# Real convergence in some emerging countries: a fractionally integrated approach

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## 1 Introduction

Real convergence –the tendency for per capita output of different economies to equalize over time– has recently received a great deal of attention in economic literature. The interest in this subject may be explained, at least to a certain extent, as a prediction test of the neoclassical growth model (Solow, 1956) as opposed to the "new" endogenous growth models (Romer, 1986; Lucas, 1988). At it is well known, one prediction of the neoclassical model is conditional convergence: the lower the starting level of real per capita output, relative to the long-run or steady-state position, the faster is the growth rate. Assuming that technologies are identical and exogenous, the dynamics of convergence rest on decreasing returns to scale to capital: the lower the ratio of capital per worker, the higher the return on investing in capital and thus, the faster the rate of capital accumulation and the growth rate of output per worker. On the contrary, in endogenous growth models there is no tendency for income levels to converge, since divergence can be generated by relaxing some of the neoclassical assumptions. For example, Romer (1986) shows that, assuming non-diminishing returns to capital, there will be no tendency towards convergence since a lower ratio of capital per worker does not guarantee a higher return to investment in capital. In the approaches proposed by Lucas (1988) and Romer (1990) or Aghion and Howitt (1992),

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divergence in long-term per capita output can be generated by increasing returns on human capital or on R&D investment.

Furthermore, the great differences observed in per capita output and in growth rates across countries justify a deeper study on convergence. The different economic growth experience of the developing countries in Asia and Latin America during the last three decades is a good example. From 1965 to 1985, among the countries which experienced higher growth rates were Brazil, the four Asian Tigers (Singapore, Korea, Taiwan and Hong Kong), Indonesia and Japan, while among the countries with lower growth rates we find countries such as Venezuela. These episodes of rapid growth rates of some of these countries together with even negative rates in other countries in the same area help to explain the interest in economic growth and convergence. Examples of empirical works on these countries are among others Young (1992, 1995), Easterly (1995) and De Gregorio (1999).

Empirical testing of the convergence hypothesis provides several definitions of convergence and thus, different methodologies to test it. In a time series approach, stochastic convergence asks whether permanent movements in one country's per capita output are associated with permanent movements in another country's output, that is, it examines, whether common stochastic elements matter and how persistent the differences among countries are. Thus, stochastic convergence implies that output differences between economies cannot contain unit roots. Empirical tests on this hypothesis have been carried out by Campbell and Mankiw (1989), Cogley (1990), Bernard (1991), Carlino and Mills (1993), Bernard and Durlauf (1995) and, in general, they do not find evidence of convergence.

In this paper, we define real convergence as mean reversion in the differences in per capita output between countries, and we test this hypothesis using a methodology based on fractional integration. The fractional integration approach has recently been applied to test real convergence in Michelacci and Zaffaroni (2000) and Silverberg and Verspagen (1999). In these two papers, they use semiparametric techniques, which may be too sensitive to the choice of the bandwidth parameter number. Here, we use a fully parametric procedure of Robinson's (1994), which is the most efficient one when directed against the appropriate (fractional) alternatives, and we test the real convergence hypothesis in Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, India, Indonesia, Taiwan and South Korea with respect to the US and also with respect to Japan for the Asian countries. The outline of the paper is as follows. Section 2 describes the main results on real convergence. In Section 3, we present the procedure employed in the article. Section 4 covers the empirical analysis, while Section 5 offers some conclusions.

## 2 Main results on real convergence

According to Bernard and Durlauf (1996), stochastic convergence means the following: "Countries i and j converge if the long-term forecasts of output for both countries are equal at a fixed time t:

$$\lim_{k \to \infty} E(y_{i,\,t+k} - y_{j,\,t+k} | I_t) = 0 .$$

Therefore, in order for countries i and j to converge, the difference $y_{i,\,t+k} - y_{j,\,t+k}$ must be a stationary I(0) process. Since most of the procedures for testing this hypothesis include the cases of no regressors, an intercept, and an intercept and a linear trend, we can distinguish between long-run convergence (unconditional or conditional depending on the significance of the intercept) and convergence as a catch-up (with a linear time trend) [1]. Using this methodology, Bernard and Durlauf (1991) find that they can only reject the presence of a unit root in the difference for the pair France-Italy among the G7. Bernard and Durlauf (1995) and Cellini and Scorcu (2000) also find little evidence of income convergence, the first authors when analyzing convergence among 15 OECD countries over the period 1900-1987, while Cellini and Scorcu (2000) can only reject the non-convergence hypothesis for the pairs US-Germany, US-Japan and France-Italy. However, Carlino and Mills (1993) and Loewy and Papell (1996) find support for convergence among the US regions, a result that might be explained due to the more homogenous nature of the economies studied by these authors.

As far as the countries in Latin America are concerned, De Gregorio (1999) finds no evidence of convergence neither within Latin America nor to OECD income levels for the period 1965-95. For the Asian countries, Lim and McAleer (2000) apply different time series tests of convergence to determine if there is a convergence club for five ASEAN (Association of South-East Asian Nations) members over the period 1965-1992 and find no evidence of convergence among them and the US.

When the convergence hypothesis is analyzed by means of applying methodologies based on fractional integration, the results are mixed. Michelacci and Zaffaroni (2000) could not reject the hypothesis that relative per capita output of all the fourteen OECD countries examined are non-stationary and mean reverting ($0.5 < d < 1$). Therefore, according to these authors, the convergence hypothesis cannot be rejected, and thus, convergence takes place, although at a hyperbolic very slow rate. However, Silverberg and Verspagen (1999) obtain a different result: they analyse the GDP per capita series relative to the US for the same OECD countries as in Michelacci and Zaffaroni (2000), and find no evidence of convergence except for Australia,

1 In the definition of "convergence as a catch-up", we follow Carlino and Mills (1993): initially, rich countries should exhibit slower growth than those having initially lower per-capita income catch-up, testing the convergence hypothesis by means of tests of stationarity around a linear time trend.

Austria, the UK and Japan, although their overall conclusions depend strongly on the specific model used. For the emerging countries, these authors find evidence of convergence with respect to the US for Argentina, Brazil, Colombia, Peru, Venezuela, Indonesia and Taiwan.

## 3 Long memory processes and convergence

For the purpose of the present paper, we define an I(0) process $\{u_t, t = 0, \pm 1, ...\}$ as a covariance stationary process with spectral density function that is positive and finite at zero frequency. In this context, we say that a given raw time series $\{x_t, t = 0, \pm 1, ...\}$ is I(d) if:

$$(1-L)^d \quad x_t = u_t, \; t = 1, 2, \ldots, \tag{1}$$

$$x_t = 0\,; \; t \le 0, \tag{2}$$

where $u_t$ is I(0) and where L means the lag operator ($Lx_t = x_{t-1}$) [2]. Note that the polynomial above can be expressed in terms of its Binomial expansion, such that for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots$$

The macroeconomic literature has stressed the cases of d = 0 and 1, however, d can be any real number. Clearly, if d = 0 in (1), $x_t = u_t$, and a "weakly autocorrelated" $x_t$ is allowed for. However, if d > 0, $x_t$ is said to be a long memory process, because of the strong association between observations widely separated in time, and as d increases beyond 0.5 and through 1, $x_t$ can be viewed as becoming "more nonstationary", in the sense, for example, that the variance of partial sums increases in magnitude.

To determine the appropriate degree of integration in a given time series is important from both economic and statistical viewpoints. Thus, if d = 0, the series is covariance stationary and possesses 'short memory', with the autocorrelations decaying fairly rapidly. If d belongs to the interval (0, 0.5), $x_t$ is still covariance stationary, having autocovariances which decay much more slowly than those of an ARMA process, in fact, so slowly as to be nonsummable; if d ∈ [0.5, 1), the series is no longer covariance stationary, but it is still mean reverting, with the effect of the shocks dying away in the long run. Finally, if d ≥ 1, $x_t$ is nonstationary and non-mean reverting. Thus, the fractional differencing parameter d plays a crucial role in describing the persistence in the time series behaviour: the higher the d is, the higher will be the level of association between the observations.

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2 Eq.(2) is a standard assumption to be made in the context of I(d) statistical models. (See, *e.g.*, Gil-Alana and Robinson, 1997). For an alternative definition of fractionally integrated process (the type I class), see Marinucci and Robinson (1999).

There exist many approaches for estimating and testing the fractional differencing parameter d (see, *e.g.* Geweke and Porter-Hudak, 1983; Dahlhaus, 1989; Sowell, 1992; Tanaka, 1999; Dolado et al., 2002; etc.). In this article we present a parametric testing procedure due to Robinson (1994) that permits us to test I(d) statistical models in raw time series. In the final part of the article we also display some results based on a semiparametric approach.

A very simple version of the tests of Robinson (1994) consists of testing the null hypothesis:

$$H_o : d = d_o. \tag{3}$$

in a model given by

$$y_t = \beta' z_t + x_t; \; t = 1, 2, \ldots, \tag{4}$$

and (1), for any real value $d_o$, where $y_t$ is the observed time series; $\beta = (\beta_1, \ldots, \beta_k)'$ is a $(k \times 1)$ vector of unknown parameters; and $z_t$ is a $(k \times 1)$ vector of deterministic regressors that may include, for example, an intercept, (*e.g.*, $z_t \equiv 1$), or an intercept and a linear time trend, (in case of $z_t = (1,t)^T$). The functional form of the test statistic, (denoted by $\hat{r}$ is given in Appendix A.

Based on the null hypothesis (3), Robinson (1994) established that under certain regularity conditions [3]:

$$\hat{r} \rightarrow_d \quad N(0, 1) \quad as \quad T \rightarrow \infty, \tag{5}$$

and also the Pitman efficiency of the tests against local departures from the null. Thus, we are in a classical large sample-testing situation: an approximate one-sided 100α% level test of $H_o$ (3) against the alternative: $H_a$: $d > d_o$ ($d < d_o$) will be given by the rule: "Reject $H_o$ if $\hat{r} > z_\alpha$ ($\hat{r} < -z_\alpha$)", where the probability that a standard normal variate exceeds $z_\alpha$ is α.

There exist other procedures for estimating and testing the fractionally differenced parameter, some of them also based on the likelihood function. We believe that, as in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives will have the same null and local limit theory as the LM tests of Robinson (1994). Sowell (1992) essentially employed such a Wald testing procedure but it requires an efficient estimate of d, and while such estimates can be obtained, no closed-form formulae are available and so the LM procedure of Robinson (1994) seems computationally more attractive. Also, the fact that the limit distribution of Robinson's (1994) tests is standard across different values of d makes the tests particularly attractive, especially if we compare them with most of the unit root testing procedures embedded in AR alternatives (*e.g.* Fuller, 1976; Dickey and Fuller, 1979; Kwiatkowski et al., 1992; etc), where a non-standard limit distribution is obtained, and critical values must be calculated numerically on a case by case basis. Moreover, the null N(0, 1) distribution of $\hat{r}$ holds across a broad class of exogenous regressors $z_t$, including $z_t \equiv 1$ and $z_t = (1,t)'$,

3 These conditions are very mild, regarding technical assumptions to be satisfied by model (1) and (4).

as is the case in other standard large-sample tests. On the other hand, in unit-root tests directed against AR alternatives (*e.g.* Schmidt and Phillips, 1992), the null limit distribution can vary with features of the regressors.

In the following section, we use the procedure described above to examine the convergence hypothesis in some Latin American and Asian countries with respect to the US and Japan by looking at their orders of integration. Thus, if the order of integration of the original series is higher than that of its differences, the latter series is "less nonstationary" than the original one, implying that is less explosive if $d > 1$ (and thus reducing its degree of divergence) or mean reverting if $d < 1$ (and thus showing real convergence) [4].

# 4 Data and test results

The data used in this section are annual log real GDP per capita in 1990 Geary-Khamis PPP-adjusted dollars. The series run from 1900 to 1999 for Argentina, Brazil, Chile, Venezuela, India and Indonesia. For Colombia, Mexico and Peru, the series run from 1925, 1921 and 1913 to 1999, and for Taiwan and South Korea from 1903 and 1911 to 1999. The data for the period 1900-1994 were obtained from Maddison (1995) and they have been updated using the GGDC (Groningen Growth and Development Center) Database 2002. The GGDC database contains information of about 75 countries. However, for all except those used in this application, the data start around 1947, reducing the number of observations to about 50, which may be too small to implement Robinson's (1994) parametric tests [5].

We start by performing Robinson's tests (1994) to the Latin American series as well as their differences with respect to the US. Denoting each of the time series by $y_t$, we employ through the model given by (1) and (4), with $z_t = (1,t)'$. Thus, under the null hypothesis (3):

$$y_t = \beta_0 + \beta_1 t + x_t, \quad t = 1, 2, ... \tag{6}$$

$$(1 - L)^{d_o} x_t = u_t, \quad t = 1, 2, ..., \tag{7}$$

and we treat separately the cases $\beta_0 = \beta_1 = 0$ a priori; $\beta_0$ unknown and $\beta_1 = 0$ a priori; and $\beta_0$ and $\beta_1$ unknown, i.e., we consider respectively the cases of no regressors in the undifferenced regression (6), an intercept, and an intercept and a linear time trend. In other words, we distinguish between long-run unconditional and conditional convergence (the cases $\beta_0 = \beta_1 = 0$, and $\beta_0$ unknown and $\beta_1 = 0$) and convergence as a catch-up ($\beta_0$ and $\beta_1$ unknown). We take $d_o = 0, (0.01), 2$, and model the I(0) process $u_t$ to be both white noise and to have parametric autocorrelation.

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4 Though the hypothesis of $d > 1$ has little sense in most of economic growth models, we justify its use in the context of unit roots nested in fractional alternatives because of the smoothness in its behaviour around $d = 1$.

5 Gil-Alana (2000) shows that Robinson's (1994) tests perform relatively well in finite samples if $T \geq 100$.

Table 1 reports the results based on white noise disturbances [6]. Thus, when d = 1, for example, the differences $(1-L)y_t$ behave, for t > 1, like a random walk when $\beta_1 = 0$, and a random walk with drift when $\beta_1 \neq 0$. However, instead of reporting the test statistics for all countries and all values of $d_o$, we present 95%-confidence intervals of those values of $d_o$ where $H_o$ (3) cannot be rejected [7]. Starting with the case of no regressors, we see that for all countries except Venezuela, the confidence intervals include the unit root, the values of d ranging between 0.69 and 1.19. Including an intercept or an intercept and a linear time trend, the results are similar in both cases and the unit root null hypothesis is excluded in favour of d > 1 for Brazil, Mexico and Venezuela. The fact that d > 1 can be interpreted as saying that the growth rate series still present a component of long memory behaviour. For the remaining four countries (Argentina, Chile, Colombia and Peru), the intervals are all centred around the unit root. If we concentrate on the differences with respect to the US, we see that the intervals are very similar to those of the original series, suggesting that there is no evidence of convergence nor catch-up at least for this simple case of white noise disturbances. We have marked in bold type in all the tables those intervals where the lowest and the highest values of each interval were smaller with the differenced series. We observe that only for Brazil and Venezuela in the case of no regressors, is there a reduction in the orders of integration, though for the latter country, the values are still above 1 and, for Brazil, the unit root is still included in the interval.

| Country | No regressors | | An intercept | | A linear time trend | |
|---|---|---|---|---|---|---|
| | Original | Dif. US | Original | Dif. US | Original | Dif. US |
| ARGENTINA | [0.86 - 1.13] | [0.87 - 1.40] | [0.80 - 1.16] | [0.87 - 1.40] | [0.80 - 1.16] | [0.87 - 1.40] |
| BRAZIL | [0.98 - 1.19] | [0.91 - 1.19] | [1.02 - 1.28] | [1.02 - 1.46] | [1.02 - 1.29] | [1.02 - 1.46] |
| CHILE | [0.80 - 1.10] | [0.77 - 1.20] | [0.69 - 1.06] | [0.75 - 1.14] | [0.63 - 1.06] | [0.74 - 1.14] |
| COLOMBIA | [0.82 - 1.29] | [0.83 - 1.21] | [0.86 - 1.38] | [1.08 - 1.73] | [0.82 - 1.35] | [1.08 - 1.73] |
| MEXICO | [0.85 - 1.17] | [0.90 - 1.22] | [1.01 - 1.26] | [0.94 - 1.44] | [1.01 - 1.27] | [0.94 - 1.44] |
| PERU | [0.69 - 1.07] | [0.84 - 1.20] | [0.72 - 1.08] | [0.89 - 1.44] | [0.72 - 1.08] | [0.88 - 1.44] |
| VENEZUELA | [1.18 - 1.52] | [1.01 - 1.33] | [1.16 - 1.50] | [1.14 - 1.56] | [1.16 - 1.50] | [1.14 - 1.56] |

**Table 1:** *Confidence intervals for the non-rejection values of d in the context of white noise $u_t$*

In bold, those cases for which we find real convergence.

[6] The assumption of uncorrelated disturbances may appear unrealistic. However, it may be of interest when testing I(d) hypotheses. In fact, the autocorrelations decay hyperbolically as opposed to the AR structure where the decay is exponential.

[7] The confidence intervals were built up according to the following strategy. First, a value of d was chosen from a grid. Then, the test statistic was formed testing the null for this value. If the null was rejected at the 5% level, this value of d was discarded. Otherwise, it was kept. An interval was then obtained after considering all the values of d in the grid.

| Country | No regressors | | An intercept | | A linear time trend | |
|---|---|---|---|---|---|---|
| | Original | Dif. US | Original | Dif. US | Original | Dif. US |
| ARGENTINA | [0.69 – 1.25] | **[0.32 – 0.88]** | [0.59 - 1.07] | **[0.47 – 0.88]** | [0.33 - 1.06] | **[0.03 – 0.86]** |
| BRAZIL | [1.00 – 1.45] | [0.76 – 1.27] | [0.96 - 1.36] | [0.49 – 1.23] | [0.91 – 1.40] | [0.32 – 1.23] |
| CHILE | [0.54 – 1.05] | **[0.20 – 0.88]** | [0.48 - 0.71] | [0.47 – 0.89] | [0.02 – 0.63] | [0.05 – 0.88] |
| COLOMBIA | [0.65 – 1.14] | [0.36 – 1.16] | [0.73 – 0.96] | [0.03 – 1.04] | [0.21 – 0.95] | [0.03 – 1.04] |
| MEXICO | [0.73 – 1.45] | [0.75 – 1.27] | [1.00 – 1.49] | [0.33 – 1.10] | [1.00 – 1.51] | [0.45 – 1.10] |
| PERU | [0.41 – 0.66] | [0.58 – 1.06] | [0.50 – 0.70] | [0.30 – 0.73] | [0.36 – 0.71] | [0.28 – 0.74] |
| VENEZUELA | [0.93 – 1.37] | [0.79 – 1.22] | [0.93 – 1.42] | [0.82 – 1.28] | [0.95 – 1.39] | [0.81 – 1.28] |

**Table 2:** *Confidence intervals for the non-rejection values of d in the context of Bloomfield (1)* $u_t$

In bold, those cases for which we find real convergence.

The significance of the above results, however, might be in large part due to the un-accounted for I(0) autocorrelation in $u_t$. Thus, we also fitted other models, taking into account a weakly autocorrelated structure on the disturbances. First, we imposed AR processes and, though not reported in the paper, the results showed a lack of monotonicity in the value of $\hat{r}$ with respect to $d_0$. Such monotonicity is a characteristic of any reasonable statistic, because, for example, we would wish that if d = 0.75 is rejected against d > 0.75, an even more significant result in this direction would be obtained when d = 0.70 or 0.65 is tested. This lack of monotonicity could be explained in terms of model misspecification as is argued, for example, in Gil-Alana and Robinson (1997): frequently misspecification inflates both numerator and denominator of $\hat{r}$ to varying degrees, and thus affects $\hat{r}$ in a complicated way. However, it may also be due to the fact that the AR coefficients are Yule-Walker estimates and thus, though they are smaller than one in absolute value, they can be arbitrarily close to 1. A problem then may occur in that they may be capturing the order of integration of the series by means, for example, of a coefficient of 0.99 in the case of using AR(1) disturbances. In order to solve this problem, we use other forms of I(0) processes. One that seems especially relevant and convenient in the context of the present tests is that proposed by Bloomfield (1973). In his model, the spectral density function is given by:

$$f(\lambda\ ;\ \tau) = \frac{\sigma^2}{2\pi} \exp\left(2 \sum_{r=1}^{m} \tau_r \cos(\lambda r)\right), \tag{8}$$

where m is the number of parameters required to describe the short run dynamics. Like the stationary AR(p) model, the Bloomfield (1973) model has exponentially decaying autocorrelations and thus we can use a model like this for $u_t$ in (7). Formulae for Newton-type iteration for estimating the $\tau_r$

are very simple (involving no matrix inversion), updating formulae when m is increased are also simple, and we can replace $\hat{A}$ in Appendix A by the population quantity:

$$\sum_{l=m+1}^{\infty} l^{-2} = \frac{\pi^2}{6} - \sum_{l=1}^{m} l^{-2},$$

which indeed is constant with respect to the $\tau_r$ (unlike what happens in the AR case). Note that the inclusion of Bloomfield disturbances in the context of fractionally integrated models permits us to consider both the long run and the short run components simultaneously, unlike what happened in the previous case of white noise $u_t$ where only the long run effect was taken into account.

Table 2 displays the results based on Bloomfield (with m = 1) disturbances. Other values for m were also tried and the results were very similar to those reported here [8]. Looking at the original series, we observe that the intervals are generally smaller to the previous case of white noise $u_t$, which may be explained by the fact that the autocorrelated structure is now competing with the order of integration in describing partly the nonstationary character of the series. Here, we observe more cases where the intervals are smaller for the differenced data. Following Bernard and Durlauf (1995) we interpret this result as evidence of a set of common long-run factors which jointly determine the per capita output of the analyzed countries, which could be explained by the increasing openness and trade relationships among these countries. Thus, for example, Argentina, Brazil and Venezuela present smaller intervals for the three cases of no regressors, an intercept and a linear trend. We also observe smaller degrees of integration in some cases for Chile and Mexico, while for Colombia and Peru, we can infer that there is no reduction in the orders of integration. In any case, the most interesting cases are those where the intervals for the differenced series are strictly below 1, and this specifically happens for Argentina (in all cases) and Chile (with no regressors).

Next, we concentrate on the Asian countries and their differences with respect to the US and Japan, performing the same statistics as in Tables 1 and 2, again with white noise (Table 3) and autocorrelated (Table 4) disturbances. Assuming that $u_t$ is white noise, we see that for India, there is no reduction in the intervals neither with respect to the US nor to Japan. However, for the remaining three countries, (Indonesia, Taiwan and South Korea), the intervals are smaller with respect to both countries, which as before, may be interpreted as evidence of a long-run relationship between the per capita output of each country with respect to both the US and Japan.

[8] Using (10), the $\tau_r$ in (9) were estimated by a Gauss-Newton iteration, convergence being achieved within about seven iterative steps throughout.

This reduction seems to be more remarkable with respect to Japan in the cases of Indonesia and Taiwan. Thus, for example, the confidence intervals for Taiwan range between 1.07 and 1.45, while the differences with respect to Japan are between 0.71 and 0.98, implying that real convergence (with respect to Japan) takes place in this country [9]. This economy has experienced an extraordinarily rapid and sustained growth of output per capita (see Young, 1995) in recent decades. From 1966 to 1990, the GDP per capita growth rate averaged 8.5%, investment rate grew from a constant price investment to a GDP ratio of 10% in the early 1950s to 20% in 1990, and human capital accumulation has also rapidly increased. Furthermore, there have been large intersectoral reallocations of labour from the agricultural sector towards the services and industry sectors, and a rapid increase in its manufacturing exports. Some authors, such as Hsiao and Hsiao (2003) argue that the increasing openness of this economy and its trade and economic relationships with Japan and the US is the major driving force of Taiwan's "miracle growth". Furthermore, De Gregorio and Lee (2003) find that the main factors which explain the difference in per capita GDP growth rates between East Asian and Latin American countries between 1960-2000 are investment, population growth, the quality of human resources and economic policy and institutional factors such as macroeconomic stability and the degree of openness.

| Country | No regressors | | An intercept | | A linear time trend | |
|---|---|---|---|---|---|---|
| | Original | Dif. US<br>Dif. JAPAN | Original | Dif.US<br>Dif . JAPAN | Original | Dif. US<br>Dif. JAPAN |
| INDIA | [0.82 – 1.00] | [0.83 - 1.14]<br>[0.82 - 1.12] | [0.88 – 1.02] | [0.87 – 1.18]<br>[0.94 – 1.21] | [0.87 – 1.02] | [0.87 – 1.17]<br>[0.93 – 1.21] |
| INDONESIA | [1.26 – 1.69] | [0.98 - 1.33]<br>[0.89 - 1.19] | [1.33 – 1.83] | [1.31 – 1.82]<br>[0.92 – 1.18] | [1.33 – 1.83] | [1.31 – 1.83]<br>[0.91 – 1.18] |
| TAIWAN | [1.07 – 1.45] | [0.93 - 1.24]<br>**[0.71 – 0.99]** | [1.07 – 1.45] | [1.09 – 1.58]<br>**[0.73 – 0.98]** | [1.08 – 1.45] | [1.09 – 1.58]<br>**[0.73 – 0.98]** |
| SOUTH KOREA | [1.01 - 1.28] | [0.88 - 1.18]<br>[0.94 - 1.20] | [1.01 – 1.28] | [1.00 – 1.24]<br>[1.00 – 1.25] | [1.01 – 1.29] | [1.00 – 1.25]<br>[1.00 – 1.25] |

**Table 3:** *Confidence intervals for the non-rejection values of d in the context of white noise* $u_t$

In bold, those cases for which we find real convergence.

[9] However, a detailed inspection of the data suggests that the real convergence process in this country has not been uniform across the whole period. In the pre-war period (1911-1940), Taiwan's average growth rate was 1.18% and that of Japan was 2.64%, while the differences between the per capita GDP of these economies experienced an important decrease since the 70s. In the transition period, the differences between the two economies increased since the Japanese recovery occurred earlier and Japan was the most successful country to adapt and transform its economy to that of electronics, a transformation which occurred later in Taiwan (see, Hsiao and Hsiao, 2003).

| Country | No regressors | | An intercept | | A linear time trend | |
|---|---|---|---|---|---|---|
| | Original | Dif. US<br>Dif . JAPAN | Original | Dif.US<br>Dif. JAPAN | Original | Dif. US<br>Dif. JAPAN |
| INDIA | [0.79 - 1.11] | [0.47 - 1.11]<br>[0.65 - 1.11] | [1.10 - 1.40] | [0.73 - 1.22]<br>[0.83 - 1.39] | [1.11 - 1.42] | [0.71 - 1.23]<br>[0.78 - 1.38] |
| INDONESIA | [0.81 - 1.70] | [0.63 - 1.37]<br>[0.73 - 1.31] | [0.75 - 1.39] | [0.57 - 1.37]<br>[0.83 - 1.30] | [0.67 - 1.39] | [0.56 - 1.36]<br>[0.78 - 1.29] |
| TAIWAN | [0.80 - 1.07] | [0.70 - 1.20]<br>**[0.44 - 0.85]** | [0.79 - 1.05] | [0.71 - 1.05]<br>**[0.59 - 0.90]** | [0.76 - 1.06] | [0.68 - 1.06]<br>**[0.58 - 0.90]** |
| SOUTH KOREA | [0.88 - 1.24] | [0.72 - 1.19]<br>[0.60 - 1.13] | [0.90 - 1.27] | [0.95 - 1.43]<br>[0.93 - 1.26] | [0.88 - 1.28] | [0.94 - 1.44]<br>[0.93 - 1.26] |

**Table 4:** *Confidence intervals for the non-rejection values of d in the context of Bloomfield (1) $u_t$*

In bold, those cases for which we find real convergence.

If $u_t$ is autocorrelated, we find evidence of smaller degrees of integration in all the differenced series with respect to both, the US (specially, in the cases of India and Indonesia) and Japan (specially, Taiwan and South Korea). Additionally, and similarly to the previous table, we observe that the difference in Taiwan with respect to Japan is the only series where the intervals are strictly below 1, implying mean reversion, and giving us strong evidence of real convergence. Moreover, since the tests include the cases of no regressors, an intercept and an intercept with a linear trend, we can distinguish between long-run unconditional or conditional convergence and convergence as a catch-up (in the case of a linear trend). In the cases of Argentina with respect to the US and Taiwan with respect to Japan, we obtain a significant intercept and a non-significant linear trend, thus suggesting the existence of conditional convergence. However, we find evidence of unconditional convergence for the case of Chile with respect to US [10].

The results presented so far, based on Robinson's (1994) parametric tests, show that there is evidence of convergence for the cases of Argentina and Chile with respect to the US and for Taiwan with respect to Japan. In order to check if these results are robust to the different methods of fractional integration, we also tried Sowell's (1992) procedure of estimation by maximum likelihood in the time domain. The results here were completely in line with those based on Robinson's (1994) tests, which is not surprising if we take into account that Robinson (1994) is based on the Whittle function, which is an approximation to the likelihood function. On the other hand, the use of fully parametric models (Sowell, 1992; Robinson, 1994) may lead to inconsistent estimates of the fractional differencing parameter if the model is not correctly specified. Thus, we also employed a semiparametric approach, (Robinson, 1995a) that we now describe below.

[10] Note that the coefficients of the intercept and the linear time trend are OLS, which are based on the $d_o$-differenced model, which has short memory under the null. Thus, standard t-tests still remain valid.

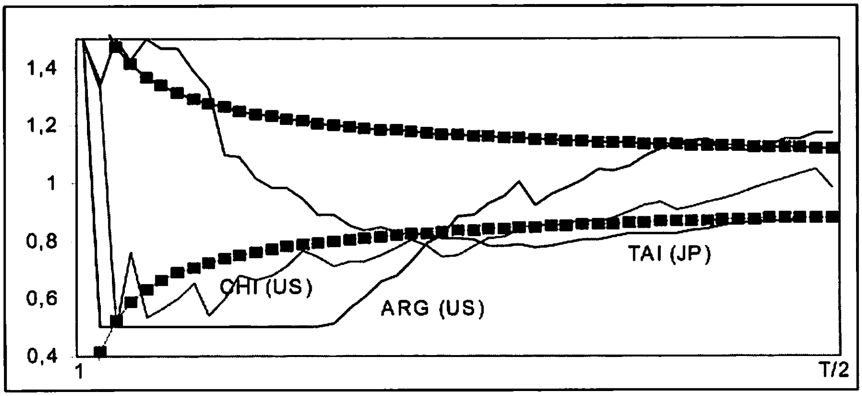
The Whittle semiparametric method of Robinson (1995a) is basically a Whittle estimator in the frequency domain, using a band of frequencies that degenerates to zero. The estimate ($\hat{d}$) is described in Appendix B.

Under finiteness of the fourth moment and other mild conditions, Robinson (1995a) proved that:

$$\sqrt{m}\,(\hat{d} - d_0) \to_d N(0, 1/4) \quad \text{as} \quad T \to \infty,$$

where $d_0$ is the true value of d.

Using the Whittle semiparametric method, the results were once more in line with the parametric ones. In fact, the unit root null hypothesis cannot be rejected in the differenced series in most of the cases, the main exceptions being Argentina and Chile (in the case of their differences with respect to the US) and Taiwan (with respect to Japan).




*Estimates of d based on the Whittle semiparametric approach (Robinson, 1995a)*

The horizontal axe refers to the bandwidth number m, while the vertical one is the estimated value of d.

Figure 1 displays the results based on Robinson (1995a) for the three differenced series. We report the results for the whole range of values of the bandwidth number m (= 1, 2, ..., T/2), along with the 95% confidence interval corresponding to the I(0) hypothesis. It is observed for the three series that the estimates of d are in many cases below the I(0) interval, suggesting thus the existence of convergence for the three countries.

## 5 Concluding remarks

In this article we have examined the real convergence hypothesis in eleven emerging Latin American and Asian countries by means of fractional integration techniques. In particular, we have examined the order of integration of the log real GDP per capita series in Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, India, Indonesia, Taiwan and South Korea, along with their differences with respect to the US for all of the above countries, and also with respect to Japan for the Asian countries. For this purpose we have employed a parametric testing procedure due to Robinson (1994). This method has several distinguishing features compared with other procedures. Thus, it allows us to consider unit and fractional roots with no effect on its standard null limit distribution, which is also unaffected by the inclusion of deterministic trends and different types of I(0) disturbances. These tests are the most efficient ones when directed against the appropriate (fractional) alternatives. In addition, we also employed a semiparametric approach.

Using the parametric procedure of Robinson (1994), the results support that all the individual series may be specified in terms of a unit root model and, though not reported across the tables, evidence of unit roots was also found for the cases of the US and Japan [11]. Performing the same tests on the differenced data, the results vary substantially depending on how we specify the I(0) disturbances. Thus, if they are white noise, we observe smaller degrees of integration for the differenced series only in the cases of Brazil and Venezuela among the Latin American countries and Taiwan, South Korea and Indonesia among the Asian countries, though in all except Taiwan (with respect to Japan), the confidence intervals include the unit root. Thus, evidence of real convergence is only explicitly shown for the Taiwanese case.

If the disturbances are weakly autocorrelated, smaller degrees of integration for the differenced series are obtained in all Latin American countries except Colombia and Peru, though Argentina and Chile seem to be the only ones where mean reversion takes place. For the Asian countries, we find smaller degrees of integration for all the four countries (including India) with respect to both the US (especially in the cases of India and Indonesia) and Japan (in the cases of Taiwan and South Korea). This result may suggest the existence of different convergence clubs among Asian countries, since we observe a different performance of two of the Asian Tigers (as Taiwan and South Korea) compared to other countries in the same region (such as India or Indonesia). Finally, the differences in Taiwan with respect to Japan appear once more as the only series where the intervals are strictly below 1, implying that mean reversion (and thus real convergence) really takes place in this country. Moreover, we find evidence of conditional convergence for the cases of Argentina-US and Taiwan-Japan and unconditional convergence for the case of Chile-US.

The same type of analysis was also performed using other parametric and semiparametric methods for estimating and testing the fractional differencing parameter (*e.g.*, Sowell, 1992, Tanaka, 1999, Robinson, 1995a,b).

[11] Other unit-root tests based on autoregressive (AR) models (i.e., Dickey and Fuller, 1979, Kwiatkowski et al., 1992) were also performed on the original series and the evidence was in favour of unit roots in all cases.

Using parametric methods, the results were qualitatively similar to those reported here, finding evidence of convergence for the same pairs of countries as here. Using, however, semiparametric methods, the conclusions were a bit more ambiguous, the results being very sensitive to the choice of the bandwidth parameter numbers.

This article can be extended in several directions. First, the tests of Robinson (1994) can be extended to a multivariate set-up and this would lead to the study of cointegration for a panel of the Latin American or Asian countries. Moreover, within each region, we could successively consider each country as the reference one. In doing so, we could determine the composition of the cluster of convergence but, on the other hand, using that approach we would lose the information regarding the leading economies of the US and Japan. Also, Bloomfield's (1973) model seems to perform well in our work and it can also be elaborated in a multivariate context. Note that in this paper, we have employed a very simplistic version of cointegration, i.e., imposing the restriction (1, -1) on the cointegrating vector. Of course, these coefficients can also be estimated, though the literature on fractional cointegration is still in its infancy. (See, *e.g.*, Gil-Alana, 2003; Robinson and Hualde, 2002, 2003; etc.). In that respect, we have considered it more convenient to report the results based on the original (differenced) data rather than on the estimated values. The potential presence of structural breaks is another issue that may be examined in connection with these data. Note that the Robinson's tests (1994) described in this paper permit us to include dummy variables to take into account breaks, with no effect on its standard null limit distribution. However, a proper study on this would require a detailed examination of the time and the type of the break, and this is not within the scope of the present work. Other issues such as the inclusion of explanatory variables in the regression model can also be studied. How the implementation of these issues affect the conclusions obtained in this article and will be addressed in future papers.

## References

Aghion, P. and P. Howitt, (1992), "A model of growth through creative destruction", *Econometrica*, vol. 60, pp. 323-351.

Bernard, A.B., (1991), "Empirical Implications of the Convergence Hypothesis", Working Paper, *Center for Economic Policy Research*, Stanford University.

Bernard, A.B. and S.N. Durlauf, (1991), "Convergence of international output movements", *NBER, Working Paper* 3717.

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

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

Bloomfield, P., (1973), "An exponential model in the spectrum of a scalar time series", *Biometrika*, 60, pp. 217-226.

Campbell, J.Y. and N.G. Mankiw (1989), "International evidence on the persistence of economic fluctuations", *Journal of Monetary Economics*, vol. 23, pp. 319-333.

Carlino, G.A. and L.O. Mills (1993), "Are U.S. regional incomes converging? A time series analysis", *Journal of Monetary Economics*, vol. 32, pp. 335-346.

Cellini, R. and A. Scorcu, (2000), Segmented Stochastic Convergence Across the G7 Countries, Empirical Economics, 25, pp. 463-474.

Cogley, T., (1990), "International evidence on the size of the random walk in output", *Journal of Political Economy*, vol. 98, pp. 501-518.

Dahlhaus, R., (1989), "Efficient parameter estimation for self-similar process", *Annals of Statistics*, vol. 17, pp, 1749-1766.

De Gregorio, J., (1999), "Economic growth in Latin America: sources and prospects", *Universidad de Chile, Documentos de trabajo* 66.

De Gregorio, J. and J.W. Lee (2003), "Growth and adjustment in East Asia and Latin America", *Central Bank of Chile, Working Papers* 245.

Dickey, D. A. and W. A. Fuller (1979), "Distribution of the estimators for autoregressive time series with a unit root", *Journal of the American Statistical Association*, vol. 74, pp. 27-431.

Dolado, J.J., J. Gonzalo and L. Mayoral (2002), "A fractional Dickey-Fuller tests", *Econometrica*, vol. 70, pp. 1973-2006.

Easterly, W., (1995), "Explaining miracles: Growth regressions meet the gang of four", in T. Ito and A. O. Krueger (eds.), Growth Theories in Light of the East Asian Experience, University of Chicago Press, Chicago, 267-290.

Fuller, W.A., (1976), "Introduction to statistical time series", Wiley, New York, NY.

Geweke, J. and S. Porter-Hudak (1983), "The estimation and application of long memory time series models", *Journal of Time Series Analysis*, vol. 4, pp. 221-238.

Gil-Alana, L.A., (2000), "Evaluation of Robinson's (1994) tests in finite sample", *Journal of Statistical Computation and Simulation*, vol. 68, pp. 39-54.

Gil-Alana, L.A., (2003), "Testing of fractional cointegration in macroeconomic time series", *Oxford Bulletin of Economics and Statistics*, vol. 65, pp. 517-529.

Hsiao, F.S.T. and M.C.W. Hsiao, (2003), "Miracle growth in the twentieth century-international comparisons of east asian development", *World Development*, vol. 31, pp. 227-257.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt, and Y. Shin (1992), "Testing the null hypothesis of stationarity against the alternative of a unit root", *Journal of Econometrics*, vol. 54, pp. 159-178.

Lim, L.K. and M. McAleer (2000), "Convergence and catching up in South-East Asia: A comparative Analysis", *Econometric Society World Congress* 2000, Contributed Paper 1844.

Loewy, M. and D. Papell (1996), "Are US regional income converging? Some further evidence", *Journal of Monetary Economics*, vol. 38, pp. 587-598.

Lucas, R., (1988), "On the mechanics of economic development", *Journal of Monetary Economics*, vol. 22, pp. 3-41.

Maddison, A., (1995), "Monitoring the world economy 1820-1992", Paris, OECD.

Marinucci, D. and P.M Robinson (1999), "Semiparametric fractional cointegration models", *Journal of Statistical Planning and Inference*, vol. 80, pp. 111-122.

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

Robinson, P.M., (1994), "Efficient tests of nonstationary hypotheses", *Journal of the American Statistical Association*, vol. 89, pp. 1420-1437.

Robinson, P.M., (1995a), "Gaussian semiparametric estimation of long range dependence", *Annals of Statistics*, vol. 23, pp. 1630-1661.

Robinson, P.M., (1995b), "Log-periodogram regression of time series with long range dependence", *Annals of Statistics*, 23, 1048-1072.

Robinson, P.M. and J. Hualde (2002), "Root-N consistent estimation of weak fractional cointegration", *Preprint.*

Robinson, P.M. and J. Hualde (2003), "Cointegration in fractional systems with unknown integration orders", *Econometrica*, vol. 71, pp. 1727-1766.

Romer, P., (1986), "Increasing returns and long-run growth", *Journal of Political Economy*, vol. 94, pp. 1002-1037.

Schmidt, P. and P.C.B. Phillips (1992), "LM tests for a unit root in the presence of deterministic trends", *Oxford Bulletin of Economics and Statistics*, vol. 54, pp. 257-287.

Silverberg, G. and B. Verspagen (1999), "Long memory in time series of economic growth and convergence", *Eindhoven Centre for Innovation Studies, Working Paper* 99.8.

Solow, R.M., (1956), "A contribution to the theory of economic growth", *Quarterly Journal of Economics*, vol. 70, pp. 65-94.

Sowell, F., (1992), "Maximum likelihood estimation of stationary univariate fractionally integrated time series models", *Journal of Econometrics*, vol. 53, pp. 165-188.

Tanaka, K., (1999), "The nonstationary fractional unit root", *Econometric Theory*, vol. 15, pp. 549-582.

Young, A., (1992), "A tale of two cities: Factor accumulation and technical change in Hong Kong and Singapore", *NBER Macroeconomics Annual*, pp. 13-54.

Young, A., (1995), "The tyranny of numbers: Confronting the statistical realities of the east Asian growth experience", *Quarterly Journal of Econometrics*, vol. 110, pp. 641-680.

## Appendix A

The test statistic proposed by Robinson (1994) is based on the Lagrange Multiplier (LM) principle, and is given by:

$$\hat{r} = \frac{T^{1/2}}{\hat{\sigma}^2} \hat{A}^{-1/2} \hat{a},$$

where T is the sample size and

$$\hat{a} = \frac{-2\pi}{T} \sum_{j=1}^{T-1} \psi(\lambda_j) g(\lambda_j\,;\,\hat{\tau})^{-1} I(\lambda_j)\,;\; \hat{\sigma}^2 = \sigma^2(\hat{\tau}) = \frac{2\pi}{T} \sum_{j=1}^{T-1} g(\lambda_j\,;\,\hat{\tau})^{-1} I(\lambda_j)$$

$$\hat{A} = \frac{2}{T}\left( \sum_{j=1}^{T-1} \psi(\lambda_j)^2 - \sum_{j=1}^{T-1} \psi(\lambda_j)\hat{\varepsilon}(\lambda_j)' \times \left( \sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\hat{\varepsilon}(\lambda_j)' \right) \times \sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\psi(\lambda_j) \right)$$

$$\psi(\lambda_j) = \log \left| 2 \sin \frac{\lambda_j}{2} \right|\,;\; \hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial \tau} \log g(\lambda_j\,;\,\hat{\tau})\,;\; \lambda_j = \frac{2\pi j}{T}$$

$$\hat{\tau} = \arg\min_{\tau \in T^*} \sigma^2(\tau),$$

where $T^*$ is a compact subset of the $R^q$ Euclidean space. $I(\lambda_j)$ is the periodogram of $u_t$ evaluated under the null, $\hat{u}_t = (1-L)^{d_o} y_t - \hat{\beta}' w_t$;

$\hat{\beta} = \left( \sum_{t=1}^{T} w_t w_t' \right)^{-1} \sum_{t=1}^{T} w_t (1-L)^{d_0} y_t\,;\quad w_t = (1-L)^{d_0} z_t$ and g above is a known function coming from the spectral density of $u_t$, $f = (\sigma^2/2\pi)g$. Note that these tests are purely parametric and therefore, they require specific modelling assumptions regarding the short memory specification of $u_t$. Thus, if $u_t$ is white noise, $g \equiv 1$, (and thus, $\hat{\varepsilon}(\lambda_j) = 0$), and if $u_t$ is an AR process of form $\phi(L)u_t = \varepsilon_t$, $g = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of $\tau$.

## Appendix B

The estimate of Robinson (1995) is implicitly defined by:

$$\hat{d} = \arg\min_d \left( \log \overline{C(d)} - 2d \frac{1}{m} \sum_{j=1}^{m} \log \lambda_j \right)$$

$$\text{for } d \in (-1/2, 1/2)\,;\ \overline{C(d)} = \frac{1}{m} \sum_{j=1} I(\lambda_j)\lambda_j^{2d}\,;\ \lambda_j = \frac{2\pi j}{T},\ \frac{m}{T} \to 0$$

where m is a bandwidth parameter number.