PRODUCTIVITY ANALYSIS IN GLOBAL MANUFACTURING PRODUCTION*

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This version: 2nd November 2010

Abstract: Despite the widely recognised importance of the manufacturing industry for successful development few studies investigate this sector in cross-country analysis. We fill this gap in the literature by analysing manufacturing production across a large number of developing and developed economies. Our empirical framework allows for heterogeneous production technology and accounts for endogeneity as well as cross-section dependence in the panel. Our results imply that differences in production technology are of crucial importance for understanding cross-country differences in labour productivity and their underlying causes. In the light of these findings the interpretation of regression intercepts as TFP level estimates collapses and we introduce an alternative measure which is robust to parameter heterogeneity.

Keywords: Cross-Country Analysis; Parameter Heterogeneity; Productivity Levels; Panel Time Series Econometrics; Common Factor Model

JEL classification: C23, O14, O47

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*We are grateful to Michael Binder, Steve Bond, Steven Durlauf, David Hendry, John Muellbauer, Hashem Pesaran, Ron Smith and Jonathan Temple for helpful comments and suggestions. We further benefited from comments during presentations at the 2nd Advanced Summer School at the Department of Economics of the University of Crete, the Gorman Student Research Workshop and the Productivity Workshop, University of Oxford, the Nordic Conference for Development Economics in Stockholm, the Economic & Social Research Council (ESRC) Development Economics conference in Brighton, the International Conference for Factor Structures for Panel and Multivariate Time Series Data in Maastricht and the DEGIT XV conference in Frankfurt. All remaining errors are our own. This document is an output from research funded by the UK Department for International Development (DfID) as part of the iiG, a research programme to study how to improve institutions for pro-poor growth in Africa and South-Asia. The first author further acknowledges financial support from the ESRC [grant numbers PTA-031-2004-00345 and PTA-026-27-2048]. The views expressed are not necessarily those of DfID or the ESRC.

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1 Introduction

The central importance of the manufacturing sector for successful development has become a widely recognised 'stylised fact' in development economics. Yet in contrast to the literature on cross-country growth regressions using aggregate economy data (see survey by Durlauf, Johnson and Temple, 2005) there is limited empirical work dedicated to the analysis of the manufacturing sector in a large cross-section of countries — with the notable exception of Martin and Mitra (2002), cross-country empirical analysis *at the sectoral level* is typically based on Total Factor Productivity (TFP) accounting and/or limited to OECD countries (Bernard and Jones, 1996a; Harrigan, 1999; Malley, Muscatelli and Woitek, 2003; Hultberg, Nadiri and Sickles, 2004). If manufacturing matters for development it seems self-evidently important to learn about the production process and its drivers in this industrial sector.

In this paper we attempt to fill this gap in the literature by estimating cross-country production functions for the manufacturing sector in 48 developing and developed countries using annual data from 1970 to 2002 (UNIDO, 2004). Building on earlier work on growth empirics (Eberhardt and Teal, 2010) we show that technology differences are of crucial importance for understanding cross-country differences in labour productivity and their causes (Durlauf, Kourtellos and Minkin, 2001). Note that we refer to heterogeneity in 'technology parameters' to indicate differential production parameters on observable and unobservable inputs across countries, not merely country-specific TFP growth terms. This aside our study emphasises the importance of time-series properties of inputs and TFP (Nelson and Plosser, 1982; Bernard and Jones, 1996b; Funk and Strauss, 2003; Bond, Leblebicioglu and Schiantarelli, 2010) as well as of accounting for cross-section correlation in the panel (Moscone and Tosetti, 2009; Chudik, Pesaran and Tosetti, 2010; Sarafidis and Wansbeek, 2010).[1] We adopt a common factor modelling framework (Bai and Ng, 2004; Pesaran, 2006; Bai, 2009b; Kapetanios, Pesaran and Yamagata, 2011) and employ empirical estimators that can accommodate all of the above matters (Pesaran, 2006; Bond and Eberhardt, 2009).[2]

Our findings have important implications for productivity analysis both at the sectoral and the aggregate economy level: *first*, like firms in different industries, different countries are characterised by different production technologies. Our study shows that attempts at estimating cross-country production functions in pooled models, where by construction the same technology applies in all countries, are fundamentally misspecified and yield biased estimates for the technology parameters and thus any TFP estimates derived from them. *Second*, merely allowing for technology heterogeneity is also insufficient to capture the complex production process at the country-level: in a globalising world economies interact through trade, cultural, political and other ties and at the same time are affected differentially by global phenomena such as the recent financial crisis or the emergence of China as a major economic player. This creates a web of interdependencies within and across economies, leading to the breakdown of standard panel estimators employed in the existing cross-country studies. Our empirical strategy accommodates this interplay of endogeneity, heterogeneity and commonality to provide evidence for the fundamental forces driving manufacturing development across the globe. *Third*, following on from these findings the conventional interpretation of regression intercepts as TFP level estimates breaks down once production technology is allowed to differ across countries. We introduce an alternative methodology for TFP level determination which is robust to this feature and provide an analysis for the manufacturing case.

[1] Empirical productivity analysis which allows for cross-section dependence is still *relatively* limited, e.g. production functions for Italian regions (Costantini and Destefanis, 2009) or Chinese provinces (Fleisher, Li and Zhao, 2010).

[2] In order to avoid confusion with the 'common factor model' terminology we refer to 'factor inputs' (i.e. the factors of production, labour and capital) simply as inputs. Whenever we talk of 'factors' we mean to refer to $\boldsymbol{f}_t$.

The analysis here represents a step toward making cross-country empirics relevant to individual countries by moving away from empirical results that characterise the average country and toward a deeper understanding of the differences (Ranis and Fei, 1988), a notion which is clearly echoed elsewhere in the literature (Quah, 1997; Temple, 1999; Durlauf, 2001; Durlauf et al., 2001, 2005). Cross-country regressions of time averages, in the neoclassical tradition of Barro (1991) and Mankiw, Romer and Weil (1992), emphasise the variation in the data across countries ('between variation') and implicitly assume that the processes driving capital accumulation in, say, the United States are the same as those in Malawi, and that at a distant point in time the latter can feasibly reach the capital-labour ratio of the former to achieve the same level of development. However, this is not how development takes place. Instead, the very word 'development' suggests an evolution over time, which requires that apart from recognising the potential for differences across countries we analyse the individual evolution paths of countries over time (thus emphasising the 'within variation' in the data). The empirical methods used in this paper enable us to incorporate all of these concerns within one unifying empirical framework. At present our results only *allow for* technology differences across countries. Future work in this area will have to follow the call toward an integrated treatment of the production technology in its entirety, which is able "to explain *why* this parameter heterogeneity exists" (Durlauf et al., 2001, p.935).

The remainder of the paper is structured as follows: in the first part of the paper in Sections 2 to 4 we concern ourselves with the conceptual motivation, set out the empirical model and discuss empirical implementation. In the second part in Section 5 we introduce the data and present our empirical results. The third part in Section 6 covers the implications of these findings for conventional TFP determination in the parametric literature, providing a simple alternative methodology. Section 7 concludes.

2 Modelling technology over time and across countries

In this section we motivate the concerns with which we approach the estimation of cross-country production functions. Technology heterogeneity as well as the time-series and cross-section correlation properties of macro panel data have not been considered in great detail in the *empirical* growth literature (Durlauf and Quah, 1999; Temple, 1999; Durlauf et al., 2005), but have solid foundations in the *theoretical* literatures on growth and econometrics. We discuss each of these issues in some more details in the following.

A theoretical justification for heterogeneous technology parameters can be found in the 'new growth' literature. This strand of the theoretical growth literature argues that production functions differ across countries and seeks to determine the sources of this heterogeneity (Durlauf et al., 2001). Intuitively, the heterogeneity in production technology could be taken to mean that countries can choose an 'appropriate' production technology from a menu of feasible options. The model by Azariadis and Drazen (1990) can be seen as the 'grandfather' for many of the theoretical attempts to allow countries to possess different technologies from each other. Their model incorporates a qualitative change in the production function, whereby upon reaching a critical 'threshold' of human capital, economies will jump to a higher steady-state equilibrium growth path represented by a different production function. Further theoretical work leads to multiple equilibria interpretable as differential production technology across countries (e.g. Murphy, Shleifer and Vishny, 1989; Durlauf, 1993; Banerjee and Newman, 1993). A simpler justification for heterogeneous production functions is offered by Durlauf et al. (2001), namely that the Solow model was never intended to be valid in a homogeneous specification for *all* countries, but may still be a good way to investigate *each* country, i.e. if we allow for parameter differences *across* countries.

In the long-run, variable series such as value-added or capital stock often display high levels of persistence, such that it is not unreasonable to suggest for these series to be 'nonstationary' processes in *some* countries (Nelson and Plosser, 1982; Granger, 1997; Lee, Pesaran and Smith, 1997; Rapach, 2002; Bai and Ng, 2004; Pedroni, 2007; Canning and Pedroni, 2008). Although economic time-series in practice are usually not precisely integrated of any given order, it is for our purposes sufficient to assume that nominal and real value series typically behave as I(2) and I(1) respectively (Hendry, 1995; Jones, 1995). Pedroni has suggested that variable (non)stationarity should not be seen as a 'global' property, valid for all times, but as a "feature which describes local behaviour of the series within sample" (Pedroni, 2007, p.432).

In our general empirical model we emphasise a view of TFP as a 'measure of our ignorance' (Abramowitz, 1956), incorporating a wider set of factors that can shift the production possibility frontier (for instance "resource endowments, climate, institutions, and so on", Mankiw et al., 1992, p.410/1). This is in contrast to the notion of TFP as a definitive efficiency index, as commonly adopted in the microeconometric literature on production analysis. Furthermore, it is important to allow for the possibility that TFP is *in part* common to all countries, e.g. representing the global dissemination of non-rival scientific knowledge or global shocks, such as the recent financial crisis or the 1970s oil crises. Alternatively, we can think of multiple economic, social, political and cultural ties between countries from which commonality (cross-section correlation) may arise. The individual evolution paths of the unobservables making up TFP should feasibly not be restrained to follow simple linear trends, but instead be allowed to evolve in a non-linear and even nonstationary fashion. For instance, a number of empirical papers report that their measures of TFP display nonstationarity, whether analysed at the economy level (Coe and Helpman, 1995; Coe, Helpman and Hoffmaister, 1997; Kao, Chiang and Chen, 1999; Engelbrecht, 2002; Bond, Leblebicioglu and Schiantarelli, 2007) or at the sectoral level (Bernard and Jones, 1996b; Funk and Strauss, 2003). Further, Coakley, Fuertes and Smith (2006) state explicitly with reference to cross-country production function estimation that technology shocks are plausibly nonstationary. At the same time a highly flexible approach to empirical modelling using annual data raises the question of how business cycles influence or distort the empirical estimates (Eberhardt and Teal, 2010). All of these concerns point to the adoption of a multi-factor TFP structure that allows for common as well as country-specific elements. We implement this structure by using the uniquely suited common factor modelling framework (Bai, 2009b).

Taking these insights about heterogeneity, cross-section dependence and nonstationarity at face value one may then suggest that the macro production process is representative of a cointegrating relationship between output and 'some set of inputs', likely *including* TFP (Pedroni, 2007; Canning and Pedroni, 2008). Our analysis here will incorporate an investigation of the cointegration properties of production inputs and TFP in the long-run equilibrium production function. It is important to note that existing empirical work has primarily concerned itself with the (potential) endogeneity of regressors in the empirical framework (e.g. Caselli, Esquivel and Lefort, 1996; Bond, Hoeffler and Temple, 2001), an issue that is given considerably more attention in the literature than the data properties or the potential misspecification of the empirical regression model. While the empirical methods adopted here can address the simultaneity between TFP shocks and input accumulation, we need to resort to an alternative estimation approach following Pedroni (2001) to rule out the potential of reverse causality and assure us that our regressions represent production function models and not investment or labour demand equations in disguise. Thus in addition to incorporating much desirable technology heterogeneity, our empirical analysis addresses all the concerns that have occupied the standard literature.

3 Empirical framework

We adopt a common factor representation for a standard log-linearised Cobb-Douglas production function model: for $i = 1, \ldots, N$, $t = 1, \ldots, T$ and $m = 1, \ldots, k$ let

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

where $\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$. y_{it} represents value-added and $\boldsymbol{x}_{it}$ is a vector of observable inputs including labour and capital stock (all in logarithms). For unobserved TFP we employ the combination of a country-specific TFP level α_i and a set of common factors $\boldsymbol{f}_t$ with country-specific factor loadings $\boldsymbol{\lambda}_i$ — TFP is thus in the spirit of a 'measure of our ignorance' (Abramowitz, 1956) and operationalised via an unobserved common factor representation. In equation (2) we provide an empirical representation of the k observable input variables, which are modeled as linear functions of the unobserved common factors $\boldsymbol{f}_t$ and $\boldsymbol{g}_t$, with country-specific factor loadings respectively. The model setup thus introduces cross-section dependence in the observables and unobservables. As can be seen, some of the unobserved common factors driving the variation in y_{it} in equation (1) also drive the regressors in (2). This setup leads to endogeneity whereby the regressors are correlated with the unobservables of the production function equation (u_{it}), making it difficult to identify $\boldsymbol{\beta}_i$ separately from $\boldsymbol{\lambda}_i$ and $\boldsymbol{\rho}_i$ (Kapetanios et al., 2011).[3] Technology parameters $\boldsymbol{\beta}_i$ can differ across countries but are assumed constant over time.[4] Equation (3) specifies the evolution of the unobserved factors, which includes the potential for nonstationary factors ($\boldsymbol{\varrho} = 1$, $\boldsymbol{\kappa} = 1$) and thus nonstationary inputs and output variables. Note that the common factor framework is sufficiently general to allow for common and heterogeneous business cycles which are commonly seen to distort empirical analysis using annual data.[5]

The three most important features of the above setup are the potential nonstationarity of observables and unobservables (y_{it}, $\boldsymbol{x}_{it}$, $\boldsymbol{f}_t$, $\boldsymbol{g}_{mt}$), the potential heterogeneity in the impact of observables and unobservables on output across countries (α_i, $\boldsymbol{\beta}_i$, $\boldsymbol{\lambda}_i$) as well as the endogeneity of observable input variables created by the common factor structure. These properties have important bearings on estimation and inference in macro panel data which are at the heart of this paper.

4 Empirical implementation

The matters of parameter heterogeneity, data time-series properties and cross-section dependence in empirical analysis using macro panel data are developed at great length elsewhere (Eberhardt and Teal, 2010). In this section we therefore restrict ourselves to the discussion of the identification problem highlighted above, before we introduce two estimators which allow for heterogeneity in the impact of observables and unobservables.

[3]Note that the common factor setup is transferable to the micro-level setup where Arellano and Bond (1991); Blundell and Bond (1998) and Levinsohn and Petrin (2003) (amongst others) are concerned about 'unobserved productivity shocks' (see Bai, 2009a).

[4]The latter assumption is clearly restrictive, but given the focus on cross-country technology heterogeneity against the background of data restrictions in the time-series dimension we cannot relax this assumption for the *heterogeneous* regression models. For the *pooled* models we ran separate regressions using pre- and post-1985 subsamples for the value-added models. Estimates for POLS, CCEP and FD-OLS are virtually identical for the two sub-periods. Period estimates for the FE estimator differ somewhat but the 95% confidence intervals still show *considerable* overlap.

[5]For details see Eberhardt and Teal (2010, Section 4).

If we assume factors $\boldsymbol{f}_t$ (and $\boldsymbol{g}_{mt}$) in our general model above are *stationary*, the consistency of standard panel methods such as a pooled Fixed Effects or a Pesaran and Smith (1995) Mean Group estimator rests on the factor loadings of the unobserved common factors *contained in both the y and $\boldsymbol{x}$-equations* ($\boldsymbol{\lambda}_i$, $\boldsymbol{\rho}_i$): if their averages are jointly non-zero a regression of y on $\boldsymbol{x}$ and N intercepts will be subject to the omitted variable problem and hence misspecified, since regression error terms will be correlated with the regressor, leading to biased estimates and incorrect inference (Coakley et al., 2006; Pesaran, 2006). In the case of *nonstationary* factors the consistency issues are altogether more complex and will depend on the exact specification of the model. However, regardless of their order of integration, standard estimation approaches neglecting common factors will not yield an estimate of β or the mean of $\boldsymbol{\beta}_i$, but of $\boldsymbol{\beta}_i + \boldsymbol{\lambda}_i \boldsymbol{\rho}_i^{-1}$, as shown by Kapetanios et al. (2011): $\boldsymbol{\beta}_i$ is *unidentified*. Under the specification described, a standard pooled Fixed Effects or Pesaran and Smith (1995) Mean Group estimator will therefore likely yield an inconsistent estimator (due to residual nonstationarity) of a parameter we are not interested in (due to the identification problem).

Our empirical approach emphasises the importance of parameter and factor loading heterogeneity across countries. The following 2×2 matrix indicates how the various estimators implemented below account for these matters.[6] We abstract from discussing the *standard* panel estimators here and refer to the overview article by Coakley et al. (2006), as well as the articles by Pedroni (2000, 2001) for more details.

	Factor loadings:	
Technology parameters:	homogeneous	heterogeneous
homogeneous	POLS, FE, FD-OLS	CCEP
heterogeneous	MG, RCM, GM-FMOLS	CMG, AMG, ARCM

Essentially, in our model setup all estimators *neglecting* the heterogeneity in unobservables (left column) suffer from the identification problem described above. In addition, the time-series properties of both observable and unobservable processes create further difficulties for estimation and inference in these empirical approaches as errors may be nonstationary. Inference is problematic in this case since conventional standard errors will be invalid (Kao, 1999). Among these estimators the Pedroni (2000) GM-FMOLS is the only one avoiding this issue by adopting a nonstationary panel econometric approach relying on cointegrated variables.

The estimators *allowing for* heterogeneity in factor loadings adopted here (right column) operate through augmenting the regression equation(s) with 'proxies' or estimates for the unobserved common factors. This augmentation avoids the identification problem and is also an appropriate strategy to account for other cross-section dependence, e.g. spatial correlation, in the presence of nonstationary variables (Pesaran and Tosetti, 2010; Chudik et al., 2010; Kapetanios et al., 2011). The Pesaran (2006) CCE estimators account for the presence of unobserved common factors by including cross-section averages of the dependent and independent variables in the regression equation — in the pooled version (CCEP) these averages are interacted with country-dummies to allow for country-specific parameters, whereas in the heterogeneous version (CMG) this is achieved by construction and the estimates are obtained as averages of the individual country estimates, following the Pesaran and Smith (1995) MG approach. A related approach which we term the Augmented Mean Group (AMG) estimator accounts for cross-section dependence by inclusion of a 'common dynamic process' in the country regression. This

[6] Abbreviations: POLS — Pooled OLS, FE — Fixed Effects, FD-OLS — OLS with variables in first differences, MG — Pesaran and Smith (1995) Mean Group, RCM — Swamy (1970) Random Coefficient Model, GM-FMOLS — Pedroni (2000) Group-Mean Fully Modified OLS, CCEP/CMG — Pesaran (2006) Common Correlated Effects estimators, and AMG/ARCM — Augmented MG and RCM, described in detail below. Note that our FE estimator (like the OLS and FD-OLS) is augmented with $T-1$ year dummies such that it is in effect a 'Two-Way Fixed Effects' (2FE) estimator.

process is extracted from the year dummy coefficients of a pooled regression in first differences (FD-OLS) and represents the levels-equivalent mean evolution of unobserved common factors across all countries. Provided the unobserved common factors form part of the country-specific cointegrating relation (Pedroni, 2007), the augmented country regression model encompasses the cointegrating relationship, which is allowed to differ across i.

$$\text{Stage (i)} \qquad \Delta y_{it} = \boldsymbol{b}'\Delta \boldsymbol{x}_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \qquad \Rightarrow \hat{\boldsymbol{c}}_t \equiv \hat{\mu}_t^{\bullet} \tag{4}$$

$$\text{Stage (ii)} \qquad y_{it} = a_i + \boldsymbol{b}_i'\boldsymbol{x}_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \qquad \hat{\boldsymbol{b}}_{AMG} = N^{-1}\sum_i \hat{\boldsymbol{b}}_i \tag{5}$$

Stage (i) represents a standard FD-OLS regression with $T-1$ year dummies in first differences, from which we collect the year dummy coefficients (relabelled as $\hat{\mu}_t^{\bullet}$). This process is extracted from the pooled regression *in first differences* since nonstationary variables and unobservables are believed to bias the estimates in the pooled *levels* regressions. In stage (ii) $\hat{\mu}_t^{\bullet}$ is included in each of the N standard country regressions which also include a linear trend term to capture omitted idiosyncratic processes evolving in a linear fashion over time. Alternatively we can subtract $\hat{\mu}_t^{\bullet}$ from the dependent variable, which implies the common process is imposed on each country with unit coefficient. In either case estimates are averaged across countries following the Pesaran and Smith (1995) MG approach. Based on the results of Monte Carlo simulations (Bond and Eberhardt, 2009) we posit that the inclusion of $\hat{\mu}_t^{\bullet}$ allows for the *separate* identification of $\boldsymbol{\beta}_i$ or $\mathbb{E}[\boldsymbol{\beta}_i]$ and the unobserved common factors driving output and inputs, like in the Pesaran (2006) CCE approach. In analogy, we can use $\Delta\hat{\mu}_t^{\bullet}$ in the country equations in first differences and can augment the Swamy (1970) RCM estimator in a similar fashion to yield the Augmented Random Coefficient Model (ARCM) estimators in levels and first differences — results for the ARCM were very similar to those in the AMG and in the interest of space are therefore omitted in the empirical section. We also applied an alternative version of the estimator where the first stage allows for heterogeneous slopes across countries: results for the AMG second stage are next to identical to those presented in Table 2.

The focus of the CCE estimators is the estimation of consistent $\hat{\boldsymbol{b}}$ and not the nature of the unobserved common factors or their factor loadings: we cannot obtain an explicit estimate for the unobserved factors $\boldsymbol{f}_t$ or the factor loadings $\boldsymbol{\lambda}_i$, since the *average* impact of the factors ($\bar{\boldsymbol{\lambda}}$) is unknown. Our augmented estimators use an *explicit* rather than implicit estimate for $\boldsymbol{f}_t$ from the pooled first stage regression. Compared with the CCE approach we can obtain a simple but economically meaningful construct from the AMG setup: the common dynamic process $\hat{\mu}_t^{\bullet} = h(\bar{\boldsymbol{\lambda}}\boldsymbol{f}_t)$ represents common TFP evolution over time, whereby *common* is defined either in the literal sense, or as the sample mean of country-specific TFP evolution. The country-specific coefficient on the common dynamic process, $\hat{d}_i$ from equation (5), represents the implicit factor loading on common TFP.

Immediate concerns about this augmented estimator relate to the issue of second stage 'regressions with generated regressors' (Pagan, 1984). However, simulation results (Bond and Eberhardt, 2009) suggest that the average standard error of the AMG estimates is of similar magnitude to the empirical standard deviation. A theoretical explanation is provided in Bai and Ng (2008), who show that second stage standard errors need not be adjusted for first stage estimation uncertainty if $\sqrt{T}/N \rightarrow 0$, as is arguably the case here.

5 Data and main empirical results

5.1 Data

For our empirical analysis we employ aggregate sectoral data for manufacturing from developed and developing countries for the period 1970 to 2002 (UNIDO, 2004). Our sample represents an unbalanced panel of 48 countries with an average of 24 time-series observations (min: 11, max: 33). A detailed discussion of the data and descriptive statistics can be found in the Appendix. *All* of the results presented are strikingly robust to the use of a reduced sample constructed with application of a set of rigid 'cleaning' rules. Furthermore, we carried out all regressions below in a gross-output model with materials as additional input — VA-equivalent results are virtually identical to those presented here (detailed results available on request).

5.2 Time-series properties of the data

We carried out a range of stationarity and nonstationarity tests for individual country time-series as well as the panel as a whole (full results available on request). The panel unit root tests conducted include first (Im, Pesaran and Shin, 1997; Maddala and Wu, 1999) and second generation procedures (Pesaran, 2007) — see Technical Appendix. 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 suggest *most conservatively* that nonstationarity cannot be ruled out in this dataset.

5.3 Pooled regressions

We estimate pooled models with variables in levels or first differences, including $T-1$ year dummies or country-specific period-averages *à* la Pesaran (2006). By construction, the slope coefficients on the inputs in these models are restricted to be *the same* across all countries. Our results are presented in Table 1, with unrestricted models and models with CRS imposed in the upper and lower panel respectively.

Estimates for the input parameters in the regressions without any restrictions on the returns to scale are statistically significant at the 5% level or 1% level. The POLS results in [1] suggest that failure to account for time-invariant heterogeneity across countries (fixed effects) yields biased results: at around .8 the capital coefficient is considerably inflated. Inclusion of country intercepts in [2] reduces these coefficient estimates somewhat. The same parameter in the CCEP results in [3] is yet lower still, around .6. In both the FE and CCEP estimators the fixed effects are highly significant (F-tests reported in the Table footnote). For all three estimators in levels the regression diagnostics suggest serial correlation in the error terms, while constant returns to scale are rejected at the 1% level of significance except for POLS. Note that for the FE estimator the data rejects CRS in favour of increasing returns — an unusual finding. The OLS regressions in first differences in [4] yield somewhat different technology estimates: the capital coefficient is now around .3 in both specifications. CRS cannot be rejected, the AR(1) tests show serial correlation for this model, which is to be expected given that errors are now in first differences. There is however evidence of some higher order autocorrelation.[7]

[7] Note that we obtain identical results for models in [1], [2] and [4] if we use data in deviation from the cross-sectional mean (results not presented) instead of using a set of year dummies. Replacing year dummies with cross-sectionally demeaned data is only valid if parameters are homogeneous across countries (Pedroni, 1999, 2000).

Table 1: Static pooled regressions

Panel (A): Unrestricted Returns to Scale

	[1]	[2]	[3]	[4]
estimator	**POLS**	**FE**	**CCEP**	**FD**
dependent variable	lY	lY	lY	ΔlY
log labour	0.2100	0.4402	0.6009	
	[12.08]**	[17.43]**	[19.48]**	
Δlog labour				0.6849
				[7.43]**
log capital	0.7896	0.7174	0.6144	
	[67.34]**	[32.17]**	[22.76]**	
Δlog capital				0.3463
				[3.40]**
intercept	1.1510	-0.0470	-0.5160	
	[7.99]**	[0.13]	[0.98]	
CRS: F	.96	.00	.00	.72
FE: F		.00	.00	
AR(1)	.00	.00	.00	.00
AR(2)	.00	.00	.00	.01
I(1)	1.00	1.00	.00	.00
RMSE	.462	.130	.102	.103

Panel (B): CRS imposed

	[1]	[2]	[3]	[4]
estimator	**POLS**	**FE**	**CCEP**	**FD**
dependent variable	ly	ly	ly	Δly
log capital pw	0.7895	0.6752	0.5823	
	[72.97]**	[29.89]**	[23.38]**	
Δlog capital pw				0.3195
				[3.61]**
intercept	1.1474	2.3786	0.2489	
	[8.47]**	[9.98]**	[0.63]	
FE: F		.00	.00	
AR(1)	.00	.00	.00	.00
AR(2)	.00	.00	.00	.01
I(1)	1.00	.78	.00	.00
RMSE	.462	.135	.113	.103

Notes: Values in brackets are absolute t-statistics, based on White heteroskedasticity-consistent standard errors. We indicate statistical significance at the 5% and 1% level by * and ** respectively. Regressions are for $N = 48$ countries, $n = 1,194$ ($n = 1,128$) observations in the levels (first difference) regressions. Dependent variables: lY (ly) — log value-added (per worker), ΔlY(Δly) — growth rate of value-added (per worker). For the CCEP estimator we include sets of cross-section period averages of value-added, labour, and capital stock (in the CRS equations the respective variables in per worker terms), all in logs (estimates not reported) — see Pesaran (2006) for details. All other models include $T - 1$ year dummies in levels or FD (estimates not reported). For all diagnostic tests (except RMSE) we report p-values: (i) The null hypothesis for the Wald tests is constant returns. (ii) The F-tests in the FE and CCEP regressions reject the null that fixed effects do not differ across countries. (iii) The Arellano and Bond (1991) AR test on the residuals has the null of no serial correlation. (iv) 'I(1)' reports results for a Pesaran (2007) CIPS test with 2 lags, null of nonstationarity (full results available on request). (v) RMSE is the root mean squared error.

Under intercept *and* technology parameter heterogeneity, given nonstationarity in (some of) the country variable series the pooled FE estimates in column [2] asypmtotically converge to the 'long-run average' relation at speed $\sqrt{N}$ (Phillips and Moon, 1999) provided $T/N \to 0$ (joint asymptotics) and cross-section independence. In the present sample, however, nonstationary error terms and unobserved common factors seem to influence the results considerably: a capital coefficient of around .7 is more than twice the magnitude of the macro data on factor shares in income (Mankiw et al., 1992; Gomme and Rupert, 2004), a common finding in the literature (Islam, 2003; Pedroni, 2007). Further recall that t-ratios are invalid for the estimations *in levels* if error terms are nonstationary (Kao, 1999; Coakley, Fuertes and Smith, 2001). The CCEP estimator accounts for cross-section dependence and the residual analysis suggests, stationary errors terms. The difference estimator in [4] converges to the common cointegrating vector $\boldsymbol{\beta}$ or $\boldsymbol{\beta}$ or the mean of the individual country cointegrating relations, $\mathbb{E}[\boldsymbol{\beta}_i]$, at speed $\sqrt{TN}$ (Smith and Fuertes, 2007). investigation regarding alternative specification with parameter heterogeneity as well as residual diagnostics will be necessary to judge the bias of the CCEP results.

Our pooled regression analysis suggests that time-series properties of the data play an important role in estimation: we suggest that the bias in the levels models is the result of nonstationary errors, which are introduced into the pooled OLS and FE equations by the imposition of parameter homogeneity. In contrast, the FD-OLS regressions where variables are stationary yield more sensible capital parameters. This pattern of results fits the case of I(1) level-series in at least some of the countries in our sample. The results for the CCEP are somewhat surprising and we would speculate that these are driven by outliers.

5.4 Common TFP

Following our argument above, the FD-OLS regression represents the only pooled regression 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 model to obtain an estimate of the common dynamic process $\hat{\mu}_t^\bullet$, which represents an estimate of the common TFP evolution. Figure 1 illustrates the evolution path of this common dynamic process for the unrestricted and CRS models.

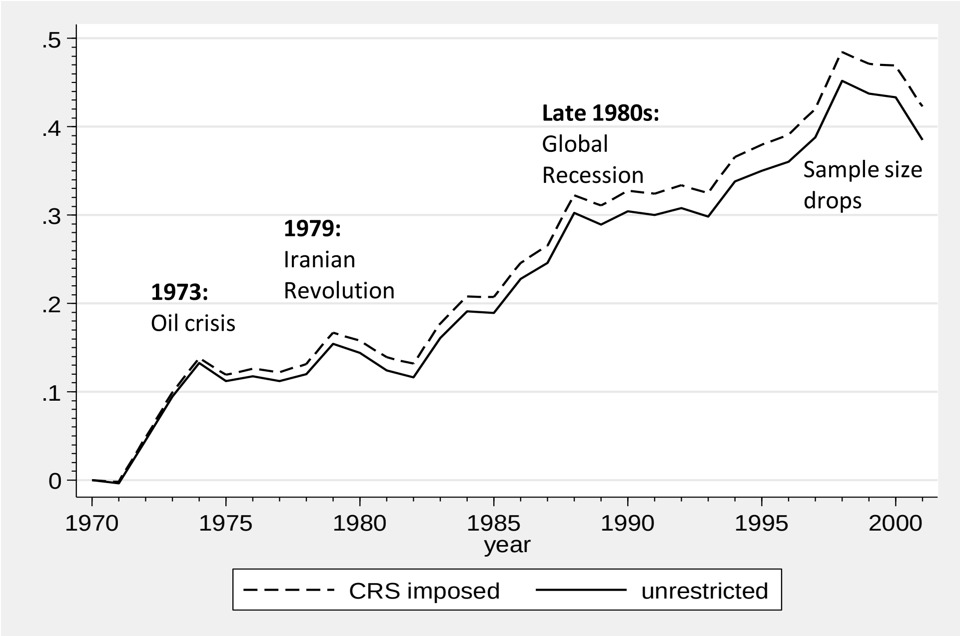
The graphs show severe slumps following the two oil shocks in the 1970s, while the 1980s and 1990s indicate considerable upward movement.[8] If we follow the 'measure of our ignorance' interpretation of TFP, then a decline in global manufacturing TFP as evidenced in the 1970s should not be interpreted as a decline in knowledge, but a worsening global manufacturing *environment*, which seems plausible. An alternative explanation may be that our variable deflation does not adequately capture all the price changes in general, and material input price changes vis-à-vis output prices in particular, occurring in the post-oil shock periods.

5.5 Country regressions

In the following we relax the assumption implicit in the pooled regressions that all countries possess the same production technology. At the same time, we maintain that common shocks and/or cross-sectional dependence have to be accounted for in some fashion. We consider: **[1]** the standard Pesaran and Smith (1995) Mean Group (MG) estimator; the Augmented Mean Group (AMG) estimator either **[2]** with the common dynamic process ($\hat{\mu}_t^\bullet$) imposed with unit coefficient, or **[3]** included as additional regressor. The Mean Group version of the Common

[8]These graphs are 'data-specific': for years where data coverage is good, this can be interpreted as 'global', whereas in later years (10 countries have data for 2001, only 2 for 2002, omitted from the graph) this interpretation collapses.

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



Notes: derived from results in column [4], Panels (A) and (B) of Table 1.

Correlated Effects estimator (CMG) is estimated in two alternative specifications, namely **[4]** as defined by Pesaran (2006), and **[5]** augmented with a country-specific linear trend term.[9]

Unweighted averages of country parameter estimates are presented for regressions in levels and first differences in the upper and lower panels of Table 2 respectively. In all cases we have imposed constant returns to scale on the country regression equation, in line with the findings from our preferred pooled model in first differences.

The t-statistics for the country-regression averages reported are measures of dispersion for the sample of country-specific estimates, following Pesaran and Smith (1995).[10] We further provide the Pedroni (1999) 'panel t-statistic' $(1/\sqrt{N})\sum_i t_i$, constructed from the country-specific t-statistics (t_i) of the parameter estimates, which indicates the precision of the individual country estimates. We can see that the individual country estimates for the *levels* specification are on average more precisely estimated than those in the specifications in *first differences*.

Our first observation regarding the levels results in Table 2 is that across all specifications the means of the capital coefficients are considerably lower than in the pooled levels models: between .2 and .5, rather than between .6 and .9 in the pooled levels models. Comparing results for the levels specification with those for the specification in first differences reveals that estimates from these two sets of heterogeneous models follow very similar patterns.[11]

[9]We do not use 'demeaned' data here, since cross-sectional demeaning is only valid if all model parameters are homogeneous across countries, but creates bias in case of parameter heterogeneity (Pedroni, 2000; Smith and Fuertes, 2007). If we apply 'demeaned' data results are in line with our argument of heterogeneous factor loadings (results not reported).

[10]These are computed from the standard errors $se(\hat{\beta}_{MG}) = [\sum_i(\hat{\beta}_i - \hat{\beta}_{MG})^2]^{-1/2}$.

[11]Results presented are robust to alternative specifications for the country-level deterministics (additional squared trend in the levels models, additional trend in the models in first difference; results not reported).

Table 2: Country regression averages (CRS imposed)

Panel (A): Models in Levels

	[1]	[2]	[3]	[4]	[5]
estimator	**MG**	**AMG**	**AMG**	**CMG**	**CMG**
dependent variable	ly	ly-$\hat{\mu}_t^{va\bullet}$	ly	ly	ly
log capital pw	0.1789	0.2896	0.2982	0.4663	0.3125
	[2.25]*	[3.95]**	[3.70]**	[6.76]**	[3.72]**
common trend			0.8787		
			[4.39]**		
country trend	0.0174	0.0001	0.0023		0.0108
	[5.95]**	[0.04]	[0.56]		[3.09]**
intercept	7.6528	6.3823	6.2431	0.8961	4.7860
	[9.05]**	[8.42]**	[7.40]**	[0.89]	[3.66]**
Panel t-statistics, trends†					
capital pw	12.42	16.55	17.43	31.86	16.15
country trend	27.65	20.40	12.12		16.08
# of sign. trends (at 10%)	39	28	19		24
Diagnostics					
I(1)	.00	.00	.00	.00	.00
RMSE	.100	.097	.091	.100	.088

Panel (B): Models in First Differences

	[1]	[2]	[3]	[4]	[5]
estimator	**ΔMG**	**ΔAMG**	**ΔAMG**	**ΔCMG**	**ΔCMG**
dep. var.	Δly	Δly-Δ$\hat{\mu}_t^{va\bullet}$	Δly	Δly	Δly
Δlog capital pw	0.1642	0.2734	0.2834	0.3837	0.2577
	[1.91]	[3.48]**	[3.77]**	[5.62]**	[3.48]**
common drift			1.0497		
	-	-	[5.71]**		
country drift	0.0161	-0.0011	-0.0020		0.0123
	[5.54]**	[0.44]	[0.50]		[3.76]**
Panel t-statistics, trends†					
capital pw	4.81	8.30	7.66	12.00	7.18
country trends	9.53	5.77	7.46		7.68
# of sign. trends (at 10%)	14	6	10		11
Diagnostics					
I(1)	.00	.00	.00	.02	.06
RMSE	.097	.094	.090	.090	.088

Notes: All variables are in logs. Dependent variable: ly — log value-added per worker. Δly — growth rate of value-added (per worker). $\hat{\mu}_t^{va\bullet}$ is derived from the year dummy coefficients of a pooled regression (CRS imposed) in first differences (FD-OLS) as described in the main text. Regressions are for $N = 48$ countries, $n = 1,194$ ($n = 1,128$) observations in the levels (first difference) regressions. We omit reporting the parameters on the cross-section averages for the CMG estimators (columns [4] and [5]) to save space. Values in brackets are absolute t-statistics following Pesaran and Smith (1995). These were obtained by regressing the N country estimates on an intercept term. We indicate statistical significance at the 5% and 1% level by * and ** respectively. 'I(1)' reports p-values for a Pesaran (2007) CIPS test with 2 lags, null of nonstationarity (full results available on request). RMSE is the root mean square error. † We also report the Pedroni (2000) panel-t statistics $N^{-1/2}\sum_i t_i$ where t_i is the country-specific t-statistic of the parameter estimate.

In all cases the technology parameters are estimated reasonably precisely and a considerable number of country trends/drifts are significant at the 10% level, although much more so for the levels than for the first difference specifications. The statistically insignificant *mean* of the trends in the AMG regression is easily explained: these country-specific trends have statistically significant positive and negative magnitudes for different countries, but average out across the sample as they represent deviations from the average TFP evolution $\hat{\mu}_t^{\bullet}$. Coefficients on the common dynamic process $\hat{\mu}_t^{\bullet}$ in model [3] for both specifications are uniformly high and close to their theoretical value of unity. Closer inspection of the capital coefficients suggests the following patterns: *firstly*, estimation approaches that do not account for unobserved common factors have parameter estimates around .2. *Secondly*, for the 'augmented' estimators which account for a common dynamic process in the estimation equation the averaged coefficients are around .3. *Thirdly*, the results for the CMG with and without additional country trend differ considerably, with the former close to all other augmented regression results and the latter slightly larger, around .45.

5.6 Diagnostic testing and robustness checks

We first investigated the density estimates for country-specific technology parameters estimated in the levels regressions using standard kernel methods with automatic bandwidth selection. The plots indicate that the distribution of these parameter estimates is symmetric around their respective means and roughly Gaussian, such that no significant outliers drive our results (available on request).

We further carried out a number of residual diagnostic tests other than the analysis of stationarity (results available on request). A cautious conclusion from these procedures would be that we are more confident about the country regression residuals possessing desirable properties (stationarity, normality, homoskedasticity) than we are for their pooled counterparts.

Cointegration tests are commonly carried out as a *pre*-estimation testing procedure, however we have delayed these until *after* estimation since we hypothesise that unobservable TFP forms part of the cointegrating vector. Employing our first stage estimate $\hat{\mu}_t^{\bullet,va}$ we carried out a cointegration testing procedure based on the error correction model representation, first introduced by Westerlund (2007) and refined by Gengenbach, Urbain and Westerlund (2009). This analysis (for results see Technical Appendix) implies that there are good grounds to suggest that value-added per worker, capital per worker and our estimate for TFP are heterogeneously cointegrated.

We also investigated parameter heterogeneity across countries using a number of formal testing procedures (results available on request). Taken together these results give a strong indication that parameter homogeneity is rejected in our empirical setup. Systematic differences in the test statistics for levels and first difference specifications 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 empirical analysis in the presence of nonstationary variables.

In the analysis of empirical production functions the issue of variable endogeneity is typically of great concern, requiring means and ways to instrument for inputs. We therefore adopted the empirical approach by Pedroni (2000, 2007) and estimated country regressions by Fully-Modified OLS, whereupon parameter estimates are averaged across countries (Group-Mean FMOLS). Provided the variables are nonstationary *and* cointegrated the individual FMOLS estimates are super-consistent and thus robust to the influence of variable endogeneity and other misspecifications (Pedroni, 2007). Our results (see Technical Appendix) show that the standard Pedroni (2000) approach yields insignificant capital estimates, whereas augmentation with the common dynamic process yields statistically significant estimates very close to those arising from our previous AMG regressions. Once we include $\hat{\mu}_t^{\bullet,va}$ we thus obtain the same empirical results in the Group-Mean Fully-Modified OLS and Mean Group OLS approaches. Alternative CCE-type specifications similarly mirror the results in Table 2; furthermore, our analysis is robust to a restriction of the sample to countries for which value-added and capital stock per worker 'pass' two (non)stationarity tests (the sample almost halves) and are thus not driven by sample selection. We take these results as a vindication of our previous findings.

5.7 Discussion of the main empirical results

We investigated the changing parameter estimates across a number of empirical specifications and estimators. Our pooled estimators in levels are suggested to be severely biased, given the diagnostic tests and the fact that their capital coefficients range from .6 to .8, far in excess of the macro evidence of around 1/3. This bias may arise from the misspecification of homogeneity and/or the failure to account for unobserved common factors appropriately. The fact that CCEP yields very similar results to POLS and FE suggests that interplay of parameter heterogeneity and variable stationarity plays an important role. The first difference estimator (FD-OLS) in contrast has sound diagnostics and yields sensible parameter coefficients.

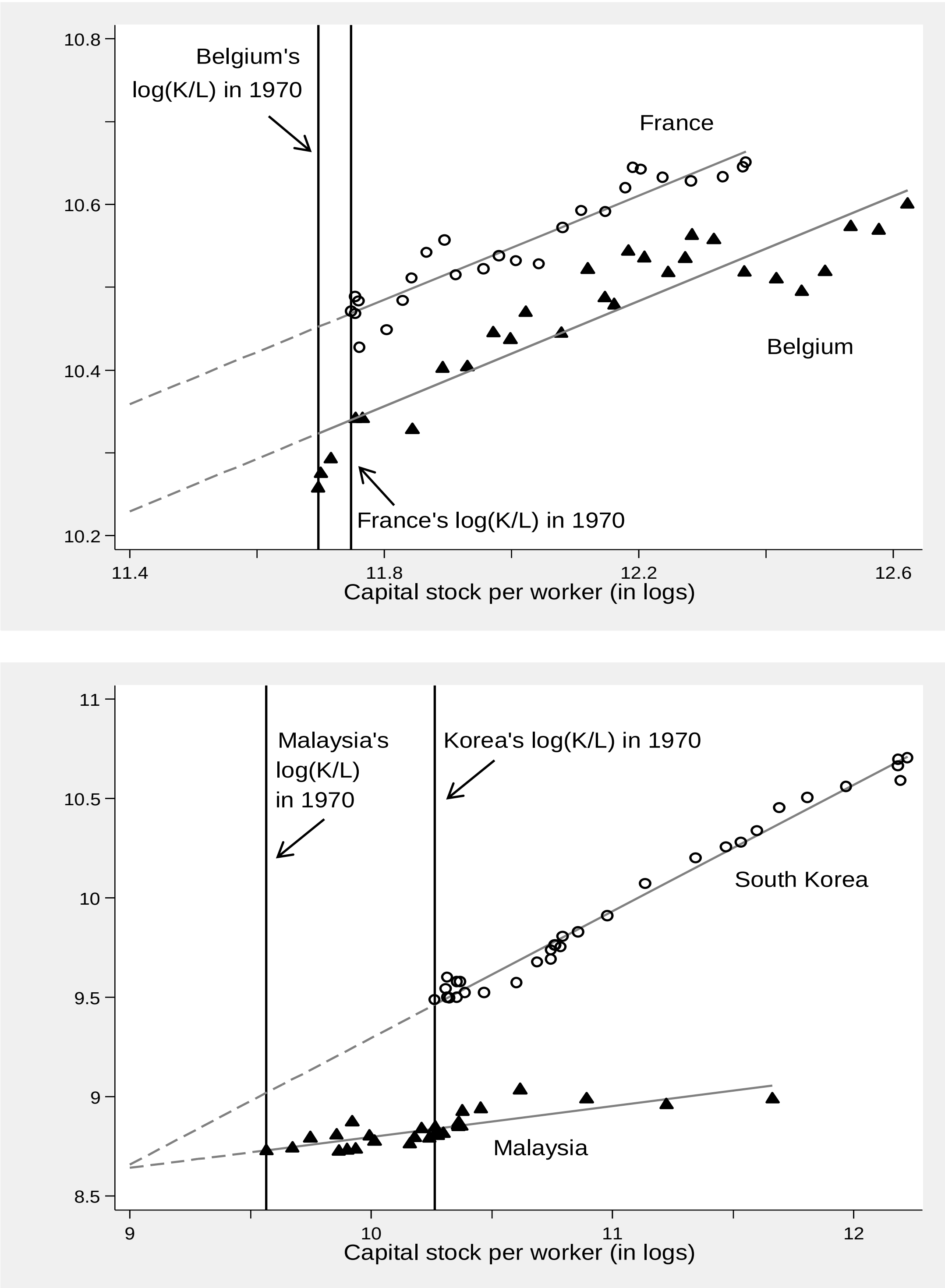
The heterogeneous parameter estimators yield uniformly lower capital coefficients, more in line with the aggregate economy factor income share data. Across levels and first difference, gross-output and value-added specifications (former available on request) there seems to be a consistent pattern whereby the standard heterogeneous MG estimator obtains qualitatively different results from the augmented estimators (AMG, CMG). Diagnostic tests cannot differentiate between these two groups of estimators, however we can argue that the MG estimator is likely to be biased: *firstly*, it uses an overly simplistic representation for TFP evolution (linear trend) which requires stationarity; *secondly*, it is argued to suffer from the identification problem introduced above.

Turning to the augmented estimators, we suggest that the combination of a common dynamic process and a linear country trend is confirmed by the data: a considerable number of country trends are statistically significant, while in the models which include $\hat{\mu}_t^{\bullet}$ as additional regressor its cross-country average coefficient is close to unity. The CMG estimator provides results broadly in line with those for the AMG, with the latter on the whole more consistent across specifications. The comparison between the country regression results presented above and the results for 'demeaned' variables (available on request) indicate that the unobserved common factors exert *differential* impact across countries, thus meriting the adoption of approaches which allow for heterogeneous factor loadings (and thus TFP).

6 TFP in a heterogeneous parameter world

For many applications the estimation of production functions is just the first step in an empirical analysis that concentrates on the magnitudes and determinants of TFP — at times TFP is almost treated as if it were an observable variable. In our analysis we have thus far focused on the magnitudes and robustness of the technology parameter estimates across different production function specifications. We now want to provide some estimates for TFP and its evolution, highlighting some conceptual difficulties arising in the process. From the preferred country regressions we can obtain estimates for the intercept, technology parameters, idiosyncratic and common trend coefficients or the parameters on the cross-section averages for AMG and CMG specification respectively. One may be tempted to view the coefficients on the intercepts as TFP level estimates, just like in the pooled fixed effects case. However, once we allow for heterogeneity in the slope coefficients, the interpretation of the intercept as an estimate for base-year TFP level is no longer valid. In order to illustrate our case, we employ a simple linear relationship between value-added and capital where the contribution of TFP *growth* has already been accounted for.

Figure 2: Regression intercepts and TFP level estimates



In Figure 2 we provide scatter plots for 'adjusted' log value-added per worker (y-axis) against log capital per worker (x-axis) as well as a fitted regression line for these observations in each of the following four countries: in the upper panel France (circles) and Belgium (triangles), in the lower panel South Korea (circles) and Malaysia (triangles). The 'adjustment' is based on the country-specific estimates from the AMG regression (Table 2, Panel (A), column [3]): we compute

$$y_{it}^{adj} = y_{it} - \hat{c}_i t - \hat{d}_i \hat{\mu}_t^{\bullet} \tag{6}$$

where $\hat{c}_i$ and $\hat{d}_i$ are the country-specific estimates for the linear trend term and the common dynamic process respectively. We then plot this variable against log capital per worker for each country separately. This procedure in essence provides a two-dimensional visual equivalent of the estimates for the capital coefficient (slope) and the TFP level (intercept) in the augmented country regression. The upper panel of Figure 2 shows two countries (France, Belgium) with virtually identical capital coefficient estimates (slopes). The in-sample fitted regression line is plotted as a solid line, the out-of-sample extrapolation toward the y-axis is plotted in dashes. The country-estimates for the intercepts can be interpreted as TFP levels, since these countries have very similar capital coefficient estimates ($\hat{b}_{FRA} \approx \hat{b}_{BEL}$). In this case, the graph represents the linear model $y_{it}^{adj} = \hat{a}_i + \hat{b} \log(K/L)_{it}$, where $\hat{a}_i$ possesses the *ceteris paribus* property. In contrast, the lower panel shows two countries (Malaysia, South Korea) which exhibit very different capital coefficient estimates. In this case $\hat{a}_i$ cannot be interpreted as possessing the *ceteris paribus* quality since $\hat{b}_{MYS} \neq \hat{b}_{KOR}$: *ceteris non paribus*! In the graph we can see that Malaysia has a considerably higher intercept term than South Korea, even though the latter's observations lie above those of the former at any given point in time. This illustrates that once technology parameters in the production function differ across countries the regression intercept can no longer be interpreted as a TFP-level estimate.

We can suggest an alternative measure for TFP-level which is robust to parameter heterogeneity. Referring back to the scatter plots in Figure 2, we marked the base-year level of log capital per worker by vertical lines for each of the four countries. We suggest to use the locus where the solid (in-sample) regression line hits the vertical base-year capital stock level as an indicator of TFP-level in the base year. These *adjusted* base-year and final-year TFP-levels are thus

$$\hat{a}_i + \hat{b}_i \log(\mathrm{K/L})_{0,i} \qquad \text{and} \qquad \hat{a}_i + \hat{b}_i \log(\mathrm{K/L})_{0,i} + \hat{c}_i \tau + \hat{d}_i \hat{\mu}_\tau^{\bullet} \tag{7}$$

respectively, where $\log(K/L)_{0,i}$ is the country-specific base-year value for capital per worker (in logs), τ is the total period for which country i is in the sample and $\hat{\mu}_\tau^{\bullet}$ is the accumulated *common* TFP growth for this period τ with the country-specific parameter $\hat{d}_i$ — it is easy to see that the intercept-problem discussed above only has bearings on TFP-*level* estimates. A similar formula applies for the CMG estimator.

Focusing exclusively on the TFP-levels in the base-year, Table 3 presents the rank (by magnitude) for adjusted TFP levels derived from the AMG and CMG estimators. We further show the country ranking based on a pooled fixed effects estimation, such as that presented in Table 2, column [2]. As can be seen in the right half of the table, the rankings differ considerably between the AMG or CMG results on the one hand and standard fixed effects results on the other (median absolute rank difference (MARD): 10, respectively), but not between the results for AMG and CMG (MARD: 1).

Table 3: Country rankings by TFP-level

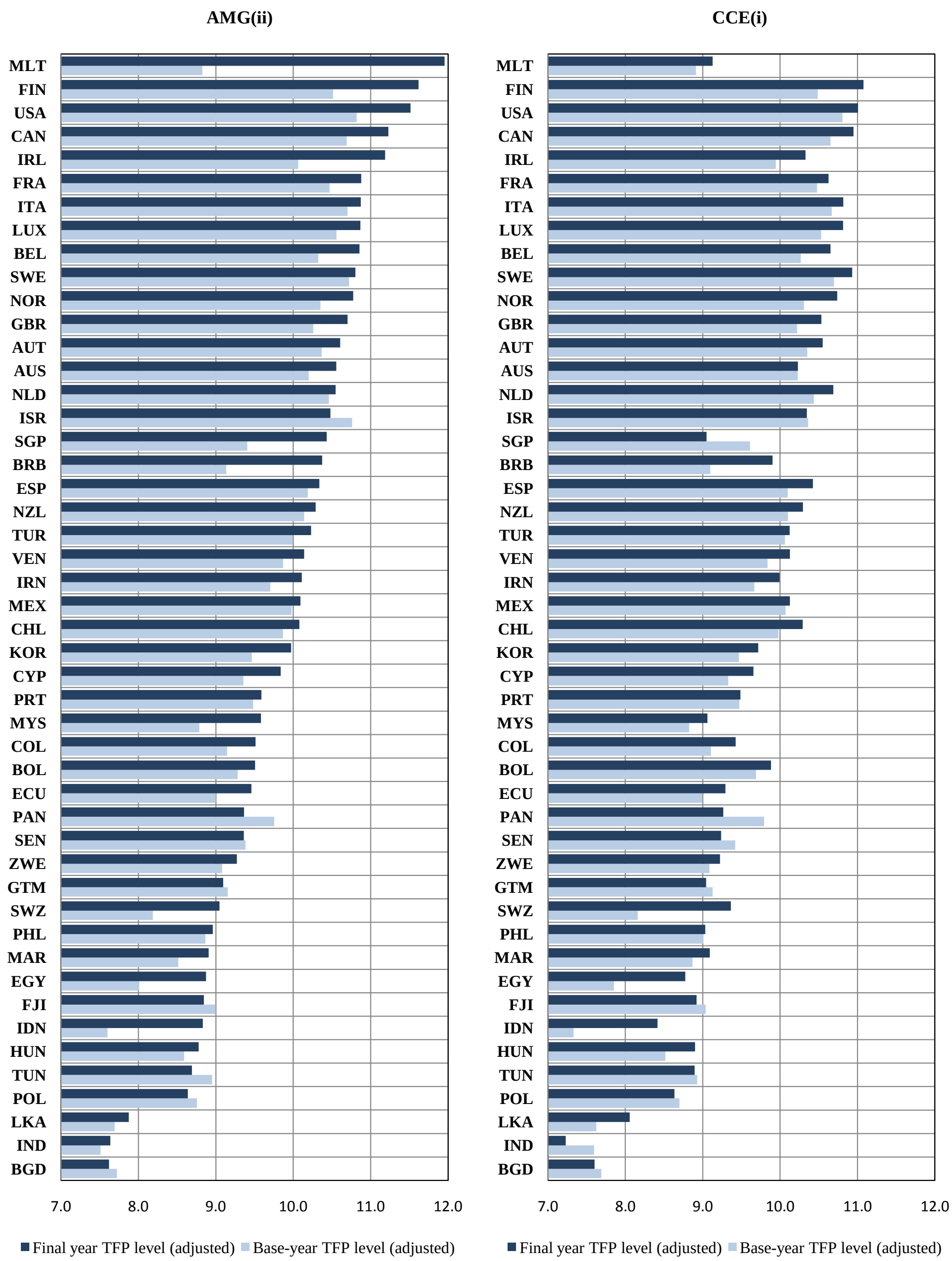
Comparison of Country Ranking across Estimators

	Country Rank			**Absolute Rank Difference**		
	[1]	[2]	[3]	abs([2]-[1])	abs([3]-[1])	abs([3]-[2])
Country	**FE**	**AMG†**	**CMG‡**	**AMG-FE**	**CMG-FE**	**CMG-AMG**
AUS	12	14	13	2	1	1
AUT	22	10	10	12	12	0
BEL	24	12	12	12	12	0
BGD	34	45	45	11	11	0
BOL	4	29	23	25	19	6
BRB	33	32	32	1	1	0
CAN	6	5	4	1	2	1
CHL	3	21	19	18	16	2
COL	11	31	31	20	20	0
CYP	20	28	29	8	9	1
ECU	41	34	36	7	5	2
EGY	48	44	44	4	4	0
ESP	5	15	16	10	11	1
FIN	14	7	6	7	8	1
FJI	43	35	34	8	9	1
FRA	18	8	7	10	11	1
GBR	19	13	14	6	5	1
GTM	17	30	30	13	13	0
HUN	45	41	42	4	3	1
IDN	44	47	48	3	4	1
IND	46	48	47	2	1	1
IRL	2	17	20	15	18	3
IRN	23	23	24	0	1	1
ISR	21	2	9	19	12	7
ITA	15	4	3	11	12	1
KOR	13	25	27	12	14	2
LKA	31	46	46	15	15	0
LUX	39	6	5	33	34	1
MAR	32	42	39	10	7	3
MEX	9	19	17	10	8	2
MLT	8	38	38	30	30	0
MYS	35	39	40	4	5	1
NLD	27	9	8	18	19	1
NOR	25	11	11	14	14	0
NZL	29	16	15	13	14	1
PAN	37	22	22	15	15	0
PHL	30	37	35	7	5	2
POL	47	40	41	7	6	1
PRT	36	24	26	12	10	2
SEN	38	27	28	11	10	1
SGP	10	26	25	16	15	1
SWE	16	3	2	13	14	1
SWZ	40	43	43	3	3	0
TUN	42	36	37	6	5	1
TUR	7	18	18	11	11	0
USA	1	1	1	0	0	0
VEN	28	20	21	8	7	1
ZWE	26	33	33	7	7	0
Median				**10.3**	**10.1**	**1.0**

Notes: The table provides the respective TFP level ranking (by magnitude) for each country derived from the three regression models, as well as the absolute rank differences between them. Country codes are detailed in Table A-II in the Appendix. † AMG refers to the Augmented Mean Group estimator, Table 2, upper panel, column [3]. ‡ CMG refers to the Mean Group version of the Pesaran (2006) CCE estimator, ibid. column [4]. The TFP-level adjustment is detailed in Section 6.

We present adjusted TFP base-year and final-year levels for these AMG and CMG models in Figure 3.[12] The countries in both charts are arranged in order of magnitude of their final-year adjusted TFP levels in the AMG(ii) model, for which results are shown in the left bar-chart. With exception of a small number of countries (e.g. MLT — Malta, SGP — Singapore) the general ordering of countries by final-year TFP levels is very similar in the two specifications: countries such as Finland, Canada, the United States or Ireland can be found toward the top of the ranking, with Bangladesh, India, Sri Lanka and Poland closer to the bottom.

Figure 3: TFP levels — adjusted from AMG and CMG estimates*



Notes: Models with CRS imposed. *AMG(ii) has $\hat{\mu}_t^{\bullet}$ *included* as additional regressor, CCE(i) refers to the standard CMG estimator (see Table 2, columns [3] and [4]). Countries are ranked by AMG(ii) final period TFP-level. Levels adjustment as described in the main text.

[12] Note that in our sample base- and final-year differ across countries (see Table A-II in the Appendix).

7 Concluding remarks

In this paper we investigated how technology differences in manufacturing across countries can be empirically modelled. We adopted an encompassing framework which allows for the possibility that the impact of observable and unobservable inputs on output differs across countries, as well as for nonstationary evolution of these processes. We employed empirical estimators which allow for a globally common, unobserved factor (or factors) interpreted either as common TFP or an average of country-specific TFP evolution. While in the CMG this common dynamic process is only implicit, the AMG approach uses an explicit estimate for this process in the augmentation of country-regressions.

Our empirical framework allowed us to model a number of characteristics which are likely to be prevalent in manufacturing data from a diverse sample of countries: *firstly*, we allowed for technology heterogeneity across countries. Empirical results are confirmed by formal testing procedures to suggest that technology parameters in manufacturing production indeed differ across countries. This result supports earlier findings by Durlauf (2001) and Pedroni (2007) using aggregate economy data: if production technology differs in cross-country manufacturing, aggregate economy technology is unlikely to be homogeneous. The result of production technology heterogeneity across countries has immediate implications for standard TFP analysis: it leads to the breakdown of the interpretation of regression intercepts as TFP-level estimates. We therefore introduced a new procedure to compute 'adjusted' TFP-level estimates, which is robust to parameter heterogeneity and can thus be compared across countries and between pooled and heterogeneous parameter models.[13] Further analysis highlighted the significant differences between 'adjusted' TFP-level estimates derived from our preferred heterogeneous parameter estimators on the one hand and the standard pooled fixed effects estimator on the other. The finding of cross-country technology heterogeneity thus questions the validity of standard development accounting practices to impose *common* coefficients on capital stock to extract country-specific measures of TFP, a recognised shortcoming in this literature (Caselli, 2008).

Secondly, we allowed for unobserved common factors to drive output, but with differential impact across countries, thus inducing cross-section dependence. These common factors are visualised by our common dynamic process, which follows patterns over the 1970-2002 sample period that match historical events. The interpretation of this common dynamic process $\hat{\mu}_t^\bullet$ would be that for the manufacturing sector *similar factors* drive production in all countries, *albeit to a different extent*. This is equivalent to suggesting that the 'global tide' of innovation can 'lift all boats', and that technology transfer from developed to developing countries is possible but dependent on the country's production technology and absorptive capacity, among other things.

Thirdly, our empirical setup allows for a type of endogeneity which is arguably very intuitive, namely that some of the unobservables driving output are also driving the evolution of inputs. This leads to an identification problem, whereby standard panel estimators cannot identify the parameters on the observable inputs as distinct from the impact of unobservables. Additional Monte Carlo simulations (Bond and Eberhardt, 2009) have highlighted the ability of the Pesaran (2006) CCE estimators and the AMG approach to deal with this problem successfully. Furthermore, additional analysis confirms that the empirical results are robust to the use of a panel time-series econometric approach. The Pedroni (2000) Group-Mean FMOLS approach suggests that failure to account for unobserved common factors when analysing cross-country manufacturing production leads to the breakdown of the empirical estimates, whereas the inclusion of the common dynamic process yields results very close to those from the AMG and CMG. Stan-

[13] Issues of estimate precision could be addressed using bootstrapping to construct standard errors.

dard practices to deal with endogeneity (Arellano and Bond, 1991; Blundell and Bond, 1998) are only appropriate in a stationary framework with homogeneous technology (Pesaran and Smith, 1995). This aside many researchers have expressed concerns over instrument validity in macro panel data (e.g. Clemens and Bazzi, 2009). Adopting a nonstationary panel econometric approach that accounts for cross-section dependence in our view is a sound empirical alternative to address both these concerns and should be applied more widely to cross-country productivity-analysis.

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Appendix: 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 1963-2002. The capital stocks are calculated from investment data which has been transformed into constant US$ (see below) following the 'perpetual inventory' method discussed in Klenow and Rodriguez-Clare (1997).

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$,[a] using current LCU and exchange rate data from UNIDO, and GDP deflators from the UN Common Statistics database (UN, 2005), for which data are available from 1970-2003. Since our model is for a small open economy, we prefer using a single market exchange rates (LCU-US$ exchange rate for 1990) to purchasing-power-parity (PPP) adjusted exchange rates, since the latter are more appropriate when non-traded services need to be accounted.

The resulting panel is unbalanced and has gaps within individual country time-series. We have a total of $n = 1,194$ observations from $N = 48$ countries, which have a time-series dimension between $T = 11$ and $T = 33$, with average $T = 24$. Note that we do *not* carry out any interpolation to fill these gaps and do not account for missing observations in any way. Recently Smith and Tasiran (2010) have investigated this issue in the context of the Swamy (1970) random coefficient model (RCM). The preferred empirical specifications presented in the main section of our paper are based on heterogeneous parameter models, where arguably the unbalancedness (around 25% of observations in the balanced panel are missing) comes less to bear on the estimation results than in the homogeneous models due to the averaging of estimates. Table A-I provides the descriptive statistics for the raw variables and variables in logs used in our regressions, further country-specific information is contained in Table A-II.

As a robustness check we also produced a 'cleaned' dataset where we applied mechanical 'cleaning rules' in order to address the most serious issues of measurement error,[b] which created a sample of $n = 872$ observations for $N = 38$ countries. The empirical results for this sample are virtually the same to those from the larger sample (available on request).

[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.

[b] We used the capital-to-materials ratio (K/M) to define a rule, bounded as $0.02 < K/M < 2$, and then dropped countries for which we had less than ten observations.

Table A-I: Descriptive statistics

Variables in Level Terms

Variable	obs	mean	median	std. dev.	min.	max.
levels						
value-added	1,194	5.47E+10	9.04E+09	1.78E+11	1.76E+07	1.50E+12
labour	1,194	1,469,186	502,214	2,924,524	5,552	1.97E+07
capital	1,194	1.32E+11	2.61E+10	3.12E+11	5.78E+07	2.27E+12
logs						
value-added	1,194	22.70	22.93	2.15	16.68	28.04
labour	1,194	12.92	13.13	1.79	8.62	16.79
capital	1,194	23.72	23.98	2.22	17.87	28.45
annual growth rate						
value-added	1,128	3.9%	3.5%	12.3%	-78.3%	92.7%
labour	1,128	1.7%	0.7%	8.1%	-38.8%	78.1%
capital	1,128	4.1%	3.1%	4.4%	-2.4%	47.8%

Variables in per worker terms

Variable	obs	mean	median	std. dev.	min.	max.
levels						
value-added	1,194	76,932	45,865	72,843	2,007	346,064
capital	1,194	25,305	17,867	19,385	1,660	91,011
logs						
value-added	1,194	9.78	9.79	0.92	7.41	11.42
capital	1,194	10.80	10.73	1.00	7.60	12.75
annual growth rate						
value-added	1,128	2.2%	2.5%	10.8%	-90.3%	74.4%
capital	1,128	2.5%	2.5%	7.9%	-68.0%	45.4%

Notes: We report the descriptive statistics for value-added, labour and capital stock for $N = 48$ countries and $n = 1,194$ ($n = 1,128$) observations in the levels (growth) specification. Monetary values are in real US$ (base year 1990). Labour is in number of workers.

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

		Sample				
Country	Code	*levels*	*FD*	$t=1$	$t=T$	I(1)*
Australia	AUS	20	17	1970	1993	✓
Austria	AUT	30	28	1970	2000	✓
Belgium	BEL	28	27	1970	1997	✓
Bangladesh	BGD	14	12	1970	1992	✓
Bolivia	BOL	11	10	1987	1997	
Barbados	BRB	26	25	1970	1995	
Canada	CAN	21	20	1970	1990	✓
Chile	CHL	25	24	1974	1998	✓
Colombia	COL	30	29	1970	1999	✓
Cyprus	CYP	33	32	1970	2002	✓
Ecuador	ECU	30	29	1970	1999	
Egypt	EGY	26	25	1970	1995	
Spain	ESP	26	25	1970	1995	
Finland	FIN	28	26	1970	2000	✓
Fiji	FJI	25	24	1970	1994	✓
France	FRA	26	25	1970	1995	
United Kingdom	GBR	23	22	1970	1992	✓
Guatemala	GTM	16	15	1973	1988	✓
Hungary	HUN	26	25	1970	1995	
Indonesia	IDN	26	25	1970	1995	✓
India	IND	32	31	1970	2001	
Ireland	IRL	22	21	1970	1991	
Iran	IRN	24	22	1970	2001	
Israel	ISR	13	12	1989	2001	
Italy	ITA	31	30	1970	2000	
Korea	KOR	32	31	1970	2001	
Sri Lanka	LKA	20	17	1970	2000	✓
Luxembourg	LUX	23	22	1970	1992	✓
Morocco	MAR	17	16	1985	2001	✓
Mexico	MEX	16	14	1984	2000	✓
Malta	MLT	32	31	1970	2001	✓
Malaysia	MYS	28	25	1970	2001	
Netherlands	NLD	24	23	1970	1993	✓
Norway	NOR	32	31	1970	2001	✓
New Zealand	NZL	21	20	1970	1990	
Panama	PAN	30	28	1970	2000	
Philippines	PHL	26	25	1970	1995	
Poland	POL	31	30	1970	2000	✓
Portugal	PRT	31	30	1970	2000	✓
Senegal	SEN	17	14	1970	1990	
Singapore	SGP	33	32	1970	2002	✓
Sweden	SWE	18	17	1970	1987	✓
Swaziland	SWZ	24	22	1970	1995	
Tunisia	TUN	21	19	1970	1997	
Turkey	TUR	27	25	1970	1997	
United States	USA	26	25	1970	1995	✓
Venezuela	VEN	26	24	1970	1998	✓
Zimbabwe	ZWE	27	26	1970	1996	
Obs		1,194	1,128			644

Notes: *This refers to the sample used in the second set of GM-FMOLS regressions (see Technical Appendix).

Technical Appendix

Table TA-1: First generation panel unit root tests

Im, Pesaran & Shin (1997) Panel Unit Root Tests — IPS♯

output		value-added		labour		capital		materials	
lags	[t-bar]	lags	[t-bar]	lags	[t-bar]	lags	[t-bar]	lags	[t-bar]
in levels									
1.42	-1.57	1.96	-1.54	1.48	-1.78 **	1.50	-1.92 **	1.65	-1.67
in per worker terms									
1.44	-0.92	1.65	-1.03			1.71	-0.97	1.83	-1.05

Maddala & Wu (1999) Panel Unit Root Tests — MW†

output			value-added			labour			capital			materials		
lags	p_λ	(p)	lags	p_λ	(p)	lags	p_λ	(p)	lags	p_λ	(p)	lags	p_λ	(p)
in levels														
0	129.37	(.01)	0	125.69	(.02)	0	142.42	(.00)	0	274.01	(.00)	0	126.47	(.02)
1	126.57	(.02)	1	109.99	(.16)	1	141.35	(.00)	1	67.05	(.99)	1	133.62	(.01)
1.42	69.12	(.98)	1.96	85.44	(.77)	1.48	114.54	(.10)	1.50	55.16	(1.00)	1.65	66.65	(.99)
2	114.75	(.09)	2	124.13	(.03)	2	105.34	(.24)	2	80.86	(.87)	2	134.85	(.01)
3	74.36	(.95)	3	56.97	(1.00)	3	88.76	(.69)	3	87.84	(.71)	3	108.31	(.18)
in per worker terms														
0	107.76	(.19)	0	102.23	(.31)				0	54.16	(1.00)	0	102.35	(.31)
1	70.70	(.98)	1	84.92	(.78)				1	60.09	(1.00)	1	77.74	(.91)
1.44	30.08	(1.00)	1.65	63.13	(1.00)				1.71	32.32	(1.00)	1.83	32.45	(1.00)
2	75.85	(.94)	2	65.26	(.99)				2	34.04	(1.00)	2	77.85	(.91)
3	61.41	(1.00)	3	44.65	(1.00)				3	66.85	(.99)	3	87.42	(.72)
in first difference														
0	924.25	(.00)	0	976.37	(.00)	0	608.63	(.00)	0	248.03	(.00)	0	931.98	(.00)
1	500.47	(.00)	1	547.05	(.00)	1	405.04	(.00)	1	214.11	(.00)	1	428.13	(.00)
2	320.97	(.00)	2	358.92	(.00)	2	248.07	(.00)	2	154.10	(.00)	2	281.42	(.00)
3	322.88	(.00)	3	334.27	(.00)	3	310.84	(.00)	3	169.69	(.00)	3	331.29	(.00)
in first difference of per worker terms														
0	1007.23	(.00)	0	1061.64	(.00)				0	769.82	(.00)	0	979.89	(.00)
1	593.33	(.00)	1	590.67	(.00)				1	439.72	(.00)	1	610.50	(.00)
2	348.43	(.00)	2	396.30	(.00)				2	253.49	(.00)	2	301.62	(.00)
3	296.79	(.00)	3	285.86	(.00)				3	372.73	(.00)	3	354.89	(.00)

Notes: All variables are in logarithms. ♯ We report the average of the country-specific 'ideal' lag-augmentation (via AIC) and the t-bar statistic, constructed as $t\text{-bar} = (1/N)\sum_i t_i$ (t_i are country ADF t-statistics). Under the H_0 of all country series containing a nonstationary process this statistic has a non-standard distribution: the critical values (-1.73 for 5%, -1.69 for 10% significance level — distribution is approximately t) are reported in Table 2, Panel A of their paper. We indicate the cases where the null is rejected with **. † We report the MW statistic, constructed as $p_\lambda = -2\sum_i log(p_i)$ (p_i are country ADF statistic p-values) for different lag-augmentations, including the 'ideal' augmentation determined via AIC (levels variables only). Under the H_0 of all country series containing a nonstationary process this statistic is distributed $\chi^2(2N)$. We further report the p-values for each of the MW tests.

Table TA-2: Second generation panel unit root tests

Pesaran (2007) Panel Unit Root Tests — CIPS♯

output			value-added			labour			capital			materials		
lags	Z[t-bar]	(*p*)	lags	Z[t-bar]	(*p*)	lags	Z[t-bar]	(*p*)	lags	Z[t-bar]	(*p*)	lags	Z[t-bar]	(*p*)
in levels														
0	-1.22	(.11)	0	-1.85	(.03)	0	2.39	(.99)	0	5.11	(1.00)	0	0.29	(.62)
1	0.01	(.51)	1	0.06	(.52)	1	1.26	(.90)	1	3.79	(1.00)	1	0.89	(.81)
1.42	1.13	(.87)	1.96	3.54	(1.00)	1.48	3.74	(1.00)	1.50	4.55	(1.00)	1.65	3.68	(1.00)
2	2.65	(1.00)	2	2.30	(.99)	2	4.21	(1.00)	2	3.96	(1.00)	2	1.05	(.85)
3	7.04	(1.00)	3	3.59	(1.00)	3	4.76	(1.00)	3	7.64	(1.00)	3	4.21	(1.00)
in per worker terms														
0	-1.08	(.14)	0	-2.55	(.01)				0	1.92	(.97)	0	0.57	(.72)
1	2.91	(1.00)	1	-0.73	(.23)				1	1.33	(.91)	1	3.74	(1.00)
1.44	5.98	(1.00)	1.65	3.77	(1.00)				1.71	5.92	(1.00)	1.83	9.62	(1.00)
2	5.02	(1.00)	2	2.37	(.99)				2	4.60	(1.00)	2	5.96	(1.00)
3	8.73	(1.00)	3	5.48	(1.00)				3	7.34	(1.00)	3	8.08	(1.00)
in first differences														
0	-17.71	(.00)	0	-19.75	(.00)	0	-15.22	(.00)	0	-6.64	(.00)	0	-18.14	(.00)
1	-9.46	(.00)	1	-11.95	(.00)	1	-8.93	(.00)	1	-5.26	(.00)	1	-8.34	(.00)
2	-2.00	(.02)	2	-3.65	(.00)	2	-3.14	(.00)	2	-1.20	(.12)	2	-1.59	(.06)
3	1.65	(.95)	3	0.67	(.75)	3	0.49	(.69)	3	2.27	(.99)	3	3.16	(1.00)
in first difference of per worker terms														
0	-19.54	(.00)	0	-20.91	(.00)				0	-15.40	(.00)	0	-18.43	(.00)
1	-10.89	(.00)	1	-11.40	(.00)				1	-9.60	(.00)	1	-9.52	(.00)
2	-1.95	(.03)	2	-4.21	(.00)				2	-3.37	(.00)	2	-1.83	(.03)
3	2.53	(.99)	3	0.11	(.54)				3	0.54	(.71)	3	2.86	(1.00)

Notes: All variables are in logarithms. ♯ In the third row for each variable in levels we present the CIPS test statistic for 'ideal' lag augmentation of the underlying ADF regression (based on Akaike information criteria); the value for lags reported here is the *average* across countries.

Table TA-3: Gengenbach, Urbain & Westerlund (2009) cointegration tests

ECM-based Cointegration Test

no intercept	**AIC**		**BIC**		**10%**	**5%**	**1%**
$\bar{\tau}^*$ (truncated)	-2.58	*	-2.75	**	-2.48	-2.55	-2.67
$\bar{\omega}^*$ (truncated)	25.66	**	25.61	**	12.10	12.43	13.07
avg. lag length	2.0		1.7				
intercept	**AIC**		**BIC**		**10%**	**5%**	**1%**
$\bar{\tau}^*$ (truncated)	-2.63		-2.78		-2.86	-2.92	-3.03
$\bar{\omega}^*$ (truncated)	17.04	**	17.12	**	14.08	14.42	15.04
avg. lag length	2.3		1.7				
intercept, trend	**AIC**		**BIC**		**10%**	**5%**	**1%**
$\bar{\tau}^*$ (truncated)	-2.44		-2.61		-3.227	-3.282	-3.395
$\bar{\omega}^*$ (truncated)	12.54		13.13		16.23	16.59	17.31
avg. lag length	2.1		1.8				

Notes: The $\bar{\tau}^*$ and $\bar{\omega}^*$ statistics are averages of the N t-ratios and F-statistics from the country ECM regressions, where extreme t-ratios/F-statistics have been replaced by bounds (truncated; we used $\varepsilon = .000001$) following the strategy devised in Gengenbach et al. (2009). This paper also provides simulated critical values we present here ($N = 50$). Both test statistics are one-sided: for the $\bar{\tau}^*$ large negative values lead to rejection of the null, whereas for the $\bar{\omega}^*$ it is large positive values which lead to rejection. H_0 in all cases: no error correction, i.e. no cointegration; lag-length p_i determined using AIC or BIC as indicated.

Table TA-4: Country regressions using FMOLS

Panel A: Full Sample (N=48)

	[1]	[2]	[3]	[4]	[5]
estimator: **FMOLS-**	**MG**	**AMG**	**AMG**	**CMG**	**CMG**
dependent variable	ly	ly-$\hat{\mu}_t^{\bullet,va}$	ly	ly	ly
log capital pw	0.1663	0.2659	0.2937	0.5544	0.3042
	[1.99]	[3.32]**	[3.18]**	[8.05]**	[3.33]**
common process			0.8977		
			[3.49]**		
country trends	0.0171	0.0004	0.0014		0.0108
	[5.50]**	[0.12]	[0.29]		[2.95]**
intercept	-4.6095	6.5985	7.1405	5.6737	-1.6007
	[1.63]	[2.69]**	[1.52]	[5.57]**	[0.57]
Panel-t statistics, diagnostics					
capital pw	18.29	14.73	15.36	40.59	15.88
trends	24.94	18.93	12.71		20.70
# of sign. trends (at 10%)	37	25	23		28
RMSE	.099	.096	.090	.103	.088

Panel B: I(1) Sample (N=26)

	[1]	[2]	[3]	[4]	[5]
estimator: **FMOLS-**	**MG**	**AMG**	**AMG**	**CMG**	**CMG**
dependent variable	ly	ly-$\hat{\mu}_t^{\bullet,va}$	ly	ly	ly
log capital pw	0.0816	0.2675	0.2784	0.5528	0.2485
	[1.27]	[4.11]**	[3.08]**	[7.38]**	[3.13]**
common process			0.8034		
			[4.61]**		
country trends	0.0179	-0.0012	0.0019		0.0108
	[5.64]**	[0.40]	[0.41]		[2.56]*
intercept	-4.9092	6.1012	5.2980	5.3936	-2.3070
	[1.59]	[2.63]*	[1.50]	[4.60]**	[0.76]
Panel-t statistics, diagnostics					
capital pw	11.45	10.37	9.97	34.96	10.16
trends	23.28	14.63	10.56		17.10
# of sign. trends (at 10%)	23	15	15		16
RMSE	.071	.068	.065	.080	.062

Notes: The results in [1] are for the Pedroni (2000) Group-Mean FMOLS estimator; the results in the remaining columns allow for cross-section dependence using either $\hat{\mu}_t^{\bullet,va}$ or cross-section averages in the FMOLS country regressions. In all cases the estimates presented are the unweighted means of the FMOLS country estimates. Panel B uses observations from only those countries for which variables were determined to be nonstationary (via ADF and KPSS testing).