 'mirroring' coefficients on labour, capital and materials, with a unit parameter on log output[14] — in the following we do not report estimates for the period-averages.

[14]This makes sense: we are regressing log output for country i at time t on the period average of all countries at time t, where the latter also contains the value for country i

We obtain identical results for models in [1], [3], and [5] if we use data in deviation from the cross-sectional mean instead of using a set of year dummies (results not presented).[15]

Under intercept and factor parameter heterogeneity, given nonstationarity in (some of) the country variable series, the pooled levels estimators yield spurious results. Estimates of around .8 (VA-equivalent) suggest that this is the case in our models [1]-[4].[16]
In the same econometric setup, the difference estimators converges to the mean of the individual country cointegrating relations, $E(\Theta_i)$, at speed $\sqrt{TN}$ (Smith & Fuertes, 2004).

Given that the preferred model in first differences does not reject constant returns to scale (CRS), we impose this on all models — given that we are investigating a 'global' production function, the assumption of constant returns should be far from controversial. Table 2 presents these results.

Table 2: Pooled regressions (restricted returns to scale)

Pooled regressions (CRS imposed)$^\natural$ dependent variable: log output per worker (lo) in [1]-[4], Δlog output per worker [5] & [6]						
regressors†	[1] **POLS**	[2] **CCEP**	[3] **FE***	[4] **CCEPFE**	[5] **ΔOLS**	[6] **ΔCCEP**
log capital/worker ($\hat{\beta}$)	.0342	.0342	.1946	.1946	.0451	.0451
t-stat	(3.08)	(3.13)	(15.97)	(16.24)	(1.42)	(1.42)
log materials/worker ($\hat{\gamma}$)	.9579	.9579	.7531	.7531	.8074	.8074
t-stat	(71.29)	(72.51)	(55.78)	(56.74)	(26.44)	(26.93)
intercept	.5191					
t-stat	(10.56)					
We do not report the coefficients for the period averages in [2], [4] and [6] to save space.						
capital coeff. (VA)‡	.812	.812	.788	.788	.233	.234
t-stat	(9.92)	(10.01)	(26.15)	(26.60)	(1.40)	(1.42)
obs (countries)	872 (38)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)
Arellano-Bond Serial Correlation Test, H_0: no serial correlation in the residuals						
AR(1) (p)	16.7 (.00)	16.7 (.00)	10.7 (.00)	10.8 (.00)	-3.7 (.00)	-3.7 (.00)
AR(2) (p)	16.7 (.00)	16.7 (.00)	7.8 (.00)	7.8 (.00)	-0.8 (.44)	-0.8 (.44)

See Table 1 for all notes and additional information.

Imposition of CRS alters the results to an extent, although our preferred estimator in [5] still has capital and materials coefficients within the 95% confidence intervals of the unrestricted equation. The capital coefficient is now somewhat lower at .05, just outside the 10% level of statistical significance. The VA-equivalent capital coefficient for this model is reduced to .23. The imprecision might arise from the fact that the capital coefficient in a gross-output based model is relatively modest, below .1, which may make it more difficult to distinguish statistically from zero. If we regress growth in value-added per worker on growth in capital per worker and a set of year dummies we obtain a capital coefficient of .328 (t = 3.17). The VA-based models (see Table C-1 in the appendix) replicate the patterns of results in Tables 1 and 2.

[15] Replacing year dummies with cross-sectionally demeaned data is only valid if parameters are homogeneous across countries (Pedroni, 1999, 2000) — in the pooled regressions we force this homogeneity onto the data, such that identical results are to be expected.

[16] Note that t-values are invalid for the estimations *in levels* if error terms are nonstationary (Coakley, Fuertes, & Smith, 2001; Kao, 1999), i.e. potentially for all models [1]-[4].

Our pooled regression analysis suggests that time-series properties of the data play an important role in estimation: the levels regressions, where some country variable series may be I(1), yield VA-equivalent capital coefficients of around .8. We suggest that the bias is the result of nonstationary errors, which are introduced into the pooled equation by the imposition of parameter homogeneity on heterogeneous country equations. In contrast, the regressions where variables are in first difference and thus stationary have yielded capital parameters broadly consistent with factor shares. This pattern of results fits the case of level series being I(1) in at least some of the countries in our sample.

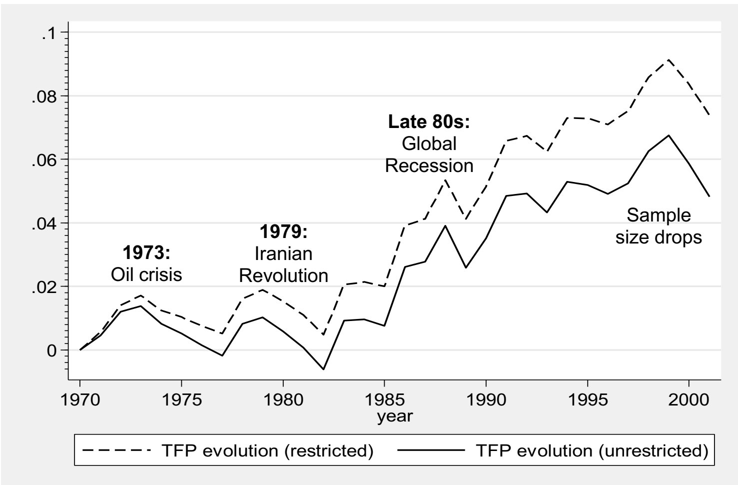
3.4 Country regressions

We now relax the assumption that all countries possess the same production technology, and allow for country-specific slope coefficients on factor inputs. At the same time, we maintain that a common dynamic process and/or cross-sectional dependence have to be accounted for in some fashion.

3.4.1 Accounting for common TFP evolvement

Following our discussion above, the ΔOLS regression represents the only pooled model which estimates a cross-country average relationship *safe from difficulties introduced by nonstationarity*. We therefore make use of the year dummy coefficients derived from our preferred pooled regressions (ΔOLS, column [5] in Table 2 for the restricted model with CRS imposed, and in Table 1 for the model with unrestricted returns to scale, respectively) to obtain what we term the 'common dynamic process' $\hat{\mu}_t^\bullet$. Figure 1 illustrates the evolvement paths of the common dynamic process for these two gross-output based specifications.[17]

Figure 1: Evolvement of the 'common dynamic process' $\hat{\mu}_t^\bullet$



[17]A VA-equivalent path scales the year dummies by $1/(1-\hat{\gamma})$ to account for material inputs. The resulting TFP evolvement path is very similar to that derived from a VA specification (not presented).

The graphs show severe slumps following the two oil shocks in the 1970s, while the 1980s and 1990s indicate considerable upward movement.[18] We favour the 'measure of ignorance' (Abramowitz, 1956) interpretation of TFP, such that a decline in global manufacturing TFP as evidenced in the 1970s should not be interpreted as a decline in knowledge, but a worsening of the global manufacturing *environment*.

Each country regression equation in levels can be augmented with this common process. In practice, we have a choice over the way in which we model the common dynamic process to affect each country, if indeed it has any impact at all:

$$(a) \quad O_{it} = \alpha_i L_{it} + \beta_i K_{it} + \gamma_i M_{it} + A_{0,i} + \mu_i t + u_{it} \tag{15}$$

$$(b) \quad \{O_{it} - \hat{\mu}_t^\bullet\} = \alpha_i L_{it} + \beta_i K_{it} + \gamma_i M_{it} + A_{0,i} + \mu_i t + u_{it} \tag{16}$$

$$(c) \quad O_{it} = \alpha_i L_{it} + \beta_i K_{it} + \gamma_i M_{it} + A_{0,i} + \mu_i t + \kappa_i \hat{\mu}_t^\bullet + u_{it} \tag{17}$$

(a) is the standard MG estimator with a country-specific linear trend and no common dynamic process. The AMG estimator in (b) imposes the common dynamic process $\hat{\mu}_t^\bullet$ with a unit coefficient, whereas in (c) it is included as a regressor. In (b) and (c) we allow for a country-specific TFP trend in addition to any global process.

The econometric interpretation of these alternatives is as follows: for options (b) and (c) the inclusion of $\hat{\mu}_t^\bullet$ can account for nonstationary processes omitted from the individual country-regression and enables country equations with nonstationary factor variables to cointegrate — in either case, we require $\hat{\mu}_t^\bullet$ *to be part of the cointegrating relation* (Pedroni, 2007). Option (a) in contrast does not account for any common dynamic process or cross-section dependence and we would therefore expect that (some of) the country regressions will yield spurious estimation results.

The t-statistics for the country-regression averages reported in all tables below represent measures of dispersion for the sample of country-specific estimates.[19] We provide an additional statistic $(1/\sqrt{N})\sum_i t_i$, constructed from the country-specific t-statistics (t_i), which indicates the precision of the country estimates for capital (and materials).
Given the earlier findings we impose CRS on each country regression[20] — this decision is discussed in more detail below. For ease of comparison we report both the results of the regressions based on gross-output and value-added models. These will turn out to be qualitatively very similar throughout.

[18] $\hat{\mu}_t^\bullet$ is 'sample-specific': for years where data coverage is good, it can be interpreted as 'global', whereas for years from 2000 (9 countries have data for 2001, 2 for 2002 which is omitted from the graph) this interpretation collapses.

[19] They simply indicate whether the mean of this dispersion is significantly different from zero.

[20] The common TFP evolvement is in analogy derived from a pooled regression in first difference where CRS is imposed.

3.4.2 Models with country-specific TFP growth — option (a)

In Table 3 we present the average estimates from **[1]** the standard Mean Group (MG) estimator, and **[2]** the Swamy (1970) Random Coefficient Model estimator (RCM). We also apply these two estimators to the data in first differences in **[3]** & **[4]**.

Table 3: Country regressions (CRS) without $\hat{\mu}^{\bullet}_t$ — Option (a)

Average coefficients from country regressions (CRS imposed)$^\natural$ estimates presented are unweighted means of the country coefficients†				
	[1]	[2]	[3]	[4]
	MG	**RCM**	**ΔMG**	**ΔRCM**
	Gross output specification			
dep. variable	lo	lo	Δlo	Δlo
log capital/worker ($N^{-1}\sum\hat{\beta}_i$)	.0658	.0812	.0556	.0562
t-stat	(1.99)	(2.27)	(2.37)	(1.94)
log materials/worker ($N^{-1}\sum\hat{\gamma}_i$)	.7183	.7352	.7603	.7745
t-stat	(26.61)	(26.25)	(37.71)	(32.56)
trend/drift term ($N^{-1}\sum\hat{\mu}_i$)	.0040	.0032	.0024	.0030
t-stat	(3.14)	(2.33)	(2.05)	(1.98)
intercept ($N^{-1}\sum\hat{A}_{0,i}$)	2.6264	2.3071		
t-stat	(7.03)	(5.74)		
capital/worker (VA) mean‡	.234	.307	.232	.249
t-stat	(2.09)	(2.41)	(2.40)	(1.97)
$(1/\sqrt{N})\sum_i t_{\hat{\beta},i}$	9.52	10.67	4.14	6.76
$(1/\sqrt{N})\sum_i t_{\hat{\gamma},i}$	87.27	96.44	80.59	99.44
	Value-added specification			
dep. variable	ly	ly	Δly	Δly
log capital/worker ($N^{-1}\sum\hat{\beta}^{va}_i$)	.2240	.3117	.1916	.2151
t-stat	(2.21)	(2.88)	(2.15)	(2.06)
trend/drift term ($N^{-1}\sum\hat{\mu}^{va}_i$)	.0157	.0132	.0155	.0171
t-stat	(4.13)	(3.26)	(4.57)	(3.78)
intercept ($N^{-1}\sum\hat{A}^{va}_{0,i}$)	7.2014	6.3153		
t-stat	(6.66)	(5.47)		
$(1/\sqrt{N})\sum_i t_{\hat{\beta}^{va},i}$	15.03	15.87	4.87	6.62
obs (countries)	872 (38)	872 (38)	807 (38)	807 (38)

$\natural$ Values in parentheses are absolute t-statistics. These were obtained by regressing the N country estimates on an intercept term, except for the Swamy t-stats, which are provided by `xtrc` in `STATA` and represent $\sum_i(\hat{\Sigma}+\hat{\mathbf{V}}_i)$ where $\hat{\Sigma}$ is a measure of dispersion of the country OLS estimates and $\hat{V}$ is the variance of the N OLS estimates scaled by $\sum x_i^2$.
† We report averaged t-statistics for country-specific t-statistics t_i of the factor estimates at the bottom of each panel.
‡ This is obtained using a non-linear combination of the capital and materials coefficients accounting for the precision of these estimates.

With the exception of the Swamy estimates in levels, the gross-output as well as the VA-based model results have average capital coefficients somewhat below the macro evidence of around .3, but in comparison with the pooled regression results, these estimates represent dramatic improvements. The pattern of averaged t-statistics indicates that the country estimates are more precise in the regression models in levels.

3.4.3 Models with common and country-specific TFP growth — option (*b*)

We present averaged country regression results for option (*b*) in Table 4. We estimate **[1]** the Augmented Mean Group (AMG) estimator developed above; **[2]** the Mean Group version of the Common Correlated Effects estimator (CCEMG); and **[3]** the Swamy Random Coefficient Model estimator, augmented with the 'common dynamic process' (ARCM). We also apply the same estimators to the data in first differences **[4]**-**[6]**.
As can be seen, the factor parameter estimates are now relatively stable across the different estimators and specifications, implying a VA-equivalent capital coefficient of around 1/3. *All* estimates lie within each other's 95% confidence interval.[21]

Table 4: Country regressions (CRS) with $\hat{\mu}_t^\bullet$ — Option (*b*)

Average coefficients from country regressions (CRS imposed)$^\natural$ estimates presented are unweighted means of the country coefficients	[1] **AMG**	[2] **CCEMG***	[3] **ARCM**	[4] **ΔAMG**	[5] **ΔCCEMG**	[6] **ΔARCM**
	Gross output specification					
dep. variable$^\sharp$	lo-$\hat{\mu}_t^\bullet$	lo	lo-$\hat{\mu}_t^\bullet$	Δlo-$\Delta\hat{\mu}_t^\bullet$	Δlo	Δlo-$\Delta\hat{\mu}_t^\bullet$
log capital/worker ($N^{-1}\sum\hat{\beta}_i$)	.0734	.0726	.0869	.0662	.0863	.0623
t-stat	(2.28)	(2.21)	(2.50)	(3.02)	(3.63)	(2.27)
log materials/worker ($N^{-1}\sum\hat{\gamma}_i$)	.7435	.7406	.7616	.7814	.7570	.7943
t-stat	(28.17)	(29.91)	(26.32)	(38.39)	(36.50)	(33.24)
trend/drift term ($N^{-1}\sum\hat{\mu}_i$)	.0006	.0037	-.0003	-.0011	-.0017	-.0003
t-stat	(0.45)	(2.83)	(0.25)	(0.99)	(0.72)	(0.22)
intercept ($N^{-1}\sum\hat{A}_{0,i}$)	2.3002		1.9817			
t-stat	(5.81)		(4.69)			
We do not report estimates on the period averages in [2] and [5] to save space.						
capital/worker (VA) mean‡	.285	.280	.364	.303	.355	.303
t-stat	(2.35)	(2.29)	(2.59)	(3.15)	(3.46)	(2.36)
$(1/\sqrt{N})\sum_i t_{\hat{\beta},i}$	9.70	8.89	11.50	5.15	5.05	6.75
dto. bootstrap (1,000 reps)	1.78		3.31	1.17		2.92
$(1/\sqrt{N})\sum_i t_{\hat{\gamma},i}$	97.21	86.14	104.26	85.73	73.53	99.44
dto. bootstrap (1,000 reps)	18.04		32.73	17.46		47.07
	Value-added specification					
dep. variable$^\sharp$	ly-$\hat{\mu}_t^\bullet$	ly	ly-$\hat{\mu}_t^\bullet$	Δly-$\Delta\hat{\mu}_t^\bullet$	Δly	Δly-$\Delta\hat{\mu}_t^\bullet$
log capital/worker ($N^{-1}\sum\hat{\beta}_i^{va}$)	.3130	.2898	.3872	.2878	.2849	.2967
t-stat	(3.28)	(2.94)	(3.80)	(3.65)	(3.35)	(3.14)
trend/drift term ($N^{-1}\sum\hat{\mu}_i^{va}$)	-.0016	.0140	-.0036	-.0019	-.0000	-.0001
t-stat	(0.47)	(3.56)	(0.99)	(0.63)	(0.01)	(0.03)
intercept ($N^{-1}\sum\hat{A}_{0,i}^{va}$)	6.2147		5.4834			
t-stat	(6.16)		(5.09)			
We do not report estimates on the period averages in [2] and [5] to save space.						
$(1/\sqrt{N})\sum_i t_{\hat{\beta}^{va},i}$	17.89	15.40	19.31	7.58	6.13	9.60
dto. bootstrap (1,000 reps)	5.10		4.70	1.77		4.26
obs (countries)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)	807 (38)

See also Table 3 for notes and additional information.
♯ We subtract the common dynamic trend $\hat{\mu}_t^\bullet$ from log output (log value-added) per worker for country i in models [1] and [3], and the common growth rate $\Delta\hat{\mu}_t^\bullet$ from output growth in models [4] and [6].
∗ Variables were transformed (within-group transformation) to do away with the intercept term.
† We report averaged t-statistics for country-specific t-statistics t_i of the factor estimates at the bottom of each panel. We also provide averaged t-statistics based on country regression with bootstrapped standard errors (1,000 replications).

[21] We present the pooled and averaged country regression results (options (*a*) and (*b*)) for the 'raw' sample ($n = 1,194$, $N = 48$) in Tables C-4 and C-5 in the appendix, respectively. Even though this sample is about 35% larger, the estimates are virtually identical to those in Table 4.

The kernel densities for the capital and materials coefficients in the gross-output models with $\hat{\mu}^{\bullet}_t$ imposed are presented in Figure D-1 in the appendix — these provide little evidence of outliers. The value-added based estimates similarly confirm a capital coefficient around .3, with kernel density estimates indicating almost perfectly normal distribution for the AMG and ARCM estimators (not reported).

The models where $\hat{\mu}^{\bullet}_t$ is included as additional regressor, option (c), yield very similar result for the factor parameters and are therefore not reported separately. Note that the averaged coefficients (mean of $\hat{\kappa}_i$) on the additional regressors ($\hat{\mu}^{\bullet}_t$ or $\Delta\hat{\mu}^{\bullet}_t$) are close to unity, in particular in the specifications in first differences.[22]

The additional average t-statistics constructed follow the same pattern as that described in the previous table. We also report these statistics for the case where individual country parameter t-statistics are based on standard errors which were bootstrapped using 1,000 replications. As can be seen, this yields some low t-statistics for the capital coefficients in the AMG estimations. Qualitatively, though, there is an almost perfect match between the AMG mean estimates and their CCEMG cousins — since the latter do not include stochastic variables in the regression equation (no $\hat{\mu}^{\bullet}_t$) there should be no concern about the validity of their standard errors. We take this close match (which also applies to the country trends/drifts) as an indication that the AMG and ARCM estimates are robust.

The *mean* trend/drift coefficients across countries are insignificant in all models presented with the exception of the levels CCEMG (for both VA and gross-output) — we would expect a zero average since these values represent deviations from the common (average) TFP evolvement $\hat{\mu}^{\bullet}_t$. For the models in levels, the majority of country-specific trend terms tend to be statistically significant,[23] whereas this is only the case for a maximum of one in four drift terms in the first difference models.[24] The CCEMG trends are systematically higher than the AMG and ARCM trends — the difference between the two is however found to be the common TFP growth $\hat{\mu}^{\bullet}_t$. Once we adjust each AMG and ARCM country trend estimate the three levels estimators yield very similar results (not presented).
In Figure D-2 in the appendix we present country-specific TFP levels and growth rates for the AMG value-added specification.[25] The first graph shows the computed base and final year TFP levels,[26] ranked by magnitude of the latter: the US, Ireland, Finland, and South Korea hold the top spots, whereas Bangladesh, Sri Lanka, Indonesia, and Fiji are

[22]Coefficients on the $\hat{\mu}^{\bullet}_t$ terms in models with additional country trend for (i) gross-output models: MG .775, RCM .792, ΔMG .960, ΔRCM .846; (ii) value-added models: MG .793, RCM .817, ΔMG .989, ΔRCM .852.

[23]For the gross-output models: [1] AMG, 23 country trends have $t > 1.645$ (10%), for [2] CCEMG 24 and for [3] ARCM 22. In the VA models, the numbers are 25, 25 and 24 respectively.

[24]For [4] ΔAMG, we have 5 country trends with $t > 1.645$ (10%), for [5] ΔCCEMG 9 and for [6] ΔARCM again only 5. In the VA-specification, these numbers are 5, 8 and 7 respectively.

[25]We prefer to present the VA results since all gross-output results need to be scaled by $1/(1-\hat{\gamma}_i)$.

[26]The base-year and final year TFP levels are computed as

$$\hat{\beta}^{va}_i (K/L)_{0,i} + \hat{A}^{va}_{0,i} \qquad \text{and} \qquad \hat{\beta}^{va}_i (K/L)_{0,i} + \hat{A}^{va}_{0,i} + \hat{\mu}_i \tau + \hat{\mu}^{\bullet}_{\tau}$$

respectively, where τ is the total period for which country i is in the sample and $\hat{\mu}^{\bullet}_{\tau}$ is the accumulated *common* TFP growth for this period τ. Base and final year differ across countries (see Table A-1).

at the bottom. The second graph ranks countries by their average annual TFP growth rates, derived from the trend estimates in the country regressions: South Korea, Ireland, Singapore and Malta top the rankings, whereas Panama, Bangladesh, Fiji and Guatemala are at the bottom.[27]

We briefly review the results for country regressions where the data was first transformed into deviations from the cross-sectional mean to account for any common dynamic process. The averaged results for this exercise are presented in Table C-2 in the appendix. Here, all estimators (MG, Swamy) and specifications (levels, FD) yield capital coefficients between .42 and .55 (VA-equivalent). We take these results as an indication of factor parameter heterogeneity, since the transformation of variables into deviations from the cross-section mean introduces nonstationarity into the errors if the underlying production technology differs across countries (Pedroni, 1999, 2000).

3.4.4 The importance of constant returns to scale

Further investigation reveals that the imposition of constant returns to scale plays an important role. We repeat the regressions where the country equation is augmented with the common dynamic process and a linear trend, equivalent to option (*b*) above, but with all variables in 'raw' form, rather than in per worker terms. Results are presented in Table C-3 in the appendix.
The failure to impose constant returns to scale leads to severely biased results in the levels specifications, whereas in the first difference specification the MG and Swamy estimates are relatively close to the hypothesised capital parameter of .3 (VA-equivalent). The averaged capital coefficients for all specifications in first differences are much less precise than in previous results, and their 95% confidence intervals include the mean estimates of our preferred specification (*b*) where CRS is imposed. An explanation for the inflated average CCEMG estimate may be sought in the number of parameters estimated, 8 per country equation, thus more than in any other model so far.

3.5 Robustness and Diagnostics

3.5.1 Dynamic specification; testing parameter heterogeneity

The static empirical model adopted in our general framework assumes that the regressors $\mathbf{X}_{it}$ are orthogonal to the error terms u_{it}. Our serial correlation tests for the pooled models in first difference suggest that $\Delta\mathbf{X}_{it}\perp\Delta u_{it}$, evidenced by the lack of higher order autocorrelation, but this in itself is not an entirely convincing test. We can specify the model in a dynamic form so as to allow for serial correlation explicitly. This approach requires us to instrument for the lagged dependent variable in the pooled model in first

[27] The graph also shows common TFP growth, which differs by country depending on the country-specific time-series dimension. Total country TFP growth per annum is the sum of the common and the idiosyncratic components.

difference — it becomes evident that our instrumentation is weak, although in the VA-model the the Cragg-Donald statistic does reject the weak instrument null ($F = 28.88$, critical value for 10% is 19.93). AMG regressions in levels for gross-output and value-added (results not reported) qualitatively replicate the results in the static models. The long-run capital coefficients in these models are next to identical to those in the static specifications. We take this result as an indication that potential serial correlation does not grossly distort the results for the static pooled model in first differences.

The individual country coefficients emerging from the regressions in section 3.4 imply considerable parameter heterogeneity across countries. However, this apparent heterogeneity may be due to sampling variation and the relatively limited number of time-series observations in each country individually (Pedroni, 2007). We therefore carried out a number of formal parameter heterogeneity tests for the results from the AMG, ARCM and CCEMG estimations in levels and first difference. The results (not reported) suggest that parameter homogeneity is rejected. Systematic differences in the test statistics for levels and first difference specifications however indicate that nonstationarity may drive some of these results. Nevertheless, even if heterogeneity were not very significant in qualitative terms, our contrasting of pooled and country regression results has shown that it nevertheless matters greatly for correct empirical analysis in the presence of nonstationary variables.

3.5.2 Other potential sources of endogeneity

The issue of distinction between correlation and causation is commonly raised in applied econometrics. In our case, it is natural to ask whether higher capital investments may not be caused by a higher growth rate, rather than exclusively the other way round (reverse causality). In a pooled regression of heterogeneously cointegrated groups there is correlation between the errors and the regressors *by construction*, since regression errors contain shares of the independent variables — in the levels equation this leads to the breakdown of the cointegrating relationship.

We carry out a number of endogeneity tests for specifications in levels and first differences following and expanding on Wooldridge (2002, p.285), using pooled and heterogeneous factor parameter regression models. The results from these tests (not reported) are somewhat mixed, rejecting factor exogeneity in some cases/countries but not in others — if we focus on country-specific results, the vast majority of country-specific tests cannot reject factor exogeneity. However, variable nonstationarity may affect the validity of these tests, which were devised with stationary data in mind. Traditionally, the endogeneity of factor variables was seen as one of the major reasons for the empirical puzzle of inflated capital coefficients (Caselli et al., 1996). Our approach has shown that we can arrive at factor parameters consistent with macro data if we make allowances for heterogeneity and nonstationarity. A corollary of our findings may be that other sources of endogeneity may not exert strong bias on the estimation results.

It is questionable whether a valid instrumentation strategy can be developed at the macro-level, as it is difficult to think of exogenous variables which could act as valid instruments (a sentiment echoed in Caselli et al., 1996). Further, 'own-instrumentation' via lags of levels and/or differences like in the Arellano and Bond (1991) and Blundell and Bond (1998) estimators is not appropriate in moderate to long panels such as the present one: the wealth of instruments becomes a curse, with overfitting bias severely influencing the results (Bowsher, 2002). In addition there are serious concerns about the informativeness of instruments in the case where variables are nonstationary.

4 Overview and conclusions

In this paper we have investigated how technology differences in manufacturing across countries should be modeled. We began by presenting an encompassing empirical framework which allowed for the possibility that technology parameters differ and that there are both effects common to all countries and factors which are country-specific. We have introduced the Augmented Mean Group estimator (AMG), which is conceptually close to the Mean Group version of the Pesaran (2006) Common Correlated Effects estimator (CCEMG). Both of these estimators allow for a 'common dynamic process', a globally common, unobserved factor or factors, which in the context of production functions can be interpreted as common TFP evolvement or an average of country-specific evolvement paths of omitted variables. The AMG, ARCM and CCEMG estimators allow for consistent estimation when cross-sectional dependence takes this form.

Our empirical findings for a manufacturing panel dataset indicate that allowing for factor parameter heterogeneity, a 'common dynamic process' across all countries and linear country-specific TFP growth terms yields factor parameter averages across countries of around 0.3 (VA-equivalent). This empirical finding is close to macro data on capital share in income of around 1/3 and is replicated using the CCEMG approach. These results contrast with our pooled estimates, assuming parameter homogeneity, which gave capital coefficients of around 0.8. The 'common dynamic process' extracted is argued to be in line with historical events. The country-specific linear trends, which capture stationary processes omitted from the model, are statistically significant in the majority of countries.

The model we have presented is agnostic with respect to what may determine the magnitudes of factor coefficients and country TFP growth terms, or the evolvement of common TFP. From an econometric point of view, it would seem that the AMG, ARCM and CCEMG estimators allow us to specify the cointegrating vector to be made up of factor inputs, output and the unobserved common dynamic process. Failing to allow for all three crucial elements of empirical specification — parameter heterogeneity, common dynamic process and country specific technology change — is likely to result in seriously biased estimates of the production technology. In light of the quotes from Durlauf et al. (2001) and Phillips and Moon (2000) this paper began with, we suggest that the assumptions of parameter homogeneity and variable stationarity are rejected by the data.

References

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

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.

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

Basu, S., & Fernald, J. G. (1995). Are apparent productive spillovers a figment of specification error? *Journal of Monetary Economics*, *36*(1), 165-188.

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

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

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

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.

Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters*, *77*(2), 211-220.

Breitung, J., & Pesaran, M. H. (2005). *Unit roots and cointegration in panels* (Discussion Paper Series 1: Economic Studies No. 2005-42). Deutsche Bundesbank, Research Centre.

Canning, D., & Pedroni, P. (2004). *The effect of infrastructure on long run economic growth.* (Harvard University, unpublished working paper)

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.

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

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., & Smith, R. (2002). *A principle components approach to cross-section dependence in panels.* (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.

Dickey, D., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427-431.

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., Kourtellos, A., & Minkin, A. (2001). The local Solow growth model. *European Economic Review*, *45*(4-6), 928-940.

Engle, R., & Granger, C. (1987). Cointegration and error correction: representations, estimation and testing. *Econometrica*, *55*(2), 252-276.

Funk, M., & Strauss, J. (2003). Panel tests of stochastic convergence: TFP transmission within manufacturing industries. *Economics Letters*, *78*(3), 365-371.

Gollin, D. (2002). Getting income shares right. *Journal of Political Economy*, *110*(2), 458-474.

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.

Hendry, D. (1995). *Dynamic Econometrics*. Oxford University Press.

Im, K., Pesaran, M. H., & Shin, Y. (1997). *Testing for unit roots in heterogeneous panels.* (Discussion Paper, University of Cambridge)

Im, K., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74.

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., & 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. (2006). *Panels with nonstationary multifactor error structures* (IZA Discussion Papers No. 2243). Institute for the Study of Labor.

Klenow, P. J., & Rodriguez-Clare, A. (1997). Economic growth: A review essay. *Journal of Monetary Economics*, *40*(3), 597-617.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1-3), 159-178.

Larson, D. F., Butzer, R., Mundlak, Y., & Crego, A. (2000). A cross-country database for sector investment and capital. *World Bank Economic Review*, *14*(2), 371-391.

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.

Liu, Z., & Stengos, T. (1999). Non-linearities in Cross-Country Growth Regressions: A Semiparametric Approach. *Journal of Applied Econometrics*, *14*(5), 527-38.

Maddala, G. (1999). On the use of panel data methods with cross-country data. *Annales D'Économie et de Statistique*, *55/56*, 429-449.

Maddala, G., & 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.

Martin, W., & Mitra, D. (2002). Productivity Growth and Convergence in Agriculture versus Manufacturing. *Economic Development and Cultural Change*, *49*(2), 403-422.

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.

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. (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. (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.

Phillips, P., & Moon, H. R. (1999). Linear regression limit theory for nonstationary panel data. *Econometrica*, *67*(5), 1057-1112.

Phillips, P., & Moon, H. R. (2000). Nonstationary panel data analysis: An overview of some recent developments. *Econometric Reviews*, *19*(3), 263-286.

Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346.

Ryan, K., & Giles, D. (1998). *Testing for unit roots with missing observations* (Department Discussion Papers No. 9802). Department of Economics, University of Victoria.

Smith, R. P., & Fuertes, A.-M. (2004). *Panel Time Series.* (cemmap mimeo, April 2004.)

Smith, R. P., & Fuertes, A.-M. (2007). *Panel Time Series.* (cemmap mimeo, April 2007.)

Söderbom, M., & Teal, F. (2003). *Openness and human capital as sources of productivity growth: An empirical investigation* (Working Paper Series No. 188). Centre for the Study of African Economies.

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. (1970). *Growth theory: an exposition.* Oxford: Oxford University Press.

Swamy, P. A. V. B. (1970). Efficient inference in a random coefficient regression model. *Econometrica*, *38*(2), 311-23.

UN. (2004). *National accounts statistics: Main aggregates and detailed tables, 1992* (New York: UN Publications Division). United Nations.

UN. (2005). *UN Common Statistics 2005* (Online database, New York: UN). United Nations.

UNIDO. (2004). *UNIDO Industrial Statistics 2004* (Online database, Vienna: UNIDO). United Nations Industrial Development Organisation.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Mass: MIT Press.

Appendix

A Data construction and descriptives

Data for output, value-added, material inputs and investment in manufacturing, all in current local currency units (LCU), are taken from the UNIDO Industrial Statistics 2004 (UNIDO, 2004), where material inputs were derived as the difference between output and value-added. The labour data series is taken from the same source, which covers 1963-2004. The capital stocks are calculated from investment data in current LCU following the 'perpetual inventory' method developed in Klenow and Rodriguez-Clare (1997) and described in detail in Söderbom and Teal (2003). In this process we apply some mechanical rules regarding the average investment/value-added ratio and the imputed base-year capital/value-added ratio. It is important to reiterate that *all* results presented are robust to the omission of these and the cleaning rules defined below.

In order to make data in monetary values internationally comparable, it is necessary to transform all values into a common unit of analysis. We follow the transformations suggested by Martin and Mitra (2002) and derive all values in 1990 US$,[a] using current LCU and exchange rate data from UNIDO, and GDP deflators from the UN Common Statistics database (UN, 2005), for which data are available from 1970-2003.
Since our model is for a small open economy, we prefer using market exchange rates to purchasing-power-parity (PPP) adjusted exchange rates, since the latter are more appropriate when non-traded services need to be accounted. All monetary values are thus derived from constant local currency units and made internationally comparable by the application of a single LCU-US$ exchange rate.

In order to address the most serious issues of measurement error we used the capital-to-materials ratio (K/M) to define a rule, bounded as $0.02 < K/M < 2$. In a final step we exclude all countries for which we have less than ten time-series observations. The resulting panel is unbalanced and has gaps within individual country time-series. We have a total of $n = 857$ observations from $N = 38$ countries, which have a time-series dimension between $T = 13$ and $T = 33$, with average $T = 23$. The country-specific information (number of observations, first and final year in the dataseries) is contained in table A-1.

Table A-2 provides the descriptive statistics for the variables in logs used in our regressions (panel 3). The second line for each variable here presents the log value in first differences, as applied in our preferred OLS regression. Log variables in first difference are of course equivalent to the raw variable growth rate. For reference we also present the descriptives for the raw data in levels (panel 1) and in per worker terms (panel 2). It can be seen that the mean value-added (VA) per worker is around US$25,000 in 1990 value-terms.

[a]Martin and Mitra (2002) apply a single exchange-rate (that for 1990) to the whole data series, whereas for instance Larson, Butzer, Mundlak, and Crego (2000) apply the annual exchange rate. The latter approach is deemed less appropriate, since the variable series would also capture international price and exchange rate movements.

Table A-1: Sample — number of observations, first and final year†

Country	Code	levels ($n = 872$)			first diff. ($n = 807$)	'raw' ($n = 1,194$)		
		obs.	first yr	final yr	obs.	obs.	first yr	final yr
Australia	AUS	20	1970	1993	17	20	1970	1993
Austria	AUT	19	1974	2000	15	30	1970	2000
Belgium	BEL	15	1970	1984	14	28	1970	1997
Bangladesh	BGD	14	1970	1992	12	14	1970	1992
Bolivia	BOL	11	1987	1997	10	11	1987	1997
Barbados	BRB	24	1970	1995	21	26	1970	1995
Canada	CAN	21	1970	1990	20	21	1970	1990
Chile	CHL	24	1975	1998	23	25	1974	1998
Colombia	COL	30	1970	1999	29	30	1970	1999
Cyprus	CYP	33	1970	2002	32	33	1970	2002
Ecuador	ECU	19	1973	1991	18	30	1970	1999
Egypt	EGY					26	1970	1995
Spain	ESP	26	1979	1995	25	26	1970	1997
Finland	FIN	23	1970	2000	21	28	1970	2000
Fiji	FJI	25	1970	1994	24	25	1970	1994
France	FRA					26	1970	1995
Great Britain	GBR					23	1970	1992
Guatemala	GTM	16	1973	1988	15	16	1973	1988
Hungary	HUN					26	1970	1995
Indonesia	IDN	26	1970	1995	25	26	1970	1995
India	IND	32	1970	2001	31	32	1970	2001
Ireland	IRL	22	1970	1991	21	22	1970	1991
Iran	IRN	18	1970	2001	15	24	1970	2001
Israel	ISR	12	1989	2001	10	13	1989	2001
Italy	ITA	25	1974	2000	22	31	1970	2000
South Korea	KOR	31	1970	2001	29	31	1970	2001
Sri Lanka	LKA	20	1970	2000	17	20	1970	2000
Luxembourg	LUX					23	1970	1992
Morocco	MAR	17	1985	2001	16	17	1984	2001
Mexico	MEX	16	1984	2000	14	16	1983	2000
Malta	MLT	32	1970	2001	31	32	1970	2001
Malaysia	MYS	27	1970	2000	24	28	1970	2001
Netherlands	NLD					24	1970	1993
Norway	NOR	28	1974	2001	27	32	1970	2001
New Zealand	NZL	18	1970	1989	17	21	1970	1990
Panama	PAN	26	1973	2000	23	30	1970	2000
Philippines	PHL	26	1970	1995	25	26	1970	1995
Poland	POL					31	1970	2000
Portugal	PRT	30	1971	2000	29	31	1970	2000
Senegal	SEN	16	1974	1990	14	17	1970	1990
Singapore	SGP	33	1970	2002	32	33	1970	2002
Sweden	SWE					18	1970	1987
Swaziland	SWZ					24	1970	1995
Tunisia	TUN	21	1970	1997	19	21	1970	1997
Turkey	TUR	27	1970	1997	25	27	1970	1997
USA	USA	26	1970	1995	25	26	1970	1995
Venezuela	VEN					26	1970	1998
Zimbabwe	ZWE	23	1970	1996	20	27	1970	1996
average T		23			21	25		

† Recall that the panel is unbalanced, and that some countries have missing observations in their time-series. **levels** and **first diff.** refer to the samples for pooled and country regressions in levels and first differences respectively. **'raw'** refers to the levels dataset where we do not apply our cleaning algorithms.

Table A-2: Descriptive statistics

(1) Raw data: monetary values in constant 1990 US$					
Variable	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
output	1.40e+11	2.27e+10	4.53e+11	2.39e+08	3.15e+12
Growth rate	0.051	0.043	0.099	-0.437	1.001
value-added	5.57e+10	3.05e+10	6.85e+09	5.70e+07	1.50e+12
Growth rate	0.047	0.041	0.120	-0.571	0.927
labour	1,408,990	446,525	3,213,541	6,723	19,667,000
Growth rate	0.024	0.013	0.086	-0.388	0.781
capital	1.09e+11	1.53e+10	3.21e+11	1.40e+08	2.27e+12
Growth rate	0.05	0.042	0.044	-0.024	0.478
materials	8.41e+10	1.47e+10	2.52e+11	1.44e+08	1.65e+12
Growth rate	0.052	0.042	0.107	-0.393	1.031

(2) Raw data in per worker terms: monetary values in constant 1990 US$					
Variable	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
output/worker	69,512	49,922	52,121	4,711	286,509
Growth rate	0.026	0.026	0.083	-0.445	0.850
VA/worker	24,036	16,793	18,779	1,660	91,011
Growth rate	0.023	0.026	0.104	-0.903	0.744
capital/worker	60,031	38,967	54,935	2,007	270,976
Growth rate	0.026	0.028	0.084	-0.680	0.454
materials/worker	45,475	33,826	34,445	2,596	195,497
Growth rate	0.028	0.027	0.095	-0.538	0.879

(3) Data in logs: levels and in per worker terms					
Variable	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
log output	23.620	23.838	2.094	19.292	28.779
per worker	10.835	10.824	0.853	8.458	12.566
log value-added	9.739	9.731	0.903	7.415	11.419
per worker	9.739	9.731	0.903	7.415	11.419
log labour	12.786	13.009	1.762	8.813	16.794
log capital	23.374	23.45	2.148	18.758	28.451
per worker	10.588	10.573	0.968	7.605	12.510
log materials	23.196	23.41	2.084	18.783	28.132
per worker	10.411	10.428	0.852	7.862	12.183

B Variable time series properties

As a first step we carry out 'naïve' AR(1) regressions $ln\, Z_{it} = \rho\, ln\, Z_{i,t-1} + v_{it}$ where $v_{it} = \varepsilon_{it} + \eta_t$ for Z_{it} as output, value-added capital, labour and materials, following Bond (2002). This approach imposes a homogeneous autoregressive parameter ρ on all country series, which is clearly restrictive, but provides crude insights into the data properties. Year dummies are included in all four regression models (pooled OLS, fixed effects, Difference GMM and Systems GMM) to account for possible common development in the variable series (η_t, not constrained to linearity). The results for *levels* and *per capita* transformations of the variables (not reported) provide evidence that the data series are extremely persistent and for a considerable number of countries are likely to constitute unit root processes.

Since the time dimension of the panel is sizeable (T ranges from 13 to 33, average $T = 23$), we carry out Augmented Dickey-Fuller (Dickey & Fuller, 1979) and KPSS (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) tests for the variable series within each individual country.[b] We use this combination of tests since the ADF test has the null of nonstationary variable series, whereas the KPSS test has the null of stationary variable series. The results for variables in *levels* and in *per worker terms* (not reported) show that for the majority of countries the ADF tests cannot reject nonstationarity, whereas the majority of country KPSS tests reject the null of level stationarity — these results are stronger for variables in per worker terms than for those in levels.[c] The overall pattern of test results is reversed when we run ADF and KPSS tests on variables in *first-difference* (not reported), indicating that variable series are indeed stationary in first differences.

Our dataset is an unbalanced panel with missing observations — properties that may affect the unit root tests. A simulation exercise by Ryan and Giles (1998) suggests that (with respect to the ADF tests) filling the gaps with the last known observation produces more powerful unit root tests in comparison with tests where gaps were ignored.[d] We carried out ADF tests for the altered dataset (levels, first difference) and obtained very similar patterns of rejection as when testing original data with gaps (not reported). Thus the results from these country unit-root tests are a further indication of the potential for integrated processes in our data.

Next we applied panel unit root tests to the data. It is important to stress that rejection of the unit root null hypothesis does not imply that the panel is stationary, but rather that the variable series does not follow a unit root process *in all countries*. We first present the results for the Maddala and Wu (1999) panel unit root test, and the working paper version of the Im, Pesaran, and Shin (1997) test, both of which do not account for cross-sectional dependence. Results in Table B-1 show that for the 'levels' variable series these tests cannot agree on the level of integration prevalent in the data. For the per capita variable series, however, neither test can reject the null hypothesis that all countries have I(1) series.

Over the past decade panel unit root tests which explicitly allow for cross-sectional dependence in the variable series have been developed. These include a simple augmentation to the Im et al. (1997) panel unit root test (Im, Pesaran, & Shin, 2003), and the Pesaran (2007) ADF test (CIPS). In addition to cross-section dependence these tests allow for the alternative that *a fraction* of countries, rather than all, are stationary. For the former we are required to use a *balanced* panel; we therefore use a balanced subset of the sample where missing values have been filled in using the last non-missing observation (see above), which considerably reduces our sample size ($T, N = 22, 22$; $n = 484$) compared to the *unbalanced* panel ($T_{max} = 33$, $N = 38$; $n = 872$).

---

[b]Whereas the `STATA` command for ADF allows us to run country regressions with gaps in the data, this is not possible for the KPSS tests. We therefore reduce the sample to contain only time-series without gaps. This reduces the overall sample to 732 observations.

[c]The results are largely replicated by country-specific Phillips and Perron (1988) tests for all variables in levels and per worker terms (not reported). This uses Newey-West standard errors to account for serial correlation, while the augmented Dickey-Fuller test uses additional lags of the first-difference variable.

[d]They also point out that regular Dickey-Fuller critical values remain valid for either approach.

Table B-1: First generation panel unit root tests

Im, Pesaran & Shin (1997) and Maddala and Wu (1999) I(1) tests[♯] no adjustment for cross-sectional dependence					
variable (in levels)[†]	lO	lY	lL	lK	lM
IPS Test statistic	-1.68	-1.08	-1.98	-2.09	-1.51
Reject H_0 of unit root	*no*	*no*	*yes*	*yes*	*no*
MW Test statistic	106.70	65.43	142.10	60.13	75.74
Reject H_0 of unit root	*yes*	*no*	*yes*	*no*	*no*
variable (in per worker terms)[†]	lo	ly		lk	lm
IPS Test statistic	-0.81	-1.01		-0.81	-1.10
Reject H_0 of unit root	*no*	*no*		*no*	*no*
MW Test statistic	28.38	59.64		26.85	30.79
Reject H_0 of unit root	*no*	*no*		*no*	*no*

† We test output (lO), VA (lY), labour (lL), capital (lK) and materials (lM) in levels and per worker terms (all in logs).
♯ The IPS and MW statistics are constructed as $P = -2\sum_i log(p_i)$ for the former and $\bar{t} = N^{-1}\sum_i t_i$ for the latter, where t_i are the country ADF statistics (t-values) and p_i the corresponding p-values. For the Im et al. (1997) test the critical values (-1.78 for 5%, -1.72 for 10% significance level — distribution is approximately t) are reported in Table 2, Panel A of their paper (we used $T = 25$, $N \approx 40$). For the Maddala and Wu (1999) test the critical values are 97.35 for 5% and 92.16 for 10% — distribution is $\chi^2(2N)$.

Table B-2: Second generation panel unit root tests

Im, Pesaran & Shin (2003) and Pesaran (2007) panel unit root tests H_0: unit root process; augmentation with 2 lags unless indicated					
variable (in levels)[†]	lO	lY	lL	lK	lM
IPS test[♯] $t-bar$	-0.68	-0.86	-1.23	-0.45	-0.78
Reject H_0 of unit root	*no*	*no*	*no*	*no*	*no*
IPS test[♯] $Wt-bar$ (p-value)	3.75 (1.00)	3.04 (.99)	1.06 (.86)	4.90 (1.00)	3.27 (.99)
Pesaran CIPS (p-value)	1.02 (.85)	3.11 (.99)	2.22 (.99)	8.14 (1.00)	0.94 (.83)
Pesaran CIPS w/ 'ideal' augmentation[♮] (p)	4.34 (1.00)	11.01 (1.00)	3.34 (1.00)	9.82 (1.00)	4.57 (1.00)
variable (in per worker terms)[†]	lo	ly		lk	lm
IPS test[♯] $t-bar$	-0.89	-0.93		-1.14	-1.09
Reject H_0 of unit root	*no*	*no*		*no*	*no*
IPS test[♯] $Wt-bar$ (p-value)	2.73 (.99)	2.51 (.99)		1.49 (.93)	1.77 (.96)
Pesaran CIPS (p-value)	4.91 (1.00)	5.01 (1.00)		5.65 (1.00)	3.43 (1.00)
Pesaran CIPS w/ 'ideal' augmentation[♮] (p)	5.14 (1.00)	8.72 (1.00)		8.87 (1.00)	5.82 (1.00)

† See Table B-1 for further details.
♯ Reduced sample: balanced panel where gaps are filled with last non-missing observations ($n = 484$, $T = 22$). The critical values are now -1.85 and -1.78 for 5% and 10% respectively.
♮ We used the lag-lengths determined from AIC in ADF tests of variables in deviation from the cross-sectional means.

We reiterate the difficulties relating to panel unit root tests (Smith & Fuertes, 2004, 2007), in particular in a (relatively) short, unbalanced panel with gaps like in our own case. The difficulties of these tests to produce meaningful results is highlighted by the Pesaran (2007) CIPS test results in Table B-2, for which computed p-values are unity for all variable series in per worker terms — 'perfect' certainty is never a good sign in a stochastic world. Results are contingent on the inclusion of lags: for augmentation with one lag or none, nonstationarity cannot be rejected with sensible p-values less than unity (except for log capital where p=1). Thereafter, p-values are unity throughout. If we apply the CIPS test to data in first difference, we reject nonstationarity throughout if we augment with one lag (or none); for more lags the p-value jumps to unity (not reported). The Im et al. (2003) tests cannot reject the nonstationarity null, either — again with 'perfect' certainty in case of the log capital series.

C Additional tables

Table C-1: Pooled regressions for value-added specifications

Pooled regressions (VA-based model)♮ dependent variable: log value-added (lY) [1]-[4], Δlog value-added [5] & [6]						
regressors†	[1] **POLS**	[2] **CCEP***	[3] **FE****	[4] **CCEPFE**	[5] **ΔOLS**	[6] **ΔCCEP**
log labour ($\hat{\alpha}$)	.1896	.1896	.3644	.3644	.6814	.6814
t-stats	(8.92)	(9.07)	(11.66)	(11.86)	(6.38)	(6.50)
log capital ($\hat{\beta}$)	.8317	.8317	.7908	.7908	.3841	.3841
t-stats	(57.31)	(58.29)	(34.54)	(35.13)	(3.16)	(3.22)
intercept	.6231					
t-stats	(3.76)					
We do not report the coefficients for the period averages in [2], [4] and [6] to save space.						
sum of coeff.	1.02	1.02	1.16	1.16	1.07	1.07
F-Test for CRS (p)	4.2 (.04)	4.3 (.04)	53.5 (.00)	45.3 (.00)	0.4 (.52)	0.4 (.51)
obs (countries)	872 (38)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)
Arellano-Bond Serial Correlation Test, H_0: no serial correlation in the residuals						
AR(1) (p)	16.4 (.00)	16.4 (.00)	11.2 (.00)	11.2 (.00)	-3.2 (.00)	-3.2 (.00)
AR(2) (p)	16.0 (.00)	15.9 (.00)	7.9 (.00)	7.9 (.00)	-1.6 (.12)	-1.6 (.12)

Pooled regressions (VA-based model) with CRS imposed♮ dependent variable: log value-added per worker (ly) [1]-[4], Δlog value-added per worker [5] & [6]						
regressors†	[1] **POLS**	[2] **CCEP***	[3] **FE****	[4] **CCEPFE**	[5] **ΔOLS**	[6] **ΔCCEP**
log capital/worker ($\hat{\beta}$)	.8379	.8379	.7848	.7848	.3271	.3271
t-stats	(63.34)	(64.51)	(32.17)	(32.74)	(3.15)	(3.21)
intercept	.8250					
t-stats	(5.25)					
We do not report the coefficients for the period averages in [2], [4] and [6] to save space.						
obs (countries)	872 (38)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)
Arellano-Bond Serial Correlation Test, H_0: no serial correlation in the residuals						
AR(1) (p)	17.4 (.00)	17.4 (.00)	10.6 (.00)	10.6 (.00)	-3.2 (.00)	-3.2 (.00)
AR(2) (p)	16.9 (.00)	16.9 (.00)	7.9 (.00)	7.9 (.00)	-1.5 (.13)	-1.5 (.13)

♮ Values in parentheses are absolute t-statistics. †For columns [5] and [6] all variables are in first differences.
* Note the missing intercept term: we can include this if we set the cross-section averages for the base year 1970 to zero. In this case the factor parameters are identical to those in column [1], but the coefficient on the cross-section averages no longer follow the pattern in [2]. ** Implemented via manual 'within' transformation and a *full* set of year dummies (Bond et al., 2004).

Table C-2: Country regressions — data in deviations from X-section mean

Average coefficients from country regressions (CRS imposed) — 'demeaned' data♮ estimates presented are unweighted means of the country coefficients	[1] **MG**	[2] **RCM**	[3] **ΔMG**	[4] **ΔRCM**
	Gross-output specification			
dep. variable	lo	lo	Δlo	Δlo
log capital/worker	.1147	.1190	.0895	.0727
t-stat	(5.62)	(5.14)	(4.89)	(3.28)
log materials/worker	.7703	.7818	.8185	.8286
t-stat	(26.47)	(24.60)	(34.64)	(30.61)
trend/drift term	-.0010	-.0009	-.0016	-.0005
t-stat	(1.36)	(1.05)	(2.29)	(0.46)
intercept	.0105	.0060		
t-stat	(0.38)	(0.21)		
capital/worker (VA) mean	.499	.545	.493	.424
t-stat	(7.59)	(6.91)	(5.91)	(4.01)
parameters estimated	4	4	3	3
$(1/\sqrt{N})\sum_i t_{\hat{\beta},i}$	16.25	18.14	7.81	9.27
$(1/\sqrt{N})\sum_i t_{\hat{\gamma},i}$	84.43	98.47	88.02	95.27
	Value-added specification			
dep. variable	ly	ly	Δly	Δly
log capital/worker	.5172	.5619	.5458	.5254
t-stat	(12.57)	(11.89)	(11.70)	(9.51)
trend/drift term	-.0016	-.0012	-.0024	-.0003
t-stat	(0.83)	(0.55)	(1.39)	(0.08)
intercept	.0490	.0539		
t-stat	(0.57)	(0.60)		
parameters estimated	3	3	2	2
$(1/\sqrt{N})\sum_i t_{\hat{\beta}^{va},i}$	32.33	40.33	21.59	27.33
obs (countries)	872 (38)	872 (38)	807 (38)	807 (38)

♮ Factor and output variables are transformed into deviations from the cross-section mean of the sample at time t. All variables in columns [3] and [4] are in first difference.
Note that specification without a country-specific trends leads to even larger capital coefficients in both gross-output and value-added models.

Table C-3: Country regressions (unrestricted returns to scale)

Average coefficients from country regressions (unrestricted returns to scale)[♮] estimates presented are unweighted means of the country coefficients						
	[1]	[2]	[3]	[4]	[5]	[6]
regressors†	**AMG**	**CCEMG***	**ARCM**	**ΔAMG**	**ΔCCEMG**	**ΔARCM**

	Gross-output specification					
dep. variable[♯]	lO-$\hat{\mu}_t^\bullet$	lO	lO-$\hat{\mu}_t^\bullet$	ΔlO-$\Delta\hat{\mu}_t^\bullet$	ΔlO	ΔlO-$\Delta\hat{\mu}_t^\bullet$
log labour ($N^{-1}\sum\hat{\alpha}_i$)	.1419	.1362	.1429	.1533	.1549	.1485
t-stat	(5.05)	(3.75)	(4.55)	(6.10)	(4.44)	(4.72)
log capital ($N^{-1}\sum\hat{\beta}_i$)	.2011	.1418	.1550	.0846	.1911	.0613
t-stat	(2.50)	(2.99)	(1.82)	(1.51)	(1.52)	(0.90)
log material ($N^{-1}\sum\hat{\gamma}_i$)	.7718	.7531	.7791	.7804	.7612	.7942
t-stat	(35.15)	(29.72)	(31.47)	(37.57)	(37.13)	(32.50)
trend/drift term ($N^{-1}\sum\hat{\mu}_i$)	-.0043	-.0001	-.0033	-.0007	-.0130	-.0001
t-stat	(1.35)	(0.42)	(0.96)	(0.33)	(1.04)	(0.04)
intercept ($N^{-1}\sum\hat{A}_{0,i}$)	-.9214		.0490			
t-stat	(0.55)		(0.03)			
We do not report estimates on the period averages in (2) and (5) to save space.						
labour coeff. (VA-equiv) mean[‡]	.622	.551	.647	.698	.645	.722
t-stat	(5.75)	(4.08)	(5.19)	(7.40)	(5.67)	(5.61)
capital coeff. (VA-equiv) mean[‡]	.882	.574	.702	.385	.800	.298
t-stat	(2.58)	(3.37)	(1.88)	(1.54)	(1.50)	(0.91)
F-test CRS (p)	2.96 (.09)	0.57 (.45)	1.17 (.28)	0.14 (.70)	0.71 (.40)	0.00 (.95)
$(1/\sqrt{N})\sum_i t_{\hat{\alpha},i}$	14.29	11.18	17.47	10.38	9.91	14.42
$(1/\sqrt{N})\sum_i t_{\hat{\beta},i}$	6.67	13.58	8.49	2.03	2.63	3.33
$(1/\sqrt{N})\sum_i t_{\hat{\gamma},i}$	96.07	83.51	111.11	81.05	66.09	98.61

	Value-added specification					
dep. variable[♯]	lY-$\hat{\mu}_t^\bullet$	lY	lY-$\hat{\mu}_t^\bullet$	ΔlY-$\Delta\hat{\mu}_t^\bullet$	ΔlY	ΔlY-$\Delta\hat{\mu}_t^\bullet$
log labour ($N^{-1}\sum\hat{\alpha}_i^{va}$)	.6673	.6132	.6539	.7362	.6564	.7144
t-stat	(7.07)	(5.57)	(6.42)	(10.03)	(8.42)	(7.91)
log capital ($N^{-1}\sum\hat{\beta}_i^{va}$)	.6805	.7399	.5923	.3079	.3813	.2738
t-stat	(2.50)	(8.02)	(2.54)	(1.65)	(1.56)	(1.22)
trend/drift term ($N^{-1}\sum\hat{\mu}_i^{va}$)	-.0155	.0000	-.0114	-.0012	-.0210	.0023
t-stat	(1.70)	(0.05)	(1.16)	(0.15)	(0.82)	(0.23)
intercept ($N^{-1}\sum\hat{A}_{0,i}^{va}$)	-2.0510		.2473			
t-stat	(0.45)		(0.05)			
We do not report estimates on the period averages in (2) and (5) to save space.						
F-test CRS (p)	3.63 (.06)	32.89 (.00)	1.58 (.21)	0.09 (.76)	0.03 (.87)	0.00 (.95)
$(1/\sqrt{N})\sum_i t_{\hat{\alpha}^{va},i}$	23.58	18.73	26.67	21.03	18.37	26.20
$(1/\sqrt{N})\sum_i t_{\hat{\beta}^{va},i}$	13.39	36.00	14.24	1.82	1.60	4.28
obs (countries)	872 (38)	872 (38)	872 (38)	807 (38)	807 (38)	807 (38)

See Table 3 for notes and additional information.

Table C-4: Pooled Regressions (Value-Added) — 'raw' sample

Pooled VA regressions (CRS imposed)[♮] dep. var.: log value-added per worker (ly) [1]-[4], Δlog value-added per worker [5] & [6]						
	[1] **POLS**	[2] **CCEP**	[3] **FE**	[4] **CCEPFE**	[5] **ΔOLS**	[6] **ΔCCEP**
log capital/worker	.7895	.7895	.7273	.7273	.3195	.3195
t-stat	(72.97)	(73.94)	(28.99)	(29.36)	(3.61)	(3.61)
intercept	1.1474					
t-stat	(8.47)					
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,128 (48)	1,128 (48)

♮ All variables in [5]&[6] are in first differences. We do not report period average estimates in [2], [4] and [6].

Table C-5: Averaged Country Regressions (VA) — 'raw' sample

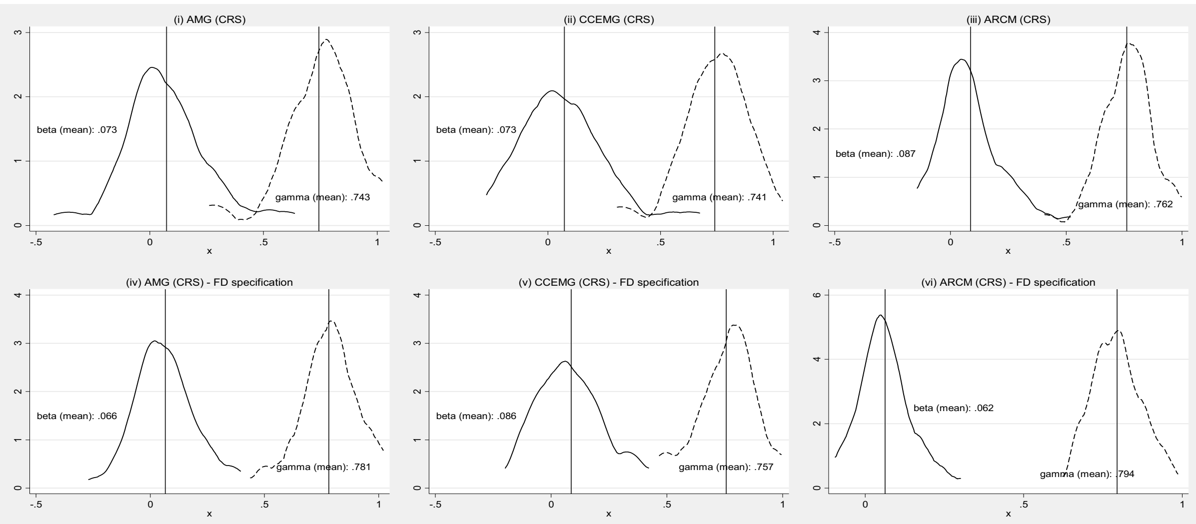
Average coefficients from VA country regressions (CRS imposed)$^\natural$
estimates presented are unweighted means of the country coefficients

	[1] **MG**		[2] **Swamy**	[3] **ΔMG**		[4] **ΔSwamy**
	Option (*a*): no common dynamic process					
dep. variable$^\sharp$	ly		ly	Δly		Δly
log capital/worker ($N^{-1}\sum\hat{\beta}_i^{va}$)	.1789		.2691	.1642		.2085
t-stat	(2.25)		(3.31)	(1.93)		(2.13)
trend/drift term ($N^{-1}\sum\hat{\mu}_i^{va}$)	.0174		.0148	.0161		.0171
t-stat	(5.95)		(4.77)	(5.60)		(4.42)
intercept ($N^{-1}\sum\hat{A}_{0,i}^{va}$)	7.6528		6.7191			
t-stat	(9.05)		(7.35)			
$(1/\sqrt{N})\sum_i t_{\hat{\beta}_i^{va}}$	12.42		20.34	4.81		6.91
# of sign. $\hat{\mu}_i$ (at 10%)	39		27	14		15

	[1] **AMG**	[2] **CCEMG***	[3] **ARCM**	[4] **ΔAMG**	[5] **ΔCCEMG**	[6] **ΔARCM**
	Option (*b*) : $\hat{\mu}_t^\bullet$ imposed, country-trends included					
dep. variable$^\sharp$	ly-$\hat{\mu}_t^\bullet$	ly	ly-$\hat{\mu}_t^\bullet$	Δly-Δ$\hat{\mu}_t^\bullet$	Δly	Δly-Δ$\hat{\mu}_t^\bullet$
log capital/worker ($N^{-1}\sum\hat{\beta}_i^{va}$)	.2896	.2877	.3557	.2734	.3203	.3053
t-stat	(3.95)	(3.62)	(4.49)	(3.52)	(4.02)	(3.37)
trend/drift term ($N^{-1}\sum\hat{\mu}_i^{va}$)	.0001	.0155	-.0018	-.0011	.0015	-.0001
t-stat	(0.04)	(5.41)	(0.66)	(0.44)	(0.30)	(0.03)
intercept ($N^{-1}\sum\hat{A}_{0,i}^{va}$)	6.3823		5.7380			
t-stat	(8.42)		(6.98)			
$(1/\sqrt{N})\sum_i t_{\hat{\beta}_i^{va}}$	16.55	15.34	20.34	8.30	7.11	9.15
# of sign. $\hat{\mu}_i$ (at 10%)	28	32	27	6	8	16
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,128 (48)	1,128 (48)

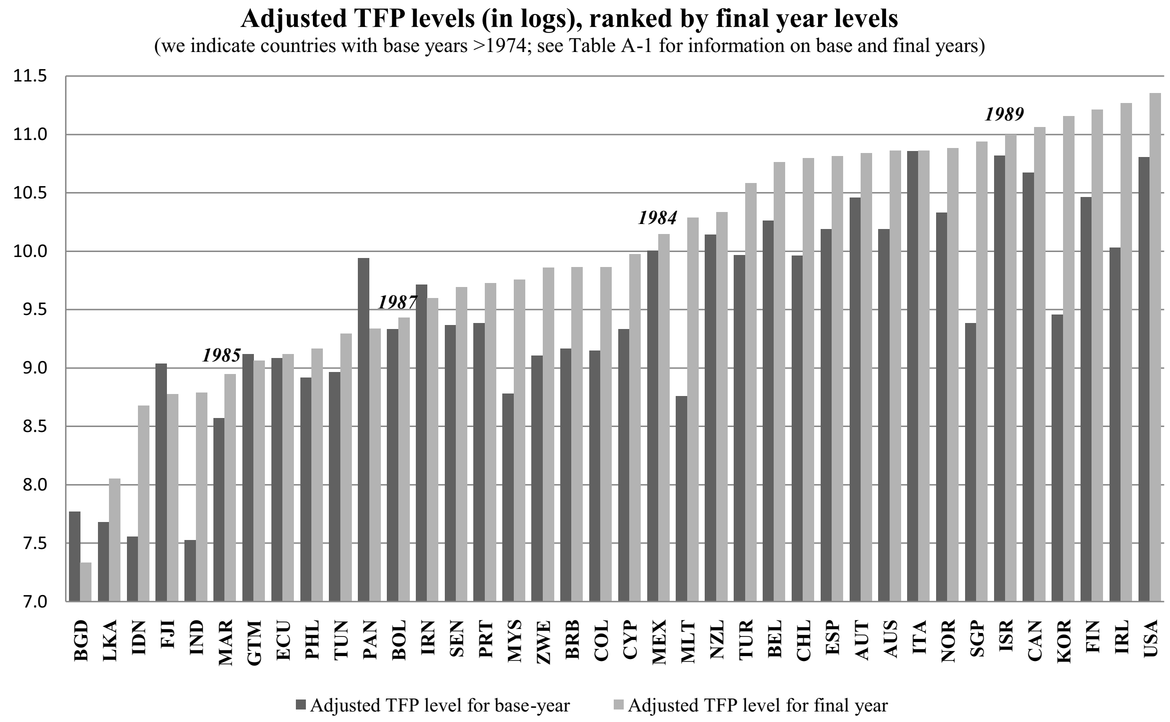
D Additional graphs

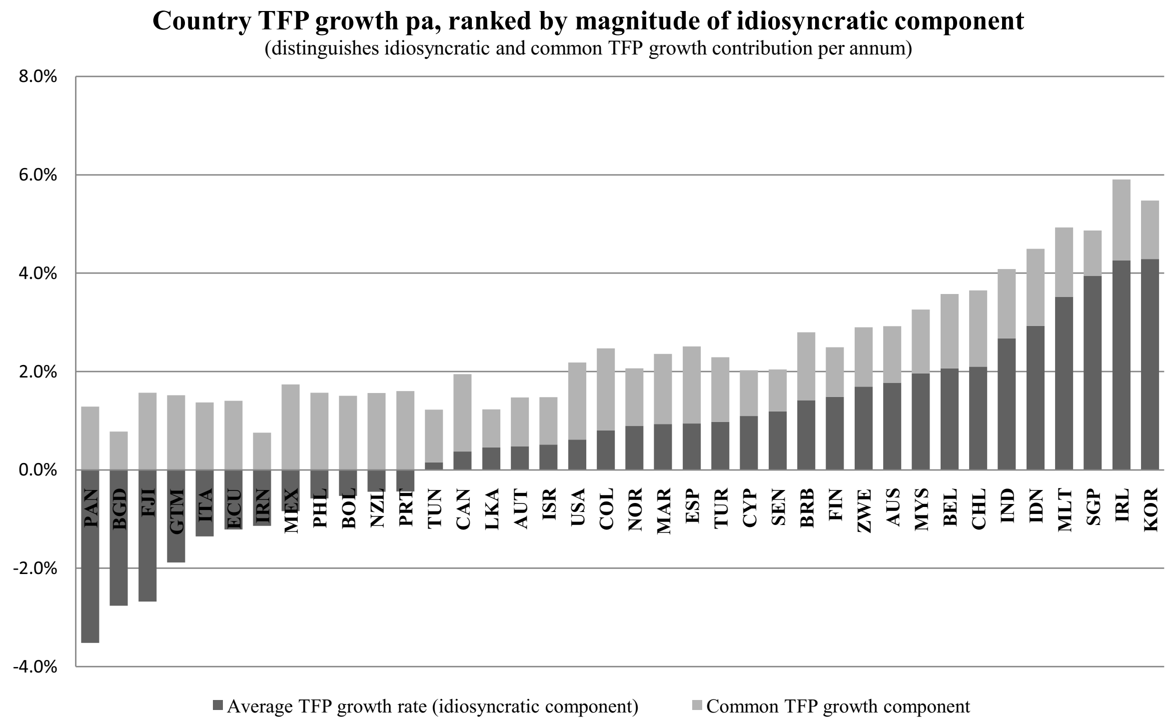
Figure D-1: Kernel densities for factor parameter estimates (gross-output)



Kernel density plot for capital ($\hat{\beta}_i$) and material ($\hat{\gamma}_i$) coefficients from the country regressions (gross-output based analysis, CRS and common dynamic process imposed, country trends included).

Figure D-2: Adjusted TFP levels and growth rates pa (VA specification) (computed from AMG estimates in Table 4)





Total average TFP growth rates are the sums of the idiosyncratic components (dark bars) and the common components (light bars). The latter are derived from the value-added version of the 'common dynamic process' $\hat{\mu}_t^\bullet$. Since countries do not all have identical time-series dimensions (T ranges from 11 to 33) and $\hat{\mu}_t^\bullet$ is nonlinear (see Figure 1) the contribution of common TFP differs by country.