Macroeconomic Dynamics, **18**, 2014, 753–782. Printed in the United States of America.
doi:10.1017/S1365100512000594

PERSISTENCE IN CONVERGENCE

THANASIS STENGOS
University of Guelph

M. EGE YAZGAN
Istanbul Bilgi University

In this paper, we examine the convergence hypothesis using a long memory framework that allows for structural breaks and does not rely on a benchmark country. We find that even though the long memory framework of analysis is much richer than the simple $I(1)/I(0)$ alternative, a simple absolute divergence and rapid convergence dichotomy produced by the latter is sufficient to capture the behavior of the gaps in per capita GDP levels and growth rates results respectively. This is in contrast to the findings of Dufrénot, Mignon, and Naccache [The Slow Convergence of Per Capita Income between the Developing Countries: Growth Resistance and Sometimes Growth Tragedy. Discussion paper, University of Nottingham (2009)], who found strong evidence of long memory for output gaps. The speed of convergence as captured by the estimated long memory parameter d, is explained by differences in physical and human capital as well as fiscal discipline characteristics of economic policies pursued by different countries.

Keywords: Growth Convergence, Long Memory

1. INTRODUCTION

One of the main predictions of neoclassical growth theory put forward by Solow is that in the long run, all countries with similar technological characteristics will converge to a balanced growth path (steady state) equilibrium that will be entirely determined by the exogenously given growth rate of technical progress, which will equal labor productivity growth. In the absence of exogenous technical progress, long-run growth would be zero, as labor productivity, because of diminishing returns, would also eventually become zero. This is the so-called convergence hypothesis, which has been one of the main focal points of the empirical growth literature. On the other hand, endogenous growth theories came to offer alternative ways of producing labor productivity growth generated by profit-seeking activities endogenously in the economy. These models offered explanations of why certain countries managed to grow faster than others, of how human capital and R&D accumulation could result in steady growth, and of why imperfect competition and international trade permitted productivity gains that could not be reached by closed economies with controlled markets. The growth empirics literature has

We thank two anonymous referees and an associate editor for very helpful comments. The first author acknowledges financial support from the SSHRC of Canada. Address correspondence to: Thanasis Stengos, Department of Economics and Finance, University of Guelph, Guelph, ON N1G 2W1, Canada; e-mail: tstengos@uoguelph.ca.

 1365-1005/13

been one of the most important areas of applied research in the last twenty years, and from a methodological point of view, different studies incorporate different techniques for testing the convergence hypothesis, using cross-sectional, panel data and pure time series methods. Overall, the evidence in favor of convergence has been more present in cross-sectional studies, where convergence simply embodies the catching-up growth effect in which less developed, poorer countries approach in equilibrium the (per capita) income levels of richer, more developed ones; see Durlauf et al. (2005) for a survey of the recent evidence. In the time series literature, Bernard and Durlauf (1995, 1996) have introduced time series interpretations of the convergence hypothesis that can be cast in terms of unit root and cointegration analysis. Pesaran (2007) has extended the time series convergence concept to the case where there is no requirement that the converging economies to be identical in all aspects, including initial endowments. The main result is that for two economies to be convergent it is necessary that their output gap be stationary with a constant mean, irrespective of whether the individual country's output is trend stationary and/or contains unit root. Furthermore, testing for convergence in that case does not rely on using a benchmark country to define the output gaps that are used in the analysis, and uses a pairwise approach to test convergence. Pesaran (2007) rejects convergence in output levels and suggests that the evidence in favor of convergence clubs may be spurious. Cheung and Garcia-Pascual (2004), using panel data methods, are more supportive of the convergence hypothesis for the G7 group of countries.

However, most of the empirical work so far assumes that the empirical analysis of growth convergence can be carried out within an $I(0)$ or $I(1)$ framework; yet it may be that a long memory framework is more appropriate for such an analysis. In this paper, we examine the convergence hypothesis within a long memory analytical framework that allows two new directions of research. We allow for structural breaks and we do not rely on a benchmark country for the comparison, something that has not yet been examined in the long memory empirical growth literature. If per capita output actually follows a fractionally integrated process because of aggregation over heterogeneous units, firms as in Abadir and Talman (2002) or sectors as in Haubrich and Lo (2001), then empirical results based on a simple $I(1)/I(0)$ classification will spuriously find support for, or reject, convergence. Michelacci and Zaffaroni (2000) introduce fractional integration within a Solow growth model allowing cross-sectional heterogeneity in how firms adjust their production levels, and they find that the standard beta convergence rate is attributable to a long memory parameter lying between 0.5 and 1.

More recently, Dufrénot et al. (2009), henceforth DMN, also use fractional integration analysis to test convergence for a group of developing countries. They introduce an ARFIMA model and they allow the long memory parameter d to be greater than 0.5. In other words, they do not simply restrict d to be in the interval $(-0.5,0.5)$ but also allow it to be between 0.5 and 1 as well as greater than 1. This gives rise to a rich classification of convergence cases, and DMN are careful to examine the different cases that arise. Their analysis is contrasted with that of transient divergence—see Phillips and Sul (2007a, 2007b)—where convergence will take place eventually, as divergent dynamics implied by idiosyncratic growth factors will diminish and will be dominated by the common components of economic growth. The main message of DMN is that for developing countries there is evidence of divergence and growth tragedy in which countries do not share common factors and those with initial low income will stay behind others, with negative growth rates forever. However, the analysis carried out by DMN is subject to two main caveats. The first is that they use a benchmark to construct output gaps, and the second is that they do not consider the issue of structural breaks that will affect the time series properties of the series under consideration. In the case of structural breaks, events that alter the steady state levels of per capita income will also change the mean reversion properties of relative outputs. This is the case in the work of Li and Papell (1999) and Datta (2003), among others. In the standard $I(1)/I(0)$ analysis, when structural breaks are present, standard tests of convergence may lack power to reject the null of nonstationarity. The same will be true for an ARFIMA process, in which the presence of structural breaks may contaminate the dynamics and distort the estimation of d, the parameter that determines the speed of convergence. The issue of relying on a benchmark also renders the analysis problematic, as perceived leaders used as benchmark economies may not retain the leader title over the whole period of analysis. In that respect, Pesaran's (2007) pairwise analysis becomes relevant.

In this paper, we extend DMN in these two important directions. We examine the effects of structural breaks and we do not rely on a benchmark country in a long memory analytical framework for the convergence hypothesis. The focus in the paper is, first, the estimation of d, that is, the parameter that determines the speed of convergence between different economies, and second, the examination of the effect on this parameter of certain important characteristics that are embedded in the majority of growth models, such as human capital and macroeconomic stability. The main finding of our paper is that even though the long memory framework of analysis that we adopt is much richer than the simple $I(1)/I(0)$ alternative, which produces a simple absolute divergence and rapid convergence dichotomy, the latter seems to be sufficient to capture the behavior of the gaps in per capita GDP levels and growth rates. The former produces a pattern of divergence whereas the latter produces one of rapid convergence. Any evidence of mean reversion and long memory that we find is not strong enough, contrary to the findings of DMN. The reason for these differences lies in the fact that we do not rely on a benchmark, something that introduces a higher degree of persistence in the output gap series. The speed of convergence (divergence), as captured by the estimated d parameter is explained by differences in investment rates and human capital stocks, and in fiscal discipline characteristics of economic policies pursued by different countries. The more dissimilar countries are in terms of these factors, the more likely they are to have divergent paths.

The paper is organized as follows. The next section presents the methodology that we follow. We then proceed to present the results first for the output gaps in levels and then for the growth rates, and we also present some additional results from a subsample of the data that refer to different continents and to developing countries only. The next section presents the analysis from the determinants of the estimated speed of convergence. Finally we conclude.

2. TESTING FRAMEWORK WITH LONG MEMORY

Following DMN, we will define the pairwise difference between the log of the per capita incomes of countries i and j at time t as

$$U_t = Y_t^i - Y_t^j = \beta(t) + Z_t \;\; Z_t \sim I(d),\; i = 1, \ldots, N,\; i \neq j,\; t = 1, \ldots, T. \quad \mathbf{(1)}$$

The process Z_t is described as $(1-L)^d Z_t = \varepsilon_t$, where L is the lag operator and ε_t is the disturbance term. The fractional integration parameter is given by d under the assumption that the process is invertible ($d > -0.5$). The $\beta(t)$ is a deterministic function of the time trend t. For example, DMN assumed that this function is linear, $\beta(t) = \beta_0 + \beta_1 t$, but following Ludlow and Enders (2000) and Becker et al. (2004, 2006), we let the $\beta(t)$ function be defined in a way that admits structural breaks:

$$\beta(t) = \beta_0 + \beta_1 \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \cos\left(\frac{2\pi kt}{T}\right). \quad \mathbf{(2)}$$

This functional form allows for the presence of (smooth) structural breaks. Note here that different values of k will have different implications for the permanent or transitory nature of the breaks. If k is an integer then this will result in temporary breaks, whereas fractional frequencies would imply permanent breaks, as the function would not complete a full oscillation. One advantage of adopting this specification for structural breaks is that it does not require any prior knowledge of the dates when those breaks occur. On the contrary, it assumes that breaks happen smoothly instead of abruptly, something that would make their detection more difficult.[1]

We follow DMN in distinguishing between the different convergence cases that are implied by these processes. Different values of d, β_0, β_1, and β_2 will define different types of convergence, and we enumerate these different convergence cases subsequently. We will only concentrate on the parameter d and not pay attention to the β's, even though the latter are important in the underlying DGP and the classification between unconditional and conditional convergence. For different values of d,

Case 1. $-0.5 < d \leq 0$. This is the case of a short memory process, where there is "fast catching up" or "short memory catching up."

Case 2. $0 < d < 0.5$. This is the case of a long memory but still stationary process, where there is a slow or smooth decay in the catching-up process. Here, output differences in the remote past will linger on in the current output difference, although with a smaller influence. This is the situation when a country spends a long time on a transition path toward a common long-run trend.

Case 3. $0.5 < d < 1$. This is the case of a long memory process that is nonstationary but still mean-reverting. In that case the process is characterized by high persistence, whereby any output differences in the distant past will still have a long-lasting influence in the present.

Case 4. $d \geq 1$. This is the case of a unit root or an explosive process. This is the situation in which any initial difference is not expected to be reversed in the future or there is a strong magnification effect. When $d > 1$ this is the case of "stochastic divergence."

For completeness, following DMN, we also present the distinction between conditional and absolute convergence, which depends on the combination of $\beta-$values:

Conditional Convergence (CC). *Deterministic convergence or conditional convergence* ($\beta_0 \neq 0$, $\beta_1 = 0$, $\beta_2 = 0$). Similarly, in this case depending on the value of d, we can distinguish three cases:

Case CC.1. $-0.5 < d \leq 0$. This is the case of strict or rapid conditional convergence and has been looked at by Li and Papell (1999).

Case CC.2. $0 < d < 0.5$. This is the case of a long memory conditional stationary convergence. Here, output differences in the remote past will linger on in the current output difference, although with a declining influence, and convergence will ultimately take place.

Case CC.3. $0.5 < d < 1$. This is the case of a long memory process that is nonstationary but still mean-reverting. In that case output differences in the distant past will have a long-lasting influence in the present, but mean reversion and hence convergence will take place.

Conditional Catching Up (CCU). This is the case where $\beta_0 \neq 0$, $\beta_1 \neq 0$, and $\beta_2 \neq 0$, and the difference vanishes.[2] This is contrasted to the simpler case of CC presented earlier, where the convergence dynamics is simply driven by d, as examined by Li and Papell (1999). Depending on the value of d, we will have

Case CCU.1. $-0.5 < d \leq 0$. This is the case of strict or rapid catching up.

Case CCU.2. $0 < d < 0.5$. This is the case of long memory conditional stationary catching up.

Case CCU.3. $0.5 < d < 1$. This is the case of nonstationary long memory catching up.

Absolute Convergence (AC). *Absolute or stochastic convergence* ($\beta_0 = 0$, $\beta_1 = 0$, $\beta_2 = 0$). In this case, depending on the value of d, we may have

Case AC.1. $d = 0$. This is the case of zero mean convergence of Bernard and Durlauf (1996).

Case AC.2. $0 < d < 0.5$. This is the case of long memory stochastic stationary convergence.

Case AC.3. $0.5 < d < 1$. This is the case of long memory mean-reverting convergence.

Finally, if $\beta_0 \neq 0$, $\beta_1 \neq 0$, $\beta_2 \neq 0$, and $d = 0$, output gaps get bigger and bigger over time if the function $\beta(t)$ is such that it gets bigger and bigger with t. This would be the case of conditional divergence, and it implies that the long-run mean of the output gap shifts upward over time.

These definitions of the different convergence cases allow a much richer classification of convergence types, whereby one can distinguish between stationary convergence and mean-reverting nonstationary convergence, and this applies within the conditional as well as the absolute framework. An additional feature of this classification scheme is that it allows initial differences either to linger on and have a long-lasting influence in the present or to decay rapidly and play no role or be somewhere in between these two cases. This is something that cannot be captured by the simple $I(0)/I(1)$ classification where there are only two extreme cases, that is perfect persistence or no persistence at all. In our case we will concentrate on the four cases that depend on the values of d.[3]

The long memory parameter d is estimated by Whittle estimators that are immune to the presence of nonstationarity. Let $I_Z(\omega_j)$ denote the periodogram of a series Z_t based on a discrete Fourier transform $W_Z(\omega_j)$ at frequency $\omega_j = \frac{2\pi j}{T}$ for $j = 0, \ldots, T-1$, such that $I_Z(\omega_j) = W_Z(\omega_j)W_Z^*(\omega_j)$, with $W_Z^*(\omega_j)$ being the complex conjugate of $W_Z(\omega_j)$, defined as

$$W_Z(\omega_j) = \frac{1}{\sqrt{2\pi T}} \left| \sum_{t=1}^{T} Z_t e^{it\omega_j} \right|^2. \tag{3}$$

The discrete Fourier transform $W_Z(\omega_j)$ can be used to define a Whittle estimator of d obtained by minimizing the objective function with respect to d,

$$\mathrm{WH}(G, d) = \frac{1}{\upsilon} \sum_{j=1}^{\upsilon} \left[\ln\left(G\omega_j^{-2d}\right) + \frac{I_Z(\omega_j)\omega_j^{2d}}{G} \right], \quad G \in (0, \infty), \tag{4}$$

where υ is the number of frequencies used in the estimation. The best-known Whittle estimator that is valid under nonstationarity is the exact local Whittle (ELW) estimator of Shimotsu and Phillips (2005, 2006). This estimator is consistent and has the same $N(0, 1/4)$ limit values for all values of d. The word "exact" is used to distinguish this estimator, which relies on exact algebraic manipulation, from the conventional local Whittle of Kuensch (1987) and Robinson (1995) (LW), which is based on an approximation of the Whittle likelihood function and is not a good general-purpose estimator[4] when the value of d may take on values in the nonstationary zone beyond $3/4$.

However, the ELW estimator has also been shown to have some undesirable properties. As shown by Shimotsu (2008), if an unknown mean (initial value) is replaced by its sample average, simulations suggest that the ELW estimator is inconsistent for $d > 1$. Furthermore, if an unknown mean is replaced by the first observation, the consistency and normality of ELW estimator for $d \in (0, 1/2)$ require a strong assumption on the number of ordinates used in estimation, and simulations suggest that the estimator is inconsistent for $d \leq 0$. Hence, an unknown mean needs to be estimated carefully in the ELW estimation. Shimotsu (2008) modifies the ELW objective function to estimate the mean by combining two estimators, the sample average and the first observation, and denotes the resulting estimator as 2-stage feasible exact local Whittle (2FELW). The 2FELW estimator, which uses the tapered estimator of Velasco (1999) in the first stage, has the same $N(0, 1/4)$ limit distribution for $d \in (-1/2, 2)$ and is consistent when $d > 1/2$. Moreover, the finite sample performance of the 2FELW estimator inherits the desirable properties of the ELW estimator. This estimator can also be computed with prior detrending (2FELWd) of the data; see Shimotsu (2008). Finally, we also apply the fully extended local Whittle estimator (FELW) of Abadir et al. (2007), which uses a fully extended discrete Fourier transform. The FELW estimator is shown to be consistent and has an $N(0, 1/4)$ distribution for $d \in (-3/2, \infty)$. As in the case of 2FELWd, the FELW estimator is also computed with prior detrending (FELWd). The 2FELW and FELW estimators can be regarded as being complementary to each other for a variety of reasons. The FELW estimator has the advantage over the 2FELW estimator in that it covers a wider range of d, and it does not require estimating the mean. However, the FELW estimator excludes the values of $d = 1/2, 3/2, \ldots,$ which results in "holes" in the confidence intervals at these points, whereas the two-step approach does not [see Shimotsu (2008) for a comprehensive comparison and discussion of the two estimators].[5]

All LW, ELW FELW, FELWd, 2FELW, 2FELWd estimators are used to estimate d, and υ is chosen as $\upsilon = T^{0.6}$, as suggested by Shimotsu (2008). Then, following DMN, we perform the following tests:

Test 1. $H_0^0 : d = 0$ against $H_1^0 : d > 0$ (short memory against long memory)

Test 2a. $H_0^{1/2a} : d = 0.5$ against $H_1^{1/2a} : d < 0.5$ ("limit" stationary long memory against stationary convergence)

Test 2b. $H_0^{1/2b} : d = 0.5$ against $H_1^{1/2b} : d > 0.5$ ("limit" stationary long memory against non-stationary convergence or mean reverting process)

Test 3. $H_0^1 : d = 1$ against $H_1^1 : d < 1$ (unit root against a mean reverting process)

Test 4. $H_0^1 : d = 1$ against $H_1^{1\exp l} : d > 1$ (unit root against stochastic divergence)

We conduct Monte Carlo simulations to compute the critical values of the statistic corresponding to each of the preceding tests under the null hypothesis under consideration. The test statistic is computed as

$$\frac{\sqrt{\upsilon}(\widehat{d} - d_0)}{\sigma(\widehat{d})}, \tag{5}$$

where d_0 is the value of d under the null hypothesis, $\widehat{d}$ is the estimate of d, and $\sigma(\widehat{d})$, is its asymptotic standard error. For the simulations of the critical values, we consider 50,000 iterations. For each iteration we generate a series from $Z_t = U_t \sim I(d)$ for different values of d corresponding to the different null hypotheses listed earlier. Note that in this case we do not rely on a specific $\beta(t)-$function with particular parametric values of the $\beta-$parameters to obtain the critical values of the various test statistics. The latter will be obtained on the assumption that we are looking at "detrended" data. As explained in Section 3.1, we detrend the data by estimating the $\beta_0, \beta_1, \beta_2$ in equation (1) for 30 different values of k.

Under the asymptotic theory provided in Shimotsu (2008), among others, all the Whittle estimators considered here, except LW, which exhibits nonstandard behavior when $d > 3/4$, are distributed as $N(0, 1/4)$ under all of the null hypotheses defined previously. Hence the preceding test statistic is expected to be distributed as standard normal under each null. Therefore the purpose of the present Monte Carlo analysis is to control for small sample deviations from the asymptotic distribution. In Table A.1 of the Appendix we provide critical values at 5% and 10% significance levels for $T = 100, 200, 500$.[6] These critical values are then used in the empirical analysis that follows.

3. EMPIRICAL FINDINGS

The data consist of annual GDP data for the period 1945–2006 and for 139 countries.[7] The data come from Maddison (2008)[8] and they include all countries available, not just the group of developing countries considered by DMN; hence our sample corresponds to $T = 62$ and $N = 139$. The four tests outlined earlier are applied to all possible pairs of $U_t = Y_t^i - Y_t^j, i = 1, 2, \ldots, N-1$ and $j = 1, 2, \ldots, N$. We first investigate the convergence of GDP per capita and GDP data for all 139 countries taken together as a group and then separately as belonging to different continents (Middle East and Central Asia, Europe, Asia and Pacific, sub-Saharan Africa, Western hemisphere).[9]

As in Pesaran (2007), we analyze output convergence across 139 countries without the pitfalls that surround the use of a benchmark to construct the output differences. We examine all $N(N-1)/2 = 9{,}591$ output gaps. Under the null hypothesis of each test, we would expect the fraction of output gap pairs for which the null hypothesis is rejected to be close to the size of the test applied to the individual output gap pairs. Hence, in the tables, rejection frequencies that greatly exceed a nominal size of, say, 0.05 would be taken as evidence against the null. Conversely, rejection frequencies that are less than the nominal size value will be taken as evidence in favor of the null.[10] Furthermore, following DMN, we will analyze the nature of convergence depending on the classification presented in Table 1.

3.1. Detrending for Structural Breaks

To control for structural breaks we "detrend" the data by estimating the $\beta_0, \beta_1, \beta_2$ in equation (1) for 30 different values of $k = 0.1, 0.2, \ldots, 2.9, 3.0$ and by subtracting

TABLE 1. Type and nature of convergence according to the estimate of d

	H_0^0 rejected ($d > 0$)		
	$H_0^{1/2a}$ rejected ($d < 0.5$)	$H_0^{1/2b}$ not rejected ($d \geq 0.5$)	H_0^0 not rejected ($d = 0$)
H_0^1 is rejected ($d < 1$)	Stationary convergence	Mean-reverting convergence	Rapid convergence
H_0^1 is not rejected against H_1^1 ($d = 1$) or rejected against $H_1^{1\,\exp l}$ ($d > 1$)	Absolute divergence		Indeterminate outcome

the estimated $\beta(t)$ function from the data series U_t, before estimating the d's and performing the different tests. In the simulations where we obtained the critical values for the various test statistics we assumed that the data had already been detrended. Detrending for structural breaks after estimating the $\beta(t)$ function avoids the problem of having to rely on specific values of the β parameters to obtain critical values in the simulations. Hence the test results will avoid possible misspecification because of reliance on "incorrect" β parameter values.[11]

3.2. Pairwise Results for Per Capita Output Gaps

The first horizontal panel (denoted by ALL) of Table 2 summarizes the results of the five tests applied to all 9,591 output gap pairs over the period 1945–2006 ($T = 62$; $N = 139$) for the level GDP per capita data at the 5% significance level based on critical values computed for $T = 100$, and Table 3 for $T = 200$.[12] The tables show the rejection frequencies of the five tests defined earlier. We report the minimum (Min), median (Med), and maximum (Max) of these rejection frequencies obtained from the 30 different detrended series as explained earlier.

As can be seen from these tables, all the maximum, median, and even minimum rejection frequencies of test 2a are well below the significance level (0.05) for all of the estimators of the d parameter and for critical values using both $T = 100$ and $T = 200$ estimators. Similarly the evidence from tests 2b and 3 suggests that d is greater than its limit value 0.5 and possibly unity or greater than unity; in short, $d > 0.5$. These results point to the low power of the tests used. However, even though we cannot distinguish between a long memory nonstationary mean-reverting and a nonstationary unit root or even explosive process, the evidence strongly rejects stationarity. Overall, even though we cannot entirely exclude the possibility of mean reversion, the evidence points strongly toward a non-mean-reverting process for the per capita output gaps. As a result, we may conclude that output gaps for GDP per capita for the all-country group are consistent with any variety of nonstationary behavior: long memory, unit root, or even explosive.[13] We repeat the analysis for different groups of countries, the Middle East and Central Asia, Europe, Asia and the Pacific, sub-Saharan Africa, and the Western

TABLE 2. Fraction of rejections for GDP per capita ($T = 100$, 5% significance level)

	Test1			Test2a			Test2b			Test3			Test4			Abs. divergence		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
ALL																		
FELW	0.963	0.973	0.985	0.006	0.011	0.016	0.749	0.787	0.841	0.061	0.095	0.143	0.212	0.276	0.325	0.061	0.095	0.143
FELWd	0.969	0.973	0.977	0.006	0.007	0.008	0.762	0.795	0.836	0.067	0.085	0.102	0.212	0.276	0.327	0.067	0.085	0.102
2FELW	0.961	0.972	0.984	0.006	0.011	0.016	0.747	0.787	0.841	0.069	0.102	0.140	0.212	0.277	0.325	0.069	0.102	0.140
2FELWd	0.968	0.972	0.977	0.006	0.007	0.008	0.758	0.793	0.834	0.084	0.105	0.125	0.213	0.277	0.327	0.084	0.105	0.125
MEA																		
FELW	0.963	0.979	0.986	0.000	0.006	0.010	0.739	0.786	0.828	0.068	0.102	0.153	0.216	0.235	0.261	0.068	0.102	0.153
FELWd	0.971	0.978	0.989	0.000	0.005	0.006	0.755	0.792	0.816	0.069	0.081	0.105	0.216	0.235	0.261	0.069	0.081	0.105
2FELW	0.962	0.978	0.986	0.000	0.006	0.010	0.739	0.786	0.829	0.075	0.109	0.155	0.217	0.236	0.264	0.075	0.109	0.155
2FELWd	0.971	0.977	0.989	0.000	0.004	0.006	0.754	0.791	0.816	0.090	0.111	0.141	0.217	0.236	0.264	0.090	0.111	0.141
EUR																		
FELW	0.927	0.954	0.972	0.011	0.020	0.026	0.718	0.731	0.762	0.129	0.159	0.200	0.090	0.118	0.148	0.129	0.159	0.200
FELWd	0.940	0.953	0.964	0.011	0.014	0.016	0.729	0.747	0.780	0.139	0.156	0.180	0.090	0.122	0.154	0.139	0.156	0.180
2FELW	0.908	0.938	0.962	0.015	0.026	0.032	0.692	0.708	0.749	0.140	0.175	0.218	0.090	0.119	0.149	0.140	0.175	0.218
2FELWd	0.923	0.940	0.950	0.015	0.018	0.020	0.704	0.724	0.756	0.150	0.176	0.205	0.090	0.122	0.154	0.150	0.176	0.205
AAP																		
FELW	0.961	0.975	0.988	0.004	0.008	0.015	0.791	0.848	0.903	0.039	0.068	0.118	0.201	0.324	0.440	0.039	0.068	0.118
FELWd	0.969	0.977	0.985	0.002	0.004	0.006	0.799	0.852	0.900	0.039	0.059	0.084	0.201	0.324	0.443	0.039	0.059	0.084
2FELW	0.954	0.972	0.986	0.004	0.008	0.015	0.786	0.843	0.898	0.048	0.077	0.118	0.201	0.324	0.440	0.048	0.077	0.118
2FELWd	0.963	0.974	0.984	0.002	0.004	0.006	0.796	0.847	0.896	0.053	0.080	0.108	0.201	0.324	0.443	0.053	0.080	0.108

									SSA									
FELW	0.959	0.970	0.979	0.009	0.013	0.019	0.730	0.759	0.814	0.077	0.114	0.148	0.197	0.248	0.283	0.077	0.114	0.148
FELWd	0.961	0.968	0.979	0.007	0.009	0.011	0.744	0.765	0.808	0.079	0.095	0.108	0.197	0.248	0.282	0.079	0.095	0.108
2FELW	0.960	0.970	0.980	0.008	0.012	0.017	0.732	0.760	0.815	0.091	0.125	0.147	0.198	0.249	0.283	0.091	0.125	0.147
2FELWd	0.964	0.970	0.981	0.007	0.008	0.010	0.745	0.766	0.809	0.102	0.121	0.139	0.198	0.248	0.283	0.102	0.121	0.139
									WHE									
FELW	0.959	0.967	0.977	0.009	0.013	0.016	0.690	0.710	0.754	0.101	0.146	0.180	0.160	0.194	0.205	0.101	0.146	0.180
FELWd	0.944	0.958	0.978	0.007	0.013	0.019	0.700	0.719	0.742	0.122	0.142	0.159	0.160	0.194	0.206	0.122	0.142	0.159
2FELW	0.956	0.965	0.974	0.008	0.013	0.015	0.686	0.708	0.753	0.120	0.161	0.177	0.160	0.194	0.205	0.120	0.161	0.177
2FELWd	0.941	0.955	0.981	0.007	0.013	0.019	0.693	0.714	0.736	0.150	0.159	0.185	0.160	0.194	0.206	0.150	0.159	0.185
									DEV									
FELW	0.963	0.972	0.983	0.007	0.012	0.016	0.751	0.783	0.835	0.063	0.097	0.142	0.216	0.265	0.310	0.063	0.097	0.142
FELWd	0.967	0.971	0.977	0.006	0.008	0.009	0.764	0.789	0.826	0.072	0.089	0.103	0.217	0.265	0.312	0.072	0.089	0.103
2FELW	0.963	0.972	0.983	0.007	0.011	0.015	0.752	0.784	0.835	0.071	0.104	0.135	0.217	0.265	0.311	0.071	0.104	0.135
2FELWd	0.967	0.972	0.977	0.006	0.007	0.008	0.763	0.788	0.826	0.089	0.107	0.121	0.218	0.266	0.312	0.089	0.107	0.121

Notes: The table reports the minimum (Min), median (Med), and maximum (Max), rejection frequencies obtained over 30 different k values. Abs. divergence, absolute divergence; 2FELW, 2-stage feasible exact local Whittle estimator; 2FELWd, 2-stage feasible exact local Whittle estimator with detrending; ALL, all countries; MEA, Middle Eastern and Central Asian countries; EUR, European countries; AAP, Asian and Pacific countries; SSA, sub-Saharan countries; WHE, Western hemisphere countries; DEV, developing countries.

Test 1 : $H_0^0 : d = 0$ against $H_1^0 : d > 0$.
Test 2a : $H_0^{1/2a} : d = 0.5$ against $H_1^{1/2a} : d < 0.5$.
Test 2b : $H_0^{1/2b} : d = 0.5$ against $H_1^{1/2b} : d > 0.5$.
Test 3 : $H_0^1 : d = 1$ against $H_1^1 : d < 1$.
Test 4 : $H_0^1 : d = 1$ against $H_1^{1\,\exp l} : d > 1$.
Abs. divergence: Test 3 is not rejected (or Test 4 is rejected) together with Test 1 is rejected

TABLE 3. Fraction of rejections for GDP per capita ($T = 200$, 5% significance level)

	Test1			Test2a			Test2b			Test3			Test4			Abs. divergence		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
ALL																		
FELW	0.969	0.977	0.987	0.007	0.012	0.018	0.770	0.807	0.858	0.068	0.103	0.152	0.243	0.309	0.361	0.068	0.103	0.152
FELWd	0.973	0.976	0.980	0.009	0.010	0.012	0.786	0.817	0.854	0.097	0.123	0.147	0.243	0.309	0.363	0.097	0.123	0.147
2FELW	0.967	0.977	0.986	0.007	0.012	0.018	0.773	0.812	0.863	0.076	0.110	0.149	0.243	0.310	0.362	0.076	0.110	0.149
2FELWd	0.973	0.976	0.980	0.008	0.010	0.011	0.790	0.820	0.857	0.097	0.121	0.144	0.244	0.310	0.363	0.097	0.121	0.144
MEA																		
FELW	0.970	0.983	0.989	0.000	0.007	0.013	0.762	0.810	0.852	0.074	0.109	0.158	0.249	0.269	0.301	0.074	0.109	0.158
FELWd	0.976	0.981	0.993	0.000	0.007	0.009	0.774	0.811	0.838	0.105	0.126	0.156	0.247	0.267	0.301	0.105	0.126	0.156
2FELW	0.969	0.982	0.989	0.000	0.008	0.014	0.767	0.814	0.857	0.080	0.115	0.161	0.250	0.270	0.301	0.080	0.115	0.161
2FELWd	0.976	0.981	0.993	0.000	0.006	0.008	0.782	0.816	0.844	0.104	0.128	0.158	0.247	0.267	0.301	0.104	0.128	0.158
EUR																		
FELW	0.937	0.960	0.977	0.012	0.022	0.029	0.739	0.753	0.781	0.138	0.167	0.203	0.119	0.148	0.176	0.138	0.167	0.203
FELWd	0.948	0.958	0.969	0.013	0.017	0.019	0.752	0.769	0.798	0.158	0.177	0.200	0.119	0.152	0.184	0.158	0.177	0.200
2FELW	0.920	0.948	0.970	0.016	0.028	0.034	0.720	0.738	0.776	0.147	0.183	0.221	0.119	0.148	0.177	0.147	0.183	0.221
2FELWd	0.937	0.947	0.956	0.020	0.022	0.026	0.732	0.751	0.779	0.168	0.193	0.219	0.119	0.152	0.184	0.168	0.193	0.219
AAP																		
FELW	0.965	0.979	0.989	0.005	0.009	0.017	0.809	0.862	0.913	0.042	0.071	0.121	0.254	0.368	0.483	0.042	0.071	0.121
FELWd	0.978	0.984	0.988	0.004	0.007	0.009	0.826	0.871	0.914	0.054	0.083	0.118	0.255	0.369	0.487	0.054	0.083	0.118
2FELW	0.960	0.976	0.988	0.005	0.010	0.017	0.812	0.863	0.913	0.051	0.082	0.122	0.255	0.368	0.484	0.051	0.082	0.122
2FELWd	0.973	0.981	0.987	0.004	0.007	0.009	0.830	0.871	0.913	0.058	0.086	0.119	0.256	0.369	0.487	0.058	0.086	0.119

									SSA									
FELW	0.966	0.975	0.982	0.010	0.015	0.021	0.755	0.780	0.832	0.086	0.128	0.159	0.224	0.278	0.316	0.086	0.128	0.159
FELWd	0.965	0.971	0.979	0.008	0.013	0.016	0.768	0.789	0.828	0.118	0.144	0.165	0.225	0.278	0.316	0.118	0.144	0.165
2FELW	0.967	0.976	0.983	0.009	0.014	0.020	0.761	0.785	0.837	0.101	0.135	0.158	0.226	0.279	0.317	0.101	0.135	0.158
2FELWd	0.968	0.973	0.981	0.007	0.011	0.013	0.777	0.798	0.834	0.118	0.139	0.159	0.226	0.279	0.317	0.118	0.139	0.159
									WHE									
FELW	0.967	0.973	0.981	0.011	0.016	0.019	0.712	0.729	0.778	0.111	0.157	0.190	0.187	0.218	0.232	0.111	0.157	0.190
FELWd	0.948	0.961	0.979	0.007	0.016	0.024	0.730	0.747	0.770	0.162	0.179	0.203	0.187	0.219	0.234	0.162	0.179	0.203
2FELW	0.967	0.972	0.980	0.010	0.015	0.018	0.718	0.735	0.784	0.128	0.171	0.187	0.187	0.218	0.232	0.128	0.171	0.187
2FELWd	0.946	0.960	0.982	0.007	0.016	0.024	0.730	0.749	0.771	0.166	0.176	0.203	0.187	0.219	0.234	0.166	0.176	0.203
									DEV									
FELW	0.969	0.976	0.986	0.008	0.013	0.018	0.772	0.802	0.852	0.070	0.106	0.150	0.247	0.297	0.346	0.070	0.106	0.150
FELWd	0.971	0.975	0.980	0.008	0.010	0.013	0.788	0.811	0.845	0.103	0.127	0.146	0.248	0.296	0.347	0.103	0.127	0.146
2FELW	0.969	0.977	0.986	0.007	0.012	0.017	0.778	0.807	0.858	0.079	0.113	0.144	0.248	0.298	0.347	0.079	0.113	0.144
2FELWd	0.971	0.975	0.980	0.008	0.010	0.012	0.795	0.817	0.850	0.101	0.122	0.139	0.248	0.297	0.347	0.101	0.122	0.139

Notes: The table reports the minimum (Min), median (Med), and maximum (Max), rejection frequencies obtained over 30 different k values. Abs. divergence, absolute divergence; 2FELW, 2-stage feasible exact local Whittle estimator; 2FELWd, 2-stage feasible exact local Whittle estimator with detrending; ALL, all countries; MEA, Middle Eastern and Central Asian countries; EUR, European countries; AAP, Asian and Pacific countries; SSA, sub-Saharan countries; WHE, Western hemisphere countries; DEV, developing countries.

Test 1 $:H_0^0 : d = 0$ against $H_1^0 : d > 0$.
Test 2a $:H_0^{1/2a} : d = 0.5$ against $H_1^{1/2a} : d < 0.5$.
Test 2b $:H_0^{1/2b} : d = 0.5$ against $H_1^{1/2b} : d > 0.5$.
Test 3 $:H_0^1 : d = 1$ against $H_1^1 : d < 1$.
Test 4 $:H_0^1 : d = 1$ against $H_1^{1\,\exp l} : d > 1$.
Abs. divergence: Test 3 is not rejected (or Test 4 is rejected) together with Test 1 is rejected

hemisphere. The results are reported in the lower horizontal panels of Tables 2 and 3. The classification of countries falling into one of these regions is given in Table A.2 of the Appendix. Except for Europe and the Western hemisphere countries, where the results indicate a long memory process with possibly mean-reverting behavior and little or no evidence of divergence, the results for all the other regions are qualitatively similar to those obtained for the group of countries taken as a whole. They point to a long memory or a unit root process for the per capita output gap series and strong evidence for divergence.

We use the classification of Table 1 to examine the nature of the convergence that was established in Tables 2 and 3. We compute the rejection frequencies of the cases consistent with the stationary, mean-reverting, rapid convergence, and absolute divergence and indeterminacy hypotheses based on the estimate of the long memory parameter d over all 9,591 output gaps for GDP per capita. As before, we compute these fractions for the thirty different detrended series and report only minimum, median, and maximum values. The results strongly support rejection of all forms of convergence considered. We only report the case of absolute divergence in the last vertical panel of Tables 2 and 3, as this is the only one where the evidence is supportive of the null. The evidence here is consistent with the test results for d, as it points toward a non-mean-reverting diverging process for the per capita output gaps. Note that the distinction between absolute and conditional convergence is of importance only if one operates in a "convergence" regime, and it is not relevant if there is lack of convergence. Hence, because the test statistics that we obtain based on the estimated d-values suggest lack of convergence, the conditional/absolute distinction becomes irrelevant.

Overall, with the possible exception of European and Western hemisphere countries, the evidence in favor of divergence is quite striking. Given these results, there is no scope for further investigating the distinction between absolute and conditional convergence based on the estimated β values. The results that we find are partly in agreement with DMN, who also found strong evidence of long memory and absolute divergence. However, we find more support for divergence than they do. One of the main reasons for the differences between our results and theirs is that using pairwise comparisons for all possible pairs within a group, as opposed to relying on a benchmark, produces greater gap differences, which correspond to divergence. These differences are smoothed out if gaps are only constructed as differences of individual countries from the leader in the group. Interestingly enough, even though the evidence does not rule out the possibility of long memory behavior in the transitional dynamics of the output gaps, it is absolute divergence behavior that seems to be the dominant pattern.

3.3. Pairwise Results for Gaps in Per Capita Growth Rates

The main premise of the absolute convergence hypothesis is based on the "catching up" effect, where less developed poorer countries approach in equilibrium the (per capita) income levels of richer more developed ones by growing faster than them. In that case, a "large" initial output gap in GDP per capita levels between two countries can be reversed if only there is a "reverse" gap in growth rates between these two counties. In other words, divergence in the gaps of growth rates is consistent with convergence in the per capita output gaps in levels. Strong evidence having been found of absolute divergence in the output level gaps, it is interesting to see the pattern of convergence in the growth gaps and see how it differs from that in levels. Therefore, in this section we repeat the preceding analysis by looking at gaps in output growth instead of output levels. Table 4 summarizes the results of the tests applied to all 9,591 GDP per capita growth gap pairs over the period 1946–2006 ($T = 61$, $N = 139$) at the 5% significance level for $T = 100$ and Table 5 for $T = 200$.

For the whole group of countries, as can be seen from Tables 4 and 5, rejection frequencies of test 3 are all well above the significance level. Hence, the evidence points strongly toward a mean-reverting process for the output growth gaps. All of the rejection frequencies for test 2b are below the 0.05 level, providing evidence against stochastic divergence, nonstationary long memory but in favor of "limit" stationary long memory. The evidence of test 1 suggests that the process may not be difference stationary, although the rejection frequencies are not far from the 0.10 level. As a result, we may conclude that for the group of countries taken as a whole, output growth gaps for GDP per capita point toward d being in the range $0 \leq d < 0.5$. As a result, the evidence is somehow mixed and weak (if any) on long memory, but strong on limit stationarity with mean-reverting behavior. Compared to the GDP per capita case, where the evidence on long memory (with unit root) was quite clear, the evidence here points toward mean-reverting behavior rather than unit root. For the output levels we found strong evidence that $d > 0.5$, whereas for the growth rates $d < 0.5$.

We also examined the nature of convergence as we did in the case of the per capita output gaps. We found, in contrast to the GDP per capita case, that the only type that cannot be ruled out is rapid convergence. The results are reported in the last vertical panel of Tables 4 and 5. The rest of the convergence types (stationary and mean-reverting) are decisively rejected, and so is absolute divergence, unlike the GDP per capita levels.[14] Hence, the process that best characterized the output gap GDP per capita growth series is a short memory process with evidence for rapid convergence.

The analysis is repeated for the other regions, the Middle East and Central Asia, Europe, Asia and the Pacific, sub-Saharan Africa, and the Western hemisphere and the results are presented in the lower horizontal panels of Tables 4 and 5. The results are qualitatively similar to those obtained for the whole group of countries, with some exceptions. For the Middle East and sub-Saharan Africa the case for rapid convergence is weaker, whereas for Europe and the Western Hemisphere, the evidence for rapid convergence is strongest, as expected.

Overall, however, gaps in growth per capita rates point toward a rapid convergence pattern characterized by short memory. Interestingly, even though the framework of analysis that we have pursued provides a richer set of possibilities

TABLE 4. Fraction of rejections for GDP growth ($T = 100$, 5% significance level)

	Test1			Test2a			Test2b			Test3			R. convergence		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
ALL															
FELW	0.138	0.148	0.194	0.617	0.697	0.722	0.029	0.030	0.031	0.962	0.963	0.965	0.138	0.148	0.194
FELWd	0.143	0.155	0.175	0.564	0.603	0.632	0.030	0.033	0.034	0.954	0.960	0.961	0.143	0.155	0.175
2FELW	0.128	0.137	0.182	0.625	0.705	0.730	0.008	0.010	0.011	0.982	0.983	0.983	0.128	0.137	0.182
2FELWd	0.134	0.145	0.168	0.571	0.610	0.638	0.009	0.011	0.013	0.977	0.980	0.981	0.134	0.145	0.168
MEA															
FELW	0.165	0.180	0.191	0.628	0.652	0.683	0.000	0.000	0.000	0.971	0.985	0.989	0.167	0.181	0.192
FELWd	0.155	0.169	0.217	0.537	0.582	0.597	0.000	0.000	0.000	0.967	0.982	0.985	0.155	0.169	0.217
2FELW	0.167	0.182	0.191	0.627	0.651	0.682	0.000	0.000	0.000	0.989	0.994	0.996	0.167	0.182	0.191
2FELWd	0.157	0.171	0.217	0.537	0.580	0.594	0.000	0.000	0.000	0.989	0.992	0.995	0.157	0.171	0.217
EUR															
FELW	0.173	0.210	0.241	0.598	0.657	0.707	0.127	0.127	0.129	0.845	0.846	0.857	0.173	0.210	0.241
FELWd	0.183	0.198	0.203	0.515	0.570	0.576	0.127	0.134	0.135	0.835	0.839	0.853	0.183	0.198	0.203
2FELW	0.077	0.100	0.122	0.679	0.742	0.785	0.029	0.035	0.039	0.947	0.953	0.964	0.077	0.100	0.122
2FELWd	0.090	0.096	0.100	0.576	0.637	0.646	0.033	0.039	0.044	0.943	0.949	0.956	0.090	0.096	0.100
AAP															
FELW	0.108	0.162	0.275	0.503	0.647	0.737	0.011	0.013	0.014	0.959	0.960	0.967	0.108	0.162	0.275
FELWd	0.141	0.158	0.184	0.498	0.524	0.582	0.013	0.016	0.019	0.958	0.961	0.963	0.141	0.158	0.184
2FELW	0.102	0.154	0.264	0.505	0.648	0.737	0.004	0.006	0.007	0.970	0.972	0.978	0.102	0.154	0.264
2FELWd	0.137	0.155	0.178	0.497	0.522	0.580	0.004	0.008	0.011	0.971	0.973	0.978	0.137	0.155	0.178

							SSA								
FELW	0.115	0.125	0.165	0.649	0.724	0.749	0.003	0.004	0.004	0.981	0.984	0.992	0.115	0.125	0.165
FELWd	0.118	0.130	0.147	0.602	0.627	0.657	0.003	0.004	0.004	0.978	0.980	0.983	0.118	0.130	0.147
2FELW	0.121	0.131	0.168	0.647	0.721	0.744	0.003	0.004	0.004	0.993	0.993	0.993	0.121	0.131	0.168
2FELWd	0.126	0.136	0.157	0.602	0.626	0.654	0.003	0.004	0.004	0.988	0.991	0.991	0.126	0.136	0.157
							WHE								
FELW	0.137	0.148	0.158	0.741	0.772	0.781	0.021	0.024	0.026	0.952	0.955	0.960	0.133	0.147	0.158
FELWd	0.147	0.151	0.160	0.671	0.687	0.712	0.023	0.027	0.029	0.948	0.951	0.960	0.146	0.150	0.160
2FELW	0.113	0.119	0.126	0.767	0.799	0.804	0.006	0.009	0.010	0.975	0.977	0.980	0.113	0.118	0.125
2FELWd	0.118	0.122	0.138	0.690	0.708	0.733	0.008	0.009	0.010	0.973	0.976	0.978	0.119	0.122	0.138
							DEV								
FELW	0.123	0.132	0.180	0.630	0.708	0.733	0.003	0.004	0.004	0.978	0.978	0.979	0.123	0.132	0.180
FELWd	0.128	0.143	0.165	0.563	0.609	0.640	0.003	0.003	0.004	0.967	0.976	0.977	0.128	0.143	0.165
2FELW	0.125	0.136	0.180	0.629	0.706	0.731	0.004	0.005	0.006	0.984	0.985	0.986	0.125	0.136	0.180
2FELWd	0.132	0.146	0.169	0.561	0.607	0.637	0.004	0.005	0.006	0.979	0.983	0.984	0.132	0.146	0.169

Notes: The table reports the minimum (Min), median (Med), and maximum (Max), rejection frequencies obtained over 30 different k values. R. convergence, rapid convergence; 2FELW, 2-stage feasible exact local Whittle estimator; 2FELWd, 2-stage feasible exact local Whittle estimator with detrending; ALL, all countries; MEA, Middle Eastern and Central Asian countries; EUR, European countries; AAP, Asian and Pacific countries; SSA, sub-Saharan countries; WHE, Western hemisphere countries; DEV, developing countries.

Test 1 : $H_0^0 : d = 0$ against $H_1^0 : d > 0$.
Test 2a : $H_0^{1/2a} : d = 0.5$ against $H_1^{1/2a} : d < 0.5$.
Test 2b : $H_0^{1/2b} : d = 0.5$ against $H_1^{1/2b} : d > 0.5$.
Test 3 : $H_0^1 : d = 1$ against $H_1^1 : d < 1$.
Test 4 : $H_0^1 : d = 1$ against $H_1^{1\,\exp l} : d > 1$.
R. convergence : Test 3 rejected together with Test 1 is not rejected

TABLE 5. Fraction of rejections for GDP growth ($T = 200$, 5% significance level)

	Test1			Test2a			Test2b			Test3			R. convergence		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
							ALL								
FELW	0.162	0.173	0.229	0.647	0.722	0.744	0.032	0.034	0.036	0.966	0.966	0.967	0.162	0.173	0.229
FELWd	0.161	0.175	0.200	0.636	0.674	0.698	0.036	0.039	0.044	0.965	0.969	0.971	0.161	0.175	0.200
2FELW	0.152	0.164	0.217	0.656	0.731	0.753	0.011	0.013	0.018	0.984	0.985	0.986	0.152	0.164	0.217
2FELWd	0.152	0.165	0.192	0.643	0.682	0.706	0.015	0.017	0.020	0.983	0.985	0.986	0.152	0.165	0.192
							MEA								
FELW	0.193	0.208	0.226	0.658	0.683	0.708	0.000	0.000	0.000	0.978	0.988	0.992	0.193	0.208	0.226
FELWd	0.178	0.195	0.243	0.601	0.654	0.673	0.000	0.001	0.004	0.975	0.989	0.992	0.178	0.195	0.243
2FELW	0.194	0.209	0.227	0.658	0.683	0.708	0.000	0.000	0.000	0.989	0.995	0.997	0.194	0.209	0.227
2FELWd	0.179	0.196	0.243	0.601	0.654	0.672	0.001	0.002	0.004	0.989	0.994	0.996	0.179	0.196	0.243
							EUR								
FELW	0.183	0.224	0.261	0.626	0.679	0.735	0.127	0.130	0.132	0.846	0.848	0.857	0.183	0.224	0.261
FELWd	0.208	0.214	0.218	0.601	0.643	0.649	0.133	0.141	0.144	0.840	0.843	0.857	0.208	0.214	0.218
2FELW	0.088	0.116	0.147	0.713	0.772	0.822	0.031	0.038	0.042	0.948	0.953	0.964	0.088	0.116	0.147
2FELWd	0.108	0.113	0.118	0.670	0.722	0.729	0.037	0.043	0.049	0.944	0.949	0.957	0.108	0.113	0.118
							AAP								
FELW	0.140	0.193	0.316	0.536	0.675	0.761	0.014	0.016	0.018	0.962	0.964	0.967	0.140	0.193	0.316
FELWd	0.162	0.184	0.210	0.588	0.615	0.663	0.022	0.024	0.026	0.962	0.964	0.966	0.162	0.184	0.210
2FELW	0.135	0.187	0.307	0.540	0.677	0.763	0.006	0.008	0.009	0.973	0.975	0.978	0.135	0.187	0.307
2FELWd	0.156	0.181	0.203	0.588	0.611	0.662	0.013	0.015	0.017	0.973	0.976	0.978	0.156	0.181	0.203

							SSA								
FELW	0.136	0.147	0.198	0.674	0.744	0.767	0.003	0.004	0.004	0.984	0.987	0.993	0.136	0.147	0.198
FELWd	0.135	0.149	0.168	0.668	0.693	0.717	0.004	0.004	0.005	0.992	0.992	0.993	0.135	0.149	0.168
2FELW	0.143	0.155	0.201	0.671	0.740	0.762	0.004	0.004	0.004	0.993	0.994	0.994	0.143	0.155	0.201
2FELWd	0.144	0.156	0.178	0.667	0.691	0.714	0.004	0.004	0.005	0.993	0.993	0.994	0.144	0.156	0.178
							WHE								
FELW	0.150	0.162	0.174	0.759	0.786	0.797	0.024	0.027	0.029	0.955	0.956	0.960	0.150	0.162	0.174
FELWd	0.159	0.164	0.179	0.720	0.742	0.761	0.030	0.033	0.034	0.955	0.957	0.961	0.158	0.164	0.179
2FELW	0.127	0.131	0.141	0.789	0.815	0.821	0.008	0.011	0.013	0.978	0.980	0.981	0.130	0.132	0.142
2FELWd	0.130	0.135	0.157	0.738	0.767	0.784	0.010	0.013	0.014	0.979	0.980	0.982	0.131	0.135	0.157
							DEV								
FELW	0.147	0.161	0.214	0.660	0.734	0.756	0.004	0.005	0.005	0.980	0.982	0.982	0.148	0.161	0.215
FELWd	0.146	0.164	0.190	0.634	0.679	0.707	0.005	0.006	0.006	0.978	0.985	0.986	0.147	0.164	0.191
2FELW	0.149	0.164	0.214	0.659	0.732	0.754	0.004	0.005	0.006	0.986	0.988	0.988	0.150	0.165	0.215
2FELWd	0.150	0.166	0.195	0.632	0.677	0.704	0.005	0.006	0.007	0.985	0.988	0.988	0.151	0.167	0.195

Notes: The table reports the minimum (Min), median (Med), and maximum (Max), rejection frequencies obtained over 30 different k values. R. convergence, rapid convergence; 2FELW, 2-stage feasible exact local Whittle estimator; 2FELWd, 2-stage feasible exact local Whittle estimator with detrending; ALL, all countries; MEA, Middle Eastern and Central Asian countries; EUR, European countries; AAP, Asian and Pacific countries; SSA, sub-Saharan countries; WHE, Western hemisphere countries; DEV, developing countries.

Test 1 $:H_0^0 : d = 0$ against $H_1^0 : d > 0$.
Test 2a $:H_0^{1/2a} : d = 0.5$ against $H_1^{1/2a} : d < 0.5$.
Test 2b $:H_0^{1/2b} : d = 0.5$ against $H_1^{1/2b} : d > 0.5$.
Test 3 $:H_0^1 : d = 1$ against $H_1^1 : d < 1$.
Test 4 $:H_0^1 : d = 1$ against $H_1^{1\exp l} : d > 1$.
R. convergence: Test 3 rejected together with Test 1 is not rejected

than the rapid convergence and absolute divergence dichotomy, it is the latter two possibilities that have emerged as the dominant hypotheses from the results that we have obtained. In other words, it seems that the $I(0)/I(1)$ dichotomy is what drives the results here, and other values of d, even though they cannot be ruled out because of low power considerations, do not seem to be important. $I(1)$ has emerged as the dominant characterization of output gaps in per capita GDP levels and $I(0)$ for the gaps in per capita growth rates. The results produce a picture where the diverging GDP levels are not reversed by higher and reverse growth rates. In fact, it seems that growth rates do not make up for the differences in initial GDP levels, and if anything the latter keep diverging between countries. The main premise of the convergence hypothesis, that countries with lower initial endowments will grow faster to catch up with richer economies, is not borne out by the evidence here.

3.4. Developing World

To make our work more comparable to DMN, which considers only the developing world, we now repeat the preceding analysis by excluding developed countries from our sample. By doing so, we recalculate rejection frequencies for 118 developing countries for levels and growth rates.[15] The results are presented in the last horizontal panels of Tables 2–5.

The results are very clear in giving strong support to the dichotomy between absolute divergence and rapid convergence. Overall, the convergence patterns in the developing world are best characterized by absolute divergence in output gaps and (weak) rapid convergence in growth rates.

3.5. Pesaran's Measures of Pairwise Convergence

In the preceding cases (levels and growth rates), we also look at Pesaran's (2007) measures of pairwise convergence; see also Mello (2010), who applied these measures to check for stochastic convergence of income among U.S. states:

$$D_t^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (y_{it} - y_{jt})^2 \tag{6}$$

and

$$MD_t = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |y_{it} - y_{jt}|. \tag{7}$$

The first measure captures the notion of σ-convergence and the second one is related to the Gini coefficient.[16] Both of these measures use all pairs of incomes, and plotting them allows a quick view of the presence of convergence patterns consistent with σ-convergence. Figures 1 and 2 present the graphs of D^2 and MD for the per capita GDP and per capita GDP growth differences, respectively. It is

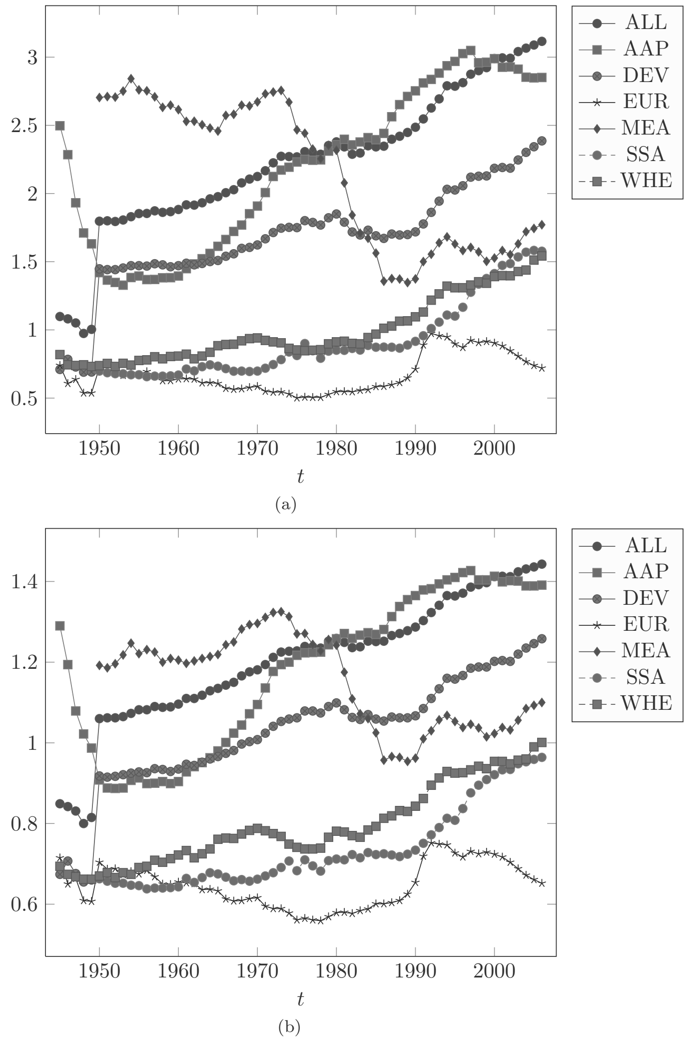
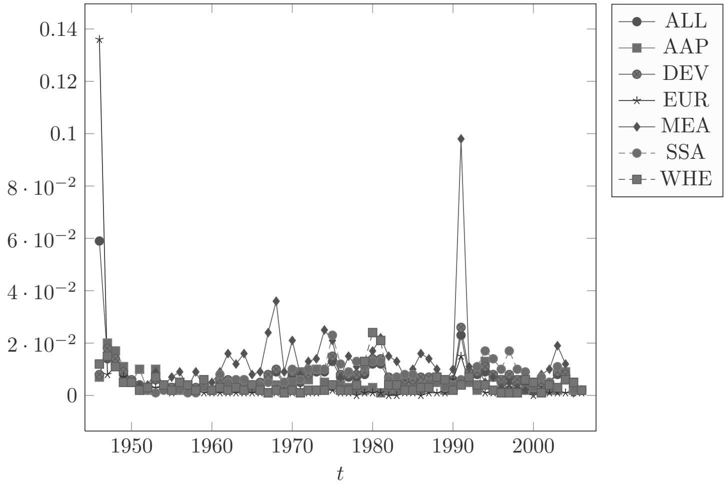
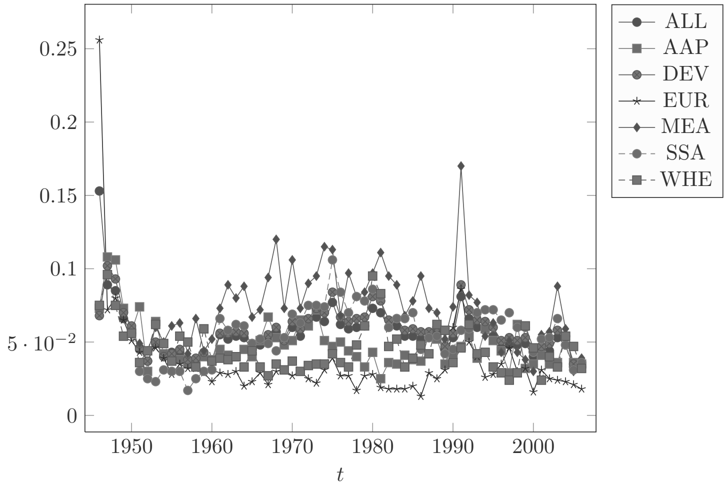


FIGURE 1. Pesaran statistics: (a) $D_t^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (y_{it} - y_{jt})^2$ and (b) $MD_t = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |y_{it} - y_{jt}|$ for GDP per capita of different country groups. ALL, all countries; AAP, Asian and Pacific countries; DEV, developing countries; EUR, European countries; MEA, Middle Eastern and Central Asian countries; SSA, sub-Saharan African countries; WHE, Western hemisphere countries.

clear from the graphs that for all GDP per capita series, except for the group of European countries, there is strong evidence of divergence, whereas there is strong evidence of convergence for the per capita GDP growth series. These findings are consistent with the results of absolute divergence that we have found for the per capita series and those of rapid convergence for the growth series.



(a)



(b)

FIGURE 2. Pesaran statistics: (a) $D_t^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (y_{it} - y_{jt})^2$ and (b) $MD_t = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |y_{it} - y_{jt}|$ for GDP growth rate of different country groups. ALL, all countries; AAP, Asian and Pacific countries; DEV, developing countries; EUR, European countries; MEA, Middle Eastern and Central Asian countries; SSA, sub-Saharan African countries; WHE, Western hemisphere countries.

4. DETERMINANTS OF PERSISTENCE

The preceding analysis strongly points to the presence of high persistence and divergence in the output level gap pairs. However in growth rates the process seems to follow a mean-reverting and rapidly converging path. In this section, we analyze the determinants of these different paths of output gaps in levels and

TABLE 6. Regression results

	Level (divergence)		Growth (convergence)	
	1970–2001	1960–2001	1970–2001	1960–2001
INV	0.029 (0.000)	0.058 (0.000)	0.006 (0.000)	0.020 (0.000)
BUD	0.094 (0.000)	0.119 (0.000)	0.032 (0.000)	0.040 (0.000)
INF	0.004 (0.000)	NS	−0.001 (0.002)	NS
INY	NS	0.088 (0.029)	−0.036 (0.006)	NS
POP	0.202 (0.000)	0.165 (0.000)	0.045 (0.000)	NS
HC	0.069 (0.000)	0.053 (0.000)	0.018 (0.000)	NS
σ	0.494	0.476	0.314	0.311

Note: P-values calculated from HACSE standard errors are in parentheses; σ refers to regression standard error; NS stands for "not significant."

growth rates by running the regression

$$\hat{d}_{ij} = \gamma_1 \mathrm{BUD}_{ij} + \gamma_2 \mathrm{INV}_{ij} + \gamma_3 \mathrm{INF}_{ij} + \gamma_4 \mathrm{INY}_{ij} + \gamma_5 \mathrm{POP}_{ij} + \gamma_6 \mathrm{HC}_{ij} + u_{ij}, \quad i = 1, \ldots, N; \quad i \neq j. \tag{8}$$

The $\hat{d}_{ij}$'s refer to the estimated d's for the ij pairs obtained in the previous analysis. BUD_{ij} is the absolute difference between the budget deficits as a percentage of GDP for the ij country pairs. Similarly, INV_{ij}, INF_{ij}, INY_{ij}, POP_{ij}, and HC_{ij} refer to the (absolute) differences between the investment and inflation rates, initial GDP per capita , population growth, and human capital stocks, respectively. Finally, u_{ij} represents the error term, which could be cross-sectionally correlated and possibly heteroskedastic.[17]

The data set for the explanatory variables is, unfortunately, available only for a subset of countries without interruption for a given period. We use two different sets belonging to two different time periods. In the larger data set, we have the time averages of those variables for 62 countries over the period 1970–2001; hence we have 1,891 country pairs and thus 1,891 observations to run the preceding regression. In the smaller data, which covers the period 1960–2001, there are 33 countries; hence we have only 528 pairs. The list of these countries can be found in Table A.3 in the Appendix. Because a measure of the speed of convergence/divergence is given by the estimated d's, this regression aims to assess the role of the factors determining this speed. A higher value of d represents a less convergent (and possibly divergent) output gap. Hence, we expect that the larger the difference between these factors for the ij country pair, the larger the value of the $\hat{d}_{ij}$ for that pair. Thus we expect the signs of the γ's to be positive.

We run this regression for the two sets of d's, estimated from both level and growth rate data. Table 6 summarizes the results of OLS estimation for this regression.[18]

The results point to the importance of all main factors in determining the speed of convergence (divergence) of these output gaps. As expected, investment and human capital stocks play an important role in explaining whether two countries are likely have similar paths in their per capita GDP levels (and growth rates), and so does the fiscal discipline variable expressed by the budget deficit to GDP ratio. Two countries that have similar characteristics and pursue similar economic policies are likely to have converging paths, as opposed to two countries with dissimilar characteristics that may pursue different policies.

5. CONCLUSIONS

In this paper, we use a long memory framework of analysis that does not rely on a benchmark country, but allows for the presence of structural breaks to estimate the time series properties of output gaps for countries in the post-World War II period and as such provide evidence on the convergence hypothesis. The focus in the paper is first the estimation of d, which is the parameter that determines the speed of convergence between different economies, and second, the examination of the effect on this parameter of certain important characteristics that are embedded in the majority of growth models, such as human capital and macroeconomic stability. The main finding of our paper is that for per capita GDP gaps, the parameter d takes values greater than 0.5, whereas for the per capita growth rates d lies in the range $0 \leq d < 0.5$. Lack of power does not enable us to obtain more precise estimates of d, and even though the long memory framework of analysis that we adopt is much richer than the simple $I(1)/I(0)$ alternative, which produces a simple dichotomy of absolute divergence and rapid convergence, the latter seems to be sufficient to capture the behavior of the gaps in per capita GDP levels and growth rates. Although the gaps in per capita GDP levels produce a pattern of divergence, the pattern in growth rate gaps can be best characterized as rapid convergence. Any evidence of mean reversion and long memory that we find is not strong enough. The speed of convergence (divergence) captured by the estimated parameter d, is explained by differences in physical and human capital differences, as well as in the fiscal discipline characteristics of economic policies pursued by different countries. The more dissimilar countries are in terms of these factors, the more likely they are to have divergent paths. It will be interesting to consider in future research a systematic and comprehensive investigation of the reasons behind this divergence. In that context, we would like to examine in more detail the effects of such determinants as barriers to technological diffusion, as in Coe et al. (2009), as well as the effect of new technologies (information technologies) on productivity and income convergence/divergence, as in Ketteni et al. (2010).

NOTES

1. Christopoulos and Leon-Ledesma (2011) present evidence on output convergence for 14 countries relative to the U.S. even controlling for structural breaks that are modeled through a Fourier

function similar to ours. However, their approach is different from ours in both scope and analysis, as we do not rely on a benchmark country such as the United States and we include a much larger set of countries, both developed and developing.

2. This is the case where any initial output differences will disappear over time, because the values of the parameters of the trend function are such that they push these initial differences to zero. This corresponds to the case of "catching up convergence" as defined by Bernard and Durlauf (1996).

3. The reason for that will become apparent from the results that we present later, which overwhelmingly point toward lack of convergence in output levels. In that case, the distinction between conditional and unconditional types of convergence becomes superfluous.

4. Although these estimators are consistent for $d \in (\frac{1}{2}, 1)$ and asymptotically normally distributed for $d \in (1/2, 3/4)$, they are also known to exhibit nonstandard behavior when $d > 3/4$. For instance, they have a nonnormal limit distribution for $d \in (3/4, 1)$, and they converge to unity in probability and are inconsistent for $d > 1$ [see Shimotsu and Phillips (2005, 2006)].

5. Hence, FEWL estimators cannot be used under the null hypothesis of test 3 following. Nevertheless, we still used them for this case for completeness, and they yielded similar results.

6. It becomes clear from the table that the quantiles of the reported distributions converge to those of the standard normal as T increases, but slowly, and show significant differences across estimators. The graphics and some summary statistics of these distributions are available upon request.

7. The list of the countries in different groups can be found in Table A.2 of the Appendix.

8. Some countries have some missing observations at the beginning of the period. The latest starting date in our sample is 1950. The data source is www.ggdc.net/maddison/.

9. This classification is based on the usual classification made by the International Monetary Fund's regional economic outlook documents.

10. Although the underlying individual tests are not cross sectionally independent, under the null, the fraction of rejections is expected to converge to α, as N and $T \to \infty$, where α is the size of the underlying test.

11. Ashley and Patterson (2010) suggest isolating out and separately examining both a local mean (i.e., a nonlinear trend or the realization of a stochastic trend) and deviations from it as a modeling strategy that would complement estimation of a fractionally integrated model.

12. To conserve space, we only report the results of the FELW, FELWd, 2FELW, and the 2FELWd estimators, as the other two estimators give very similar results. We also do not report the results for the 10% significance level, for the same reason. These results are available upon request. As mentioned earlier, FELWd and 2FELWd apply (linear) prior detrending to the data. Therefore we also control for linear trends that may be present in the data via these estimators.

13. The results for the GDP output gap series are similar to those for the GDP per capita gap series and are not reported. They are available upon request.

14. The results are not reported but are available on request.

15. These countries are obtained by excluding the following 21 countries from 139 countries listed in Table A.3 of the Appendix: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Note also that DMN include 98 of these 118 developing countries in their data set.

16. MD refers to the average absolute value of two numbers selected randomly from a population. MD divided by the arithmetic mean to normalize for scale becomes the relative mean difference (RMD), which is twice the Gini coefficient.

17. The data sources are the following: Barro and Lee (2001); Nehru and Dhareshwar (1993); Nehru et al. (1995); WDI World Development Indicators on CD-ROM, The World Bank (2009); WDI World Development Indicators on CD-ROM, The World Bank (2010).

18. The reported results were obtained by using the FELW estimator of d. However, we obtained qualitatively similar results with three other estimators (FELWd, 2FELW, 2FELWd) of d.

REFERENCES

Abadir, K., W. Distaso, and L. Giraitis (2007) Nonstationarity-extended local Whittle estimation. *Journal of Econometrics* 141, 1353–1384.

Abadir, K. and G. Talmain (2002) Aggregation, persistence and volatility in a macro model. *Review of Economic Studies* 69, 749–779.

Ashley, R.A. and D.M. Patterson (2010) Apparent long memory in time series as an artifact of a time-varying mean: Considering alternatives to the fractionally integrated model. *Macroeconomic Dynamics* 14(Supplement 1), 59–87.

Barro, R.J. and J-W. Lee (2001) International Data on Educational Attainment: Updates and Implications. CID working paper 42.

Becker, R., W. Enders, and S. Hurn (2004) A general test for time dependence in parameters. *Journal of Applied Econometrics* 19, 899–906.

Becker, R., W. Enders, and J. Lee (2006) A stationary test in the presence of an unknown number of smooth breaks. *Journal of Time Series Analysis* 27, 381–409.

Bernard, A.B. and S.N. Durlauf (1995) Convergence in international output. *Journal of Applied Econometrics* 10, 97–108.

Bernard A.B. and S.N. Durlauf (1996) Interpreting tests of the convergence hypothesis. *Journal of Econometrics* 71, 161–173.

Cheung, Y-W. and A.I.G. Pascual (2004) Testing for output convergence: A re-examination. *Oxford Economic Papers* 54, 45–63.

Christopoulos, D.K. and M.A. Leon-Ledesma (2011) International output convergence, breaks, and asymmetric adjustment. *Studies in Nonlinear Dynamics and Econometrics* 15, 1–30.

Coe, D.T., E. Helpman, and A.W. Hoffmaister (2009) International R&D spillovers and institutions, *European Economic Review* 53, 723–741.

Datta, A. (2003) Time series tests of convergence and transitional dynamics. *Economics Letters* 81, 233–240.

Dufrénot, G., V. Mignon, and T. Naccache (2009) The Slow Convergence of Per Capita Income between the Developing Countries: Growth Resistance and Sometimes Growth Tragedy. University of Nottingham Discussion Papers.

Durlauf, S.N., P.A. Johnson, and J.R.W. Temple (2005) Growth econometrics. In P. Aghion and S.N. Durlauf (eds.), *Handbook of Economic Growth*, pp. 555–678. Amsterdam: North Holland.

Haubrich, J.G. and A.W. Lo (2001) The sources and nature of long-term memory in aggregate output. *Federal Reserve Bank of Cleveland Economic Review* 2, 15–30.

Li, Q. and D.H. Papell (1999) Convergence of international output: Time series evidence for 16 OECD countries. *International Review of Economics and Finance* 8, 267–280.

Ludlow, J. and W. Enders (2000) Estimating non-linear ARMA models using Fourier coefficients. *International Journal of Forecasting* 16, 333–347.

Ketteni, E., T. Mamuneas and T. Stengos (2011) The effect of information technology and human capital on economicl growth. *Macroeconomic Dynamics* 5, 595–615.

Kuensch, H.R. (1987) Statistical aspects of self-similar processes. In Y. Prokhorov and V.V. Sazanov (eds.), *Proceedings of the First World Congress of the Bernoulli Society*, pp. 67–74. Utrecht, Netherlands: VNU Science Press.

Maddison, A. (2008) Statistics on world population, GDP and per capita GDP, 1–2006 AD. Available at http://www.ggdc.net/Maddison/Historical_Statistics/horizontal-file_02-2010.xls.

Mello, M. (2010) Stochastic convergence across U.S. states. *Macroeconomic Dynamics* 15, 160–183.

Michelacci, C. and P. Zaffaroni (2000) (Fractional) beta convergence. *Journal of Monetary Economics* 45, 129–153.

Nehru, V. and A. Dhareshwar (1993) A new database on physical capital stock: Sources, methodology and results. *Rivista de Analisis Economico* 8, 37–59.

Nehru, V., E. Swanson, and A. Dubey (1995) A new database on human capital stock in developing and industrial countries: Sources, methodology and results. *Journal of Development Economics* 46, 379–401.

Pesaran, M.H. (2007) A pair-wise approach for testing output and growth convergence. *Journal of Econometrics* 138, 312–355.

Phillips, P.C.B. and D. Sul (2007a) Some empirics on economic growth under heterogeneous technology. *Journal of Macroeconomics* 29, 455–469.

Phillips, P.C.B. and D. Sul (2007b) Transition modeling and econometric convergence tests. *Econometrica* 75, 1771–1855.

Robinson, P.M. (1995) Gaussian semiparametric estimation of long range dependence. *Annals of Statistics* 23, 1630–1661.

Shimotsu, K. (2008) Exact local Whittle estimation of fractional integration with unknown mean and time trend. *Econometric Theory* 26, 501–540.

Shimotsu, K. and P.C.B. Phillips (2005) Exact local Whittle estimation of fractional integration. *Annals of Statistics* 33, 1890–1933.

Shimotsu, K. and P.C.B. Phillips (2006) Local Whittle estimation of fractional integration and some of its variants. *Journal of Econometrics* 130, 209–233.

Velasco, C. (1999) Gaussian semiparametric estimation of non-stationary time series, *Journal of Time Series Analysis* 20, 87-127.

WDI (2009) World Development Indicators on CD-ROM. The World Bank.

WDI (2010) World Development Indicators on CD-ROM. The World Bank.

APPENDIX

TABLE A.1. Critical values of Tests 1–4, for $T = 100, 200$, and 500

	Test 1			Test 2a			Test 2b			Test 3			Test 4		
	(a) At 5% level of significance														
CV	95%			05%			95%			05%			95%		
T	100	200	500	100	200	500	100	200	500	100	200	500	100	200	500
EW	2.007	1.857	1.732	−2.491	−2.255	−2.020	2.013	1.910	1.839	−2.417	−2.199	−1.959	1.616	1.525	1.502
ELW	2.198	1.989	1.809	−2.365	−2.155	−2.000	2.180	1.976	1.798	−2.365	−2.155	−2.000	2.180	1.976	1.798
FELW	2.207	1.990	1.812	−2.216	−2.076	−1.930	2.254	2.071	2.084	−2.253	−2.153	−2.000	2.180	1.974	1.798
FELWd	1.945	1.765	1.624	−3.079	−2.668	−2.355	2.149	1.939	1.938	−2.647	−2.235	−2.042	2.175	1.975	1.795
2FELW	2.206	1.990	1.812	−2.216	−2.076	−1.930	2.253	2.018	1.795	−2.312	−2.153	−2.000	2.180	1.974	1.798
2FELWd	1.944	1.765	1.624	−3.079	−2.668	−2.354	2.153	1.878	1.670	−2.534	−2.235	−2.042	2.175	1.975	1.795
	(b) At 10% level of significance														
CV	90%			10%			90%			10%			90%		
T	100	200	500	100	200	500	100	200	500	100	200	500	100	200	500
EW	1.548	1.428	1.344	−1.930	1.554	−1.722	1.480	−1.551	1.447	−1.883	−1.702	−1.517	1.192	1.129	1.130
ELW	1.743	1.558	1.416	−1.778	1.728	−1.629	1.546	−1.538	1.413	−1.778	−1.629	−1.538	1.728	1.546	1.413
FELW	1.749	1.563	1.418	−1.656	1.799	−1.543	1.755	−1.469	1.723	−1.765	−1.632	−1.538	1.725	1.546	1.413
FELWd	1.437	1.305	1.200	−2.413	1.616	−2.103	1.570	−1.854	1.557	−1.880	−1.705	−1.579	1.721	1.545	1.412
2FELW	1.748	1.563	1.418	−1.658	1.768	−1.543	1.567	−1.469	1.432	−1.763	−1.632	−1.538	1.725	1.546	1.413
2FELWd	1.435	1.305	1.200	−2.413	1.590	−2.103	1.391	−1.854	1.266	−1.881	−1.705	−1.579	1.721	1.545	1.412

Notes: EW, exact Whittle; ELW, exact local Whittle; FELW, feasible exact local Whittle; 2FELW, 2-stage feasible exact local Whittle estimator; 2FELWd, 2-stage feasible exact local Whittle estimator with detrending. Simulations are carried out by assuming $\upsilon = T^{0.6}$.

TABLE A.2. Country groups definitions

Middle East and Central Asia	Algeria, Bahrain, Iran, Iraq, Kuwait, Libya, Oman, Qatar, Saudi Arabia, Sudan, United Arab Emirates, Yemen, Afghanistan, Djibouti, Egypt, Jordan, Lebanon, Mauritania, Morocco, Pakistan, Syria, Tunisia, West Bank and Gaza, Somalia
Europe	Albania, Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Israel, Netherlands, Norway, Portugal, Poland, Romania, Spain, Sweden, Switzerland, Turkey, United Kingdom, Yugoslavia
Asia and Pacific	Australia, Bangladesh, Burma, Cambodia, China, Hong Kong, New Zealand, India, Indonesia, Japan, Laos, Malaysia, Mongolia, Nepal, North Korea, Philippines, Singapore, South Korea, Sri Lanka, Taiwan, Thailand, Vietnam
Sub-Saharan Africa	Angola, Benin, Botswana, Burkina Faso, Burundi, Côte d'Ivoire, Cameroon, Cape Verde, Central African Republic, Chad, Comoro Islands, Democratic Republic of Congo (formerly Zaire), Equatorial Guinea, Eritrea and Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, São Tomé and Principe, Republic of Congo, Senegal, Seychelles, Sierra Leone, South Africa, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe
Western hemisphere	Argentina, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Trinidad and Tobago, United States, Uruguay, Venezuela

TABLE A.3. List of countries used in determinants of convergence

1960–2001	Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Canada, Chile, China, Congo, Costa Rica, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, France, Ghana, Greece, Guatemala, Honduras, Hungary, India, Iran, Ireland, Israel, Italy, Japan, Kenya, Lesotho, Malaysia, Mali, Mexico, Netherlands, New Zealand, Norway, Pakistan, Paraguay, Peru, Philippines, Portugal, Rwanda, Senegal, Singapore, South Africa, South Korea, Spain, Sri Lanka, Swaziland, Sweden, Switzerland, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, United States, Uruguay, Uruguay, Venezuela, Zambia, Zimbabwe
1970–2001	Canada, Chile, Congo, Costa Rica, Dominican Republic, Egypt, El Salvador, Finland, Greece, Guatemala, Honduras, Hungary, India, Israel, Italy, Japan, Malaysia, Mexico, Pakistan, Paraguay, Peru, Philippines, South Africa, South Korea, Sweden, Switzerland, Thailand, Trinidad and Tobago, United Kingdom, United States, Uruguay, Venezuela, Zimbabwe

Note: Maddison data includes Yugoslavia in its original early form and as the sum of the data obtained from its successor states after its dissolution.