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Abstract:

In this paper we ask how technological differences in manufacturing production across countries can best be modeled when using a standard production function approach. We emphasise the importance of allowing for differences in the impact of observables and unobservables across countries, as well as of data time-series properties. Our novel two-stage estimator, similar to the Pesaran (2006) Common Correlated Effects approach, can account for these matters. Empirical results and diagnostic testing provide strong support for technology heterogeneity. Results are supported when we adopt an econometric approach allowing for reverse causality. In the light of these findings the interpretation of regression intercepts as TFP levels collapses and we introduce an alternative measure.

Keywords: Manufacturing Production; Parameter Heterogeneity; Nonstationary Panel Econometrics; Common Factor Model; Cross-section Dependence
JEL classification: C23, O14, O47

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"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)

"Most of the work carried out on panel data has usually assumed some form of cross sectional independence to derive the theoretical properties of various inferential procedures. However, such assumptions are often suspect ..."
Kapetanios, Pesaran, and Yamagata (2008, p.2)

Why do we observe such dramatic differences in labour productivity across countries in the macro data? This question has been central to the empirical investigation of growth and development over the past decades. As the above quotes indicate the importance of parameter heterogeneity and variable nonstationarity, as well as cross-section dependence, have not been major concerns in this empirical investigation. In this paper we argue that all of these issues are important for understanding cross-country differences in labour productivity and their causes.

The possibility that technology differences across countries, in the form of parameter heterogeneity, 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).

[1] 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).

The second feature on which we will focus in the empirical analysis is the time-series properties of the macro panel data investigated. 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; Pedroni, 2007; Canning & Pedroni, 2008). In addition, a number of empirical papers report nonstationary evolvement of Total Factor Productivity (TFP), 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).

Standard empirical growth studies at the macro level abstract from interdependencies across countries resulting from common shocks to these economies. In the context of cross-country growth and development analysis, the potential for this type of data dependency is particularly salient, given the interconnectedness of countries through history, geography and trade relations. Recent work in the panel time-series literature has aimed to relax the standard assumption of cross-section independence. This has led to the development of analytical methods robust to the impact of correlation across panel units (Bai & Ng, 2004; Pesaran, 2006, 2007; Kapetanios et al., 2008). Empirical work which allows for cross-section dependence in panel data is still relatively limited, e.g. production functions for Italian regions (Costantini & Destefanis, 2009) or Chinese provinces (Fleisher, Li, & Zhao, 2009).

In this paper we argue that many of the empirical puzzles created in this literature (e.g. an excessively large capital coefficient) can be resolved once we allow for parameter heterogeneity, the nonstationary evolution of most macro data and the role of common factors in inducing cross-section dependence. Our empirical analysis uses panel data for manufacturing from 48 developing and developed countries to show that the technology parameter estimates differ significantly, depending on whether we do or do not allow for heterogeneity and cross-section dependence. Our choice of *sectoral* data is driven by the notion that it may be inappropriate to view the *aggregate economy* as basic unit of analysis when investigating growth and development against the background of structural change (Temple, 2005; Vollrath, 2009): sectors as diverse as manufacturing, services and agriculture are likely to be characterised by different production technologies, such that separate estimation is desirable. With regard to our analysis of technology heterogeneity, the manufacturing sector can be argued to be *more homogeneous* in its production technology across diverse sets of countries than a representative production technology for the aggregate economy.

The remainder of this study is structured as follows: in the *next section* we set out a model which is sufficiently general to encompass the issues raised above. *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 48 countries over the period from 1970 to 2002. *Section four* discusses formal parameter heterogeneity tests, while *Section five* tests the robustness of our findings to reverse causality. *Section six* introduces a new methodology for TFP level estimates valid in the heterogeneous technology case. *Section seven* concludes.

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

We adopt a common factor representation for the production function model with assumptions as detailed below: for $i = 1, \dots, N$ and $t = 1, \dots, T$, let

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

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

$$\text{where} \qquad m = 1, \dots, k \qquad \text{and} \qquad \boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$$

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

where y_{it} represents gross output or value-added and $\boldsymbol{x}_{it}$ is a vector of observable factor-inputs including labour, capital stock and in the gross-output specification materials (all in logarithms).[2] 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 further add an empirical representation of the k observable input variables, which are modelled as linear functions of 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., 2008). Equation (3) specifies the evolution of the unobserved factors.

We maintain the following assumptions for the empirical model and the data:

A.1 The $\boldsymbol{\beta}_i$ parameters are unknown random coefficients with fixed means and finite variances. Similarly for the factor loadings, i.e. $\boldsymbol{\lambda}_i = \boldsymbol{\lambda} + \boldsymbol{\eta}_i$ where $\boldsymbol{\eta}_i \sim \text{iid}(0, \Omega_\eta)$.[3]

A.2 Error terms $\varepsilon_{it} \sim N(0, \sigma^2)$, where σ^2 is finite. Similarly for v_{mit} and ϵ_t.

A.3 $\boldsymbol{\lambda}_i' \boldsymbol{f}_t$ captures time-varying unobservables (TFP) and can contain elements which are common across countries as well as elements which are country-specific.

A.4 The unobserved common factors $\boldsymbol{f}_t$ and $\boldsymbol{g}_{mt}$ and therefore the observable inputs $\boldsymbol{x}_{it}$ and output y_{it} are <u>not</u> *a priori* assumed to be stationary processes/variables.

A.5 There is an overlap between the unobserved common factors driving output and the regressors ($\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$), creating difficulties for the identification of the technology parameters $\boldsymbol{\beta}_i$.

[2] Parameter estimates and interpretation will differ between a value-added based and gross-output based empirical specification, but if we assume constancy of the material-output ratio we can transform results to make them directly comparable: $\boldsymbol{\beta}_i^{va} = \boldsymbol{\beta}_i/(1-\boldsymbol{\gamma}_i)$ (Söderbom & Teal, 2004).

[3] The assumption of random coefficients is for convenience. Based on the findings by Pesaran and Smith (1995, footnote 2, p.81) the coefficients could alternatively be fixed but differing across groups.

The two most important features of the above setup are the potential nonstationarity of observables and unobservables (y_{it}, $\boldsymbol{x}_{it}$, $\boldsymbol{f}_t$, $\boldsymbol{g}_{mt}$), as well as the potential heterogeneity in the impact of observables and unobservables on output across countries (α_i, $\boldsymbol{\beta}_i$, $\boldsymbol{\lambda}_i$). Taken together these properties have important bearings on estimation and inference in macro panel data which are at the heart of this paper.

2 Empirical implementation

In this Section we first discuss the investigation of variable time-series and cross-section correlation properties in macro panel datasets. The following subsection then introduces our novel estimation approach which allows for heterogeneity in the impact of observables and unobservables, and compares it to the Pesaran (2006) CCE approach.

2.1 Data time-series and cross-section correlation properties

A panel of considerable time-series dimension T opens up the opportunity to use both country-specific tests from the time-series literature as well as panel-based tests — see Enders (2004), Hamilton (1994) or Maddala and Kim (1998) for a discussion of the former, and Choi (2007), Basile, Costantini, and Destefanis (2005) or Smith and Fuertes (2004, 2007) for a discussion of the latter. Standard time-series unit root tests are well-known to have low power, such that as the autoregressive parameter approaches unity the test is less and less able to distinguish between a true unit root (the null hypothesis of the test) and a false null. "One of the primary reasons behind the application of unit root tests . . . to a panel of cross-section units was to gain statistical power and to improve on the poor power of their univariate counterparts" (Breitung & Pesaran, 2005, p.2). Many panel unit root and cointegration tests discussed in the literature however cannot shake off an inherent difficulty in terms of interpretation, whereby the null of nonstationarity (or stationarity or cointegration or noncointegration) for *all* countries in the panel is contrasted with an alternative that *at least one* country is stationary (or nonstationary or noncointegrated or cointegrated). Panel unit root test results are often highly sensitive to the number of lags included and it is unclear whether the lag structure should be the same across countries or whether information criteria should inform on individual countries' 'ideal' lag structure. More recently it was also suggested that correlation across units of the panel may bias results from 'first generation' panel unit root tests (Pesaran, 2007). Since the seminal contribution by Bai and Ng (2004) the 'second generation' literature for these tests which allows for cross-section dependence has been developing rapidly, with recent contributions integrating the impact of structural breaks (Westerlund, 2006) and changes in the volatility of innovations (Hanck, 2008).

In Pedroni (2007) empirical analysis is confined to countries where the data is argued to be I(1) and cointegrated. In this paper we propose using estimation methods that are robust to the potential for nonstationarity and cointegration within some, but not all countries in the panel. This approach is less dependent on making assumptions about the data which are difficult to test in relatively short panels.[4] Further note that unit root evolution should not be seen as continuing indefinitely ('global' property) but represents a 'local' behaviour of variables *within-sample* as suggested by Pedroni (2007).

Panel data econometrics over the recent years has seen a rising interest in models with unobserved time-varying heterogeneity induced by unobserved common shocks that affect all units (in our present interest: countries), but perhaps to a different degree (Coakley, Fuertes, & Smith, 2006). This type of heterogeneity introduces cross-section correlation or dependence between the regression error terms, which can lead to inconsistency and incorrect inference in standard panel econometric approaches (Phillips & Sul, 2003; Pesaran, 2006; Pesaran & Tosetti, 2007). The latter typically assume 'cross-section independence', not necessarily because this feature is particularly intuitive given real-world circumstances, but "in part because of the difficulties characterizing and modelling cross-section dependence" (Phillips & Moon, 1999, p.1092). In the context of cross-country productivity analysis, the presence of correlation between macro variable series across countries seems particularly salient.

[4]Here and in the following we judge the length of a panel with the eyes of a time-series econometrician, for whom annual data for, say, 25 to 35 years represents a relatively short T-dimension.

If we assume factors $\boldsymbol{f}_t$ (and $\boldsymbol{g}_{mt}$) in our general model above are *stationary*, the consistency of standard panel estimators such as a pooled fixed effect regression or a Pesaran and Smith (1995) Mean Group regression with country-specific intercepts rests on the parameter values (factor loadings) of the unobserved common factors *contained in both the y and $\boldsymbol{x}$-equations*: if their averages are jointly non-zero ($\bar{\boldsymbol{\lambda}}_i \neq 0$ *and* $\bar{\boldsymbol{\rho}}_i \neq 0$) a regression of y on $\boldsymbol{x}$ and N intercepts (in the pooled fixed effects regression case) will be subject to the omitted variable problem and hence misspecified, since regression error terms will be correlated with the regressor, leading to biased estimates and incorrect inference (Coakley et al., 2006; Pesaran, 2006). In the case of *nonstationary* factors the consistency issues in the same framework is altogether more complex and will depend on the exact overall 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. (2008) — $\boldsymbol{\beta}_i$ 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).

2.2 Empirical estimators

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.[5] We abstract from discussing the *standard* panel estimators here in great detail and refer to the overview article by Coakley et al. (2006), as well as the papers by Pedroni (2000, 2001) (GM-FMOLS) and Pesaran (2006) (CCEP/CCEMG) for more details.

[5] Abbreviations are as follows: 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/CCEMG — 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.

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

Essentially, in our model setup all estimators *neglecting* the heterogeneity in unobservables (left column) suffer from an 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: misspecification of the empirical equation can lead to nonstationary error terms, inducing the breakdown of any cointegrating relationship in the data.[6] Inference is problematic in this case since conventional standard errors will be invalid, and the associated standard t-statistics will diverge away from zero with unit probability asymptotically (Kao, 1999). Among the estimators neglecting heterogeneity in unobservables the Pedroni (2000) GM-FMOLS is the only approach to avoid 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 cross-section dependence in the presence of nonstationary variables (Kapetanios et al., 2008). It is in this context that we introduce our own estimators, namely the Augmented Mean Group (AMG) and Swamy Random Coefficient Model (ARCM) estimators which are the focus of the following discussion.

The Augmented Mean Group (AMG) estimator accounts for cross-section dependence by inclusion of a 'common dynamic process' in the country regression. This process is

[6] As developed by Phillips and Moon (1999, p.1091) estimation equations which result in nonstationary errors may be consistent estimators of "some interesting long-run relationship" in the data, however inefficiency (see Coakley et al., 2006) and difficulty to interpret economically makes this important result less useful for applied empirics.

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 countries:

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

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

The first stage represents a standard FD-OLS regression with $T-1$ year dummies in first differences,[7] from which we collect the year dummy coefficients which are 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. There is also some evidence (Monte Carlo results available on request) that the identification problem for $\boldsymbol{\beta}_i$ we discussed earlier is addressed successfully in the FD-OLS approach. FD-OLS yields an estimate of the common technology parameters or an unweighted mean of the country-specific cointegrating coefficients (Smith & Fuertes, 2007), depending on the assumptions about the underlying technology parameters $\boldsymbol{\beta}_i$. The underlying common factors (in the levels equation) can be stationary or nonstationary.

In the second stage this estimate $\hat{\mu}_t^{\bullet}$ is included in each of the N standard country regressions which also include linear trend terms 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 (not shown).[8] In either case the AMG estimates are then derived as averages of the individual country estimates, following the Pesaran and Smith (1995) MG approach. Based on the results of Monte Carlo simulations (available on request) we posit that the

[7] Year dummies in first differences result in a *levels series* for the unobserved average/common factors, rather than the annual growth rates as would be the case for levels year dummies in a model where inputs and output are in first differences.

[8] Note further that unity is also the cross-country average parameter expected for the coefficients on $\hat{\mu}_t^{\bullet}$: $\bar{d} = N^{-1} \sum_i d_i = 1$.

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 case. In analogy 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 differences. Similarly we 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.

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 in first differences. Compared with the CCE approach we can obtain an 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.

3 Data and main empirical results

3.1 Data

For our empirical analysis we concentrate on aggregate sectoral data for manufacturing from developed and developing countries for 1970 to 2002 (UNIDO, 2004). Our sample represents an unbalanced panel of 48 countries with an average of 24 time-series observations (1,162 observations in levels, 1,094 in first difference regressions — gross output based sample; for the value-added based sample we have slightly more observations, 1,194 and 1,128 for levels and first difference regressions respectively). For a detailed discussion and descriptive statistics see Appendix A. Note that *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.

3.2 Time-series properties of the data

We carry out a range of stationarity and nonstationarity tests for individual country time-series as well as the panel as a whole, results for which are presented in Appendix B.[9] The tests conducted include country-specific unit root tests and panel unit root tests of the first and second generation. 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. 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 (possibly due to the limited time-series dimension) is likely to be made up of a mixture of some countries with stationary and others with nonstationary variables.

3.3 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) to account for unobserved common factors. In all pooled regressions the slope coefficients on the factor-inputs and the year dummies are restricted to be *the same* across all countries. Our results presented in Tables 1 and 2, in each case for a gross output and value-added specification in the upper and lower panels respectively, are for the following estimators: for the data in levels we apply **[1]** the pooled OLS estimator (POLS); **[2]** the pooled fixed effects estimator (FE); **[3]** the Pesaran (2006) common correlated effects estimator in its pooled version (CCEP); and **[4]** the pooled OLS estimator for data in first differences (FD-OLS) — additional information is contained in the notes to the table. Estimation equations in columns [1], [2], and [4] of both tables include sets of $(T-1)$ year dummies.

`[Table 1 about here]`

We first discuss the results for the empirical specification without any restrictions on the returns to scale — Table 1. Estimates for the factor input parameters in all regressions are

[9] Empirical analysis in this paper is carried out using `Stata` 9 and 10, `GAUSS` 9 and `WinRATS` 6.2.

statistically significant at the 5% level or 1% level. The POLS results in column [1] suggest that failure to account for time-invariant heterogeneity across countries (fixed effects) yields severely biased results: the VA-equivalent capital coefficient from the gross-output specification in the upper panel at .9 is considerably inflated, with the capital coefficient from the VA specification in the lower panel somewhat more moderate at .8. 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 are reported in 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 in all cases except POLS in the value-added specification. 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] yields somewhat different technology estimates: the capital coefficient is now around .3 in both specifications (VA-equivalent), thus in line with observed macro data on factor share in income (Mankiw, Romer, & Weil, 1992). 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, especially in the VA-specification. 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) — in the pooled regressions we force this homogeneity onto the data, such that identical results are to be expected.

Under intercept and technology parameter heterogeneity, given nonstationarity in (some of) the country variable series the pooled FE estimates in column [3] asypmtotically converge to the 'long-run average' relation at speed $\sqrt{N}$ (Phillips & Moon, 1999) provided $T/N \rightarrow 0$ (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 (in VA-equivalent terms) is more than twice the magnitude of the macro data on factor shares in income (Mankiw et al., 1992; Gomme & Rupert, 2004), a common finding in the literature (Islam, 2003; Pedroni, 2007). Further recall that t-values are invalid for the estimations *in levels* if error terms are nonstationary (Coakley, Fuertes, & Smith, 2001; Kao, 1999). The CCEP estimator accounts for cross-section dependence and yields, as the residual analysis in Section 3.6 below suggests, stationary errors terms. The difference estimator in [4] converges to the common cointegrating vector $\boldsymbol{\beta}$ or the mean of the individual country cointegrating relations, $E(\boldsymbol{\beta}_i)$, at speed $\sqrt{TN}$ (Smith & Fuertes, 2007). Further investigation regarding alternative specification with parameter heterogeneity (CCEMG estimator) as well as residual diagnostics will be necessary to judge the bias of the present CCEP results.

As the model in first differences does not reject constant returns to scale (CRS), we impose CRS on all models and investigate the outcome — given that we are analysing a 'global' production function, the assumption of constant returns should be far from controversial and may help the data to differentiate between capital and material inputs more readily than is evidenced in the previous results. Table 2 presents the results for the pooled regression models with CRS imposed.

`[Table 2 about here]`

The imposition of CRS does not alter the pooled regression results in levels to a great extent: POLS in [1], FE in [2] and CCEP in [3] yield capital coefficient estimates of around .9, .7 and .6 respectively; in the gross output specification our preferred ΔOLS estimator in [4] now has a slightly less precisely identified capital coefficient, which is however within the 95% confidence intervals of the estimate in the unrestricted equation.[10] The VA-equivalent capital coefficient as a result has dropped to around .23. In the value-added specification, the ΔOLS estimates show very similar results for the unrestricted and restricted returns to scale models.

[10] We also carry out a Wald test for parameter equality and cannot reject the null that they are the same: $\chi^2(1) = 0.00$, $p = .98$.

Our pooled regression analysis suggests that time-series properties of the data play an important role in estimation: the pooled OLS and FE levels regressions, where some or all country variable series may be I(1), yield very high parameter coefficients on capital, which translate into VA-equivalent capital coefficients of between .6 to .9. 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 — we investigate both matters in more detail below. In contrast, the OLS regressions where variables are in first differences and thus stationary (FD-OLS) yielded more sensible capital parameters. This pattern of results fits the case of level-series being integrated of order one in at least some of the countries in our sample. The results for the CCEP are somewhat surprising, given our findings when we relax parameter homogeneity.

3.4 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 regressions with CRS imposed (FD-OLS, column [4] in Table 2) to obtain an estimate of the common dynamic process $\hat{\mu}_t^\bullet$, which represents an estimate of the common TFP evolvement (mean of the unobserved common factors evaluated at the average impact across countries). Figure 1 illustrates the evolvement path of this common dynamic process for the gross-output based model.[11]

`[Figure 1 about here]`

The graph shows severe slumps following the two oil shocks in the 1970s, while the 1980s and 1990s indicate considerable upward movement.[12] The version of this graph for results from the VA-specification shows the same patterns over time (not reported). Recall that we favour the 'measure of ignorance' interpretation of TFP, such that a decline in global

[11] In the graph we omit the data-point for 2002 for which there are only two observations. This implied 'globally common evolution' is for a gross-output specification. In order to provide a graph translated into a VA specification, we first need to scale the year dummy coefficients by $1/(1-\hat{\gamma})$ to account for material inputs. The resulting TFP evolution (not presented) is very similar to that for the VA specification.

[12] Note that these graphs are 'data-specific': for years where data coverage is good, this can be interpreted as 'global', whereas for years from 2000 (only 10 countries have data for 2001, only 2 for 2002 which is omitted from the graph) this interpretation collapses.

manufacturing TFP as evidenced in the 1970s should not be interpreted as a decline in knowledge, but a worsening of the global manufacturing *environment*. A simpler explanation may be that our variable deflation[13] 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.

3.5 Country regressions

In the following we relax the assumption implicit in the pooled regressions 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 common shocks and/or cross-sectional dependence have to be accounted for in some fashion. We contrast models that allow for unobserved common factors in different ways, with models which ignore these matters. A total of four specifications are investigated:

$$(a) \quad y_{it} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + c_i t + e_{it} \tag{6}$$

$$(b) \quad y_{it} - \hat{\mu}_t^{\bullet} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + c_i t + e_{it} \tag{7}$$

$$(c) \quad y_{it} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \tag{8}$$

$$(d) \quad y_{it} = a_i + \boldsymbol{b}_i' \boldsymbol{x}_{it} + \boldsymbol{d}_{1i}' \bar{y}_t + \boldsymbol{d}_{2i}' \bar{\boldsymbol{x}}_t \ \{+c_i t\} + e_{it} \tag{9}$$

In specification ***(a)*** we do not account for any cross-section dependence and/or common TFP — this represents standard country regressions augmented with linear country-trends (trend coefficient c_i. Our novel augmented estimator has two variants: in ***(b)*** the common dynamic process $\hat{\mu}_t^{\bullet}$ is imposed with a unit coefficient, whereas in ***(c)*** it is included as additional regressor. The augmentation with cross-section averages is represented by option ***(d)***.

These four specifications are implemented as follows: **[1]** the standard Pesaran and Smith (1995) Mean Group (MG) and **[2]** the Swamy (1970) Random Coefficient Model (RCM)

[13] Country deflators for monetary values in local currency units [LCU], which are subsequently translated into US$ at 1990 value by using the LCU-US$ exchange rate for that specific year.

estimators are representatives of option (a); the Augmented Mean Group (AMG) estimator can either **[3]** have the common dynamic process $(\hat{\mu}_t^{\bullet})$ imposed with unit coefficient like in option (b), or **[4]** have it included as additional regressor like in option (c). Similarly for the Augmented RCM (ARCM) **[7]**, **[8]**. The Mean Group version of the Common Correlated Effects estimator (CCEMG) represents option (d). We test two alternative specifications, namely **[5]** as defined by Pesaran (2006), and **[6]** augmented with a country-specific linear trend term.[14]

Unweighted averages of country parameter estimates are presented for regressions in levels and first differences in Tables 3 and 4 respectively, with gross-output models in the upper panel and value-added models in the lower panel of each table. 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 — this decision and its implications are discussed in more detail below.

The concept of 'mean-group' estimates — be they from MG, CCEMG or the weighted variant of the Swamy RCM — suggests that while *individual* country regression estimates may be unreliable, by averaging across the estimates we obtain a more reliable measure of the average relationship across groups/countries (Pesaran & Smith, 1995). The t-statistics for the country-regression averages reported in all tables for country regression results are measures of dispersion for the sample of country-specific estimates.[15] 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 for capital, materials and country-specific linear trend terms. From our results 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*. This pattern is repeated in the results for the value-added regressions.

[14]In the first instance we deliberately do not use 'demeaned' data, 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 & Fuertes, 2007). We briefly discuss the results for 'demeaned' data at the end of this section, referring to Table C-1 in Appendix D.

[15]In case of the MG-type estimators these are computed from the standard errors $se(\hat{\beta}_{MG}) = [\sum_i(\hat{\beta}_i - \hat{\beta}_{MG})^2]^{-1/2}$. For the Swamy estimators, see the footnote of the table for details.

`[Tables 3 and 4 about here]`

We begin our discussion with the averaged estimates in the levels specification in Table 3. Our first observation regarding these results is that across *all* specifications the means of the capital coefficients are considerably lower than in the pooled levels models: between .2 and .5 (VA-equivalent) rather than between .6 and .9 in the pooled levels models in Table 2. Comparing results for the levels specification with those for the specification in first differences in Table 4 reveals that estimates from the heterogeneous models in levels and first differences follow very similar patterns. Recall that for the pooled models estimates for technology parameters in levels and first differences showed radically different results. Parameter estimates are thus similar in all specifications, gross-output or value-added, levels or first-differences.

In all cases it seems that the technology parameters are estimated reasonably precisely, suggested by the reported t-statistic and the Pedroni (1999) panel t-test. 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* in all of the 'augmented' regressions (AMG, ARCM) is easily explained: these country-specific trends have positive and negative magnitudes for different countries. Coefficients on the common dynamic process $\hat{\mu}_t^\bullet$ in models [4] and [8] for all specifications are uniformly high and close to their theoretical value of unity.

Closer inspection of the VA-equivalent capital coefficients suggests the following patterns: *firstly*, estimation approaches that do not account for unobserved common factors or cross-section dependence have parameter estimates around .2. *Secondly*, for the 'augmented' estimators which include a common dynamic process in the estimation equation (either explicitly or implicitly with unit coefficient) the capital coefficients are around .3. *Thirdly*, the results for the CCEMG 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.

In Figures D-1 and D-2 in Appendix D we plot the density estimates for the sample of country-specific technology parameters estimated in the levels regressions presented in Table 3, using standard kernel methods with automatic bandwidth selection. Both sets of plots indicate that the distribution of these parameter estimates is fairly symmetric around their respective means, such that no significant outliers drive our results.

We also 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 processes. As was noted previously, this transformation is only valid if the parameters are homogeneous across countries (Pedroni, 2000). The averaged results for this exercise are presented in Table C-1 in Appendix C. Here, the gross output specifications (levels, FD) yield capital coefficients of between .44 and .48 (VA-equivalent). In stark contrast, the value-added specifications yield capital coefficients between .13 and .20. We take these results as an indication of technology parameter heterogeneity in the production function, since as was discussed above the transformation of variables into deviations from the cross-section mean introduces nonstationarity into the errors if the underlying production technology differs across countries.

3.6 Residual diagnostics

The nature of our data prevents us from implementing a number of specification tests from the nonstationary panel econometric literature: first of all, existing procedures used to investigate cross-section dependence (PCA, mean absolute correlation, Pesaran (2004) CD statistic for residual diagnostics) rely on fairly balanced panels without missing observations. Secondly, panel cointegration tests which allow for cross-section dependence (Westerlund & Edgerton, 2008) perform poorly in moderate T panels, while first generation test routines are developed with balanced panels of full time-series in mind. It is unclear how these can be implemented for a macro panel which includes data from developing countries and thus missing observations and considerable unbalance. We therefore need to resort to a mix of diagnostic tests for pooled regressions and averaged test statistics following the Fisher (1932) combination principle.

We begin with normality and homoskedasticity tests for regression residuals in Table 5. Using the D'Agostino, Balanger, and D'Agostino Jr. (1990) and Cameron and Trivedi (1990) tests virtually all of our pooled regression results reject the joint null hypothesis of normal, and normal and homoskedastic residuals respectively. In contrast the country regression residuals can be assumed as jointly normal or jointly normal and homoskedastic, based on the Fisher statistics (p_λ) constructed from these two testing procedures.

`[Table 5 about here]`

Tables 6 and 7 present panel unit root test results for pooled regression and country regression errors respectively. This analysis broadly suggests that residuals from from POLS and FE are likely to be nonstationary. Country regression residuals are more likely to be stationary across all specifications: nonstationarity is rejected for up to 4 lags in the first generation Maddala and Wu (1999) test, and still for up to 3 lags in the Pesaran (2007) CIPS test (CIPS*), where residuals are not 'demeaned' prior to testing.

`[Tables 6 and 7 about here]`

A cautious conclusion from these diagnostic tests 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.

3.7 The importance of constant returns to scale

Further investigation reveals that the imposition of constant returns to scale, justified by the CRS test for the pooled regression with variables in first differences, plays an important role in our story. We repeat all country regressions in levels, but with all variables 'levels' form, rather than in per worker terms. Results are presented in Table C-2 below. The failure to impose constant returns to scale leads to a loss of precision in the capital estimates in virtually all specifications, for the regressions in levels and first differences. The labour coefficients are however around .7 in all cases and only one out of 16 levels models rejects a parameter test for constant returns to scale — the latter result is not surprising given the sizeable standard errors on the capital coefficients. In the first difference models in the Appendix CRS is never rejected. Despite these reaffirming diagnostics, the sharp difference between the impact of imposing CRS in the country regressions (considerable loss of precision) and the pooled regressions (limited change) is somewhat puzzling and merits further investigation in the future.

3.8 Discussion of main empirical results

Our analysis 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 (VA-equivalent), far in excess of the macro evidence of around 1/3. There may be a number of possible sources for this bias: *firstly*, if parameter heterogeneity prevails and variable series are indeed nonstationary the imposition of common technology across countries leads to nonstationary errors and thus noncointegration. *Secondly*, the results may be the outcome of an identification problem, which arises if the same unobserved common factors drive both output and inputs. In this case the pooled estimates (with the exception of the CCEP) cannot identify the technology parameters $\boldsymbol{\beta}$ separately from the impact of unobserved factors $\boldsymbol{\lambda}_i$. 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 rather sound diagnostics and yields sensible parameter coefficients. The empirical properties of this estimator are somewhat unclear, especially with regard to the identification issue.

The heterogeneous parameter estimators uniformly yield lower implied capital coefficients more in line with the aggregate economy factor income share data. Across levels and first difference, gross-output and value-added specifications there seems to be a consistent pattern emerging whereby the standard heterogeneous estimators (MG, RCM) obtain qualitatively different results from the augmented heterogeneous estimators (AMG, ARCM, CCEMG). Diagnostic tests cannot differentiate between these two groups of estimators, however we can argue that the MG and RCM estimators are likely to be biased for two reasons: firstly, they use an overly simplified representation for TFP evolution (linear trend) which requires stationarity. Secondly, as was discussed above, these estimators are argued to suffer from an identification problem whereby the technology parameters $\boldsymbol{\beta}_i$ cannot be identified separately from the impact of unobserved common factors on output $\boldsymbol{\lambda}_i$ in the case where the same unobserved common factors drive output and inputs (Kapetanios et al., 2008).

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 the cross-country average coefficient for $\hat{\mu}_t^\bullet$ is close to unity in the model where it is included as additional regressor. The CCEMG estimator provides results broadly in line with those for the AMG and ARCM, with the latter two on the whole more consistent across specifications. The comparison between the country regression results presented above and the results for 'demeaned' variables in the Appendix 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).

The estimate for globally common or mean TFP evolution $\hat{\mu}_t^\bullet$ shows serious dips following the two oil crisis shocks in 1973 and 1979, with almost continuous growth thereafter from the mid-1980s to the late 1990s — this development path is arguably in line with historical events and anecdotal evidence regarding the global evolution of manufacturing over the thirty-three-year sample period.

As a further robustness test we also carry out pooled and country regressions adopting a dynamic empirical specification — results do not change considerably in comparison to the static analysis presented here (results available on request).

4 Testing parameter heterogeneity

The individual country coefficients emerging from the regressions in the previous section imply considerable parameter heterogeneity across countries. This apparent heterogeneity may however 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: firstly, we constructed predicted values based on the *mean* parameter estimates of our heterogeneous parameter models, and regressed these on input variables, a common trend and country intercepts in a pooled regression. The rationale of this test is that if parameter estimates were truly heterogeneous we would not expect significant coefficients on the input variables. Secondly, we obtained Swamy (1970) $\hat{S}$ statistics for levels and first difference specifications. Thirdly, we constructed Wald statistics following Canning and Pedroni (2008), and fourthly, we produced F-statistics for standard and augmented MG estimators following Pedroni (2007).[16]

Taken together the results for these various tests (available on request) do give a strong indication that parameter homogeneity is rejected in this dataset. 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 correct empirical analysis in the presence of nonstationary variables.

5 Reverse causality

In the analysis of empirical production functions the issue of variable endogeneity is typically of great concern, requiring means and ways to instrument for factor inputs. A popular approach to address this problem is to convert macro-panel data into a short

[16]Further tests for parameter heterogeneity (Phillips & Sul, 2003; Pesaran, Smith, & Yamagata, 2008) were considered but not pursued due to their low power in the present panel dimensions.

panel of typically 5-year averages and to employ empirical estimators originally developed for large N, small T micro-panels (Arellano & Bond, 1991; Blundell & Bond, 1998), e.g. Islam (1995) and Caselli et al. (1996) for Penn World Table data. For analysis of other macroeconomic relationships it is also not uncommon to see these estimators used for *annual* data where T becomes moderate to large, despite the difficulties arising from over-fitting (Bowsher, 2002; Roodman, 2009). When model parameters differ across countries the instrumentation strategy in these GMM-type estimators (and any other IV strategies for *pooled* regressions) however breaks down since informative instruments are invalid by construction (Pesaran & Smith, 1995). In the following we therefore adopt the empirical approach by Pedroni (2000, 2007) and estimate country regressions by Fully-Modified OLS, whereupon parameter estimates are averaged across countries (Group-Mean FM-OLS). Provided the variables are nonstationary *and* cointegrated the individual FMOLS estimates are super-consistent.

`[Table 8 about here]`

In the upper panel of Table 8 we present averaged parameter estimates for the full sample value-added-based FMOLS regressions, where column [**1**] represents the standard Group-Mean FMOLS, and columns [**2**] and [**3**] augment the country FMOLS equation with the common dynamic process $\hat{\mu}_t^{\bullet,va}$. Columns [**4**] and [**5**] apply FMOLS to a country regression with the CCE-augmentation before averaging the parameter estimates. In the lower panel of the same table our sample only includes 26 countries which 'pass' two nonstationarity test (KPSS, ADF) for value-added per worker and capital stock per worker respectively. Due to the unbalanced nature of our panel we are prevented from testing for cointegration between these two variables.

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. Similar to the results in Table 3 the CCE-augmented average estimate is somewhat larger at .55, although inclusion of a linear country-trend yields an average estimate for capital of around .3.

These results are robust to a restriction of the sample to countries for which value-added and capital stock per worker 'pass' the nonstationarity tests: for the Pedroni (2000) estimator capital stock is insignficant, whereas the inclusion of the common dynamic process replicates our earlier findings. We take these results as a vindication that the production process represents a three-way cointegration between output, factor-inputs and some unobserved common factors.

6 Estimating TFP in a heterogeneous parameter world

In most applications in the literature the estimation of production functions is just the first step in an empirical analysis that concentrates on the magnitudes and determinants of Total Factor Productivity (TFP). In our analysis we have thus far focused on the factor parameter estimates and their magnitudes and robustness across specifications. We do however also want to provide some estimates for TFP and its evolution. From the 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 CCEMG specification respectively. One could 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 estimate for base-year TFP level is no longer valid. Consider the example in Figure 2.

[Figure 2 about here]

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 left panel France (circles) and Belgium (triangles), in the right panel South Korea (circles) and Malaysia (triangles). The 'adjustment' is based on the country-specific estimates from the AMG regression (value-added version) in specification (c) and constructed in the following steps:[17] we begin with the fitted values of this estimation

$$\hat{y}_{it} = \hat{a}_i + \hat{b}_i \log(\mathrm{K/L})_{it} + \hat{c}_i t + \hat{d}_i \hat{\mu}_t^{\bullet} \tag{10}$$

where $\hat{a}_i$, $\hat{b}_i$, $\hat{c}_i$ and $\hat{d}_i$ are country-specific estimates for the intercept, log capital per worker, the common dynamic process and a linear trend term. In order to illustrate our case, we want to obtain a simple linear relationship between value-added and capital where the contribution of TFP growth has already been accounted for. We compute

$$y_{it}^{adj} = y_{it} - \hat{c}_i t - \hat{d}_i \hat{\mu}_t^{\bullet} \tag{11}$$

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 left 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 ($\hat{b}_i \approx \hat{b}_j$). 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 right panel shows two countries which exhibit very different capital coefficient estimates (slopes). In this case $\hat{a}_i$ cannot be interpreted as possessing the *ceteris paribus* quality since $\hat{b}_i \neq \hat{b}$: *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 now want to 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

[17] The results applied are those presented in the lower panel of Table 3, column [4].

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. In the value-added specification these *adjusted* base-year and final-year TFP-levels are thus

$$\hat{a}_i + \hat{b}_i \log(\mathrm{K/L})_{0,i} \qquad \text{and} \qquad \hat{a}_i + \hat{b}_i \log(\mathrm{K/L})_{0,i} + \hat{c}_i \tau + \hat{d}_i \hat{\mu}^{\bullet}_{\tau} \tag{12}$$

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 $\hat{\mu}^{\bullet}_{\tau}$ 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 CCEMG estimator.[18]

Focusing exclusively on the TFP-levels in the base-year, Table C-3 in Appendix D presents the rank (by magnitude) for adjusted TFP levels derived from the AMG estimator in specification (c), i.e. with $\hat{\mu}^{\bullet}_{t}$ included as additional regressor, and the standard CCEMG estimator (in specification (d)). We further show the country ranking based on a pooled fixed effects estimation, such as that presented in Table 3, column [2]. As can be seen in the right half of the table, the rankings differ considerably between the AMG or CCEMG 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 CCEMG (MARD: 1).

We present adjusted TFP base-year and final-year levels for these AMG and CCEMG models in Figure D-3 in Appendix D. Note that in our sample base- and final-year differ across countries (see Table A-2 in Appendix A). 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

[18] This adjustment is somewhat more complex, involving the base-year values of cross-section averages and country-specific coefficients on these averages instead of $\hat{\mu}^{\bullet}_{\tau}$, but the same logic applies.

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.

7 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 the impact of observable and unobservable inputs on output differ across countries, as well as for nonstationary observables and unobservables. We introduced our novel 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 approaches 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 CCEMG this common dynamic process is only implicit, the AMG approach uses an explicit estimate for this process in the augmentation of country-regressions.

We have shown that the adoption of a heterogeneous technology model in combination with a common factor representation for TFP and for the evolution of observable input variables enables us to conceptualise and model a number of characteristics which are likely to be prevalent in manufacturing data from a diverse sample of countries:

- *Firstly*, we allowed for parameter 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 is in support of the 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 empirical approaches to TFP analysis: it leads to the breakdown of the interpretation of regression intercept terms as TFP-levels estimates, as we have shown in Section 6. We therefore introduce 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. 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. Finally, the finding of cross-country technology heterogeneity further questions the validity of standard growth and development accounting practices which impose *common* coefficients on capital stock to extract country-specific measures of TFP.

- *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 of the global developments in manufacturing. 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. Our discussion has highlighted the ability of the Pesaran (2006) CCE estimators and our own AMG approach to deal with this problem successfully. Furthermore, our additional analysis in Section 5 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 CCEMG.

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Table 1: Pooled regressions (unrestricted returns to scale)

Static pooled regressions (unrestricted)
regression equations augmented with year dummies or cross-section means (Pesaran, 2006)

(i) Gross output regressions

	[1]	[2]	[3]		[4]
estimator	**POLS**	**FE♮**	**CCEP♮**	*estimator*	**FD-OLS**
dependent variable	lO	lO	lO	*dependent variable*	ΔlO
regressors				*regressors*	
labour	0.0106	0.1209	0.1757	**Δlabour**	0.1662
	[2.09]*	[12.83]**	[14.61]**		[4.40]**
capital	0.0452	0.1923	0.1720	**Δcapital**	0.0675
	[6.15]**	[21.08]**	[15.13]**		[2.17]*
materials	0.9500	0.7356	0.7228	**Δmaterials**	0.7879
	[101.69]**	[81.17]**	[65.11]**		[30.86]**
intercept	0.4157	0.4883	-0.5225		
	[9.45]**	[3.86]**	[2.68]**		
returns to scale				*returns to scale*	
F-Test for CRS (p)	8.0 (.01)	65.3 (.00)	53.1 (.00)	F-Test for CRS (p)	0.7 (.42)
VA-equivalent†				*VA-equivalent†*	
labour (VA)	0.213	0.457	0.637	labour (VA)	0.784
	[2.47]*	[14.27]**	[16.50]**		[5.62]**
capital (VA)	0.904	0.727	0.620	capital (VA)	0.318
	[12.70]**	[25.01]**	[19.84]**		[2.09]**
AR tests‡				*AR tests‡*	
AR(1) (p)	18.2 (.00)	12.8 (.00)	5.1 (.00)	AR(1) (p)	-2.8 (.00)
AR(2) (p)	18.1 (.00)	7.9 (.00)	0.4 (.70)	AR(2) (p)	-2.1 (.04)
AR(3) (p)	17.9 (.00)	10.5 (.00)	-0.5 (.60)	AR(3) (p)	0.9 (.35)
obs (countries)	1,162 (48)	1,162 (48)	1,162 (48)	obs (countries)	1,094 (94)

(ii) Value-added regressions

	[1]	[2]	[3]		[4]
estimator	**POLS**	**FE♮**	**CCEP♮**	*estimator*	**FD-OLS**
dependent variable	lY	lY	lY	*dependent variable*	ΔlY
regressors				*regressors*	
labour	0.2100	0.4402	0.6009	**Δlabour**	0.6849
	[12.08]**	[17.43]**	[19.48]**		[7.43]**
capital	0.7896	0.7174	0.6144	**Δcapital**	0.3463
	[67.34]**	[32.17]**	[22.76]**		[3.40]**
intercept	1.1510	-0.0470	-0.5160		
	[7.99]**	[0.13]	[0.98]		
returns to scale				*returns to scale*	
F-Test for CRS (p)	0.0 (.96)	82.2 (.00)	57.3 (.00)	F-Test for CRS (p)	0.1 (.72)
AR tests‡				*AR tests‡*	
AR(1) (p)	18.5 (.00)	12.9 (.00)	8.9 (.00)	AR(1) (p)	-3.3 (.00)
AR(2) (p)	18.0 (.00)	9.4 (.00)	4.4 (.00)	AR(2) (p)	-2.7 (.01)
AR(3) (p)	17.6 (.00)	8.0 (.00)	3.7 (.00)	AR(3) (p)	1.2 (.25)
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	obs (countries)	1,128 (94)

Notes: Values in parentheses are absolute t-statistics, based on White heteroskedasticity-consistent standard errors. We indicate statistical significance at the 5% and 1% level by * and ** respectively.
For the CCEP estimator we include sets of cross-section period averages of gross output (lO) [or value-added (lY)], labour (lL), capital stock (lK) and materials (lM), all in logs (estimates not reported) — see main text for description of this estimator. All other models include $T-1$ year dummies in levels or FD (estimates not reported).
The null hypotheses for the CRS tests are $\hat{\alpha}+\hat{\beta}+\hat{\gamma}=1$ and $\hat{\alpha}^{va}+\hat{\beta}^{va}=1$ for gross output and value-added specifications respectively.
♮ The F-tests in the FE and CCEP regressions reject the null that fixed effects do not differ across countries. $F(47,1079)=118.57\,(p=.00)$ (GO), $F(47,1112)=274.48\,(p=.00)$ (VA) for FE; $F(47,919)=8.96\,(p=.00)$ (GO), $F(47,1000)=4.38\,(p=.00)$ (VA) for CCEP.
† These can be derived as $\hat{\alpha}/(1-\hat{\gamma})$ for labour and in analogy for capital (Söderbom & Teal, 2004).
‡ Arellano and Bond (1991) AR test on the regression residuals. H_0: no serial correlation in the residuals.

Table 2: Pooled regressions (CRS)

Static pooled regressions (CRS imposed) regression equations augmented with year dummies or cross-section (Pesaran, 2006)					
(i) Gross output regressions					
	[1]	[2]	[3]		[4]
estimator	**POLS**	**FE**♮	**CCEP**♮	*estimator*	**FD-OLS**
dependent variable	lo	lo	lo	*dependent variable*	Δlo
regressors				*regressors*	
capital pw	0.0478	0.1765	0.1640	**Δcapital pw**	0.0491
	[6.56]**	[19.24]**	[15.56]**		[1.74]
materials pw	0.9493	0.7380	0.7401	**Δmaterials pw**	0.7875
	[102.18]**	[79.15]**	[67.29]**		[30.75]**
intercept	0.4695	1.2411	-0.3355		
	[11.19]**	[14.05]**	[1.78]		
VA-equivalent†				*VA-equivalent*†	
capital pw (VA)	0.942	0.673	0.631	capital pw (VA)	0.231
	[13.44]**	[23.15]**	[21.03]**		[1.72]
AR tests‡				*AR tests*‡	
AR(1) (p)	18.7 (.00)	10.9 (.00)	6.8 (.00)	AR(1) (p)	-2.8 (.00)
AR(2) (p)	18.7 (.00)	8.4 (.00)	2.1 (.03)	AR(2) (p)	-2.1 (.04)
AR(3) (p)	18.6 (.00)	7.1 (.00)	1.0 (.34)	AR(3) (p)	1.0 (.33)
obs (countries)	1,162 (48)	1,162 (48)	1,162 (48)	obs (countries)	1,094 (48)

(ii) Value-added regressions					
	[1]	[2]	[3]		[4]
estimator	**POLS**	**FE**♮	**CCEP**♮	*estimator*	**FD-OLS**
dependent variable	ly	ly	ly	*dependent variable*	Δly
regressors				*regressors*	
capital pw	0.7895	0.6752	0.5823	**Δcapital pw**	0.3195
	[72.97]**	[29.89]**	[23.38]**		[3.61]**
intercept	1.1474	2.3786	0.2489		
	[8.47]**	[9.98]**	[0.63]		
AR tests‡				*AR tests*‡	
AR(1) (p)	18.5 (.00)	13.0 (.00)	9.6 (.00)	AR(1) (p)	-3.3 (.00)
AR(2) (p)	18.0 (.00)	9.6 (.00)	4.7 (.00)	AR(2) (p)	-2.7 (.01)
AR(3) (p)	17.5 (.00)	8.2 (.00)	3.4 (.00)	AR(3) (p)	1.2 (.24)
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	obs (countries)	1,128 (48)

Notes: Values in parentheses are absolute t-statistics, based on White heteroskedasticity-consistent standard errors. For the CCEP estimator we include sets of cross-section period-averages of gross output per worker (lo) [or value-added per worker (ly)], capital stock per worker (lk) and materials per worker (lm), all in logs (estimates not reported) — see text for description of this estimator. All other models include $T-1$ year dummies (estimates not reported). We indicate statistical significance at the 5% and 1% level by * and ** respectively.

♮ The F-tests in the FE and CCEP regressions reject the null that fixed effects do not differ across countries. $F(47, 1080) = 111.81\,(p = .00)$ (GO), $F(47, 1113) = 254.20\,(p = .00)$ (VA) for FE; $F(47, 968) = 7.00\,(p = .00)$ (GO), $F(47, 1049) = 5.35\,(p = .00)$ (VA) for CCEP.

† These can be derived as $\hat{\alpha}(\text{VA}) = \hat{\alpha}/(1-\hat{\gamma})$ for labour and in analogy for capital (Söderbom & Teal, 2004).

‡ Arellano and Bond (1991) AR test on the regression residuals. H_0: no serial correlation in the residuals.

Table 3: Country regression averages (levels, CRS imposed)

Country regressions in levels

static specification with CRS imposed; estimates presented are unweighted means of the country coefficients

(i) Gross output regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**MG**	**RCM**	**AMG**	**AMG**	**CCEMG**	**CCEMG**	**ARCM**	**ARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	lo	lo	lo-$\hat{\mu}_t^{\bullet}$	lo	lo	lo	lo-$\hat{\mu}_t^{\bullet}$	lo
regressors								
capital pw	0.0525	0.0731	0.0695	0.0815	0.1216	0.0839	0.0825	0.0923
	[1.85]	[2.38]*	[2.75]**	[3.17]**	[5.25]**	[3.22]**	[3.00]**	[3.31]**
materials pw	0.7090	0.7305	0.7274	0.7303	0.7193	0.7091	0.7487	0.7480
	[26.31]**	[25.18]**	[27.32]**	[28.31]**	[22.92]**	[24.96]**	[26.24]**	[26.96]**
common trend				1.0083				0.9464
				[4.22]**				[3.63]**
country trend	0.0044	0.0034	0.0008	0.0003		0.0024	-0.0001	-0.0001
	[3.97]**	[2.82]**	[0.76]	[0.26]		[2.17]*	[0.05]	[0.07]
intercept	2.8429	2.4251	2.4713	2.3099	0.8193	1.4514	2.1392	2.0359
	[8.61]**	[6.76]**	[8.24]**	[7.38]**	[1.71]	[3.02]**	[6.56]**	[6.01]**
Panel t-statistics, trends†								
capital pw	8.40	10.59	9.98	11.64	19.02	9.37	12.37	13.48
material pw	103.13	109.32	116.50	114.56	118.90	89.52	121.59	121.65
country trend	20.61	19.57	19.11	12.92		14.06	17.10	12.75
# of sign. trends (at 10%)	30	33	26	24		26	26	23
VA-equivalent coefficients‡								
capital/worker (VA) mean	0.180	0.271	0.255	0.302	0.433	0.288	0.328	0.366
	[1.95]	[2.53]*	[2.96]**	[3.35]**	[6.14]**	[3.49]**	[3.24]**	[3.49]**
obs (countries)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)

(ii) Value-added regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**MG**	**RCM**	**AMG**	**AMG**	**CCEMG**	**CCEMG**	**ARCM**	**ARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	ly	ly	ly-$\hat{\mu}_t^{va\bullet}$	ly	ly	ly	ly-$\hat{\mu}_t^{va\bullet}$	ly
regressors								
capital pw	0.1789	0.2691	0.2896	0.2982	0.4663	0.3125	0.3557	0.3529
	[2.25]*	[3.13]**	[3.95]**	[3.70]**	[6.76]**	[3.72]**	[4.49]**	[4.08]**
common trend				0.8787				0.8751
				[4.39]**				[3.88]**
country trend	0.0174	0.0148	0.0001	0.0023		0.0108	-0.0018	0.0003
	[5.95]**	[4.77]**	[0.04]	[0.56]		[3.09]**	[0.66]	[0.06]
intercept	7.6528	6.7191	6.3823	6.2431	0.8961	4.7860	5.7380	5.7620
	[9.05]**	[7.35]**	[8.42]**	[7.40]**	[0.89]	[3.66]**	[6.98]**	[6.34]**
Panel t-statistics, trends†								
capital pw	12.42	15.45	16.55	17.43	31.86	16.15	20.34	19.68
country trend	27.65	26.65	20.40	12.12		16.08	19.14	10.99
# of sign. trends (at 10%)	39	36	28	19		24	27	19
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)

Notes: All variables are in logs. lo — log output per worker, ly — log value-added per worker. $\hat{\mu}_t^{\bullet}$ and $\hat{\mu}_t^{va\,\bullet}$ are derived from the year dummy coefficients of a pooled regression (CRS imposed) in first differences (FD-OLS) as described in the text.
We omit reporting the parameters on the cross-section averages for the CCEMG estimators (columns [5] and [6]) to save space.
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 $\sum x_i^2$.
'Specification' refers to equations (6) to (9). We indicate statistical significance at the 5% and 1% level by * and ** respectively.
♯ We subtract the common dynamic process $\hat{\mu}_t^{\bullet}$ from log output (log value-added) per worker for country i in models [3] and [7].
† We report the Pedroni (2000) panel-t statistics $(1/\sqrt{N})\sum_i t_i$ where t_i is the country-specific t-statistic of the parameter estimate.
‡ This is obtained using a non-linear combination of the capital and materials coefficients accounting for the precision of these estimates.

Table 4: Country regression averages (FD, CRS imposed)

Country regressions in first differences

static specification with CRS imposed; estimates presented are unweighted means of the country coefficients

(i) Gross output regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**ΔMG**	**ΔRCM**	**ΔAMG**	**ΔAMG**	**ΔCCEMG**	**ΔCCEMG**	**ΔARCM**	**ΔARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	Δlo	Δlo	Δlo-$\Delta\hat{\mu}_t^{\bullet}$	Δlo	Δlo	Δlo	Δlo-$\Delta\hat{\mu}_t^{\bullet}$	Δlo
regressors								
Δcapital pw	0.0476	0.0544	0.0659	0.0763	0.0836	0.0547	0.0675	0.0667
	[2.01]*	[1.92]	[2.85]**	[3.31]**	[3.98]**	[2.30]*	[2.45]*	[2.43]*
Δmaterials pw	0.7634	0.7736	0.7744	0.7672	0.7579	0.7575	0.7834	0.7779
	[42.75]**	[37.14]**	[41.69]**	[40.19]**	[36.21]**	[39.46]**	[36.63]**	[35.67]**
common drift	-	-	-	1.0363	-	-	-	0.8633
	-	-	-	[4.93]**	-	-	-	[3.64]**
country drift	0.0020	0.0028	-0.0014	-0.0016	-	0.0013	-0.0003	0.0001
	[1.67]	[1.85]	[1.17]	[1.42]	-	[0.93]	[0.23]	[0.04]
Panel t-statistics, trends†								
capital pw	4.6	5.8	6.3	5.8	7.8	4.5	7.5	7.3
materials pw	90.8	114.8	102.6	99.8	86.6	86.2	118.0	119.0
country trends	7.3	8.0	6.3	6.3	-	7.9	6.4	5.9
# of sign. trends (at 10%)	8	13	6	7	-	12	6	6
VA-equivalent coefficients‡								
capital/worker (VA) mean	0.201	0.240	0.292	0.328	0.345	0.226	0.312	0.300
	[2.03]*	[1.92]	[2.90]**	[3.30]**	[3.97]**	[2.30]*	[2.47]*	[2.43]*
obs (countries)	1,094 (48)	1,094 (48)	1,094 (48)	1,094 (48)	1,094 (48)	1,094 (48)	1,094 (48)	1,094 (48)

(ii) Value-added regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**ΔMG**	**ΔRCM**	**ΔAMG**	**ΔAMG**	**ΔCCEMG**	**ΔCCEMG**	**ΔARCM**	**ΔARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	Δly	Δly	Δly-$\Delta\hat{\mu}_t^{va\bullet}$	Δly	Δly	Δly	Δly-$\Delta\hat{\mu}_t^{va\bullet}$	Δly
regressors								
Δcapital pw	0.1642	0.2085	0.2734	0.2834	0.3837	0.2577	0.3053	0.2969
	[1.91]	[2.13]*	[3.48]**	[3.77]**	[5.62]**	[3.48]**	[3.37]**	[3.38]**
common drift	-	-	-	1.0497	-	-	-	0.8938
	-	-	-	[5.71]**	-	-	-	[4.21]**
country drift	0.0161	0.0171	-0.0011	-0.0020	-	0.0123	-0.0001	0.0017
	[5.54]**	[4.42]**	[0.44]	[0.50]	-	[3.76]**	[0.03]	[0.34]
Panel t-statistics, trends†								
capital pw	4.8	6.9	8.3	7.7	12.0	7.2	10.7	10.4
country trends	9.53	13.95	5.77	7.46	-	7.68	6.18	7.26
# of sign. trends (at 10%)	14	24	6	10	-	11	7	10
obs (countries)	1,128 (48)	1,128 (48)	1,128 (48)	1,128 (48)	1,128 (48)	1,128 (48)	1,128 (48)	1,128 (48)

Notes: Variables are in first differences of logs. Δlo — output per worker growth rate, Δly — value-added per worker growth rate.
See Table 3 for further information.

Table 5: Testing Residuals for Normality and Homoskedasticity

Regression residuals — normality, homoskedasticity♯

H_0 for respective test statistics: no heteroskedasticity, regular skewness, regular kurtosis;♭

we report the χ^2 or the Fisher p_λ statistic and corresponding p-values

	Cameron & Trivedi tests								**D'Agostino *et al* normality test**			
	Pooled regression residuals: Gross output specifications (CRS)†											
	Joint test		Heterosked.		Skewness		Kurtosis		Joint test		Skewness	Kurtosis
	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	p	p
POLS	176.1	.01	139.5	.01	36.4	.36	0.2	.64	33.6	.00	.04	.00
FE	1355.6	.01	1162.0	.49	180.2	.00	13.4	.00	69.2	.00	.00	.00
CCEP	-	-	-	-	-	-	-	-	106.2	.00	.12	.00
FD-OLS	541.3	.00	491.9	.00	43.1	.11	6.3	.01	214.2	.00	.00	.00
	Pooled regression residuals: Value-added specifications (CRS)†											
	Joint test		Heterosked.		Skewness		Kurtosis		Joint test		Skewness	Kurtosis
	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	p	p
POLS	194.3	.00	95.4	.01	95.3	.00	3.6	.06	51.2	.00	.00	.16
FE	1324.2	.16	1194.0	.49	98.1	.08	32.2	.00	53.0	.00	.00	.00
CCEP	-	-	-	-	-	-	-	-	84.7	.00	.12	.00
FD-OLS	281.7	.00	237.2	.00	36.8	.26	7.8	.01	279.4	.00	.00	.00

	Cameron & Trivedi tests								**D'Agostino *et al* normality test**					
	Country regression residuals: Gross output specifications (CRS)†													
	Joint test		Heterosked.		Skewness		Kurtosis		Joint test		Skewness		Kurtosis	
	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
MG	80.0	.88	70.4	.98	69.0	.98	39.7	1.00	51.0	1.00	55.4	1.00	43.2	1.00
AMG(i)	81.7	.85	70.9	.97	67.5	.99	41.8	1.00	46.0	1.00	47.7	1.00	41.8	1.00
AMG(ii)	64.7	.99	56.7	1.00	59.0	1.00	42.9	1.00	48.7	1.00	50.6	1.00	43.9	1.00
CCEMG(i)	46.5	1.00	44.5	1.00	42.3	1.00	50.7	1.00	45.2	1.00	41.0	1.00	46.5	1.00
CCEMG(ii)	41.7	1.00	39.0	1.00	47.7	1.00	43.9	1.00	34.4	1.00	32.4	1.00	39.8	1.00
	Country regression residuals: Value-added specifications (CRS)†													
	Joint test		Heterosked.		Skewness		Kurtosis		Joint test		Skewness		Kurtosis	
	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
MG	93.6	.55	83.8	.81	72.3	.97	43.5	1.00	56.2	1.00	57.6	1.00	47.2	1.00
AMG(i)	97.3	.44	80.1	.88	81.9	.85	46.6	1.00	56.0	1.00	57.0	1.00	47.2	1.00
AMG(ii)	81.4	.86	71.9	.97	63.8	1.00	50.0	1.00	52.4	1.00	54.2	1.00	46.7	1.00
CCEMG(i)	96.8	.46	71.8	.97	86.1	.76	43.0	1.00	58.7	1.00	63.4	1.00	45.3	1.00
CCEMG(ii)	65.7	.99	59.4	1.00	56.1	1.00	43.9	1.00	51.6	1.00	51.0	1.00	47.6	1.00

Notes: ♯ We report heteroskedasticity and normality test statistics for residual series from (a) pooled estimators: POLS — pooled OLS, FE — pooled OLS with N country dummies, CCEP — Pesaran (2006) common correlated effects estimator (pooled version), FD-OLS — pooled OLS with variables in first differences; POLS, FE and FD-OLS are augmented with $T-1$ year dummies; the regression results from which these residuals are taken are presented in Table 2; and (b) heterogeneous parameter estimators: MG — Pesaran and Smith (1995) Mean Group estimator, AMG(i) — Augmented Mean Group estimator ($\hat{\mu}_t^\bullet$ imposed with unit coefficient), AMG(ii) — dto. ($\hat{\mu}_t^\bullet$ included as additional regressor), CCEMG(i) — Pesaran (2006) common correlated effects estimator (mean group version), CCEMG(ii) — dto. with additional country trend; MG, AMG(i), AMG(ii), and CCEMG(ii) contain country-specific trend terms; the regression results from which these residuals are taken are presented in Table 3.
The Cameron and Trivedi (1990) decomposition test analyses residual heteroskedasticity, skewness and kurtosis. The D'Agostino et al. (1990) test investigates skewness and kurtosis. Both tests provide joint hypothesis tests. If a test rejects skewness or kurtosis we can no longer assume normality for the residual distribution.
♭ 'Regular' in this case is taken to mean in line with the normal distribution.
† For the pooled regressions we report χ^2 statistics and corresponding p-values. For the country regression we compute the Fisher statistic $p_\lambda = -2\sum_i log(p_i)$, where p_i is the p-value of the *country-specific* test statistic. The Fisher statistic p_λ is distributed $\chi^2(2N)$.

Table 6: Testing Residuals for Stationarity (i)

Pooled regression residuals — stationarity tests$^\sharp$
H_0 for each test: nonstationary residual series;$^\flat$
Maddala and Wu (1999) (MW) and Pesaran (2007) (CIPS) test results;
CIPS* does *not* apply cross-sectional demeaning prior to the testing procedure

Residuals from gross output specifications (CRS imposed)†										
	lags: 0		lags: 1		lags: 2		lags: 3		lags: 4	
MW	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
POLS	193.16	.00	169.00	.00	91.82	.60	105.65	.24	110.42	.15
FE	188.54	.00	216.55	.00	127.73	.02	129.72	.01	98.44	.41
CCEP	397.64	.00	370.93	.00	203.45	.00	148.20	.00	155.512	.00
FD-OLS	1164.92	.00	632.24	.00	393.81	.00	297.95	.00	140.95	.00
CIPS	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
POLS	-1.88	.03	-0.36	.36	1.27	.90	4.22	1.00	6.33	1.00
FE	-1.49	.07	-0.61	.27	1.65	.95	3.98	1.00	6.80	1.00
CCEP	-10.08	.00	-8.23	.00	-4.12	.00	2.40	1.00	7.08	1.00
FD-OLS	-20.88	.00	-10.26	.00	-1.47	.07	3.97	1.00	8.89	1.00
CIPS*	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
POLS	-2.32	.01	-1.41	.08	1.51	.93	1.19	.88	3.09	1.00
FE	-1.98	.02	-2.00	.02	1.39	.92	2.86	1.00	4.21	1.00
CCEP	-10.08	.00	-8.23	.00	-4.12	.00	2.40	.99	7.08	1.00
FD-OLS	-22.28	.00	-14.19	.00	-8.51	.00	-5.00	.00	1.72	.96

Residuals from value-added specifications (CRS imposed)†										
	lags: 0		lags: 1		lags: 2		lags: 3		lags: 4	
MW	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
POLS	151.96	.00	176.19	.00	108.60	.18	74.32	.95	72.70	.96
FE	146.64	.00	140.02	.00	94.70	.52	72.66	.96	92.21	.59
CCEP	323.84	.00	306.74	.00	196.42	.00	136.74	.00	127.54	.02
FD-OLS	2033.95	.00	1142.64	.00	580.42	.00	455.09	.00	314.48	.00
CIPS	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
POLS	-0.96	.17	0.52	.70	3.59	1.00	8.14	1.00	9.82	1.00
FE	-1.76	.04	-1.13	.13	0.78	.78	5.17	1.00	6.53	1.00
CCEP	-8.32	.00	-7.53	.00	-2.74	.00	1.41	.92	8.26	1.00
FD-OLS	-27.11	.00	-20.16	.00	-6.73	.00	-1.17	.12	4.23	1.00
CIPS*	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
POLS	-1.34	.09	-1.53	.06	1.67	.95	3.81	1.00	4.81	1.00
FE	-1.18	.12	-0.44	.33	2.28	.99	4.40	1.00	4.96	1.00
CCEP	-8.32	.00	-7.53	.00	-2.74	.00	1.41	.92	8.26	1.00
FD-OLS	-28.18	.00	-20.99	.00	-12.63	.00	-8.92	.00	-1.35	.09

Notes: † We apply the Pesaran (2007) (CIPS) and Maddala and Wu (1999) (MW) panel unit root tests; the former accounts for possible cross-section dependence in the variable tested (here: regression residuals). We also present the results for the CIPS where cross-sectional demeaning of the data prior to the testing procedure is prevented (marked as CIPS*).
See Table 5 for a description of the regressions from which these residuals are taken.

Table 7: Testing Residuals for Stationarity (ii)

Country regression residuals — stationarity tests[♯]
H_0 for each test: stationary residual series;[♭]
Maddala and Wu (1999) (MW) and Pesaran (2007) (CIPS) test results;
CIPS* does *not* apply cross-sectional demeaning prior to the testing procedure

Gross output specifications (CRS)†

	lags: 0		lags: 1		lags: 2		lags: 3		lags: 4	
MW	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
MG	429.01	.00	386.48	.00	227.16	.00	166.57	.00	138.59	.00
RCM	384.54	.00	359.93	.00	211.93	.00	154.20	.00	127.73	.02
AMG(i)	444.71	.00	388.14	.00	251.08	.00	168.88	.00	132.25	.01
AMG(ii)	551.52	.00	468.54	.00	299.32	.00	195.87	.00	145.25	.00
CCEMG(i)	581.95	.00	585.88	.00	329.75	.00	285.80	.00	201.71	.00
CCEMG(ii)	699.77	.00	624.26	.00	330.92	.00	242.79	.00	177.41	.00
ARCM(i)	397.22	.00	355.32	.00	226.16	.00	145.11	.00	127.07	.02
ARCM(ii)	485.06	.00	444.00	.00	275.65	.00	176.20	.00	132.18	.01
CIPS	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
MG	-9.63	.00	-9.28	.00	-2.65	.00	0.96	.83	8.05	1.00
RCM	-9.07	.00	-8.99	.00	-1.85	.03	1.10	.86	7.25	1.00
AMG(i)	-10.15	.00	-9.94	.00	-5.18	.00	1.62	.95	7.69	1.00
AMG(ii)	-12.23	.00	-11.32	.00	-5.62	.00	0.14	.56	5.63	1.00
CCEMG(i)	-12.88	.00	-11.18	.00	-5.61	.00	0.37	.65	8.03	1.00
CCEMG(ii)	-15.28	.00	-11.66	.00	-4.62	.00	0.49	.69	7.45	1.00
ARCM(i)	-9.35	.00	-8.20	.00	-4.37	.00	2.61	1.00	7.74	1.00
ARCM(ii)	-11.39	.00	-10.98	.00	-6.10	.00	0.66	.74	5.72	1.00
CIPS*	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
MG	-10.17	.00	-8.95	.00	-4.76	.00	-2.47	.01	0.42	.66
RCM	-9.18	.00	-8.31	.00	-4.25	.00	-2.07	.02	0.76	.78
AMG(i)	-10.69	.00	-9.09	.00	-5.48	.00	-2.79	.00	-0.14	.45
AMG(ii)	-13.35	.00	-11.26	.00	-7.05	.00	-3.66	.00	-0.35	.36
CCEMG(i)	-14.15	.00	-13.28	.00	-7.93	.00	-6.08	.00	-2.25	.01
CCEMG(ii)	-16.60	.00	-14.48	.00	-8.23	.00	-5.37	.00	-1.67	.05
ARCM(i)	-9.73	.00	-8.22	.00	-4.62	.00	-1.80	.04	0.25	.60
ARCM(ii)	-11.98	.00	-10.61	.00	-6.22	.00	-2.82	.00	0.21	.58

Value-added specifications (CRS)†

	lags: 0		lags: 1		lags: 2		lags: 3		lags: 4	
MW	p_λ	p	p_λ	p	p_λ	p	p_λ	p	p_λ	p
MG	360.10	.00	365.52	.00	236.82	.00	274.77	.00	136.90	.00
RCM	336.11	.00	349.73	.00	227.42	.00	285.17	.00	132.23	.01
AMG(i)	351.49	.00	347.73	.00	234.17	.00	160.73	.00	134.66	.01
AMG(ii)	434.12	.00	403.79	.00	254.07	.00	172.11	.00	137.53	.00
CCEMG(i)	399.32	.00	393.45	.00	270.81	.00	176.23	.00	149.47	.00
CCEMG(ii)	482.29	.00	440.86	.00	271.00	.00	184.36	.00	165.30	.00
ARCM(i)	330.71	.00	327.87	.00	217.22	.00	148.04	.00	176.24	.00
ARCM(ii)	384.88	.00	362.08	.00	224.68	.00	159.38	.00	162.32	.00
CIPS	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
MG	-8.22	.00	-7.64	.00	-3.90	.00	0.56	.71	7.78	1.00
RCM	-7.83	.00	-6.98	.00	-3.72	.00	0.50	.69	7.56	1.00
AMG(i)	-8.97	.00	-7.19	.00	-2.90	.00	2.59	1.00	7.90	1.00
AMG(ii)	-10.98	.00	-9.86	.00	-4.77	.00	1.25	.89	7.60	1.00
CCEMG(i)	-9.20	.00	-9.08	.00	-3.90	.00	1.96	.97	8.62	1.00
CCEMG(ii)	-11.78	.00	-9.57	.00	-4.05	.00	1.54	.94	6.26	1.00
ARCM(i)	-8.55	.00	-7.32	.00	-2.93	.00	1.50	.93	6.98	1.00
ARCM(ii)	-10.35	.00	-9.13	.00	-4.72	.00	2.43	.99	7.35	1.00
CIPS*	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p	Z[t-bar]	p
MG	-8.72	.00	-8.50	.00	-5.12	.00	-3.31	.00	0.01	.50
RCM	-8.18	.00	-8.07	.00	-4.82	.00	-2.91	.00	0.40	.65
AMG(i)	-8.72	.00	-8.13	.00	-4.87	.00	-2.14	.02	-0.12	.45
AMG(ii)	-10.60	.00	-9.76	.00	-5.83	.00	-2.45	.01	0.20	.58
CCEMG(i)	-9.59	.00	-8.97	.00	-5.96	.00	-2.35	.01	-0.03	.49
CCEMG(ii)	-11.78	.00	-10.45	.00	-6.26	.00	-3.35	.00	-1.21	.11
ARCM(i)	-8.23	.00	-7.55	.00	-4.35	.00	-1.48	.07	-0.14	.44
ARCM(ii)	-9.59	.00	-8.61	.00	-4.78	.00	-1.68	.05	0.16	.57

Table 8: Country regressions using FMOLS

Averaged Fully Modified OLS estimates

We apply the Phillips and Hansen (1990) FM-OLS estimator to each country; estimates reported are unweighted means of country estimates

Value-added specification: Full sample

estimator: **FMOLS-** *dependent variable*	**MG** ly [1]	**AMG** ly-$\hat{\mu}_t^{\bullet,va}$ [2]	**AMG** ly [3]	**CCEMG** ly [4]	**CCEMG** ly [5]
regressors					
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, trends†					
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
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)

Value-added specification: I(1) sample

estimator: **FM-** *dependent variable*	**MG** ly [1]	**AMG** ly-$\hat{\mu}_t^{\bullet,va}$ [2]	**AMG** ly [3]	**CCEMG** ly [4]	**CCEMG** ly [5]
regressors					
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, trends†					
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
obs (countries)	561 (26)	561 (26)	561 (26)	561 (26)	561 (26)

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. The lower panel uses observations from only those countries for which variables were determined to be nonstationary (via ADF and KPSS testing).

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

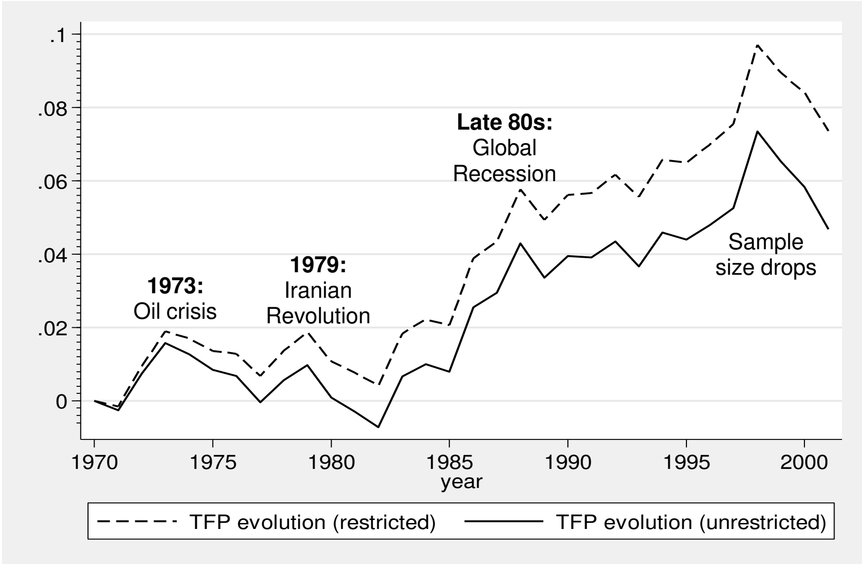
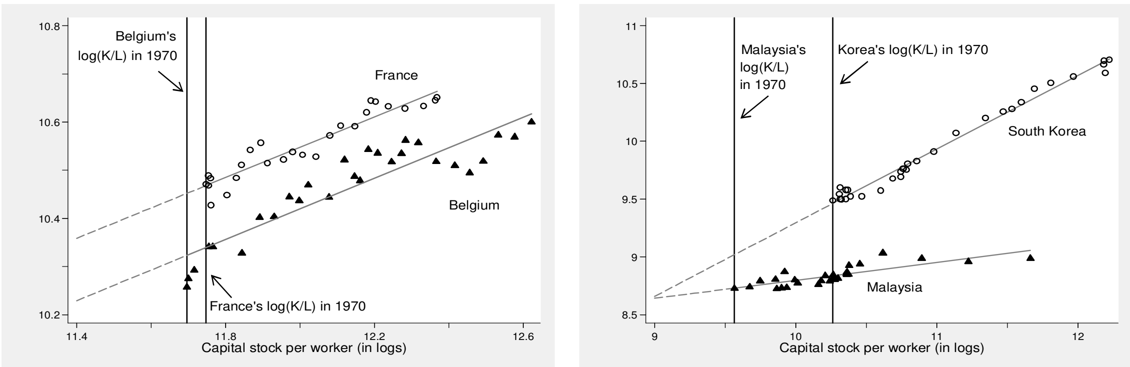


Figure 2: Regression intercepts and TFP level estimates



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 1963-2002. The capital stocks are calculated from investment data in current LCU following the 'perpetual inventory' method developed 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 ($n = 1,162$ for the gross-output specification) from $N = 48$ countries, which have a time-series dimension between $T = 11$ and $T = 33$, with average $T = 24$. This is the sample we use in the empirical analysis throughout this chapter. Table A-1 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-2.

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 surprisingly close 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-1: Descriptive statistics

Variables in level terms						
Variable	**obs**	**mean**	**median**	**std. dev.**	**min.**	**max.**
levels						
output	1,162	1.40 E+11	2.41 E+10	4.06 E+11	7.21 E+07	3.15 E+12
value-added	1,194	5.47 E+10	9.04 E+09	1.78 E+11	1.76 E+07	1.50 E+12
labour	1,162	1,442,446	5.02 E+05	2,948,201	5,552	1.97 E+07
capital	1,162	1.31 E+11	2.61 E+10	3.16 E+11	5.78 E+07	2.27 E+12
materials	1,162	8.44 E+10	1.55 E+10	2.27 E+11	5.45 E+07	1.65 E+12
logs						
output	1,162	23.74	23.91	2.12	18.09	28.78
value-added	1,194	22.70	22.93	2.15	16.68	28.04
labour	1,162	12.88	13.13	1.79	8.62	16.79
capital	1,162	23.67	23.98	2.22	17.87	28.45
materials	1,162	23.31	23.46	2.11	17.81	28.13
annual growth rate						
output	1,094	4.4%	3.9%	9.8%	-43.7%	100.1%
value-added	1,128	3.9%	3.5%	12.3%	-78.3%	92.7%
labour	1,094	1.7%	0.8%	8.1%	-38.8%	78.1%
capital	1,094	4.2%	3.1%	4.4%	-2.4%	47.8%
materials	1,094	4.6%	3.7%	10.6%	-39.3%	103.1%

Variables in per worker terms						
variable	**obs**	**mean**	**median**	**std. dev.**	**min.**	**max.**
levels						
output	1,162	71,470	51,673	52,945	4,711	286,509
value-added	1,194	25,305	17,867	19,385	1,660	91,011
capital	1,162	75,522	45,865	71,512	2,007	346,064
materials	1,162	46,261	33,958	34,881	2,596	195,497
logs						
output	1,162	10.86	10.85	0.86	8.46	12.57
value-added	1,194	9.78	9.79	0.92	7.41	11.42
capital	1,162	10.79	10.73	1.00	7.60	12.75
materials	1,162	10.42	10.43	0.85	7.86	12.18
annual growth rate						
output	1,094	2.6%	2.6%	8.3%	-44.5%	85.0%
value-added	1,128	2.2%	2.5%	10.8%	-90.3%	74.4%
capital	1,094	2.5%	2.6%	7.9%	-68.0%	45.4%
materials	1,094	2.9%	2.7%	9.5%	-53.8%	87.9%

Notes: We report the descriptive statistics for output, labour, capital and material inputs for the gross-output regression sample ($n = 1,162$) and value-added for the VA regression sample ($n = 1,194$) — descriptive statistics for capital and labour in the latter specification do not differ noticeably from those reported above and we therefore do not report them separately. Monetary values are in real US$ (1990). Labour is in number of workers.

Table A-2: Sample of countries and number of observations

Country	Code	Gross-output		Value-added				I(1)*
		levels	*FD*	*levels*	*FD*	$t = 1$	$t = T$	
Australia	AUS	20	17	20	17	1970	1993	✓
Austria	AUT	30	28	30	28	1970	2000	✓
Belgium	BEL	15	14	28	27	1970	1997	✓
Bangladesh	BGD	14	12	14	12	1970	1992	✓
Bolivia	BOL	11	10	11	10	1987	1997	
Barbados	BRB	26	25	26	25	1970	1995	
Canada	CAN	21	20	21	20	1970	1990	✓
Chile	CHL	25	24	25	24	1974	1998	✓
Colombia	COL	30	29	30	29	1970	1999	✓
Cyprus	CYP	33	32	33	32	1970	2002	✓
Ecuador	ECU	30	29	30	29	1970	1999	
Egypt	EGY	26	25	26	25	1970	1995	
Spain	ESP	26	25	26	25	1970	1995	
Finland	FIN	28	26	28	26	1970	2000	✓
Fiji	FJI	25	24	25	24	1970	1994	✓
France	FRA	26	25	26	25	1970	1995	
United Kingdom	GBR	23	22	23	22	1970	1992	✓
Guatemala	GTM	16	15	16	15	1973	1988	✓
Hungary	HUN	26	25	26	25	1970	1995	
Indonesia	IDN	26	25	26	25	1970	1995	✓
India	IND	32	31	32	31	1970	2001	
Ireland	IRL	22	21	22	21	1970	1991	
Iran	IRN	24	22	24	22	1970	2001	
Israel	ISR	13	12	13	12	1989	2001	
Italy	ITA	30	28	31	30	1970	2000	
Korea	KOR	32	31	32	31	1970	2001	
Sri Lanka	LKA	20	17	20	17	1970	2000	✓
Luxembourg	LUX	23	22	23	22	1970	1992	✓
Morocco	MAR	17	16	17	16	1985	2001	✓
Mexico	MEX	16	14	16	14	1984	2000	✓
Malta	MLT	32	31	32	31	1970	2001	✓
Malaysia	MYS	28	25	28	25	1970	2001	
Netherlands	NLD	24	23	24	23	1970	1993	✓
Norway	NOR	32	31	32	31	1970	2001	✓
New Zealand	NZL	21	20	21	20	1970	1990	
Panama	PAN	30	28	30	28	1970	2000	
Philippines	PHL	26	25	26	25	1970	1995	
Poland	POL	14	11	31	30	1970	2000	✓
Portugal	PRT	31	30	31	30	1970	2000	✓
Senegal	SEN	16	14	17	14	1970	1990	
Singapore	SGP	33	32	33	32	1970	2002	✓
Sweden	SWE	18	17	18	17	1970	1987	✓
Swaziland	SWZ	24	22	24	22	1970	1995	
Tunisia	TUN	21	19	21	19	1970	1997	
Turkey	TUR	27	25	27	25	1970	1997	
United States	USA	26	25	26	25	1970	1995	✓
Venezuela	VEN	26	24	26	24	1970	1998	✓
Zimbabwe	ZWE	27	26	27	26	1970	1996	
Obs		1,162	1,094	1,194	1,128		644	

Notes: * This refers to the sample used in Section 5 — this includes 26 countries which cannot reject nonstationarity (for ly, lk) in country ADF regressions and reject stationarity in country KPSS regressions.

B Time-series properties of the data

Since the time dimension of the panel is sizeable ($T = [11, 33]$, average $T = 24$), we carry out Augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) tests for the variable series within each individual country. [c] We use this combination of tests since the ADF and PP tests have the null of nonstationary variable series, whereas the KPSS test has the null of stationary variable series. The PP test uses nonparametric methods to account for potential serial correlation in the errors and thus does not reduce the number of time-series observations like the ADF test, which uses lagged differences for the same aim. The results for variables in *levels* and in *per worker terms* are shown in Table B-1: we report the share of countries (in %) for which the null hypothesis (stationarity or nonstationarity as indicated) is rejected.

For the majority of countries the ADF and PP 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. The overall pattern of test results is reversed when we run ADF and KPSS tests on variables in *first-difference*, indicating that variable series are indeed 'difference-stationary'.

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. They also point out that regular Dickey-Fuller critical values remain valid for either approach. We carried out ADF tests for the altered dataset (levels, first differences) 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 a test by Im, Pesaran, and Shin (1997) and the Maddala and Wu (1999) panel unit root test, both of which do not account for cross-sectional dependence in the variables. Results in Table B-2 show that for the variable series in 'levels' these tests cannot agree on the level of integration prevalent in the data. For the per worker variable series, however, neither test can reject the null hypothesis that *all* countries have I(1) series.

[c] 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. This reduces the sample to 1,109 observations ($N = 48$).

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) (IPS(ii)), and the Pesaran (2007) test based on cross-section augmented ADF regressions (CIPS). 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 interpolated, which considerably reduces our sample size ($T, N = 26, 29$; $n = 754$) compared to the *unbalanced* panel ($T_{max} = 33$, $N = 48$; $n = 1,162$).

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. In most cases these testing procedures cannot reject the null of nonstationarity. If we apply the CIPS test to data in first differences, we reject nonstationarity throughout if we augment with up to two lags (or none); for more lags the p-value for most variable tests jumps to unity (not reported).

Table B-1: Time-series unit root tests — rejection frequency

Unit root tests
share of country tests which reject H_0 (stationarity or nonstationarity as indicated);
no adjustment for cross-sectional dependence

Testing for levels-stationarity

Test	H_0	H_1	*variable*	output	value-added	labour	capital	materials
			variables in levels					
ADF without trend	nonstationary	levels-stationary		17%	21%	21%	10%	19%
PP without trend	nonstationary	levels-stationary		19%	10%	17%	17%	17%
KPSS without trend	levels-stationary	nonstationary		85%	81%	73%	98%	79%
			variables in levels (in per worker terms)					
ADF without trend	nonstationary	levels-stationary		4%	8%		6%	2%
PP without trend	nonstationary	levels-stationary		8%	17%		8%	10%
KPSS without trend	levels-stationary	nonstationary		77%	69%		71%	77%

Testing for trend-stationarity

Test	H_0	H_1	*variable*	output	value-added	labour	capital	materials
			variables in levels					
ADF with trend	nonstationary	trend-stationary		21%	29%	19%	31%	25%
PP with trend	nonstationary	trend-stationary		15%	10%	10%	4%	10%
KPSS with trend	trend-stationary	nonstationary		31%	25%	42%	46%	31%
			variables in levels (in per worker terms)					
ADF with trend	nonstationary	trend-stationary		23%	25%		31%	25%
PP with trend	nonstationary	trend-stationary		27%	13%		6%	15%
KPSS with trend	trend-stationary	nonstationary		31%	23%		31%	27%

Testing for difference-stationarity

Test	H_0	H_1	*variable*	output	value-added	labour	capital	materials
			variables in first differences					
ADF with drift	nonstationary	stationary		94%	85%	90%	83%	88%
PP with drift	nonstationary	stationary		90%	94%	71%	29%	90%
KPSS with drift	nonstationary	stationary		4%	0%	4%	10%	2%
			variables in first differences (in per worker terms)					
ADF with drift	nonstationary	stationary		94%	90%		83%	83%
PP with drift	nonstationary	stationary		96%	94%		75%	94%
KPSS with drift	nonstationary	stationary		2%	2%		2%	4%

Notes: All variables are in logs. We report the share of countries (out of $N = 48$) for which the respective unit root test is rejected at the 5% level of significance. All unit root tests for variables in levels contain an intercept term in the estimating equation. ADF refers to the augmented Dickey-Fuller test, which has the null of nonstationarity. PP refers to the Phillips and Perron (1988) unit root test, which has the null of nonstationarity. KPSS refers to the Kwiatkowski et al. (1992) unit root test, which has the null of (trend-)stationarity. Lag-augmentation or bandwidth selection in these tests to account for serial correlation in the variables is allowed to vary by country. For the ADF test we determined 'ideal' lag-augmentation using the Akaike Information Criterion (AIC). The PP test uses $int(4(T/100)^{2/9})$ lags throughout, for the KPSS tests an automated bandwidth selection following Hobijn et al. (1998) is used. For the latter we use the `kpss` command in `Stata` written by Kit Baum.

Table B-2: First generation panel unit root tests

Im, Pesaran & Shin (1997) panel unit root tests — IPS(i)$^\sharp$ H_0: unit root process (reject reported); augmentation with country-specific lag length (average reported)														
output			**value-added**			**labour**			**capital**			**materials**		
lags	[t-bar]		lags	[t-bar]		lags	[t-bar]		lags	[t-bar]		lags	[t-bar]	
1.42	-1.57		1.96	-1.54		1.48	-1.78	*reject*	1.50	-1.92	*reject*	1.65	-1.67	
output/worker			**VA/worker**						**capital/worker**			**materials/worker**		
lags	[t-bar]		lags	[t-bar]					lags	[t-bar]		lags	[t-bar]	
1.44	-0.92		1.65	-1.03					1.71	-0.97		1.83	-1.05	

Maddala and Wu (1999) panel unit root tests — MW$^\sharp$ H_0: unit root process; augmentation with lags as indicated;														
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)
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)
output/worker			**VA/worker**						**capital/worker**			**materials/worker**		
lags	p_λ	(p)	lags	p_λ	(p)				lags	p_λ	(p)	lags	p_λ	(p)
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)

Notes: $\sharp$ All variables are in logs. The IPS(i) and MW statistics are constructed as t-bar $= N^{-1}\sum_i t_i$ and $p_\lambda = -2\sum_i log(p_i)$ respectively, where t_i are the country ADF statistics and p_i corresponding p-values. For the IPS(i) 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. For the MW test the critical values are distributed $\chi^2(2N)$. IPS(i) uses 'ideal' lag-length as determined via the AIC (see notes Table B-1).

Table B-3: Second generation panel unit root tests

Im, Pesaran & Shin (2003) panel unit root tests — IPS(ii)$^\sharp$ H_0: unit root process; augmentation with lags as indicated														
output			**value-added**			**labour**			**capital**			**materials**		
lags	W[t-bar]	(p)	lags	W[t-bar]	(p)	lags	W[t-bar]	(p)	lags	W[t-bar]	(p)	lags	W[t-bar]	(p)
0	3.88	(1.00)	0	1.73	(.96)	0	1.00	(.84)	0	4.07	(1.00)	0	4.11	(1.00)
1	1.82	(.97)	1	1.51	(.94)	1	-0.68	(.25)	1	2.84	(1.00)	1	2.86	(1.00)
2	2.11	(.98)	2	2.50	(.99)	2	0.43	(.66)	2	2.28	(.99)	2	2.26	(.99)
3	3.13	(1.00)	3	3.23	(1.00)	3	0.96	(.83)	3	1.67	(.95)	3	2.74	(1.00)
output/worker			**VA/worker**						**capital/worker**			**materials/worker**		
lags	W[t-bar]	(p)	lags	W[t-bar]	(p)				lags	W[t-bar]	(p)	lags	W[t-bar]	(p)
0	0.30	(.62)	0	-0.68	(.25)				0	1.23	(.89)	0	0.16	(.56)
1	-0.10	(.46)	1	0.31	(.62)				1	-0.39	(.35)	1	-0.14	(.44)
2	-0.45	(.33)	2	1.30	(.90)				2	1.21	(.89)	2	-0.82	(.21)
3	-0.25	(.40)	3	1.74	(.96)				3	0.65	(.74)	3	-0.93	(.18)

Pesaran (2007) panel unit root tests — CIPS$^\sharp$ H_0: unit root process; augmentation with lags as indicated														
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)
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)
output/worker			**VA/worker**						**capital/worker**			**materials/worker**		
lags	Z[t-bar]	(p)	lags	Z[t-bar]	(p)				lags	Z[t-bar]	(p)	lags	Z[t-bar]	(p)
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)

Notes: $\sharp$ All variables are in logs. For the IPS(ii) tests we were forced to reduce the sample to $n = 754$ due to the requirement of a balanced panel ($N = 29, T = 26$). The data is also interpolated in this case. For the Pesaran (2006) CIPS tests we can use the original unbalanced panel dataset with missing observations. In the third row for each variable in the lower panel we present the CIPS test statistic for 'ideal' lag augmentation of the underlying ADF regression (based on information criteria); the value for lags reported here is the *average* across countries.

C Additional tables

Table C-1: Country regressions — data in deviation from x-section mean

Country regressions (demeaned data)
static specification with CRS imposed;
estimates presented are unweighted means of the country coefficients

Gross output regressions

	[1]	[2]		[3]	[4]
estimator	**MG**	**RCM**	*estimator*	**MG**	**RCM**
dependent variable	$l\breve{o}$	$l\breve{o}$	*dependent variable*	$\Delta l\breve{o}$	$\Delta l\breve{o}$
regressors			*regressors*		
capital pw	0.1125	0.1128	**Δcapital pw**	0.0989	0.0997
	[5.62]**	[5.09]**		[5.51]**	[4.67]**
materials pw	0.7429	0.7616	**Δmaterials pw**	0.7845	0.7902
	[26.79]**	[25.83]**		[38.97]**	[34.35]**
trend term	0.0000	0.0000	**drift term**	-0.0008	0.0000
	[0.04]	[0.00]		[1.08]	[0.03]
intercept	-0.0101	-0.0011			
	[0.36]	[0.04]			
Panel-t-statistics, trends†			*Panel-t-statistics, trends*†		
capital pw	14.0	17.2	Δcapital pw	10.5	13.4
materials pw	98.8	111.0	Δmaterials pw	96.4	108.5
country trends	15.6	14.5	drift terms	4.1	4.0
# of sign. trends (at 10%)	25	26	# of sign. trends (at 10%)	1	2
VA-equivalent‡			*VA-equivalent*‡		
capital-VA	0.437	0.473	capital-VA	0.459	0.475
	[6.62]**	[5.90]**		[5.74]**	[4.89]**
obs (countries)	1,162 (48)	1,162 (48)		1,094 (48)	1,094 (48)

Value-added regressions

	[1]	[2]		[3]	[4]
estimator	**MG**	**RCM**	*estimator*	**MG**	**RCM**
dependent variable	$l\breve{y}$	$l\breve{y}$	*dependent variable*	$\Delta l\breve{y}$	$\Delta l\breve{y}$
regressors			*regressors*		
capital pw	0.1325	0.2005	**Δcapital pw**	0.1401	0.1483
	[2.30]*	[3.21]**		[2.33]*	[2.17]*
trend term	0.0204	0.0192	**drift term**	0.0193	0.0214
	[9.29]**	[8.33]**		[8.47]**	[6.57]**
intercept	9.5765	9.6035			
	[79.04]**	[77.55]**			
Panel-t-statistics, trends†			*Panel-t-statistics, trends*†		
capital pw	10.7	13.17	Δcapital pw	5.96	6.75
country trends	50.7	48.55	drift terms	11.45	20.65
# of sign. trends (at 10%)	43	43	# of sign. trends (at 10%)	18	44
obs (countries)	1,194 (48)	1,194 (48)	obs (countries)	1,128 (48)	1,128 (48)

Notes: All variables are in logs and deviation from the cross-section mean. $l\breve{o}$ — log output per worker, $l\breve{y}$ — log value-added per worker (in deviation from cross-section mean).
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 indicate statistical significance at the 5% and 1% level by * and ** respectively.
† We report averaged t-statistics for country-specific t-statistics t_i of the factor estimates.
‡ This is obtained using a non-linear combination of the capital and materials coefficients accounting for the precision of these estimates.

Table C-2: Country regressions (unrestricted returns to scale)

Country regressions in levels

static specification, no restriction on returns to scale; estimates presented are unweighted means of the country coefficients

(i) Gross output regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**MG**	**RCM**	**AMG**	**AMG**	**CCEMG**	**CCEMG**	**ARCM**	**ARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	lO	lO	lO-$\hat{\mu}_t^{\bullet}$	lO	lO	lO	lO-$\hat{\mu}_t^{\bullet}$	lO
regressors								
labour	0.2143	0.1908	0.1815	0.1806	0.2004	0.2226	0.1677	0.1690
	[5.54]**	[4.62]**	[5.44]**	[4.80]**	[6.86]**	[6.83]**	[4.67]**	[4.22]**
capital	0.1206	0.0860	0.1794	0.1969	0.0764	-0.0017	0.1361	0.1250
	[0.82]	[0.57]	[1.43]	[1.33]	[1.11]	[0.02]	[1.06]	[0.82]
materials	0.7315	0.7464	0.7474	0.7380	0.7172	0.7210	0.7627	0.7570
	[26.05]**	[24.90]**	[27.95]**	[25.31]**	[24.53]**	[27.93]**	[26.75]**	[24.51]**
common process				0.9259				0.9279
				[3.44]**				[3.21]**
country trend	0.0040	0.0024	-0.0004	0.0005		0.0045	-0.0018	-0.0007
	[1.36]	[0.78]	[0.15]	[0.16]		[1.44]	[0.60]	[0.20]
intercept	0.9570	1.7807	-0.4315	-0.7703	1.3273	2.7179	0.5327	0.8579
	[0.27]	[0.48]	[0.14]	[0.21]	[0.81]	[1.08]	[0.17]	[0.23]
Returns to scale								
CRS test (p)	0.24 (.63)	0.03 (.87)	0.82 (.36)	0.61 (.43)	0.01 (.92)	0.35 (.55)	0.29 (.59)	0.11 (.74)
Panel t-statistics, trends								
labour	19.03	21.05	17.1	16.57	17.09	16.83	19.92	19.33
capital	3.50	4.53	6.76	5.69	13.74	1.75	8.33	6.87
materials	103.31	110.20	111.30	104.13	89.71	80.90	118.91	115.95
country trends	20.60	19.49	18.65	15.16		14.28	17.36	14.60
# of sign. trends (at 10%)	27	27	27	23		26	27	25
VA-equivalent coefficients‡								
labour (VA) mean	0.798	0.752	0.719	0.689	0.709	0.798	0.707	0.696
	[7.25]**	[5.90]**	[7.51]**	[6.82]**	[7.59]**	[9.35]**	[6.23]**	[5.82]**
capital (VA) mean	0.449	0.339	0.710	0.751	0.270	-0.006	0.574	0.514
	[0.84]	[0.58]	[1.50]	[1.43]	[1.18]	[0.02]	[1.09]	[0.86]
obs (countries)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)	1,162 (48)

(ii) Value-added regressions

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
estimator	**MG**	**RCM**	**AMG**	**AMG**	**CCEMG**	**CCEMG**	**ARCM**	**ARCM**
specification	(a)	(a)	(b)	(c)	(d)	(d)	(b)	(c)
dependent variable♯	lY	lY	lY-$\hat{\mu}_t^{va\bullet}$	lY	lY	lY	lY-$\hat{\mu}_t^{va\bullet}$	lY
regressors								
labour	0.7976	0.7612	0.6789	0.6638	0.6769	0.6793	0.6663	0.6684
	[8.80]**	[7.82]**	[8.79]**	[8.70]**	[7.19]**	[8.83]**	[7.93]**	[8.01]**
capital	0.1770	0.3074	0.3216	0.3453	0.5179	0.3144	0.4201	0.4295
	[0.68]	[1.15]	[1.47]	[1.52]	[5.13]**	[1.18]	[1.85]	[1.81]
common trend				1.0254				0.9019
				[5.27]**				[4.14]**
country trend	0.0105	0.0094	-0.0066	-0.0077		0.0090	-0.0069	-0.0053
	[1.53]	[1.30]	[0.91]	[0.96]		[0.81]	[0.91]	[0.62]
intercept	8.5557	5.6880	6.5479	6.0760	-0.0126	4.8980	4.2023	3.9300
	[1.48]	[0.95]	[1.34]	[1.19]	[0.01]	[0.88]	[0.83]	[0.74]
Returns to scale								
CRS test (p)	0.02 (.90)	0.10 (.75)	0.00 (.99)	0.00 (.96)	3.98 (.05)	0.00 (.98)	0.2 (.66)	0.22 (.64)
Panel t-statistics, trends								
labour	30.2	34.0	27.2	26.7	26.5	27.0	31.3	31.3
capital	7.2	9.3	10.2	9.7	26.5	9.9	12.2	11.8
country trends	20.2	19.5	16.8	14.9		18.8	16.3	13.6
# of sign. trends (at 10%)	24	28	25	20		30	25	22
obs (countries)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)	1,194 (48)

Notes: All variables are in logs. lO — log output, lY — log value-added. $\hat{\mu}_t^{\bullet}$ and $\hat{\mu}_t^{\bullet,va}$ are derived from the year dummy coefficients of a pooled regression (no restriction on returns to scale) in first differences (FD-OLS) as described in the text. We omit reporting the parameters on the cross-section averages for the CCEMG estimators (columns [5] and [6]) to save space. 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 $\sum x_i^2$. 'Specification' refers to equations (6) to (9). We indicate statistical significance at the 5% and 1% level by * and ** respectively.
♯ We subtract the common dynamic process $\hat{\mu}_t^{\bullet}$ from log output (log value-added) for country i in models [3] and [7].
† We report averaged t-statistics for country-specific t-statistics t_i of the factor estimates.
‡ This is obtained using a non-linear combination of the capital and materials coefficients accounting for the precision of these estimates.

Table C-3: Country rankings by TFP-level

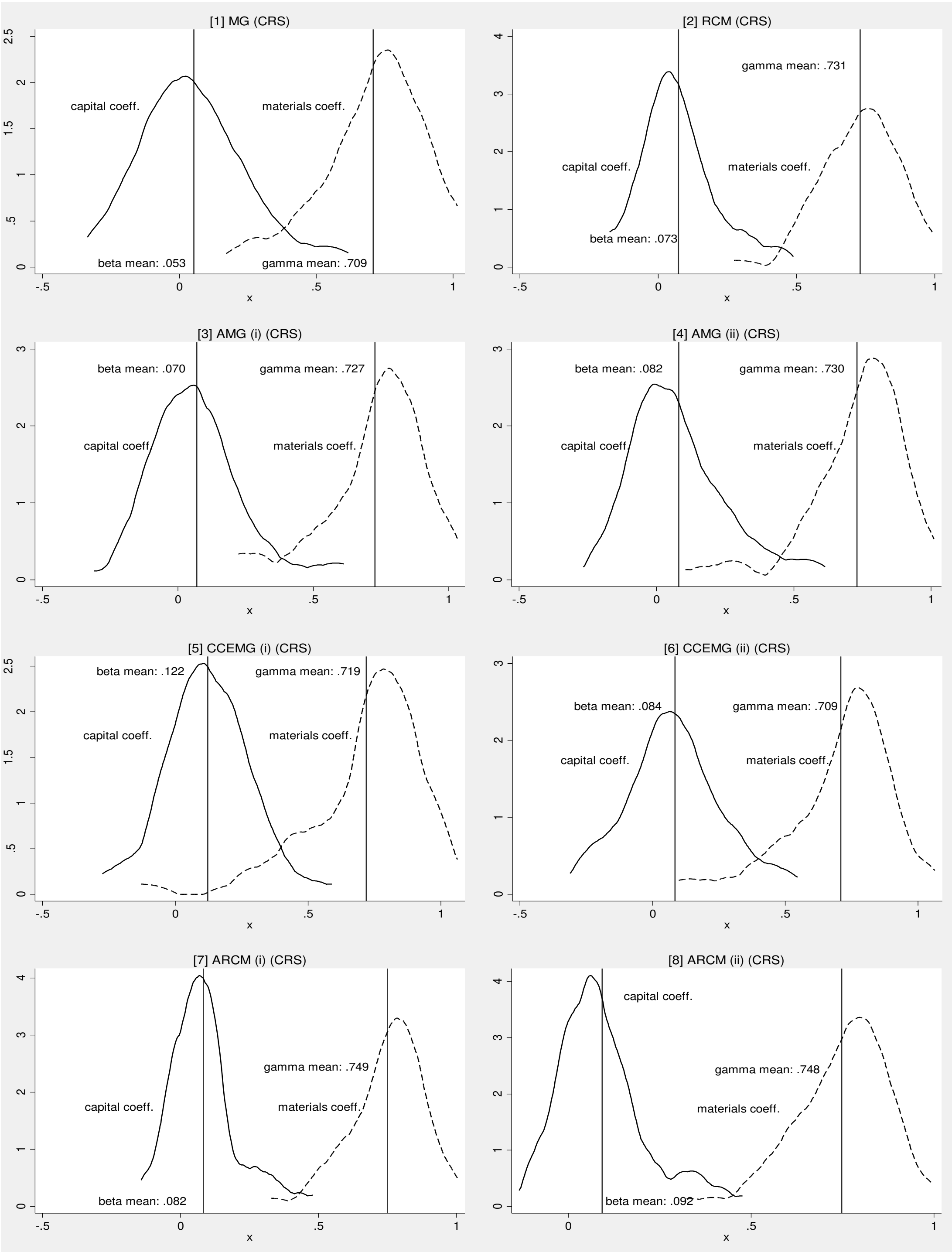
TFP-level estimates
Comparison of country ranking (by magnitude) and difference across estimators

	Rank			Absolute Rank Difference		
	[1]	[2]	[3]	abs([2]-[1])	abs([3]-[1])	abs([3]-[2])
Country	**FE**	**AMG†**	**CCE‡**	**AMG-FE**	**CCE-FE**	**CCE-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.
† AMG refers to the Augmented Mean Group estimator in specification (c), Table 3 column [4] (value-added based version), with the TFP-level adjustment detailed in Section 6.
‡ CCE refers to the Pesaran (2006) CCEMG estimator in specification (d), ibid. column [5], with the TFP-level adjustment detailed in Section 6.

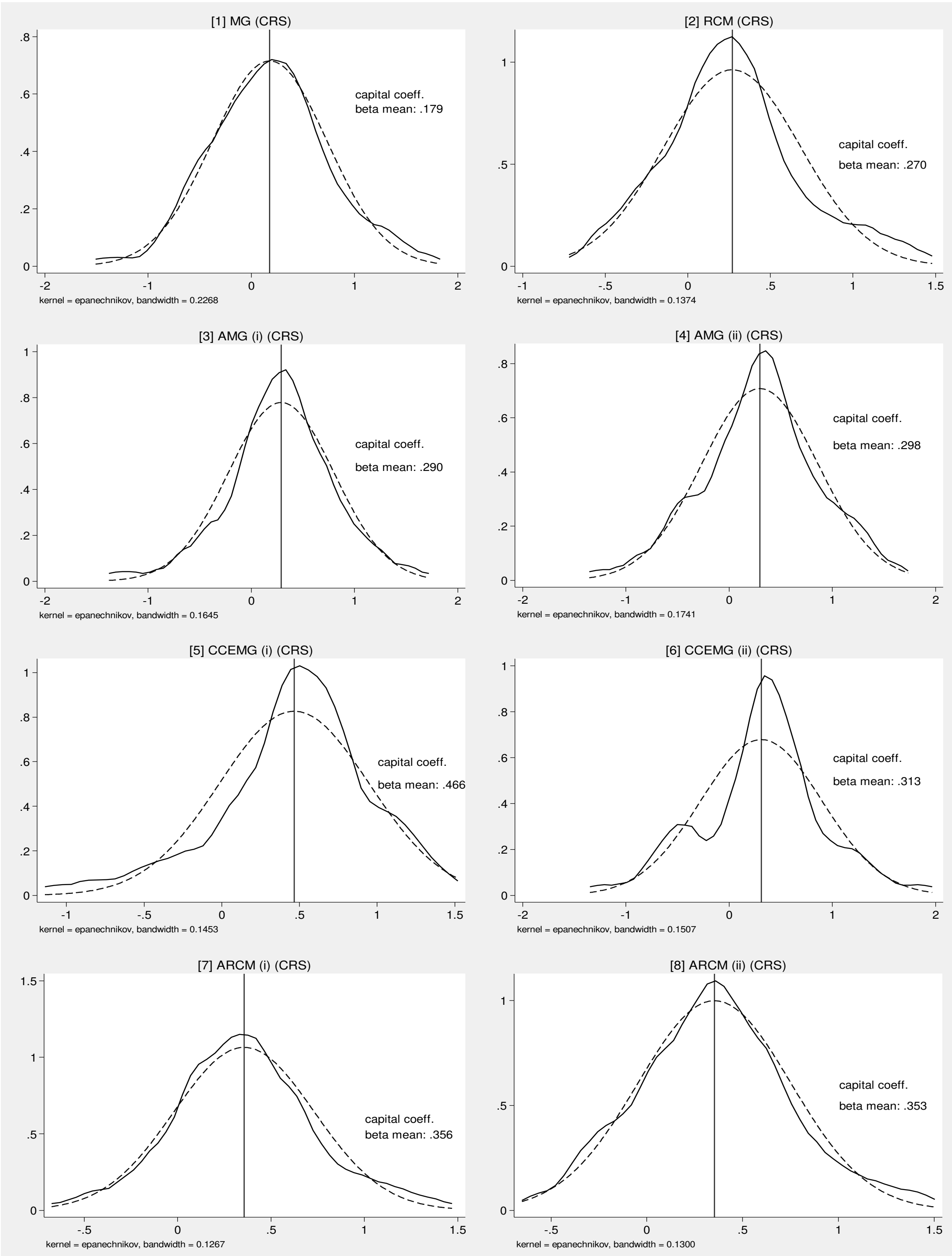
D Additional graphs

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



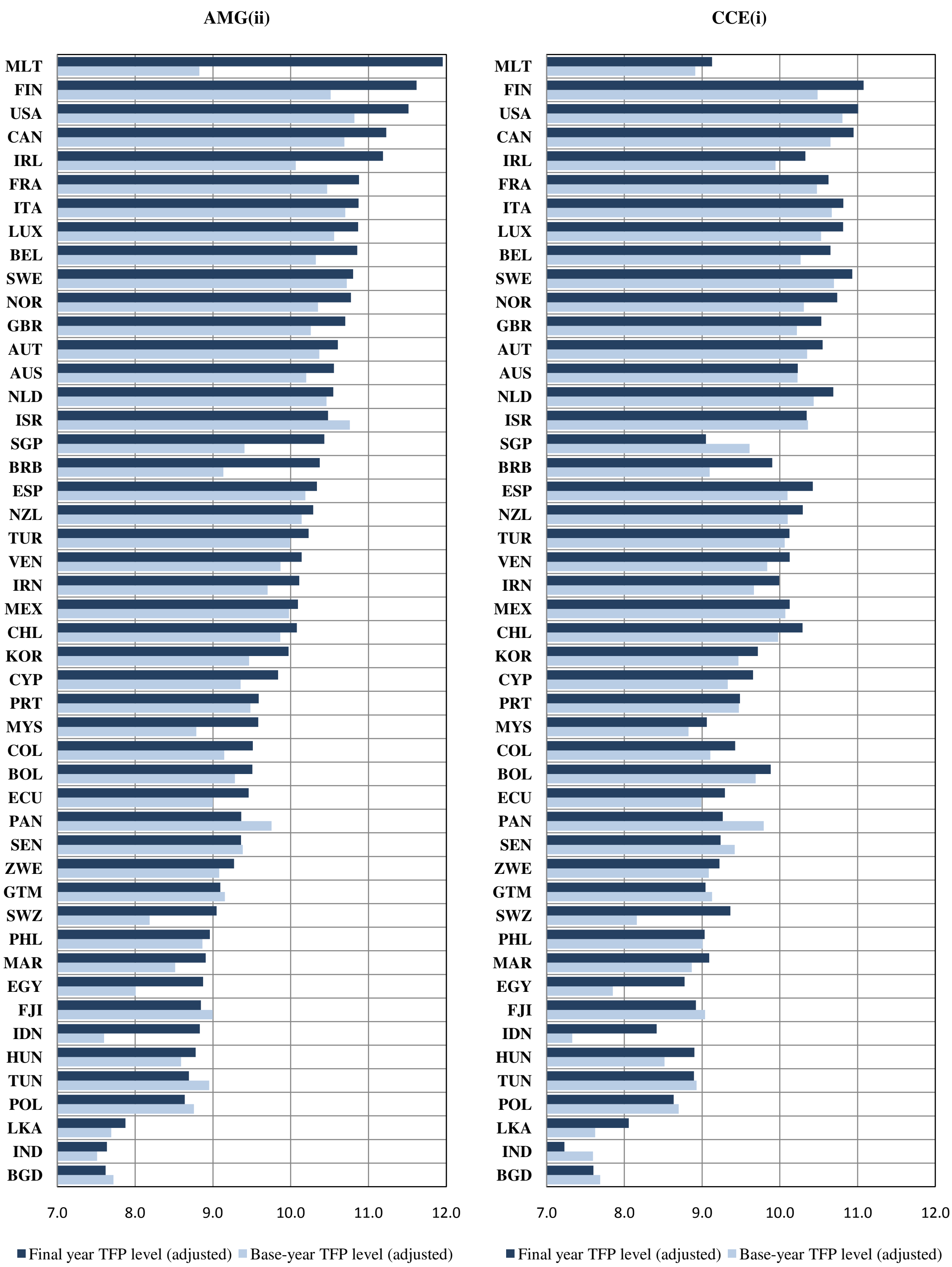
Notes: Each plot shows the distribution (kernel density) of the capital ($\hat{\beta}_i$) and material ($\hat{\gamma}_i$) coefficients from the country regressions (gross-output based analysis, CRS imposed, numbering as columns in Table 3 in the main section).

Figure D-2: Kernel densities for technology parameter estimates (value-added)



Notes: Each plot shows the distribution (kernel density) of the capital ($\hat{\beta}_i^{va}$) coefficients from the country regressions (value-added based analysis, CRS imposed, numbering as columns in Table 3 in the main section). The dashed line represents the normal distribution, the vertical line marks the mean of the parameter distribution.

Figure D-3: TFP levels — adjusted from AMG(ii) and CCE(i) estimates*



Notes: VA specification with CRS imposed, $*$ AMG(ii) has $\hat{\mu}_t^{\bullet}$ *included* as additional regressor; CCE(i) refers to the standard CCEMG estimator; the estimates from which these 'adjusted' TFP levels were constructed can be found in Table 3, columns [4] and [5] respectively. Countries are ranked by final period TFP-level based on the AMG(ii) estimates. Levels adjustment as described in the main text.