Convergence in developing countries: evidence from panel unit root tests

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Abstract: Dynamic panel unit root tests are used to investigate the convergence hypothesis for a sample of developing countries. The data are real per capita GDP for the period 1960-95, covering 80 countries grouped into three broadly defined regions. The traditional cross-section unconditional convergence model produces no evidence of intra-regional convergence. However, panel unit root tests, interpreted as tests of the conditional convergence hypothesis, produce some evidence of intra-regional convergence for Africa and Latin America/Caribbean but only weak evidence for Asia/Pacific. Overall the results lend support to some of the main hypotheses of both neo-classical and new growth theory.

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1.   Introduction

Are poorer countries able to catch up with richer ones in terms of standards of living? In recent years many studies have investigated this question with, on balance, the evidence being in favour of per capita income convergence once adjustment has been made for different steady state parameters. The notion of (conditional) convergence emerges from the Solow (1956) growth model with diminishing returns to capital. The low ratio of capital to labour in poorer countries makes the marginal product of capital high, promoting faster growth than in countries with a high capital to labour ratio. In the long run countries converge to their own steady-state income level at a common speed. In contrast, some new growth theories show how growth disparities can persist in the long run if the production function exhibits increasing returns to scale.

Most empirical studies of convergence have focused on developed and developing countries together or developed countries alone. There has been comparatively little work that specifically examines convergence within the developing world. An examination of the relative growth performance of countries within the developing world is of particular interest because of the marked differences in average growth between regions over the past 30 or so years with, on average, countries in Asia growing far more quickly than those in Africa or Latin America. An investigation of developing countries specifically should yield additional insights into the convergence process, because such countries are perhaps more likely to have similar steady-state conditions than is the case when the focus is on a more heterogeneous cohort containing both developing and developed countries.

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Previous empirical work on convergence in the developing world has predominantly used cross-section and panel estimation methods to identify convergence (Khan and Kumar, 1993; Easterly and Levin, 1997; Murthy and Ukpolo, 1999; Ferreira, 2000; Yao and Zhang, 2001; Dobson and Ramlogan, 2002; Sachs et al, 2002). McCoskey's (2002) study of sub-Saharan Africa is an exception since it employs time-series methods.[1] The present study extends this previous work in two important ways. First the empirical analysis is based on a number of recently developed panel unit root tests that offer various improvements over the tests used by previous researchers. Second the data set includes 80 developing countries in three broadly defined geographical regions: Asia/Pacific, Africa and Latin America/ Caribbean. The scope of the present study permits investigation of differences in the convergence process between developing country regions.

The remainder of the paper is structured as follows. Section 2 discusses conceptual and methodological issues that arise in the estimation of convergence. Section 3 describes the panel unit root tests used in the present study. Section 4 describes the per capita GDP data set and identifies some general patterns in developing countries' growth performance between the 1960s and 1990s. Section 5 presents the empirical convergence estimation results. Section 6 concludes.

2.   Conceptual and Methodological Issues

The empirical tests for convergence reported in this study are based on $y_{i,t} = (y_{i,t}^{u} - \bar{y}_{t}^{u})$, where $y_{i,t}^{u}$ is the (unadjusted) natural log of per capita GDP of country i at time t, and

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[1] Cross-section estimation captures the tendency for countries with low per capita GDP to catch up those with high per capita GDP. Time-series estimation, in contrast, can capture both catching up and the effect of shocks, incorporating aspects of both neoclassical and new growth theory.

$\bar{y}_t^u = \sum\limits_{i=1}^{N} y_{i,t}^u / N$. $y_{i,t}$ is the standardised per capita GDP series for country i, obtained by

subtracting the mean per capita GDP for each year across all countries within each region

from the unadjusted series $y_{i,t}^u$. The standardisation eliminates any common deterministic

trend component from the per capita GDP series. A general form for the data generating

process for observations of standardised per capita GDP is:

$$y_{i,t} - y_{i,t-1} = \alpha_i + (\beta_i-1)y_{i,t-1} + \sum\limits_{m=1}^{M_i} \gamma_{i,m}(y_{i,t-m} - y_{i,t-m-1}) + \varepsilon_{i,t} \qquad (1)$$

In (1), α_i allow for individual country effects. The parameter β_i determines the relationship

between log per capita GDP and annual log growth for country i. $\gamma_{i,m}$ allow for persistence or

autocorrelation in per capita GDP growth rates. $\varepsilon_{i,t}$ is a random disturbance, assumed to be

normal, and independent and identically distributed (IID) with $E(\varepsilon_{i,t})=0$ and $var(\varepsilon_{i,t})=\sigma_\varepsilon^2>0$.

If $\beta_i \geq 1$ in (1), it is assumed $\alpha_i=0$ for all i. $\beta_i>1$ implies the growth path is explosive: country

i's per capita GDP tends to grow faster as it gets larger. Such a pattern is conceivable for a

limited time, but presumably could not continue indefinitely. $\beta_i=1$ implies growth is non-

explosive, and unrelated to the level of per capita GDP. $\beta_i<1$ implies per capita GDP is mean-

reverting. If $\beta_i<1$ for all i, α_i can be considered as being IID with $E(\alpha_i)=0$ and $var(\alpha_i)=\sigma_\alpha^2 \geq 0$.

If $\sigma_\alpha^2=0$ the individual country effects are homogeneous and if $\sigma_\alpha^2>0$ they are heterogeneous.

For consistency with the econometrics literature on testing for unit roots, the following

discussion concentrates on the one-tail test of the form $H_0:\beta_i=1$ against $H_1:\beta_i<1$, and not the

two-tail test of H_0 against $H_1:\beta_i \neq 1$.

The traditional approach to testing for convergence uses a cross-section regression of the logarithmic growth of per capita GDP for each country over some period of duration T on initial log per capita GDP. This requires an assumption of homogeneity in β_i, or $\beta_i=\beta$ for all i in (1). Furthermore short-run dynamics in growth rates are ignored, which implies setting $\gamma_{i,m}=0$ in (1). For any T>1, the cross-section model can be obtained by reparameterising (1):

$$y_{i,T} - y_{i,0} = a_i + (b-1)y_{i,0} + u_{i,T} \qquad\qquad (2)$$

where $a_i = \sum_{j=0}^{T-1} \beta^j \alpha_i$; $b = \beta^T$; $u_{i,T} = \sum_{j=0}^{T-1} \beta^j \varepsilon_{i,T-j}$

Typically, researchers have estimated b for the sample period as a whole and for shorter sub-periods within the sample period.[2]

For (2) to be estimable in the case b<1, an assumption of homogeneity in α_i (and therefore a_i) is required: $\alpha_i = \alpha$ and therefore $a_i = a$ for all i in (2). Otherwise, either the N+2 parameters in (2) exceed the N available cross-section observations so the model cannot be estimated; or the N intercepts, a_i, have to be incorporated into the disturbance term, making the latter correlated with $y_{i,0}$ and rendering the OLS estimator of b inconsistent. If there is

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[2] The specification originally suggested by Barro and Sala-i-Martin (1991, 1995) makes explicit the link to the transitional growth process in a neo-classical model:

$(1/T)(y_{i,T} - y_{i,0}) = \tilde{g}_i + (1/T)(\tilde{y}_i - y_{i,0})(1 - \exp(-\tilde{\beta}T)) + v_{i,T}$

In this formulation, $\tilde{g}_i$ is the steady state per capita GDP growth rate, $\tilde{y}_i$ is the steady state per capita GDP, $\tilde{\beta}$ reflects the rate of convergence, and $v_{i,T}$ is a disturbance term. (2) is a reparameterisation of this expression, with $a_i = T\tilde{g}_i + (1 - \exp(-\tilde{\beta}T))\tilde{y}_i$; $b = -(1 - \exp(-\tilde{\beta}T))$; and $u_{i,T} = Tv_{i,T}$. Effectively, $\tilde{\beta}$ measures the speed at which $y_{i,t}$ approaches $\tilde{y}_i$: $\tilde{\beta} > 0$, b<1 implies convergence; $\tilde{\beta} = 0$, b=1 implies no convergence.

heterogeneity in α_i and a_i, the cross-section estimator $\hat{b}$ is inconsistent and tends to overestimate b whenever b<1.[3]

The use of additional covariates on the right hand side of a specification similar to (2) may be interpreted as an attempt to control for heterogeneous individual effects. If $a_i = \mathbf{d'z_i}$ where $\mathbf{z_i}$ is a k×1 vector of covariates (k<N), only k+2 parameters are required to estimate (2) allowing for heterogeneity. If b<1 when (2) is estimated with conditioning variables, there is conditional convergence: in the long run each country's per capita GDP is convergent towards its own steady-state value. A strong assumption, that the individual effects are fully captured by the covariates, is however required to avoid recurrence of the difficulties described above. For example, it is well known that there are persistent differences in the level of technology and the nature of institutions across countries, yet these are ignored in cross-section models (Islam, 1995).

An alternative solution to the problem of heterogeneity in α_i or a_i, not requiring the use of additional covariates in the convergence regression, is to pool the data and use panel estimation. The simplest of the panel methods includes a set of dummies to account for unobserved time invariant differences for each cross-section unit, using a least squares dummy variable (LSDV) or fixed effects (FE) model. Other panel estimators are random effects (RE) and generalized method of moments (GMM). In recent years the use of panel estimators in convergence research has become increasingly common.

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[3] Intuitively, if log per capita GDP for each country is mean-reverting but the individual country means are widely dispersed, the distribution at t=0 conveys little information about which countries are above or below their own means at t=0, and about which are expected to experience above or below average growth between

Alternatively, by treating each country separately, time-series methods can also allow for parameter heterogeneity. Bernard and Durlauf (1995, 1996) view convergence in terms of long-run forecasts of per capita income, taking initial conditions as given. Convergence occurs when there is equality of long run forecasts taken at a given fixed date; in other words when differences between the income series of two economies tend to zero as the forecasting horizon tends to infinity. Carlino and Mills (1993) suggest a weaker definition of convergence based on trend stationarity in the log of relative income.[4]

A further concern arising from the use of cross-section estimation is the implicit assumption that steady-state growth rates are homogeneous (countries converge to different levels of per capita GDP but at the same speed). In other words, (2) is based on an implicit assumption of homogeneity in β or b, which may not be justified in practice. Lee et al. (1997) suggest that this problem can be overcome with a stochastic model of growth that formalizes the notion of heterogeneity: countries may converge to different levels of per capita GDP at different speeds. In their time-series analysis, both trend stationary and difference stationary models strongly reject the restriction of a common growth rate across a large sample of countries. Lee et al. show that with heterogeneity in b, cross-section estimates based on an assumption of homogeneity fail to reveal rapid convergence even when it is present.

Time-series estimation offers a number of advantages: it can accommodate dynamics in the growth series; it can discriminate between exogenous and endogenous sources of growth; and it allows for convergence among certain types of countries (convergence clubs). Many of

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t=0 and t=T. Accordingly, the cross-section estimator returns $\hat{b}$ close to unity. However, in this case it would be incorrect to interpret $\hat{b} \cong 1$ as evidence against the convergence hypothesis (Goddard and Wilson, 2001).

these benefits are also available from tests based on panel estimation. Panel estimation offers several further advantages: in particular, there is no need to specify a 'leader' country, with which pairwise comparisons are made; all possible combinations can be tested. With time-series estimation an incorrect choice of leader may produce misleading results. Furthermore, the pooling of data with panel estimation increases the power of hypothesis tests. Of particular relevance to the convergence literature is a class of panel estimators that focus specifically on the question of whether all individual time-series within a panel are integrated, or whether some or all are non-integrated. Section 3 examines the use of panel unit root tests in investigating the convergence hypothesis, and describes the specific tests to be employed in the present study.

3. Panel Unit Root Tests of Convergence

In the early literature on testing for unit roots using panel data sets (Levin and Lin, 1993; Quah, 1994; Wu and Zhang, 1996; Im et al., 2003), it is a requirement that the data have a time-series dimension sufficient that single-series unit root tests could be applied. Panel unit root tests are preferred, however, because they have greater power. One exception is the test developed by Breitung and Meyer (1994) for data sets with many cross-section units but few time-series observations on each one. The following restrictions are imposed on the parameters of (1): $\beta_i=\beta$, $\gamma_{i,m}=\gamma_m$ and $M_i=M$ for all i. The individual effects are eliminated by deducting the first observation ($y_{i,0}$) for each country from $y_{i,t-1}$, and incorporating the same term together with the individual country effects into the disturbance term. (1) is therefore transformed as follows:

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[4] Empirical time-series studies include Carlino and Mills (1993), Oxley and Greasley (1995), St Aubyn (1999), Li and Papel (1999) and Tomljanovich and Vogelsang (2002). This research shows that the results are sensitive to the number of structural breaks and whether the break is determined endogenously or exogenously.

$$y_{i,t} - y_{i,t-1} = (\beta-1)(y_{i,t-1} - y_{i,0}) + \sum_{m=1}^{M} \gamma_m (y_{i,t-m} - y_{i,t-m-1}) + \xi_{i,t} \qquad (3)$$

where $\xi_{i,t} = \varepsilon_{i,t} + \alpha_i + (\beta-1)y_{i,0}$

The Breitung-Meyer panel estimator, obtained by applying OLS to (3) over $i=1...N$ and $t=2...T$, is unbiased under $H_0:\beta=1$, and the corresponding t-statistic is asymptotically normal. Under $H_1:\beta<1$, this estimator is upward biased because of the presence of $(\beta-1)y_{i,0}$ in $\xi_{i,t}$. However, unlike $\hat{b}$, its properties under the alternative hypothesis are unaffected by heterogeneity in α_i.

The Breitung-Meyer test avoids the imposition of the assumption of homogeneity in α_i ($\alpha_i=\alpha$), but an assumption of homogeneity in β_i ($\beta_i=\beta$) is required because the test is applicable to panels with very small T, giving insufficient observations on each country to identify separate β_i. In contrast, the panel unit root tests developed recently by Maddala and Wu (1999) and Chang (2003) allow for heterogeneity in both α_i and β_i.[5] This flexibility is achieved at the cost of requiring a panel with a larger T than is required for the Breitung-Meyer test. Both tests evaluate the null hypothesis $H_0:\beta_i=1$ for all i against the alternative $H_1:\beta_i<1$ for some i. H_1 accommodates non-stationarity among some but not necessarily all of the individual series, and is therefore more flexible than the first-generation panel unit root tests for data sets of similar dimensions cited above. Both Maddala-Wu and Chang allow different lag lengths in the autoregressive equations for each series.

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[5] The Maddala-Wu test has recently been used to test for convergence by Freeman and Yerger (2001).

Furthermore, whereas the first-generation panel unit root tests implicitly assume zero contemporaneous correlation among the disturbance terms of the autoregressive equations of the individual series, Maddala-Wu suggest a procedure for adjusting the critical values to allow for contemporaneous correlation, which involves bootstrapping the residuals from the Augmented Dickey Fuller (ADF) autoregressions. Chang eliminates the problem of cross-section dependency by using non-linear instrumental variables (IV) to estimate the ADF autoregressions.

The Maddala-Wu test requires estimation of the ADF autoregression for each cross-section unit:

$$y_{i,t} = \alpha_i + \beta_i\, y_{i,t-1} + \mathbf{x_{i,t}'}\boldsymbol{\gamma_i} + \varepsilon_{i,t} \tag{4}$$

where $y_{i,t}$ is the standardised per capita GDP series for country i defined as before; $\mathbf{x_{i,t}'}=$ $(\Delta y_{i,t-1} \;...\; \Delta y_{i,t-M_i})$; and M_i is the lag length for the i'th cross-section unit. M_i is selected for each i using the AIC+2 criterion. The test statistic for the panel unit root test is $\lambda =$ $-2\sum_{i=1}^{N}\ln(\pi_i)$, where π_i is the p-value from the standard time-series ADF test of $H_0{:}\beta_i{=}1$ against $H_1{:}\beta_i{<}1$ for series i, based on the estimated version of (4). Assuming zero contemporaneous correlation, $\lambda \sim \chi^2(2N)$ under the null hypothesis for the panel unit root test, $H_0{:}\beta_i{=}1$ for all i. Fisher (1932) first suggested this form of test statistic.

To allow for non-zero contemporaneous correlation, adjusted critical values for λ are obtained using a bootstrap procedure based on $[\hat{\varepsilon}_{1,t}^{0} \,...\, \hat{\varepsilon}_{N,t}^{0}]$, where $\hat{\varepsilon}_{i,t}^{0}$ are generated from the

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autoregressions $\Delta y_{i,t} = \eta_i \Delta y_{i,t-1} + \varepsilon_{i,t}^0$. $\hat{\eta}_i$ and the bootstrapped residuals $[\varepsilon_{1,t}^* \ldots \varepsilon_{N,t}^*]$ obtained by resampling from $[\hat{\varepsilon}_{1,t}^0 \ldots \hat{\varepsilon}_{N,t}^0]$, are used to generate the bootstrap sample:

$$y_{i,t}^* = y_{i,t-1}^* + u_{i,t}^*, \text{ with } y_{i,0}^* = 0; \ u_{i,t}^* = \hat{\eta}_i u_{i,t-1}^* + \varepsilon_{i,t}^* ; \ u_{i,0}^* = \sum_{j=0}^{30} \hat{\eta}_i^j \varepsilon_{-j}^*$$

5,000 replications of the bootstrap sample are used below to generate the empirical distribution of the panel unit root test statistic λ.

Chang (2003) develops an alternative panel unit root test that takes a non-linear instrumental variables (IV) approach to the problem of cross-section dependency. The ADF autoregression for each cross-section unit is estimated using instruments generated from an integrable transformation of the original time-series. The IV t-statistics on the lagged dependent variable are independent, even across dependent cross-section units, because non-linear transformations of integrated processes using an integrable function are asymptotically orthogonal. The test statistic for the unit root null hypothesis is the normalised sum (across the cross-section units) of these t-statistics, which follows the standard normal distribution under the null.

The Chang test requires the application of an adaptive de-meaning transformation to the standardised logarithmic per capita GDP series $y_{i,t}$, defined as before. While the standardising transformation eliminates any deterministic trend common to all countries, it is still possible that $y_{i,t}$ is stationary with non-zero mean. To eliminate the latter, the transformation is:

$$y_{i,t}^{\mu} = y_{i,t} - \hat{\mu}_i^t, \text{ where } \hat{\mu}_i^t = \sum_{\tau=1}^{t} y_{i,\tau} / t$$

In terms of the transformed series, the ADF autoregression is

$$y_{i,t}^{\mu} = \beta_i \; y_{i,t-1}^{\mu} + \mathbf{x_{i,t}^{\mu}} '\boldsymbol{\gamma_i} + \varepsilon_{i,t} \tag{5}$$

where $\mathbf{x_{i,t}^{\mu}}' = (\Delta y_{i,t-1}^{\mu} \; ... \; \Delta y_{i,t-M_i}^{\mu})$; and M_i is the lag-length in (5).

Define $\mathbf{y_i} = \{ y_{i,t}^{\mu}, \; t=1...T\}$ is a T×1 vector, $\mathbf{y_{li}} = \{ y_{i,t}^{\mu}, \; t=0...T-1\}$ is a T×1 vector, $\mathbf{X_i} = \{ \mathbf{x_{i,t}^{\mu}}',$ t=1...T} is a T×M_i matrix, and $\boldsymbol{\varepsilon_i} = \{\varepsilon_{i,t}, \; t=1...T\}$ is a T×1 vector. In matrix form, the ADF autoregression is:

$$\mathbf{y_i} = \mathbf{Y_i}\boldsymbol{\gamma_i} + \boldsymbol{\varepsilon_i} \quad \text{where } \mathbf{Y_i} = (\mathbf{y_{li}}, \mathbf{X_i}) \text{ and } \boldsymbol{\theta_i} = (\beta_i, \boldsymbol{\gamma_i}')'$$

The IV estimator $\hat{\boldsymbol{\theta}}_i$ of $\boldsymbol{\theta_i}$ is

$$\hat{\boldsymbol{\theta}}_i = (\mathbf{W_i'Y_i})^{-1}\mathbf{W_i'y_i}$$

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where $\mathbf{W_i} = (\mathbf{F(y_{li})}, \mathbf{X_i})$ is a $T \times M_i{+}1$ matrix; $\mathbf{F(y_{li})} = \{ F(y_{i,t}^\mu), t{=}0...T{-}1\}$ is a $T \times 1$ vector; and

F is a suitable non-linear instrument generating function. F must be integrable and F must

satisfy $\int\limits_{-\infty}^{\infty} xF(x) \neq 0$.[6]

To test $H_0{:}\alpha_i{=}1$ for each $i = 1...N$ individually, the t-ratio for the i'th country is $Z_i =$

$(\hat{\beta}_i - 1)/s(\hat{\beta}_i)$, where $s(\hat{\beta}_i) = \hat{\sigma}_i^2 B_T^{-2} C_T$; $\hat{\sigma}_i^2 = \sum\limits_{t=1}^{T} \hat{\varepsilon}_{i,t}^2 / T$; and $\hat{\varepsilon}_{i,t}$ are the residuals from the

estimated version of (5). The expressions for B_T and C_T are:

$B_T = \mathbf{F(y_{li})'y_{li}} - \mathbf{F(y_{li})'X_i(X_i'X_i)^{-1}X_i'y_{li}}$

$C_T = \mathbf{F(y_{li})'F(y_{li})} - \mathbf{F(y_{li})'X_i(X_i'X_i)^{-1}X_i'F(y_{li})}$

To test $H_0{:}\beta_i{=}1$ for all $i = 1...N$ jointly, the test statistic is the normalised sum of Z_i,

$S_N = \sum\limits_{i=1}^{N} Z_i / N^{1/2}$. Chang shows that S_N follows an asymptotic standard normal distribution

under H_0.

4.   Patterns of per capita GDP growth in developing countries

The data used in the present study are real per capita GDP for 80 countries covering the

period 1960-1995. All data are obtained from the Penn World Tables 5.6, and are expressed

in US dollars at constant international prices (base year=1985). Table 1 shows per capita

GDP by country for 1965, 1980 and 1995 and the percentage growth rate between 1965 and

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[6] The particular functional form suggested by Chang and adopted here is $F(y_{i,t}^\mu) = y_{i,t}^\mu \exp(-c_i| y_{i,t}^\mu |)$, where $c_i{=}K\, T_i^{-1/2}\, s(\Delta y_{i,t}^\mu)$; $s^2(\Delta y_{i,t}^\mu){=}\sum\limits_{t=1}^{T}(\Delta y_{i,t}^\mu)^2 / T$; and K is an arbitrarily chosen constant. According to Chang $K{=}5$ is a typical choice, also adopted here.

1995, together with descriptive statistics (mean and standard deviation of per capita GDP and

growth) by region.[7]

Table 1: Descriptive statistics

	Per-capita GDP			Growth		Per-capita GDP			Growth
	1965	1980	1995	65-95		1965	1980	1995	65-95
ASIA/PACIFIC					AFRICA				
Bangladesh	1136	1085	1652	45.4	Algeria	1584	2758	2554	61.3
China	577	972	2042	253.8	Benin	1191	1114	993	-16.6
Fiji	2160	3609	4185	93.8	Botswana	574	1940	2458	328.3
India	751	882	1490	98.4	Burk. Faso	373	457	500	34.1
Indonesia	608	1281	2497	310.7	Burundi	390	480	452	15.8
Korea, Rep.	1058	3093	9165	766.3	Cameroon	673	1194	924	37.3
Malaysia	1671	3799	6913	313.7	Cen.Afr.Rep.	663	706	544	-17.9
Nepal	650	892	1179	81.4	Chad	736	528	379	-48.6
Oman	1068	6521	8072	655.5	Comoros	646	631	458	-29.1
Pakistan	889	1110	1480	66.5	Congo, DR	548	476	225	-59.0
Papua NG	1700	1779	1787	5.1	Congo	1084	1931	2003	84.8
Philippines	1243	1879	1760	41.6	Cote d'Ivoire	1400	1790	1100	-21.4
Sri Lanka	1179	1635	2536	115.1	Egypt	1024	1645	1971	92.5
Syria	2011	4467	4733	135.4	Ethiopia	290	322	331	14.1
Thailand	1136	2178	4891	330.6	Gabon	2587	4797	3811	47.3
Mean	*1189*	*2345*	*3625*	*220.9*	Gambia	724	1017	737	1.7
St.dev.	*495*	*1640*	*2609*	*226.6*	Ghana	883	976	996	12.8
LATIN AMERICA/CARRIBEAN					Guinea	545	817	808	48.2
Argentina	5018	6506	5851	16.6	Guin.-Bissau	612	471	651	6.3
Barbados	3274	6379	6933	111.7	Kenya	614	911	906	47.5
Bolivia	1346	1989	1831	36.0	Lesotho	409	994	1142	179.3
Brazil	1871	4303	4307	130.2	Madagascar	1111	984	580	-47.8
Chile	3264	3892	5834	78.7	Malawi	412	554	516	25.3
Colombia	1816	2946	3766	107.4	Mali	435	532	512	17.7
Costa Rica	2459	3717	3805	54.7	Mauritania	882	885	890	0.9
Dom. Rep.	1271	2343	2400	88.8	Mauritius	3136	3988	6828	117.7
Ecuador	1591	3238	2890	81.6	Morocco	1221	1941	2102	72.2
El Salvador	1739	2014	2130	22.5	Mozambique	1265	923	805	-36.3
Guatemala	1781	2574	2357	32.3	Niger	641	717	425	-33.7
Guyana	1575	1927	1488	-5.6	Nigeria	624	1438	940	50.7
Haiti	894	1033	624	-30.2	Rwanda	350	757	568	62.2
Honduras	1121	1519	1385	23.6	Senegal	1143	1134	1089	-4.8
Jamaica	2104	2362	2455	16.7	Sierra Leone	1114	1139	636	-42.9
Mexico	3351	6054	5919	76.6	Sudan	854	866	969	13.4
Nicaragua	2246	1853	1215	-45.9	Swaziland	1705	3057	2629	54.2
Panama	2014	3392	3485	73.0	Tanzania	371	480	526	41.9
Paraguay	1277	2534	2269	77.7	Togo	489	731	505	3.3
Peru	2501	2875	2574	2.9	Tunisia	1236	2527	3162	155.9
Suriname	2272	3737	2550	12.3	Uganda	614	534	641	4.3
Trin. & Tob.	6428	11262	7461	16.1	Zambia	1110	971	619	-44.2
Uruguay	3698	5091	5459	47.6	Zimbabwe	946	1206	1168	23.4
Venezuela	7512	7401	6729	-10.4	*Mean*	*908*	*1252*	*1221*	*30.5*
Mean	*2601*	*3789*	*3571*	*42.3*	*St.dev.*	*575*	*970*	*1223*	*71.4*
St.dev.	*1654*	*2337*	*2013*	*46.1*					

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Of the three regions Latin America/Caribbean had the highest mean per capita GDP in 1965. During the period 1965-95, however, average growth was much faster in Asia/Pacific than in either of the other two regions, and by 1995 Asia/Pacific had narrowly overtaken Latin America/Caribbean in terms of mean per capita GDP. Of the three regions Africa recorded both the lowest mean per capita GDP in 1965, and the slowest mean growth between 1965 and 1995. Therefore the gap between Africa and the other two regions increased over this 30-year period.

The overall growth performance of Asia/Pacific reflects the diverse nature of the countries in this region. During the study period the ASEAN countries of Malaysia, South Korea, Indonesia and Thailand benefited from relatively high levels of investment and growth. Growth in the capital stock has been accompanied by even larger increases in the working age population and the number of hours worked while there has also been a shift in activity from low-productivity agriculture to higher-productivity industrial sectors. Relatively low levels of investment and growth in countries such as Bangladesh, Fiji, Nepal, India and Papua New Guinea reflects lower levels of human capital, technological and financial development. In China high investment, reform of the banking system and a substantial shift of activity from agriculture to industry accompanied the move towards a market-oriented economic system. However, it was not until the early-1990s that India, Pakistan, Bangladesh and Sri Lanka initiated the process of economic reform aimed towards achieving an increased export orientation. The transition of these economies has not been as rapid as in the case of China.

Many factors have contributed to low growth in Africa. These include low investment, low educational achievement, inadequate social infrastructure, ethno-linguistic diversity and

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[7] Below, up to five-lagged growth terms are included in the estimations for the panel unit root tests,

inappropriate government policies. Easterly and Levin (1997) show that high levels of ethno-linguistic diversity are associated with distorted foreign exchange markets, underdeveloped financial systems and low levels of schooling. Ethno-linguistic diversity also contributes to civil war, which in turn has a negative impact on economic growth (Collier and Hoeffler, 1998). The combined effects of climate, disease and geography may also have contributed towards Africa's poor economic performance (Sachs and Warner, 1997). Agriculture is less productive in tropical regions, while many innovations are primarily designed for temperate regions. In addition, Africa is poorly placed to benefit from trade: with a high proportion of its population living far from the coast, trading costs are relatively high.

The economic development of Latin America/Caribbean has often been linked to access to foreign capital. With the introduction of liberalisation programmes in a number of countries in the 1970s economic and social conditions became favourable for capital inflows, which helped advance the process of industrialisation in a number of the richer countries. However, the same factors that contributed to growth in the 1970s eventually created imbalances including the overproduction of non-traded goods, unparalleled debt and rampant price and exchange rate instability (Hoffman, 2000). In the early-1980s the region suffered its severest recession since the 1930s. The investment ratio fell sharply as did per capita consumption levels. The combined effect of a lack of price adjustment and heavy indebtedness caused a significant growth slowdown. Although in the late-1980s the rate of growth increased in some of the richer countries, including Brazil, Mexico, Chile, Columbia and Uruguay, for many poorer countries economic growth was insufficient to offset population growth, and living standards declined (United Nations, 1996). Many countries eventually introduced far-reaching structural and financial reforms. Central banks became independent, regulations

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necessitating the use of 1965 (rather than 1960) as the base year.

covering capital markets and banks were strengthened and privatisation programmes were

implemented. By the early-1990s, a number of countries were attracting substantial foreign

investment, and their growth performance improved accordingly.

5.   Estimation results

Table 2 shows the ordinary least squares (OLS) estimates of the coefficients $(b-1)$ on $y_{i,0}$ in

the cross-section unconditional convergence model (2). There are nine separate estimations,

for each of the periods 1965-95, 1965-80 and 1980-95, and for the regions Asia/Pacific

(N=15), Africa (N=41), and Latin America/Caribbean (N=24). None of the estimated values

of $(b-1)$ is significantly different from zero, and there is no evidence of unconditional

convergence in any of these cross-section regressions.

Table 2: Unconditional convergence estimates and Breitung-Meyer tests

	Asia/Pacific	Africa	LA/Caribbean
1965-95			
OLS	-.2899	-.0056	-.0299
	(.4051)	(.1449)	(.1421)
Breitung-Meyer	-.0143[*]	-.0195[***]	-.0358[***]
	(.0080)	(.0047)	(.0060)
1965-80			
OLS	.0645	-.0272	-.0681
	(.3086)	(.1037)	(.0999)
Breitung-Meyer	-.0125	-.0145	-.0449[***]
	(.0181)	(.0098)	(.0119)
1980-95			
OLS	-.0729	.0687	.0671
	(.1395)	(.0683)	(.0781)
Breitung-Meyer	.0403	.0540	.0245
	(.0183)	(.0138)	(.0156)

Table 2 also shows the Breiting-Meyer estimates of the coefficients $(\beta-1)$ on $(y_{i,t-1}-y_{i,0})$ in

(3). M=5 lagged growth terms are included in all estimations of (3). Again there are nine

separate versions of the test. For the period 1965-95, the Breitung-Meyer test produces

estimates of $(\beta-1)$ that are negative for all three regions, significant at the 1% level for Africa

and Latin America/Caribbean, and significant at the 10% level for Asia/Pacific. For the two 15-year sub-periods the evidence of convergent behaviour is rather weaker. For 1965-80 all three coefficients are negative. The coefficient for Latin America/Caribbean is significant at the 1% level, but the coefficients for Asia/Pacific and Africa are insignificant. For 1980-95 all three coefficients are positive.

Tables 3 to 5 show the results of the Maddala-Wu and Chang panel unit root tests. For each set of tests, M_i, the number of lagged growth terms included in (4) and (5) for country i, are determined using the AIC+2 criterion.[8] As before there are nine separate versions of each test. For the Maddala-Wu test, Tables 3 to 5 report the ADF t-statistic on $\hat{\beta}_i$ in (4) for each country, together with the corresponding p-value from the ADF test of $H_0:\beta_i=1$ against $H_1:\beta_i<1$. The p-values are obtained from the empirical distributions of the ADF statistics, generated using Monte Carlo simulations. Tables 3 to 5 also show the Maddala-Wu test statistic λ, and the relevant chi-square and bootstrap critical values and p-values as described in Section 3. For the Chang test, Tables 3 to 5 report the Z_i statistic for each country, and the corresponding S_N statistics and p-values. Comparing the results of the Maddala-Wu and Change tests, in both cases relatively few rejections of the unit root null hypothesis in the individual ADF autoregressions are typically required in order to reject the null in the panel test. However, it is also clear that the Chang test has a rather higher propensity to reject the unit root null hypothesis than the Maddala-Wu test.[9]

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[8] M_i is not necessarily the same for the two tests, because the specifications of (4) and (5) differ.

[9] In the individual ADF autoregressions the IV-ADF statistic has a higher propensity to reject the unit root null than the (standard) ADF statistic. Furthermore, while the S_N statistic has the (additive) characteristic of an arithmetic mean of the individual IV-ADF statistics, the λ statistic has the (multiplicative) characteristic of a geometric mean of p-values derived from the individual (standard) ADF statistics. This means that in the computation of the S_N statistic, the weight attached to cases where the IV-ADF statistics are negative but insignificant is greater than the weight attached to the corresponding cases in the computation of the λ statistic,

Table 3: Maddala-Wu and Chang panel unit root tests, Asia/Pacific

	1965-95			1965-80			1980-95		
	Maddala-Wu		Chang	Maddala-Wu		Chang	Maddala-Wu		Chang
	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$
Bangladesh	-2.49	0.129	-0.43	-1.31	0.604	0.20	-1.59	0.470	-1.65[**]
China	0.60	0.988	0.66	-2.62	0.118	-2.61[***]	0.12	0.959	0.88
Fiji	-0.72	0.829	-0.66	-2.04	0.276	-1.48[*]	-1.53	0.501	-0.12
India	-3.47[**]	0.019	-0.81	-2.55	0.133	0.41	-1.27	0.623	-0.79
Indonesia	-0.70	0.833	-0.28	-0.53	0.862	-0.77	-3.53[**]	0.021	0.00
Korea, Rep.	-0.22	0.934	1.14	-0.68	0.823	-0.25	-1.64	0.450	0.65
Malaysia	-0.45	0.894	0.05	-0.05	0.941	0.22	-0.28	0.908	-0.26
Nepal	-2.55	0.114	-0.45	-2.22	0.212	-0.59	-0.60	0.840	0.81
Oman	-3.84[***]	0.009	-0.95	-2.41	0.161	-0.50	-0.93	0.747	-0.35
Pakistan	-2.93[*]	0.054	-1.19	-1.75	0.394	-2.27[**]	-2.11	0.249	-2.71[***]
Papua NG	-0.71	0.831	0.59	0.36	0.976	0.13	-2.47	0.146	0.98
Philippines	0.45	0.983	1.94	-1.78	0.382	-0.05	-0.44	0.880	1.09
Sri Lanka	-2.52	0.122	-0.93	-1.94	0.314	-0.28	-1.91	0.327	-1.34[*]
Syria	-0.94	0.771	-2.18[**]	-0.28	0.909	-1.41[*]	-1.24	0.635	-0.04
Thailand	1.69	0.999	1.82	-1.27	0.624	0.02	0.56	0.984	0.95

Panel unit root test results

	1965-95	1965-80	1980-95
Maddala-Wu			
test statistic, λ	37.9	26.7	24.4
chi-square p-value	0.111	0.408	0.490
10% critical values			
Bootstrap	38.6	38.4	38.0
chi-square	40.3	40.3	40.3
5% critical values			
Bootstrap	43.0	43.2	43.2
chi-square	43.8	43.8	43.8
Chang			
test statistic, S_N	-0.43	-2.39[***]	-0.50
p-value (standard normal)	0.333	0.008	0.309

The results for the Asia/Pacific countries are shown in Table 3. For the 1965-95 period, in the Maddala-Wu test the individual ADF statistics for India and Oman are significant at the 5% level, but despite this λ falls just short of being significant. Across all of the individual estimations for the 1965-80 and 1980-95 sub-periods, there is only one significant ADF statistic (Indonesia in 1980-95), and λ is insignificant for both sub-periods. For the 1965-95 period, in the Chang test only in the case of Syria is the IV-ADF statistic significant at the 5% level. S_N is insignificant. For the 1965-80 sub-period, two significant IV-ADF statistics (China and Pakistan), together with a preponderance of negative but insignificant values for

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where the (standard) ADF statistics are in the lower half but above the bottom decile, of the (standard) ADF sampling distribution.

other countries, are sufficient to produce a significant S_N statistic. For the 1980-95 sub-period, although the IV-ADF statistics for Bangladesh and Pakistan are significant, S_N is insignificant. Overall, the Asia/Pacific results appear to show little or no evidence of convergent behaviour in the per capita GDP series.

Table 4: Maddala-Wu and Chang panel unit root tests, Africa

	1965-95			1965-80			1980-95		
	Maddala-Wu		Chang	Maddala-Wu		Chang	Maddala-Wu		Chang
	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$
Algeria	-1.25	0.641	-0.21	0.18	0.963	0.15	-2.10	0.252	-0.96
Benin	-2.66*	0.096	-0.61	-1.98	0.298	-0.71	-1.77	0.386	-2.18**
Botswana	-1.61	0.470	0.77	0.08	0.956	1.15	-1.19	0.659	0.30
Burkina Faso	-0.71	0.830	-0.93	-1.30	0.612	-0.92	-3.94***	0.010	-0.60
Burundi	-1.30	0.618	-2.06**	-2.47	0.146	-1.57*	-1.94	0.314	-1.31*
Cameroon	-1.85	0.352	-1.62*	-0.40	0.888	0.89	-2.63	0.117	-2.92***
Central Afr Rep	-1.03	0.733	0.31	-0.07	0.939	1.18	-2.31	0.187	-0.50
Chad	-1.43	0.557	-0.31	-0.20	0.920	1.56	-3.35**	0.030	-1.17
Comoros	-0.82	0.801	-0.41	-0.43	0.882	-0.25	0.03	0.950	-0.22
Congo, DRep.	0.53	0.985	0.86	1.19	0.996	-2.92***	-0.05	0.941	0.23
Congo	-1.65	0.452	-0.88	-1.75	0.398	-0.85	-2.52	0.138	-1.01
Cote d'Ivoire	-0.57	0.866	-0.40	-2.09	0.254	-1.26	-0.41	0.885	0.31
Egypt, Arab Rep.	-0.14	0.940	0.30	0.97	0.994	1.13	-1.24	0.635	0.10
Ethiopia	-1.77	0.387	-1.08	-1.38	0.575	-2.08**	-1.45	0.542	-0.84
Gabon	-2.04	0.267	-1.13	-1.31	0.606	1.40	-2.42	0.159	-0.69
Gambia	-1.63	0.461	-1.48*	-1.66	0.441	-0.50	-2.97*	0.062	-0.90
Ghana	-1.33	0.606	-0.98	-1.36	0.583	-1.33*	-1.62	0.456	-1.00
Guinea	-0.89	0.782	-0.77	-0.63	0.832	-1.69**	0.57	0.984	0.27
Guinea-Bissau	-1.80	0.374	-2.08**	0.09	0.957	-0.83	-3.15**	0.047	-3.13***
Kenya	-1.05	0.727	0.28	-1.73	0.408	-1.56*	-0.36	0.894	0.22
Lesotho	-1.09	0.712	0.16	-0.60	0.840	0.30	-0.05	0.941	0.69
Madagascar	-0.87	0.788	1.25	-0.82	0.781	-0.45	-5.03***	0.001	1.96
Malawi	-1.39	0.578	-1.45*	-2.69	0.105	-2.24**	-1.61	0.461	-1.86**
Mali	-1.30	0.618	-1.89**	-1.65	0.445	-1.16	-0.86	0.771	-0.44
Mauritania	-2.42	0.146	-1.44*	-2.07	0.260	-1.00	-0.99	0.729	-1.59*
Mauritius	-0.65	0.846	-0.51	-1.87	0.344	-1.42	-0.69	0.819	0.36
Morocco	-0.19	0.937	0.38	1.30	0.997	0.54	-0.43	0.882	0.56
Mozambique	-1.12	0.698	-0.32	0.40	0.978	1.21	-1.47	0.528	-1.02
Niger	-0.47	0.892	0.04	-1.03	0.719	-1.00	-0.49	0.870	-0.63
Nigeria	-1.63	0.459	-1.21	-0.31	0.902	0.05	-1.96	0.307	-1.03
Rwanda	-3.16**	0.037	-1.87**	-4.94***	0.001	-2.33**	-1.81	0.369	-0.92
Senegal	-2.73*	0.084	-0.67	-1.30	0.609	0.29	-2.40	0.163	-1.09
Sierra Leone	1.28	0.998	1.96	-1.05	0.708	-0.37	0.27	0.970	1.11
Sudan	-2.76*	0.078	-1.40*	-2.16	0.232	-0.25	-0.71	0.814	-1.33*
Swaziland	-2.47	0.133	-0.61	-1.32	0.599	-0.40	-1.74	0.401	-2.39***
Tanzania	-1.33	0.606	-0.82	-2.27	0.197	-0.80	-1.27	0.624	-1.10
Togo	-1.92	0.320	-1.34*	-1.76	0.390	-0.64	-1.73	0.408	-0.96
Tunisia	-0.38	0.906	0.67	0.47	0.982	0.77	-0.31	0.903	0.85
Uganda	-2.24	0.197	-1.99**	1.01	0.994	1.35	-1.96	0.304	-2.14**
Zambia	-0.21	0.935	0.85	0.11	0.958	-0.44	-2.11	0.249	2.12
Zimbabwe	-3.34**	0.025	-4.71***	-2.07	0.259	-2.54***	-2.81*	0.084	-4.46***

Panel unit root test results

	1965-95	1965-80	1980-95
Maddala-Wu			
test statistic, λ	70.0	59.3	97.5*

10% critical values			
Bootstrap	92.9	94.7	93.2
chi-square	98.8	98.8	98.8
5% critical values			
Bootstrap	99.9	103.6	101.6
chi-square	104.1	104.1	104.1
Chang			
test statistic, S_N	-4.27[***]	-3.05[***]	-4.57[***]
p-value (standard normal)	0.000	0.001	0.000

The results for Africa are shown in Table 4. For the 1965-95 period, in the Maddala-Wu test the individual ADF statistics are significant for only two out of 41 countries (Rwanda and Zimbabwe), and λ is therefore insignificant. For the 1965-80 sub-period, there is only one significant ADF statistic (Rwanda again), and λ is again insignificant. For the 1980-95 sub-period the pattern is somewhat different, with four significant ADF statistics (Burkina Faso, Chad, Guinea-Bissau and Madagascar) sufficient to produce a value for λ which just falls short of being significant at the 5% level, but which is significant at the 10% level. In contrast, the Chang test produces rather more consistent evidence of convergent behaviour for some African countries. The numbers of significant IV-ADF statistics for the 1965-95, 1965-80 and 1980-95 periods are six, six and seven, respectively. Together with a large preponderance of negative but insignificant IV-ADF statistics for other countries, this is sufficient to produce significant values for S_N for all three periods. Overall, for Africa the results of the Maddala-Wu and Chang tests are somewhat contradictory. However, based on the Chang test results in particular, there does appear to be some evidence of convergent behaviour, at least for certain countries.

The results for the Latin America/Caribbean countries are shown in Table 5. For the 1965-95 period, in the Maddala-Wu test none of the individual ADF statistics is significant, and neither is λ. Across all of the individual estimations for the 1965-80 and 1980-95 sub-periods

there is only one significant ADF statistic (Suriname in 1965-80), and λ is insignificant for

both sub-periods.

Table 5: Maddala-Wu and Chang panel unit root tests, Latin America/Caribbean

	1965-95			1965-80			1980-95		
	Maddala-Wu		Chang	Maddala-Wu		Chang	Maddala-Wu		Chang
	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$	ADF	p-value	$Z_i(\alpha_i)$
Argentina	-1.67	0.438	-0.91	-1.11	0.689	-0.23	-2.78*	0.089	-2.14**
Barbados	-1.67	0.441	0.11	-1.31	0.605	0.17	-1.75	0.396	-0.79
Bolivia	-1.65	0.451	-1.52*	-2.20	0.221	-0.81	-1.65	0.444	-1.00
Brazil	-2.11	0.243	-0.41	-1.30	0.608	-0.38	-1.20	0.654	-0.86
Chile	-0.85	0.795	-0.73	-1.25	0.631	-1.07	0.81	0.990	1.29
Colombia	0.48	0.984	0.61	-1.05	0.710	-0.99	-1.65	0.444	0.94
Costa Rica	-0.82	0.801	-0.54	-1.16	0.673	0.36	-0.49	0.870	-0.59
Dominican Rep.	-1.19	0.665	-0.56	-0.94	0.744	-0.46	-1.73	0.405	-0.15
Ecuador	-1.81	0.370	-0.46	0.06	0.953	0.21	-1.45	0.538	-1.64*
El Salvador	-1.79	0.378	-1.28*	-0.18	0.924	0.16	-0.19	0.922	-2.62***
Guatemala	-2.04	0.267	-1.78**	-1.79	0.377	-1.55*	-1.85	0.350	-1.47*
Guyana	-1.22	0.654	-0.69	-2.52	0.136	-1.65**	-2.35	0.177	-0.69
Haiti	-0.41	0.902	0.76	-2.75*	0.094	-0.85	1.12	0.995	0.62
Honduras	-2.46	0.136	-1.18	-1.84	0.354	-0.86	-1.46	0.536	-1.54*
Jamaica	-1.41	0.569	-1.51**	0.23	0.967	-5.00***	-1.23	0.639	-3.04***
Mexico	-1.37	0.588	-0.18	-0.39	0.888	1.79	-1.84	0.357	-1.44*
Nicaragua	-0.27	0.927	0.15	0.52	0.983	1.25	-0.41	0.885	-0.19
Panama	-2.03	0.269	-1.16	-1.89	0.335	0.19	-2.70	0.103	-1.49*
Paraguay	-0.94	0.769	-0.76	0.01	0.948	-0.80	-2.06	0.265	-2.04**
Peru	-1.06	0.724	-0.28	0.02	0.948	-0.11	-1.13	0.682	-1.23
Suriname	-2.16	0.224	-2.87***	-3.93**	0.011	-4.61***	-0.51	0.865	-1.56*
Trin & Tobago	-0.94	0.769	-1.09	-0.33	0.899	-0.60	-0.05	0.941	-0.22
Uruguay	-1.13	0.695	-0.97	-1.89	0.337	-0.67	-0.29	0.907	-0.20
Venezuela	-2.08	0.254	-0.43	-0.03	0.942	1.65	-2.11	0.249	-1.40*

Panel unit root test results

	1965-95	1965-80	1980-95
Maddala-Wu			
test statistic, λ	34.2	36.1	35.7
10% critical values			
Bootstrap	58.2	56.2	58.6
chi-square	60.9	60.9	60.9
5% critical values			
Bootstrap	63.2	62.2	65.4
chi-square	65.2	65.2	65.2
Chang			
test statistic, S_N	-3.61***	-3.03***	-4.79***
p-value (standard normal)	0.000	0.001	0.000

As in the case of the Africa, the Chang test produces results that are somewhat contradictory.

The numbers of significant IV-ADF statistics for the 1965-95, 1965-80 and 1980-95 periods

are three, three and four, respectively. Together with a large preponderance of negative

values among the insignificant IV-ADF statistics, this is sufficient to produce significant values for S_N for all three periods. The pattern for Latin America/ Caribbean is therefore very similar to that for Africa. For both regions the Chang test produces stronger evidence of convergent behaviour, for certain countries at least, than is the case for the Asia/Pacific countries. For 1965-95 as a whole, this pattern is also consistent with the findings of the Breitung-Meyer tests, which were significant at the 5% level for Africa and Latin America/Caribbean, but insignificant at the same level for Asia/Pacific.

6.   Conclusion

This paper sheds new light on the process of cross-country growth and convergence in the developing world by using dynamic panel unit root tests to test the convergence hypothesis in a large sample of developing countries. Time-series estimation offers a number of advantages over the traditional cross-section methods that dominated the early convergence literature: it allows for the presence of heterogeneous individual effects; it can accommodate dynamics in the growth series; it can discriminate between exogenous and endogenous sources of growth; and it allows for the possible existence of convergence clubs. Dynamic panel estimation offers further advantages: in particular, the use of pooled data increases the power of hypothesis tests.

The data used in the present study are real per capita GDP covering the period 1960-95, for 80 countries grouped into three broad regions: Asia/Pacific, Africa and Latin America/ Caribbean. Of the three regions Latin America/Caribbean had the highest mean per capita GDP at the start of the observation period, but during the period average growth was much faster in Asia/Pacific than in either of the other two regions. By the end of the period Asia/Pacific had overtaken Latin America/Caribbean in terms of mean per capita GDP.

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Africa recorded both the lowest mean per capita GDP at the start of the period, and the slowest mean growth, causing the inter-regional gap between Africa and the other two regions to increase over the period.

Estimations of the traditional cross-section unconditional convergence model produce no evidence of intra-regional unconditional convergence. Because they all allow for heterogeneous individual effects, the three panel unit root tests of Breitung and Meyer (1994), Maddala and Wu (1999) and Chang (2003) are interpreted as tests of the conditional convergence hypothesis. In common with cross-section estimation, the Breitung-Meyer test imposes an assumption of a homogeneous autoregressive coefficient that is common to all countries within the same region. In contrast, both Maddala-Wu and Chang allow for heterogenous (country-specific) autoregressive coefficients.

For the period 1965-95 as a whole, the Breitung-Meyer test produces strong evidence of intra-regional convergence for Africa and Latin America/Caribbean, and weak evidence for Asia/Pacific. For the two 15-year sub-periods within the thirty-year observation period the evidence of convergence is rather weaker, although for 1965-80 there is strong evidence of convergence for the Latin America/Caribbean region.

The results of the Maddala-Wu and Chang tests are to some extent contradictory, with the latter showing a higher propensity than the former to reject the unit root null hypothesis and to indicate convergent behaviour. Moreover, both tests evaluate the null hypothesis of a unit root in per capita GDP for all countries against the alternative of mean-reverting behaviour for some countries; rejection of the null does not imply evidence of convergence (even towards heterogeneous long run mean values) on the part of all countries within a region.

Taking the results as a whole, there is little or no evidence of convergent behaviour for countries in the Asia/Pacific region, but rather more evidence of convergent behaviour for certain countries within the Africa and Latin America/Caribbean regions. Overall the results appear to lend support to some of the main hypotheses of both neo-classical and new growth theory.

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