Persistence in Convergence

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Abstract

In this paper, we examine the convergence hypothesis using a long memory framework that allows for structural breaks and the non reliance 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 (2009) who found strong evidence of long memory for output gaps. The speed of convergence 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.

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1 Introduction

One of the main predictions of neoclassical growth theory put forward by Solow is that in the long run, all countries could only converge to a single balanced growth path (steady state) equilibrium that will be entirely determined by the exogenously given growth rate of technical progress which will equal labour productivity growth, 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 labour productivity growth generated by profit seeking activities endogenously in the economy. These models offered explanations of why certain counties 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 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 favour of convergence has been more present in cross sectional studies, where convergence simply embodies the catching up growth effect where less developed poorer countries approach in equilibrium the (per capita) income levels of richer more developed ones, see Durlauf, Johnson and Temple (2006) 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 concepts 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 is stationary with a constant mean, irrespective of whether the individual country's output is trend stationary and/or contains unit roots. Furthermore, testing for convergence in that case does not rely on using a benchmark country in order to define the output gaps that are used in the analysis and uses a pair-wise approach to test convergence. Pesaran (2007) rejects the convergence in output levels and suggests that the evidence in favour 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 a $I(0)$ or $I(1)$ framework, yet it may be that a long memory framework is more appropriate for such an analysis. If per capita output actually follows a fractionally integrated process due to 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. Michellacci and Zaffaroni (2000) introduce fractional integration within a Solow growth model allowing for 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, Mignon and Naccache (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 for 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 they allow it to be also 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 where countries do not share common factors and those with initial low income will stay behind others with negative growth rates for ever. However, the analysis carried out by DMN is subject to two main caveats. The first is that it is based on using a benchmark to construct measure 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 of 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 where the presence of structural breaks may contaminate the dynamics and the classification between different convergence cases depending on the estimates of the long memory parameter d. 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) pair-wise analysis becomes relevant and useful to in this context adapt.

In this paper, we extend DMN in these two important directions. We examine the effects of structural breaks and the non reliance on a benchmark country on a long memory empirical analysis of 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, macroeconomic stability etc. 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 that 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 results. The former produce a pattern of divergence whereas the latter on 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 of the differences lies in the fact that we do not rely on a benchmark and we allow for the presence of structural breaks in our treatment of the data, something that introduces higher a degree of persistence in the output gap series. The speed of convergence (divergence) captured by the estimated parameter d, is explained by differences in physical and human capital as well as 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 growth rates and we also presents some additional results from a subsample of the data that refer only to developing countries. 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 pair-wise difference between the log of per capita income of country i and j at time t as

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

The process Z_t is described as $(1-L)^d Z_t = B(L)\varepsilon_t$, where $\varepsilon_t \sim i.i.d.(0, \sigma_\varepsilon^2)$, L is the lag operator and $B(L)$ is a polynomial in L. The fractional integration parameter is given by d under the assumption that the process is invertible ($d > -0.5$). The $\beta(t)$ function 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 in our case we will assume a functional form that allows for the presence of (smooth) structural breaks $\beta(t)$ is given by

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

for different values of k and T. We follow DMN in distinguishing between the different convergence cases that are given from the processes above. Different values of d, β_0, β_1 and β_2 will define different types of convergence and we enumerate these different convergence cases below. We will only concentrate on the parameter d and we will not pay attention to the $\beta' s$, 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 process, 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 towards a common long-run trend.

Case 3: $0.5 < d < 1$. This is the case of a long memory process, which is non-stationary 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 an explosive process. This is the situation where there is a strong magnification effect and any initial difference is not expected to be reversed in the future. This is the case of "stochastic divergence" and can be compared to the first case of deterministic divergence.

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

Conditional Convergence CC: *Deterministic Convergence or Conditional Convergence* ($\beta_0 \neq 0,\ \beta_1 = 0,\ \beta_2 = 0$). Again 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 a strict or rapid conditional convergence and has been looked at by Li and Pappell (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 smaller influence but convergence will take place.

Case CC.3: $0.5 < d < 1$. This is the case of a long memory process, which is non-stationary but still mean reverting. In that case output differences in the distant past will have a long-lasting influence in the present, but yet 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. Depending on the value of d we will have:

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

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

Case CCU.3: $0.5 < d < 1$. This is the case of non-stationary long memory catching up.

Absolute Convergence AC: *Absolute or Stochastic Convergence* ($\beta_0 = 0$, $\beta_1 = 0$, $\beta_2 = 0$). In that 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 a long memory stochastic stationary convergence.

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

Finally, if $\beta_0 \neq 0$, $\beta_1 \neq 0$ and $\beta_2 \neq 0$ and $d = 0$, but 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** when $d = 0$.

The above definitions of the different convergence cases allow for a much richer classification of convergence types, whereby one can distinguish between stationary convergence and mean reverting non-stationary convergence and this applies within the conditional as well as the absolute framework. An additional feature of this classification scheme is that it allows for initial differences either to linger on and have a long lasting influence in the present or decay rapidly and play no role or be somewhere in-between these two cases. This is something that can not 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.[1]

2.1 Testing for convergence.

We proceed as in DMN where the long memory parameter d is estimated by some estimators that immune to the nonstationarity. Let $I_Z(\omega_j)$ denote the periodogram of a series Z_t based

[1] The reason for that will be come apparent from the results that we wil obtain that overwhelmingly points towards lack of convergence in output levels. In that case, the distinction between conditional and unconditional types of convergence becomes superfluous.

on a discrete Fourier transform $W_Z(\omega_j)$ at frequency $\omega_j = \frac{2\pi j}{T}$ for $j = 0, ...T-1$, 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

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

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

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

In our estimation of d, we use different estimators than DMN which are closely related to the well known Exact Local Whittle (ELW) estimator of Simotsu and Phillips (2006,2006). This estimator is consistent and has the same $N\left(0, \frac{1}{4}\right)$ 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 Kunsch (1987) and Robinson (1995), which is based on an approximation of Whittle likelihood function and is not a good general-purpose estimator when the value of d may take on values in the nonstationary zone beyond $\frac{3}{4}$[2].

However, the ELW estimator has also been shown to have some undesirable properties. As shown by Simotsu (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 $d \in \left(0, \frac{1}{2}\right)$ requires 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. Simotsu (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 $N\left(0, \frac{1}{4}\right)$ limit distribution for $d \in \left(-\frac{1}{2}, 2\right)$ and is consistent when $d > \frac{1}{2}$. Moreover, the finite sample performance of the 2FELW estimator inherits the desirable properties of the ELW estimator. This estimator can be also computed with prior detrending (2FELWd) of the data,

[2] Although these estimators are consistent for $d \in \left(\frac{1}{2}, 1\right)$ asymptotically normally distributed for $d \in \left(\frac{1}{2}, \frac{3}{4}\right)$, they are also known to exhibit nonstandard behavior when $d > \frac{3}{4}$. For instance, they have a nonnormal limit distribution for $d \in \left(\frac{3}{4}, 1\right)$, and they converge to unity in probability and are inconsistent for $d > 1$ (see Simotsu and Phillips 2005,2006). This is also true for Geweke and Porter-Hudak (1983), GPH estimator (see Kim and Phillips 2006, Phillips 2007)

see Simotsu (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 a $N\left(0, \frac{1}{4}\right)$ distribution for $d \in \left(-\frac{3}{2}, \infty\right)$. 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 the each others 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 $d = \frac{1}{2}, \frac{3}{2}, ...$, which results in "holes" in the confidence intervals at these points, whereas the two-step approach does not (see Simotsu, 2008, for a comprehensive comparison and disicussion of the two estimators)[3].

The FELW, FELWd, 2FELW, 2FELWd estimators are used to estimate d and υ is chosen as $\upsilon = T^{0.6}$ as suggested by Simotsu (2008). For completeness purposes, as in DMN, we also looked at six other estimators including the classical Local Whittle (LW) and ELW estimators together with 4 versions of Geweke and Porter-Hudak (1983), GPH estimators. The GPH estimators that we used include both classical and modified versions, due to Smith (2005), for two different choice of bandwidth parameters. In general, GPH estimators are less efficient than Whittle estimators (see Simotsu and Phillips, 2005) and they all are subject to the criticisms outlined above. We have obtained critical values using similar Monte Carlo methods as for the reported estimators, but to conserve space we do not report them here. The results we obtained are qualitatively similar to the ones reported[4].

Then as in DMN we perform the following tests:

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

Test 2: $H_0^0 : d = 0$ against $H_1^0 : d > 0$ (short memory against long memory)

Test 3: $H_0^{1/2} : d = 0.5$ against $H_1^{1/2} : d \neq 0.5$ ("limit" stationary long memory against any alternative)

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

2.1.1 Monte Carlo based critical values.

[3] Hence, FEWL estimators cannot be used under the null hypothesis of test 3 above. Neverthless we still used them for this case also for completeness as they yielded similar results with the others.

[4] They are available upon request

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

$$\frac{\sqrt{v}(\widehat{d}-d_0)}{\widehat{\sigma}(\widehat{d})}$$

where v is the number of frequencies used to estimate the periodogram, d_0 is the value of d under the null hypothesis, $\widehat{d}$ is the estimate of d and $\widehat{\sigma}(\widehat{d})$ its estimated standard error. For each iteration we generate a series from $U_t = \beta_0 + \beta(t) + Z_t,\;\; Z_t \sim I(d)$ for different values of d corresponding to the nulls above. Furthermore, following Becker, Enders and Hurn (2004) and Becker, Enders and Lee (2006) and Ludlow and Enders (2000) we let the $\beta(t)$ function be defined in a way that it admits structural breaks

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

In the above specification of $\beta(t)$ the presence of unknown (smooth) structural breaks depends on whether $\beta_1 = \beta_2 = 0$ or not. We look at $T = 100, 200$ and $k = 0.5, 1, 1.5, 2, 2.5$ and $\beta_1 = \beta_2 = 1, 0.5, 0.1;.\beta_0 = 1$ covering the case of a conditional convergence regime as well as values of $\beta's$, $\beta_0 = \beta_1 = \beta_2 = 0$ for unconditional (absolute) convergence[5]. 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 complete oscillation.

Hence, we conduct our Monte Carlo experiment for all possible 15 pairs of β and ks . For the simulations of the critical values, we consider 50000 iterations. In Tables A1-A4 of the appendix we provide the critical values at 5 and 10 percent significance levels under all combinations of the parameter configurations listed above for the for estimators FELW, FELWd, 2FELW, 2FELWd that we use. These critical values are then used in the empirical analysis that follows.

3 Empirical Findings.

The data consists of annual GDP data for the period 1945-2006 and for 139 countries[6]. The data is from Madison (2008)[7] and it includes all possible countries available, not just the group

[5] We have tried other constant values such as 0, 2 and 3 and concluded that the value of the constant does not seem to affect the distribution for this case.

[6] The list of the countries can be found in Table A5 of the Appendix.

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

of developing countries considered by DMN. ($T = 62; N = 139$). The four tests outlined above are applied to all possible pairs of $U_t = Y_t^i - Y_t^j, i = 1, 2, ..., N-1$, and $j = 1, 2, ..., N$. We first investigate the convergence of GDP per capita and GDP data for all the 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[8]). The list of the countries belonging to the different groups is presented in table A5 of the Appendix.

Following DMN, we will analyze the nature of convergence depending on the classification presented Table 1 below. As in Pesaran (2007), we analyze output convergence across 139 countries without being subject to the pitfalls that surround the use of a benchmark to construct the output differences. As such we examine all $N(N-1)/2 = 9591$ 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 favour of the null[9].

Table 1: Type and Nature of Convergence according to the Estimate of d

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

The classification is entirely based on the results of the 4 tests presented above irrespective of the values of $\beta's$ $(\beta_0, \beta_1, \beta_2)$. For completeness, it is worth mentioning that operating within an absolute convergence or conditional convergence (catching up) environment depends on whether the $\beta's$ $(\beta_0, \beta_1, \beta_2)$ are different from zero or not. If all the $\beta's$ are zero then we are within an

[8] This clasification is based on the usual classification made by the International Monetary Fund's regional economic outlook documents.

[9] 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.

absolute convergence/divergence framework. Otherwise, we are within a conditional convergence or catching up. Hence we have following cases referring to Table 1.

(1) (Absolute Rapid Convergence if $\beta_0 = \beta_1 = \beta_2 = 0$); (Conditional Rapid Convergence if $\beta_0 \neq 0$ and $\beta_1 = \beta_2 = 0$); (Conditional Rapid Catching Up if $\beta_0 \neq \beta_1 \neq \beta_2 \neq 0$).

(2) (Absolute Long Memory Stationary Convergence if $\beta_0 = \beta_1 = \beta_2 = 0$); (Conditional Long Memory Stationary Convergence if $\beta_0 \neq 0$ and $\beta_1 = \beta_2 = 0$); (Conditional Long Memory Stationary Catching Up if $\beta_0 \neq \beta_1 \neq \beta_2 \neq 0$).

(3) (Absolute Long Memory Mean Reverting Convergence if $\beta_0 = \beta_1 = \beta_2 = 0$); (Conditional Absolute Long Memory Mean Reverting Convergence if $\beta_0 \neq 0$ and $\beta_1 = \beta_2 = 0$); (Conditional Long Memory Mean-Reverting Catching Up if $\beta_0 \neq \beta_1 \neq \beta_2 \neq 0$).

(4) (Absolute Divergence for all βs)

Note that such a 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, if the test statistics presented above based on the estimated $d-$values suggest lack of convergence, the conditional/absolute distinction becomes irrelevant.

3.1 Pair-Wise Results for Per Capita Output Gaps.

Table 2 below summarizes the results of the four tests applied to all 9591 output gap pairs over the period 1945-2006 ($T = 62; N = 139$) for the level GDP per capita data at the 5 percent significance level[10]. The table shows the minimum (Min), median (Med) and maximum (Max) of rejection frequencies of the four tests applied using 15 sets of different critical values. These critical values are given in tables A1-A4 of the appendix and resulted from different parameter configurations of $k, \beta' s$.

Table 2

As can be seen from Table 2 all the maximum, median and even minimum of rejection frequencies of test 1 are well below the significance level (0.05) for all the of the estimators of the d parameter and for critical values using both $T = 100$ and $T = 200$ estimators. Hence the evidence points strongly towards a non-mean reverting process for the per capita output gaps. A similar

[10] To conserve space we do not report the results for the 10 percent significance level. The results are available upon request.

pattern can be observed for test 3 the evidence is in favor of "limit" stationary long memory. The rejection frequencies of the remaining 2 tests are highly above the significance level for all cases, therefore the evidence strongly points to the presence of a long memory process. As a result, we may conclude that for the group of countries taken as a whole, output gaps for GDP per capita show long memory with a possible unit root[11].

We use the classification of Table 1 above to examine the nature of convergence that was established in Table 2. 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 9591 output gaps for GDP per capita. As in Table 2, we compute these fractions for the 15 different critical values and report only minimum, median and maximum values. Table 3 reports the results obtained at the 5 percent significance level.

Table 3

It can be seen that rejection frequencies of the cases of stationary, mean-reverting, rapid convergence and indetermination are very high, hence these hypotheses are rejected unambiguously using critical values from either panel of $T = 100$ or $T = 200$. The evidence in the remaining panel supports absolute divergence at the five percent significance level (median frequencies are lower than 0.05). Overall, the results in table 3 confirm that the type of convergence found for that process is best described by absolute divergence.

The analysis presented in Tables 2 and 3 for all countries taken as a group. We repeat the analysis for different group of countries, the Middle East and Central Asia, Asia and the Pacific, Sub-Saharan Africa, the Western Hemisphere and Europe. The classification of countries falling into one of the above regions is given in Table A5 of the Appendix. Except for Europe, where the results indicate a long memory process with possibly mean reverting behavior and no evidence of divergence, the results for all the other regions are qualitatively similar to those obtained for the whole group of countries[12]. They point out towards a (long memory) unit root process for per capita output gap series and strong evidence for divergence[13].

Overall, with the possible exception for Europe, the evidence in favour of divergence is quite striking. Given these results there is no scope in further investigating the distinction between

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

[12] Note also that for Western Hepisphere countries, a few tests posit to the same outcome as European countries.

[13] To conserve space we do not report these results, but they are available upon request.

absolute and conditional convergence based on the estimated $\beta-$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 a divergence than they do. One of the main reasons for the differences between our results and theirs is that we allow for the presence of structural breaks would add to the persistence of the series. Furthermore, using pair wise comparisons for all possible pairs within a group as opposed to relying on a benchmark, produces greater gap differences that lead to divergence. These differences are smoothened out if gaps are only considered as a difference 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 the absolute divergence behavior that seems to be the dominant pattern.

The main premise of the convergence hypothesis is based on the premise of the catching up growth effect, where less developed poorer countries approach in equilibrium the (per capita) income levels of richer more developed ones by growing faster 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. Having found strong evidence of absolute divergence in the level output gaps it is interesting to see the pattern of convergence in the growth gaps and see how it differs from that in levels.

3.2 Pair-Wise Results for Gaps of Per Capita Growth Rates.

In this section we repeat the above analysis by using gaps of output growth instead of output level. Table 4 below summarizes the results of the four tests applied to all 9591 GDP per capita growth gap pairs over the period 1946-2006 ($T = 61; N = 139$) at the 5 percent significance level.

Table 4

As can be seen from table 4, rejection frequencies of test 1 are all well above the significance level. Hence, the evidence points strongly towards a mean reverting process for the output growth gaps. All of the rejection frequencies for test 2 (median values), 3 and 4 are below the 0.05, providing evidence against stochastic divergence, long memory but in favor of "limit" stationary long memory. The evidence on long memory is rather weak, though possible, if we only consider maximum rejection frequencies in test 2. As a result, we may conclude that for the group of countries taken as a whole, output growth gaps for GDP per capita show capita show somehow mixed and weak (if any) evidence on long memory, but strong evidence on limit stationary with a possibly 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 towards mean reverting behavior rather than unit root, whereas the evidence on limit stationary remains strong in both case.

Table 5 examines the nature of convergence and reports the rejection frequencies obtained at the 5 percent significance level for output growth gaps for GDP per capita for all countries. It can be seen that, unlike the GDP per capita case, the case of rapid convergence (case where $d = 0$) cannot be ruled out. In median values, the evidence is mixed, while two estimators (FELW, FELWd) indicates its rejection at the border, the others do not. The rest of convergence types (stationary and mean reverting) are clearly rejected and there is no evidence for absolute divergence unlike the GDP per capita levels. The process that characterized best the output gap GDP per capita growth series is a short memory process with evidence for rapid convergence.

The analysis presented in tables 4 and 5 for the group of all countries taken together is repeated for the other regions, the Middle East and Central Asia, Asia and the Pacific, Sub-Saharan Africa, the Western Hemisphere and Europe. The results are qualitatively similar to those obtained for the whole group of countries[14]. Some exceptions are the following. For Middle East and central Asia and Sub-Saharan Africa the case against rapid convergence is weaker, provided by only maximum values. For Europe, the evidence on long memory provided by test 2 is stronger (for 2 estimators median values indicates the rejection of short memory) and rapid convergence can be rejected.

Overall, however, again with the exception of Europe, gaps in growth per capita rates point towards a rapid convergence pattern characterized by short memory. Interestingly, even though the framework of analysis that the we have pursued provides a richer set of possibilities than the rapid convergence and absolute divergence dichotomy, it is the latter these two possibilities that have emerged as the dominant hypotheses from the results that we have obtained. The latter has emerged as the dominant characterization of output gaps in per capita GDP levels and the former 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

[14] To conserve space as in the case of GDP per capita gaps in levels we do not report these results, but they are available upon request.

initial endowments will grow faster to "catch-up" with richer economies is not borne out by the evidence here.

3.3 Developing Word.

To make our work more comparable to DMN, which consider only the developing world, we now repeat the above analysis by excluding developed countries from our sample. By doing so we recalculate rejection frequencies for 118 developing countries[15] for levels and growth rates. Table 6 to 9 present the findings.

Table 6 to 9

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 is best characterized by absolute divergence in output gaps and rapid convergence in growth rates.

4 Determinants of persistence.

The above analysis strongly points to the presence of high persistence and divergences, in the output level gap pairs. However in growth rates the process seems to follow a mean reverting rapid converging path. In this section we analyze the determinants of these different paths of output gaps in levels and growth rates by running the following regression

$$\hat{d}_{ij} = \gamma_1 BUD_{ij} + \gamma_2 INV_{ij} + \gamma_3 INF_{ij} + \gamma_4 INY_{ij} + \gamma_5 POP_{ij} + \gamma_6 HC_{ij} + u_{ij},,\ i = 1, ..., N,\ i \neq j$$

The $\hat{d}'_{ij}s$ refer to the estimated d for the ij pairs obtained in the previous analysis. BUD_{ij} is the absolute difference between the budget deficit as a percentage of GDP for the ij country pairs Similarly $INV_{ij}, INF_{ij}, INY_{ij}, POP_{ij}, HC_{ij}$ refer to the (absolute) differences between the

[15] These countries are obtained by excluding the following 21 countries from 139 countries listed in Table A5 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. DMN include 98 of these 118 developing countries into their data set.

investment as a percentage of GDP, inflation rates, initial GDPs, population growth, and human capital respectively where u_{ij} represents the error term that could be cross sectionally correlated and possibly heteroskedastic. The source and the description of the data is given in Appendix. The data set for the explanatory variables is, unfortunately, only available for a only 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 of 1970-2001, hence we have 1891 country pairs and as such1891 observations to run the above regression. In the smaller data, which covers the period of 1960-2001, there are 33 countries, hence we have only 528 pairs. The list of these countries can be found in the Appendix. Since 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. As such we expect the signs of $\gamma's$ to be positive.

We run this regression for the two sets of $d's$, estimated from both level and growth rates data. Table 10 below summarizes the results of OLS estimation for the above regression[16]

Table 10:

	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.

The results point out towards the importance of all main factors in determining the speed of

[16]The reported resuts were obtained by using FELW estimator of d. However we obtained qualitatively similar results with other 3 estimators (FELWd, 2FELW, 2FELWd) of d.

convergence (divergence) of these output gaps. As expected physical capital and human capital play an important role in explaining whether two countries will 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. It is countries that have similar characteristics and pursue similar economic policies that are likely to have converging paths as opposed countries with dissimilar characteristics that may pursue different policies.

5 Conclusions.

In this paper, we examine a long memory framework of analysis allowing for the presence of structural breaks and the non reliance on a benchmark country to estimate the time series properties of output gaps for counties in the post world war two period and as such provide evidence 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, macroeconomic stability etc. 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 that 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 results. The former produce a pattern of divergence whereas the latter on of 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 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. Simple dichotomy is enough...

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Tables

Table 2: Fraction of Rejections for GDP per Capita: All Countries

$T = 200$ CVs												
	Test1			Test2			Test3			Tes4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.011	0.011	0.016	0.559	0.947	0.999	0.000	0.000	0.000	0.347	0.383	0.390
FELWd	0.036	0.037	0.044	0.554	0.933	0.995	0.000	0.001	0.003	0.346	0.380	0.387
2FELW	0.016	0.017	0.019	0.561	0.956	0.998	0.000	0.000	0.000	0.347	0.383	0.390
2FELWd	0.036	0.038	0.043	0.554	0.941	0.995	0.000	0.001	0.004	0.346	0.380	0.387
$T = 100$ CVs												
	Test1			Test2			Test3			Tes4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.011	0.012	0.020	0.559	0.957	0.999	0.000	0.000	0.000	0.265	0.341	0.390
FELWd	0.023	0.032	0.044	0.554	0.950	0.995	0.000	0.000	0.003	0.266	0.343	0.387
2FELW	0.014	0.016	0.019	0.561	0.973	0.998	0.000	0.000	0.000	0.265	0.341	0.390
2FELWd	0.026	0.036	0.043	0.554	0.955	0.995	0.000	0.000	0.004	0.267	0.343	0.387

Note: FELW: Feasible Exact Local Whittle estimator, FELWd: Feasible Exact Local Whittle estimator with detrending, 2FELW:2-Stage Feasible Exact Local Whittle estimator, 2FELWd: 2-Stage Feasible Exact Local Whittle estimator with detrending.

Table 3: Convergence Type for GDP per Capita: All Countries

	Stationary con. or catch up $T = 200$			Stationary con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	1.000	1.000	1.000	1.000	1.000	1.000
FELWd	1.000	1.000	1.000	1.000	1.000	1.000
2FELW	1.000	1.000	1.000	1.000	1.000	1.000
2FELWd	1.000	1.000	1.000	1.000	1.000	1.000
	Mean con. or catch up $T = 200$			Mean con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.992	1.000	1.000	0.991	1.000	1.000
FELWd	0.978	0.990	1.000	0.978	1.000	1.000
2FELW	0.989	1.000	1.000	0.989	1.000	1.000
2FELWd	0.982	0.992	1.000	0.982	1.000	1.000
	Absolute divergence $T = 200$			Absolute divergence $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.011	0.045	0.441	0.011	0.043	0.441
FELWd	0.036	0.049	0.446	0.023	0.041	0.446
2FELW	0.016	0.031	0.439	0.014	0.024	0.439
2FELWd	0.037	0.047	0.446	0.026	0.038	0.446
	Rapid con. or catch up $T = 200$			Rapid con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.984	0.989	0.999	0.981	0.989	0.999
FELWd	0.956	0.963	0.995	0.956	0.977	0.995
2FELW	0.981	0.984	0.998	0.981	0.984	0.998
2FELWd	0.957	0.963	0.995	0.957	0.973	0.995
	Indetermination $T = 200$			Indetermination $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.574	0.959	1.000	0.574	0.968	1.000
FELWd	0.595	0.970	1.000	0.595	0.977	1.000
2FELW	0.579	0.973	1.000	0.579	0.990	1.000
2FELWd	0.595	0.979	1.000	0.595	0.983	1.000

Note: The explanation of the different estimators above is given in Table 2.

Table 4: Fraction of Rejections for GDP per Capita Growth: All Countries

$T = 200$ CVs												
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.931	0.935	0.951	0.001	0.022	0.343	0.001	0.001	0.001	0.000	0.000	0.000
FELWd	0.947	0.949	0.957	0.001	0.029	0.328	0.001	0.002	0.002	0.000	0.000	0.000
2FELW	0.962	0.963	0.971	0.001	0.013	0.328	0.000	0.001	0.001	0.000	0.000	0.000
2FELWd	0.966	0.967	0.973	0.001	0.017	0.315	0.001	0.002	0.002	0.000	0.000	0.000
$T = 100$ CVs												
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.931	0.939	0.955	0.001	0.026	0.343	0.000	0.001	0.001	0.000	0.000	0.000
FELWd	0.915	0.940	0.957	0.001	0.038	0.328	0.001	0.001	0.002	0.000	0.000	0.000
2FELW	0.957	0.962	0.972	0.001	0.021	0.328	0.000	0.001	0.001	0.000	0.000	0.000
2FELWd	0.931	0.964	0.973	0.001	0.026	0.315	0.001	0.001	0.002	0.000	0.000	0.000

Note: The explanation of the different estimators above is given in Table 2.

Table 5: Convergence Type for GDP per Capita Growth: All Countries

	Stationary con. or catch up $T = 200$			Stationary con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	1.000	1.000	1.000	1.000	1.000	1.000
FELWd	1.000	1.000	1.000	1.000	1.000	1.000
2FELW	1.000	1.000	1.000	1.000	1.000	1.000
2FELWd	1.000	1.000	1.000	1.000	1.000	1.000
	Mean con. or catch up $T = 200$			Mean con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.895	1.000	1.000	0.892	1.000	1.000
FELWd	0.931	0.967	1.000	0.931	1.000	1.000
2FELW	0.899	1.000	1.000	0.899	1.000	1.000
2FELWd	0.932	0.967	1.000	0.932	1.000	1.000
	Absolute divergence $T = 200$			Absolute divergence $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.931	0.975	0.999	0.931	0.974	0.999
FELWd	0.947	0.959	0.999	0.915	0.954	0.999
2FELW	0.962	0.982	0.999	0.957	0.978	0.999
2FELWd	0.966	0.974	0.999	0.931	0.967	0.999
	Rapid con. or catch up $T = 200$			Rapid con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.049	0.065	0.343	0.045	0.064	0.343
FELWd	0.043	0.052	0.328	0.043	0.082	0.328
2FELW	0.029	0.037	0.328	0.028	0.039	0.328
2FELWd	0.027	0.033	0.315	0.027	0.066	0.315
	Indetermination $T = 200$			Indetermination $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.941	0.959	1.000	0.941	0.966	1.000
FELWd	0.956	0.977	1.000	0.933	0.975	1.000
2FELW	0.966	0.979	1.000	0.966	0.981	1.000
2FELWd	0.970	0.984	1.000	0.949	0.985	1.000

Note: The explanation of the different estimators above is given in Table 2.

Table 6: Fraction of Rejections for GDP per Capita: Developing world

	$T = 200$ CVs											
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.010	0.010	0.013	0.560	0.952	0.998	0.000	0.000	0.000	0.347	0.384	0.392
FELWd	0.036	0.037	0.045	0.551	0.930	0.995	0.000	0.001	0.004	0.346	0.380	0.388
2FELW	0.014	0.015	0.018	0.560	0.957	0.998	0.000	0.000	0.000	0.347	0.384	0.392
2FELWd	0.038	0.039	0.044	0.552	0.940	0.995	0.000	0.001	0.004	0.346	0.380	0.388
	$T = 100$ CVs											
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.010	0.011	0.015	0.560	0.961	0.998	0.000	0.000	0.000	0.263	0.341	0.392
FELWd	0.022	0.031	0.045	0.551	0.948	0.995	0.000	0.001	0.004	0.266	0.343	0.388
2FELW	0.013	0.014	0.018	0.560	0.974	0.998	0.000	0.000	0.000	0.264	0.341	0.392
2FELWd	0.027	0.037	0.044	0.552	0.954	0.995	0.000	0.001	0.004	0.266	0.343	0.388

Note: The explanation of the different estimators above is given in Table 2.

Table 7: Convergence Type for GDP per Capita: Developing World

	Stationary con. or catch up $T = 200$			Stationary con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	1.000	1.000	1.000	1.000	1.000	1.000
FELWd	1.000	1.000	1.000	1.000	1.000	1.000
2FELW	1.000	1.000	1.000	1.000	1.000	1.000
2FELWd	1.000	1.000	1.000	1.000	1.000	1.000
	Mean con. or catch up $T = 200$			Mean con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.993	1.000	1.000	0.992	1.000	1.000
FELWd	0.980	0.991	1.000	0.980	1.000	1.000
2FELW	0.989	1.000	1.000	0.989	1.000	1.000
2FELWd	0.981	0.991	1.000	0.981	1.000	1.000
	Absolute divergence $T = 200$			Absolute divergence $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.010	0.041	0.440	0.010	0.039	0.440
FELWd	0.036	0.051	0.449	0.022	0.042	0.449
2FELW	0.014	0.031	0.440	0.013	0.023	0.440
2FELWd	0.038	0.048	0.449	0.027	0.039	0.449
	Rapid con. or catch up $T = 200$			Rapid con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.987	0.990	0.998	0.985	0.990	0.998
FELWd	0.955	0.963	0.995	0.955	0.977	0.995
2FELW	0.982	0.985	0.998	0.982	0.986	0.998
2FELWd	0.956	0.961	0.995	0.956	0.972	0.995
	Indetermination $T = 200$			Indetermination $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.572	0.962	1.000	0.572	0.971	1.000
FELWd	0.593	0.967	1.000	0.593	0.972	1.000
2FELW	0.577	0.972	1.000	0.577	0.989	1.000
2FELWd	0.593	0.978	1.000	0.593	0.982	1.000

Note: The explanation of the different estimators above is given in Table 2.

Table 8: Fraction of Rejections for GDP per Capita Growth: Developing world

	$T = 200$ CVs											
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.951	0.955	0.969	0.000	0.009	0.331	0.001	0.001	0.002	0.000	0.000	0.000
FELWd	0.963	0.965	0.974	0.000	0.013	0.325	0.001	0.001	0.002	0.000	0.000	0.000
2FELW	0.965	0.967	0.976	0.000	0.011	0.331	0.001	0.001	0.001	0.000	0.000	0.000
2FELWd	0.968	0.970	0.976	0.000	0.014	0.326	0.001	0.001	0.002	0.000	0.000	0.000
	$T = 100$ CVs											
	Test1			Test2			Test3			Test4		
Estimator	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
FELW	0.951	0.958	0.973	0.000	0.011	0.331	0.000	0.001	0.002	0.000	0.000	0.000
FELWd	0.932	0.956	0.974	0.000	0.020	0.325	0.001	0.001	0.002	0.000	0.000	0.000
2FELW	0.959	0.966	0.976	0.000	0.017	0.331	0.000	0.001	0.001	0.000	0.000	0.000
2FELWd	0.930	0.966	0.976	0.000	0.022	0.326	0.001	0.001	0.002	0.000	0.000	0.000

Note: Note: The explanation of the different estimators above is given in Table 2.

Table 9: Convergence Type for GDP per Capita Growth: Developing World

	Stationary con. or catch up $T = 200$			Stationary con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	1.000	1.000	1.000	1.000	1.000	1.000
FELWd	1.000	1.000	1.000	1.000	1.000	1.000
2FELW	1.000	1.000	1.000	1.000	1.000	1.000
2FELWd	1.000	1.000	1.000	1.000	1.000	1.000
	Mean con. or catch up $T = 200$			Mean con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.896	1.000	1.000	0.893	1.000	1.000
FELWd	0.930	0.967	1.000	0.930	1.000	1.000
2FELW	0.896	1.000	1.000	0.896	1.000	1.000
2FELWd	0.928	0.965	1.000	0.928	1.000	1.000
	Absolute divergence $T = 200$			Absolute divergence $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.951	0.989	1.000	0.951	0.989	1.000
FELWd	0.963	0.976	1.000	0.932	0.971	1.000
2FELW	0.965	0.985	1.000	0.959	0.981	1.000
2FELWd	0.968	0.977	1.000	0.930	0.970	1.000
	Rapid con. or catch up $T = 200$			Rapid con. or catch up $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.031	0.045	0.331	0.027	0.044	0.331
FELWd	0.026	0.036	0.325	0.026	0.066	0.325
2FELW	0.024	0.034	0.331	0.024	0.036	0.331
2FELWd	0.024	0.030	0.326	0.024	0.067	0.326
	Indetermination $T = 200$			Indetermination $T = 100$		
Estimator	Min	Med	Max	Min	Med	Max
FELW	0.955	0.965	1.000	0.955	0.972	1.000
FELWd	0.968	0.978	1.000	0.941	0.978	1.000
2FELW	0.969	0.980	1.000	0.968	0.981	1.000
2FELWd	0.972	0.984	1.000	0.946	0.985	1.000

Note: The explanation of the different estimators above is given in Table 2.

6 APPENDIX:

Table A1a. Critical values of Test 1, 5 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-2.243	-2.203	-2.166	-2.121	-2.058	-2.305	-2.265	-2.244	-2.193	-2.134
FELWd	-2.908	-2.823	-2.782	-2.687	-2.545	-2.405	-2.367	-2.352	-2.297	-2.218
2FELW	-2.378	-2.325	-2.267	-2.216	-2.127	-2.299	-2.259	-2.239	-2.187	-2.130
2FELWd	-2.994	-2.855	-2.754	-2.657	-2.465	-2.406	-2.370	-2.352	-2.298	-2.218
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-2.257	-2.233	-2.239	-2.231	-2.216	-2.275	-2.302	-2.293	-2.277	-2.255
FELWd	-2.910	-2.888	-2.884	-2.854	-2.822	-2.386	-2.413	-2.391	-2.393	-2.379
2FELW	-2.400	-2.344	-2.357	-2.356	-2.331	-2.266	-2.287	-2.290	-2.268	-2.249
2FELWd	-2.983	-2.951	-2.933	-2.877	-2.856	-2.387	-2.415	-2.393	-2.393	-2.381
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-2.247	-2.278	-2.249	-2.250	-2.247	-2.291	-2.328	-2.281	-2.305	-2.319
FELWd	-2.877	-2.922	-2.894	-2.887	-2.888	-2.406	-2.429	-2.399	-2.421	-2.420
2FELW	-2.369	-2.420	-2.377	-2.380	-2.383	-2.285	-2.316	-2.276	-2.298	-2.310
2FELWd	-2.947	-2.974	-2.934	-2.951	-2.955	-2.406	-2.431	-2.401	-2.421	-2.421

Table A1b. Critical values of Test 1, 10 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-1.914	-1.832	-1.773	-1.690	-1.586	-1.760	-1.721	-1.692	-1.629	-1.589
FELWd	-2.189	-2.026	-1.947	-1.835	-1.713	-1.847	-1.794	-1.770	-1.714	-1.659
2FELW	-1.888	-1.813	-1.757	-1.678	-1.581	-1.759	-1.721	-1.691	-1.628	-1.589
2FELWd	-2.136	-2.020	-1.952	-1.841	-1.718	-1.847	-1.794	-1.770	-1.715	-1.659
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-1.937	-1.892	-1.887	-1.875	-1.840	-1.747	-1.744	-1.745	-1.723	-1.725
FELWd	-2.195	-2.128	-2.118	-2.069	-2.016	-1.830	-1.831	-1.829	-1.821	-1.809
2FELW	-1.915	-1.872	-1.874	-1.853	-1.824	-1.747	-1.744	-1.745	-1.723	-1.724
2FELWd	-2.148	-2.105	-2.102	-2.049	-2.015	-1.830	-1.831	-1.829	-1.821	-1.809
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	-1.906	-1.939	-1.905	-1.911	-1.919	-1.756	-1.759	-1.738	-1.755	-1.758
FELWd	-2.121	-2.156	-2.147	-2.136	-2.144	-1.850	-1.852	-1.836	-1.846	-1.846
2FELW	-1.879	-1.916	-1.884	-1.888	-1.897	-1.755	-1.757	-1.738	-1.754	-1.757
2FELWd	-2.088	-2.120	-2.112	-2.110	-2.113	-1.851	-1.852	-1.836	-1.846	-1.846

Table A2a. Critical values of Test 2, 5 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	5.361	5.959	6.346	6.902	7.336	6.446	6.967	7.406	7.822	6.153
FELWd	2.057	5.675	6.428	6.873	7.316	2.613	6.936	7.241	7.798	5.829
2FELW	4.835	5.946	6.346	6.902	7.336	5.737	6.696	7.405	7.821	5.650
2FELWd	2.039	5.588	6.428	6.873	7.316	2.600	6.820	7.278	7.798	5.593
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	4.564	4.317	5.113	5.085	4.975	4.443	5.170	5.078	5.424	6.140
FELWd	1.962	4.337	4.579	5.164	4.896	2.021	4.883	5.156	5.324	5.811
2FELW	3.789	4.036	4.583	4.740	4.981	4.312	4.793	5.017	5.340	5.648
2FELWd	1.949	3.774	4.466	4.691	4.907	2.018	4.764	4.922	5.273	5.590
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	2.380	2.356	2.492	2.455	2.494	2.287	2.305	2.359	2.389	2.390
FELWd	1.930	2.054	2.213	2.214	2.263	1.768	2.134	2.102	2.200	2.197
2FELW	2.361	2.334	2.474	2.432	2.469	2.283	2.304	2.357	2.385	2.386
2FELWd	1.913	2.039	2.200	2.188	2.238	1.767	2.130	2.099	2.197	2.195

Table A2b. Critical values of Test 2, 10 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	5.240	5.478	5.973	6.523	6.916	6.296	6.813	6.843	7.477	5.736
FELWd	1.522	5.433	6.063	6.488	6.893	2.179	6.745	6.920	7.452	5.382
2FELW	4.582	5.549	5.975	6.523	6.916	5.543	6.385	7.075	7.477	5.302
2FELWd	1.515	5.075	6.063	6.487	6.893	2.176	6.484	6.922	7.452	5.225
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	3.609	3.731	4.808	4.662	4.516	4.070	4.534	4.717	5.016	5.723
FELWd	1.420	3.461	4.127	4.767	4.446	1.563	4.474	4.625	4.954	5.372
2FELW	3.454	3.638	4.241	4.298	4.456	4.032	4.469	4.697	4.996	5.301
2FELWd	1.414	3.347	4.055	4.262	4.381	1.561	4.440	4.569	4.935	5.222
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	1.899	1.866	2.015	1.969	1.974	1.871	1.876	1.943	1.952	1.964
FELWd	1.381	1.518	1.654	1.680	1.702	1.273	1.670	1.632	1.748	1.730
2FELW	1.893	1.860	2.008	1.961	1.964	1.870	1.876	1.942	1.951	1.962
2FELWd	1.376	1.511	1.648	1.669	1.691	1.272	1.668	1.630	1.746	1.729

Table A3a. Critical values of Test 3, 5 % Significance Level, $T = 100$										
	$\beta_1 = \beta_2 = 1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-1.511	2.449	-1.287	3.104	-0.567	3.390	-0.306	3.709	-0.193	4.024
FELWd	-3.375	2.235	-2.194	2.997	-1.313	3.407	-0.770	3.684	-0.652	4.010
2FELW	-1.528	2.451	-1.309	3.103	-0.620	3.390	-0.421	3.709	-0.287	4.023
2FELWd	-3.375	2.228	-2.201	2.995	-1.319	3.407	-0.811	3.683	-0.710	4.010
	$\beta_1 = \beta_2 = 0.5$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-2.144	2.311	-2.090	2.567	-1.843	2.643	-1.755	2.816	-1.730	2.937
FELWd	-3.380	2.188	-3.093	2.465	-2.827	2.621	-2.601	2.773	-2.561	2.901
2FELW	-2.146	2.311	-2.091	2.567	-1.848	2.642	-1.759	2.815	-1.738	2.937
2FELWd	-3.380	2.177	-3.095	2.462	-2.827	2.620	-1.759	2.771	-2.567	2.899
	$\beta_1 = \beta_2 = 0.1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-2.359	2.298	-2.364	2.308	-2.322	2.284	-2.343	2.326	-2.315	2.314
FELWd	-3.390	2.206	-3.393	2.232	-3.338	2.213	-3.359	2.260	-3.349	2.237
2FELW	-2.359	2.293	-2.367	2.303	-2.323	2.281	-2.343	2.324	-2.318	2.310
2FELWd	-3.390	2.198	-3.394	2.221	-3.340	2.203	-3.357	2.250	-3.349	2.227

Table A3b. Critical values of Test 3, 5 % Significance Level, $T = 200$										
	$\beta_1 = \beta_2 = 1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-1.321	2.343	-0.881	2.973	-0.595	3.257	-0.277	3.520	0.142	3.794
FELWd	-2.842	1.972	-1.342	2.977	-1.035	3.197	-0.638	3.499	-0.287	3.797
2FELW	-1.325	2.342	-0.907	2.974	-0.618	3.257	-0.310	3.520	0.002	3.794
2FELWd	-2.842	1.986	-1.351	2.977	-1.049	3.197	-0.653	3.499	-0.306	3.797
	$\beta_1 = \beta_2 = 0.5$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-1.952	2.148	-1.795	2.371	-1.722	2.480	-1.630	2.574	-1.460	2.666
FELWd	-2.889	1.928	-2.457	2.305	-2.381	2.387	-2.263	2.518	-2.064	2.632
2FELW	-1.954	2.135	-1.797	2.374	-1.722	2.479	-1.631	2.573	-1.462	2.665
2FELWd	-2.889	1.951	-2.459	2.329	-2.382	2.404	-2.263	2.517	-2.064	2.631
	$\beta_1 = \beta_2 = 0.1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
FELW	-2.139	2.067	-2.159	2.082	-2.159	2.085	-2.144	2.082	-2.134	2.087
FELWd	-2.884	1.919	-2.897	1.942	-2.883	1.930	-2.869	1.937	-2.878	1.937
2FELW	-2.139	2.069	-2.159	2.080	-2.159	2.095	-2.145	2.080	-2.135	2.075
2FELWd	-2.885	1.952	-2.898	1.962	-2.884	1.967	-2.869	1.964	-2.878	1.973

Table A3c. Critical values of Test 3, 10 % Significance Level, $T = 100$										
	$\beta_1 = \beta_2 = 1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-0.884	2.005	-0.662	2.673	0.127	2.943	0.364	3.289	0.389	3.571
FELWd	-2.671	1.665	-1.451	2.529	-0.633	2.971	-0.102	3.259	0.027	3.555
2FELW	-0.930	2.012	-0.716	2.673	-0.079	2.943	0.079	3.290	0.226	3.570
2FELWd	-2.671	1.655	-1.478	2.526	-0.654	2.971	-0.237	3.259	-0.11	3.555
	$\beta_1 = \beta_2 = 0.5$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-1.533	1.850	-1.481	2.096	-1.251	2.162	-1.157	2.344	-1.128	2.429
FELWd	-2.690	1.624	-2.379	1.956	-2.099	2.135	-1.883	2.272	-1.857	2.374
2FELW	-1.542	1.828	-1.491	2.093	-1.267	2.162	-1.179	2.343	-1.151	2.427
2FELWd	-2.693	1.616	-2.382	1.946	-2.101	2.131	-1.886	2.268	-1.864	2.370
	$\beta_1 = \beta_2 = 0.1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-1.750	1.796	-1.761	1.794	-1.730	1.803	-1.738	1.821	-1.714	1.815
FELWd	-2.702	1.631	-2.684	1.631	-2.648	1.648	-2.651	1.675	-2.649	1.659
2FELW	-1.758	1.780	-1.766	1.779	-1.733	1.788	-1.742	1.811	-1.723	1.803
2FELWd	-2.702	1.628	-2.685	1.627	-2.649	1.633	-2.652	1.675	-2.651	1.663

Table A3d. Critical values of Test 3, 10 % Significance Level, $T = 200$										
	$\beta_1 = \beta_2 = 1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-0.784	2.060	-0.321	2.572	-0.081	2.867	0.274	3.110	0.693	3.376
FELWd	-2.255	1.582	-0.743	2.588	-0.469	2.790	-0.110	3.081	0.329	3.383
2FELW	-0.805	1.925	-0.414	2.572	-0.146	2.866	0.150	3.110	0.454	3.376
2FELWd	-2.256	1.443	-0.760	2.586	-0.510	2.789	-0.142	3.081	0.214	3.383
	$\beta_1 = \beta_2 = 0.5$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-1.404	1.848	-1.257	1.995	-1.174	2.014	-1.096	2.095	-0.951	2.205
FELWd	-2.290	1.553	-1.849	1.869	-1.766	1.895	-1.643	1.960	-1.474	2.107
2FELW	-1.414	1.674	-1.265	1.912	-1.183	2.039	-1.102	2.127	-0.967	2.211
2FELWd	-2.290	1.412	-1.853	1.830	-1.769	1.911	-1.647	2.051	-1.475	2.163
	$\beta_1 = \beta_2 = 0.1$									
	$k = 0.5$		$k = 1$		$k = 1.5$		$k = 2$		$k = 2.5$	
Estimator	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
FELW	-1.603	1.754	-1.624	1.759	-1.621	1.746	-1.606	1.772	-1.604	1.764
FELWd	-2.278	1.530	-2.293	1.553	-2.272	1.539	-2.271	1.552	-2.274	1.552
2FELW	-1.605	1.577	-1.626	1.600	-1.624	1.602	-1.609	1.601	-1.607	1.606
2FELWd	-2.279	1.399	-2.294	1.443	-2.273	1.419	-2.273	1.434	-2.274	1.419

Table A4a. Critical values of Test 4, 5 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	2.196	2.237	2.313	2.417	2.511	1.975	2.042	2.057	2.096	2.149
FELWd	2.195	2.241	2.310	2.422	2.512	1.974	2.041	2.058	2.100	2.152
2FELW	2.197	2.236	2.313	2.416	2.510	1.975	2.042	2.057	2.096	2.149
2FELWd	2.195	2.240	2.310	2.421	2.512	1.974	2.041	2.058	2.100	2.152
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	2.198	2.196	2.221	2.252	2.273	1.972	1.999	1.993	2.008	2.030
FELWd	2.196	2.192	2.220	2.242	2.273	1.970	1.998	1.994	2.004	2.030
2FELW	2.198	2.195	2.221	2.251	2.273	1.972	1.999	1.993	2.008	2.030
2FELWd	2.196	2.192	2.221	2.242	2.273	1.970	1.998	1.994	2.004	2.030
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	2.179	2.176	2.205	2.175	2.175	1.970	1.993	1.967	2.002	1.994
FELWd	2.183	2.176	2.197	2.174	2.168	1.968	1.992	1.969	2.005	1.996
2FELW	2.180	2.176	2.205	2.174	2.174	1.970	1.993	1.967	2.002	1.994
2FELWd	2.183	2.177	2.197	2.174	2.169	1.968	1.992	1.969	2.005	1.996

Table A4b. Critical values of Test 4, 10 % Significance Level										
	$\beta_1 = \beta_2 = 1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	1.709	1.763	1.840	1.940	2.023	1.530	1.604	1.623	1.661	1.709
FELWd	1.707	1.763	1.835	1.939	2.023	1.528	1.600	1.620	1.658	1.710
2FELW	1.708	1.763	1.839	1.939	2.023	1.530	1.605	1.623	1.661	1.709
2FELWd	1.707	1.763	1.835	1.939	2.023	1.528	1.600	1.620	1.658	1.710
	$\beta_1 = \beta_2 = 0.5$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	1.702	1.723	1.744	1.764	1.785	1.549	1.548	1.547	1.574	1.588
FELWd	1.698	1.718	1.741	1.761	1.783	1.545	1.546	1.541	1.569	1.584
2FELW	1.702	1.723	1.744	1.763	1.785	1.549	1.548	1.547	1.574	1.588
2FELWd	1.698	1.718	1.741	1.761	1.783	1.545	1.546	1.541	1.569	1.584
	$\beta_1 = \beta_2 = 0.1$									
	$T = 100$					$T = 200$				
Estimator	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$	$k = 0.5$	$k = 1$	$k = 1.5$	$k = 2$	$k = 2.5$
FELW	1.702	1.700	1.719	1.694	1.714	1.536	1.543	1.541	1.552	1.542
FELWd	1.697	1.695	1.715	1.690	1.711	1.531	1.539	1.539	1.549	1.539
2FELW	1.702	1.700	1.719	1.694	1.714	1.536	1.543	1.541	1.552	1.542
2FELWd	1.697	1.695	1.715	1.690	1.711	1.531	1.539	1.539	1.549	1.539

Table A5 List of countries

Middle East and Central Asia	Europe	Asia and Pacific
Algeria	Albania	Australia
Bahrain	Austria	Bangladesh
Iran	Belgium	Burma
Iraq	Bulgaria	Cambodia
Kuwait	Czech Republic	China
Libya	Denmark	Hong Kong
Oman	Finland	New Zealand
Qatar	France	India
Saudi Arabia	Germany	Indonesia
Sudan	Greece	Japan
United Arab Emirates	Hungary	Laos
Yemen	Ireland	Malaysia
Afghanistan	Italy	Mongolia
Djibouti	Israel	Nepal
Egypt	Netherlands	North Korea
Jordan	Norway	Philippines
Lebanon	Portugal	Singapore
Mauritania	Poland	South Korea
Morocco	Romania	Sri Lanka
Pakistan	Spain	Taiwan
Syria	Sweden	Thailand
Tunisia	Switzerland	Vietnam
West Bank and Gaza	Turkey	
Somalia	United Kingdom	
	Yugoslavia	

Table A5 continued		
Sub-Saharan Africa		**Western Hemisphere**
Angola	Mauritius	Argentina
Benin	Mozambique	Bolivia
Botswana	Namibia	Brazil
Burkina Faso	Niger	Canada
Burundi	Nigeria	Chile
Cameroon	Rwanda	Colombia
Cape Verde	São Tomé and Principe	Costa Rica
Central African Republic	Senegal	Cuba
Chad	Seychelles	Dominican Republic
Comoro Islands	Sierra Leone	Ecuador
Congo "Brazzaville"	South Africa	El Salvador
Côte d'Ivoire	Swaziland	Guatemala
Equatorial Guinea	Tanzania	Haiti
Eritrea and Ethiopia	Togo	Honduras
Gabon	Uganda	Jamaica
Gambia	Zaire (Congo Kinshasa)	Mexico
Ghana	Zambia	Nicaragua
Guinea	Zimbabwe	Panama
Guinea Bissau		Paraguay
Kenya		Peru
Lesotho		Puerto Rico
Liberia		Trinidad and Tobago
Madagascar		United States
Malawi		Uruguay
Mali		Venezuela

Table A6 List of countries used in determinants of convergence

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