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ABSTRACT

This article examines the real convergence hypothesis in 15 OECD countries. For this purpose, we examine the order of integration of the real GDP per capita series in these countries as well as their differences with respect to the US which is used as a benchmark country. We use both parametric and semiparametric methods and the results show that convergence is only achieved in half of the countries, namely, Austria, Australia, Canada, Finland, Germany, Japan and the UK. On the contrary, the results for Belgium, Denmark, France, Italy, the Netherlands, Norway and Sweden show strong evidence against this hypothesis.

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1. Introduction

In parallel with the literature on economic growth, recent years have witnessed an emerging body of empirical literature on convergence in per capita output across different economies. The interest on this subject may be explained, at least in part, as a test of the prediction of the neoclassical growth model (Solow, 1956) as opposed to the "new" endogenous growth models (Romer, 1986, Lucas, 1988). As it is well known, the neoclassical model predicts (under some assumptions) that per capita output in an economy will convergence to each country's steady-state (conditional convergence) or to a common steady-state (unconditional convergence), regardless of its initial per capita output level. 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 (e.g., incorporating nonconvexities in the production function).

Empirical testing of the convergence hypothesis provide several definitions of convergence and thus, different methodologies to test it. In a cross-section approach, a negative (partial) correlation between growth rates and initial income is interpreted as evidence of unconditional (conditional) beta-convergence. In this context, one of the most generally accepted result is that while there is not evidence of unconditional convergence among a broad sample of countries, the conditional convergence hypothesis holds when examining more homogenous group of countries (or regions) or when conditioning for additional explanatory variables. Examples in this context are Baumol (1986), De Long (1988), Dowrick and Nguyen (1989), Grier and Tullock (1989), Barro (1991), Barro and Sala-i-Martin (1991, 1992, 1995), Mankiw, Romer and Weil (1992), etc. Using cross-sectional regressions, Dowrick and Nguyen (1989) found evidence of absolute convergence among OECD countries during the period 1950-1985. This result is reinforced when some conditioning variables are included in the regression model. For instance, Barro (1991) find a negative partial correlation between the growth rate of real per capita GDP of 98 countries in the period 1960-85 when controlling for some variables such as human capital, physical investment or different measures of political instability. Additionally, Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) used respectively 20 and 22 OECD countries from 1960 to 1985 and found evidence of conditional convergence holding population growth and capital accumulation constant.

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 countries' output, that is, it examines, whether common stochastic elements matter, and how much persistent the differences among countries are. Thus, stochastic convergence implies that output differences between economies cannot contain unit roots or time trends. 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 one when analyzing convergence among 15 OECD countries over the period 1900-1987, while the second one can only reject the non-convergence hypothesis for the pairs US-Germany, US-Japan and France-Italy. However, Carlino and Mills (1993) and Lowey 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.

When the convergence tests take into account the possibility of structural breaks, the evidence of convergence is reinforced. Greasley and Oxley (1997) found evidence of bivariate convergence between Belgium and Netherlands, France and Italy, Australia and the UK, and Sweden and Denmark. St. Aubyn (1999) finds evidence of convergence between US and each of the UK, Australia and Japan, using the Kalman filter methodology. Cellini and Scorcu (2000) detect stochastic convergence only for the US and Canada, and the US and UK when they allow for structural breaks. Strazicich, Lee and Day (2001) examine the differences in per capita incomes of fifteen OECD countries with the US economy over the period 1870-1994 allowing for two structural breaks and they reject the unit root null hypothesis in eleven of the fifteen countries, thus supporting the stochastic convergence hypothesis.

In this paper, we define real convergence as mean reversion in the differences in per capita output among countries and we test this hypothesis using a methodology based on fractional integration. The fractional integration approach has already been applied to test real convergence in Michelacci and Zaffaroni (2000), Silverberg and Verspagen (2001) and Dolado, Gonzalo and Mayoral (2002a). Michelacci and Zaffaroni (2000) use a log-periodogram regression estimate, initially proposed by Geweke and Porter-Hudak (1983) and modified later by Robinson (1995a) which is highly biased in small samples. To avoid this small sample bias problem, Silverberg and Verspagen (2001) employ the nonparametric FGN estimator due to Beran (1994) and the Sowell's (1992) parametric maximum likelihood estimation method. Dolado, Gonzalo and Mayoral (2002a) use the Fractional Dickey- Fuller test proposed by the authors in Dolado et al (2002b). In this study, we use both parametric and semiparametric techniques which have some advantages compared with other procedures. When the convergence hypothesis is analyzed by means of these methodologies based on fractional integration, the results are mixed. Michelacci and Zaffaroni could not reject the hypothesis that all the OECD countries 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 an hyperbolic very slow rate. However, Silverberg and Verspagen (1999) find significant long memory (with $d > 1$) in the time series of GDP per capita relative to the US, and thus, no evidence of convergence, although their overall conclusion depends on the application of the FGN model. Dolado, Gonzalo and Mayoral (2002a) show that, after dealing with small sample bias and a deterministic trend, there is strong evidence in favor of an integration order between 0 and 1 in most of the countries in the sample. Therefore, and similarly to Michelacci and Zaffaroni, their results support evidence that convergence among OECD countries occurs according to a long memory process. The outline of this paper is as follows. In Section 2, we describe alternative methods that will be employed in this article. Section 3 covers the empirical analysis and Section 4 offers some conclusions.

2. 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 the zero frequency. In this context, we say that a given raw time series $\{x_t, t = 0, \pm 1, ...\}$ is I(d) if

$$(1 - L)^d \; x_t \; = u_t, \qquad t \; = 1, 2, ..., \qquad (1)$$

$$x_t \; = \; 0, \qquad t \; \leq \; 0,$$

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

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

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, also called ‘strongly autocorrelated’, so-named 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. These processes were initially introduced by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981), (though earlier work by Adenstedt, 1974, and Taqqu, 1975 shows an awareness of its representation), and were theoretically justified in terms of aggregation of ARMA processes with randomly varying coefficients by Robinson (1978), Granger (1980). Similarly, Croczek-Georges and Mandelbrot (1995), Taqqu et. al. (1997), Chambers (1998) and Lippi and Zaffaroni (1999) also use aggregation to motivate long memory processes, while Parke (1999) uses a closely related discrete time error duration model. Empirical applications based on fractional models like (1) are among others Diebold and Rudebusch (1989), Baillie and Bollerslev (1994), Gil-Alana and Robinson (1997) and Gil-Alana (2000).

To determine the appropriate degree of integration in a given raw time series is important from both economic and statistical viewpoints. If d = 0, the series is covariance stationary and possesses 'short memory', with the autocorrelations decaying fairly rapid. If d belongs to the interval (0, 0.5), x_t is still covariance stationary, however, the autocorrelations take much longer time to disappear than in the previous case. If $d \in [0.5, 1)$, the series is not longer covariance stationary, but it is still mean reverting, with the effect of the shocks dying away in the long run. Finally, if $d \geq 1$, 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: higher d is, higher will be the association between the observations.

There exist many approaches of estimating and testing the fractional differencing parameter d (see, eg. Geweke and Porter-Hudak, 1983, Dahlhaus, 1989, Sowell, 1992, etc.). In this article we will make use of both parametric and semiparametric methods. First, we will present a parametric testing procedure due to Robinson (1994a) that pemits us to test I(d) statistical models in raw time series. Then, several other (semiparametric) methods will be described.

2.1 A parametric testing procedure

Robinson (1994a) proposed a Lagrange Multiplier (LM) test of the null hypothesis:

$$H_o: \; d = d_o. \qquad (2)$$

in a model given by

$$y_t \;=\; \beta' z_t \;+\; x_t, \qquad t \;=\; 1, 2, ..., \qquad (3)$$

and (1), for any real value d_o, where y_t is the time series we observe; $\beta = (\beta_1, \ldots, \beta_k)'$ is a (kx1) vector of unknown parameters; and z_t is a (kx1) vector of deterministic regressors that may include, for example, an intercept, (eg. $z_t \equiv 1$), or an intercept and a linear time trend, (in case of $z_t = (1,t)'$). Specifically, the test statistic is given by:

$$\hat{r} \;=\; \frac{T^{1/2}}{\hat{\sigma}^2}\, \hat{A}^{-1/2}\, \hat{a} \qquad (4)$$

where T is the sample size and

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

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

$$\psi(\lambda_j) = \log\left|2\sin\frac{\lambda_j}{2}\right|; \qquad \hat{\varepsilon}(\lambda_j) \;=\; \frac{\partial}{\partial \tau}\log g(\lambda_j;\hat{\tau}); \qquad \lambda_j \;=\; \frac{2\pi j}{T}; \qquad \hat{\tau} \;=\; \arg\min \sigma^2(\tau).$$

$I(\lambda_j)$ is the periodogram of u_t evaluated under the null, i.e.,

$$\hat{u}_t \;=\; (1 \,-\, L)^{d_o}\, y_t \;-\; \hat{\beta}' w_t;$$

$$\hat{\beta} \;=\; \left(\sum_{t=1}^{T} w_t\, w_t'\right)^{-1}\sum_{t=1}^{T} w_t\,(1 \,-\, L)^{d_o}\, y_t; \qquad w_t \;=\; (1 \,-\, L)^{d_o}\, z_t,$$

and the function g above is a known function coming from the spectral density function of u_t,

$$f(l;s^2;t) = \frac{s^2}{2p} g(l;t), \qquad -p < l \leq p.$$

Note that these tests are purely parametric and therefore, they require specific modelling assumptions to be made regarding the short memory specification of u_t. Thus, if u_t is white noise, g ≡ 1, 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 function of τ.

Based on the null hypothesis H_o (2), Robinson (1994a) established that under certain regularity conditions:

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

and also the Pitman efficiency theory 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 (2) 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_α is α. This version of the tests of Robinson (1994a) was used in empirical applications in Gil-Alana and Robinson (1997) and Gil-Alana (2000) and, other versions of his tests, based on seasonal, (quarterly and monthly), and cyclical data can be respectively found in Gil-Alana and Robinson (2001) and Gil-Alana (1999, 2001a).

A problem with the parametric procedures is that the model must be correctly specified. Otherwise, the estimates are liable to be inconsistent. In fact, misspecification of the short run components of the process may invalidate the estimation of the long run parameter d. This is the main reason for using also in this article a semiparametric procedure that we are now to describe.

2.2 A semiparametric estimation procedure

There exist several methods for estimating the fractional differencing parameter in a semiparametric way. Examples are the log-periodogram regression estimate (LPE), initially proposed by Geweke and Porter-Hudak (1983) and modified later by Kunsch (1986) and Robinson (1995a), the average periodogram estimate, (APE, Robinson, 1994b) and the quasi maximum likelihood estimate (QMLE, Robinson, 1995b). In this article we use the QMLE of Robinson (1995b) which we are now to describe.

It is basically a local "Whittle estimate" in the frequency domain, considering a band of frequencies that degenerates to zero. The estimate is implicitly defined by:

$$d_1 = \arg\min_d \left(\log \overline{C(d)} - 2d \, \frac{1}{m} \sum_{j=1}^{m} \log l_j \right), \qquad (6)$$

$$for \;\; d \in (-1/2\,,\, 1/2)\,; \quad \overline{C(d)} = \frac{1}{m} \sum_{j=1}^{m} I(l_j)\, l_j^{2d}, \quad l_j = \frac{2pj}{T}, \quad \frac{m}{T} \rightarrow 0.$$

Under finiteness of the fourth moment and other conditions, Robinson (1995b) proves the asymptotic normality of this estimate, while Lobato (1999) extended it to the multivariate case.

The other methods also based on semiparametric models (like the APE and the LPE) have been successfully applied to economic time series (see, eg. Gil-Alana, 2001b), however, recent empirical finding (Gil-Alana, 2002), based on Monte Carlo simulations show that the QMLE of Robinson (1995b) outperform the others in a number of cases.

3. 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 runs from 1870 to 2001 for 14 OECD countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, The

Netherlands, Norway, Sweden, UK, US) and from 1885-2001 for Japan. The data for the period 1870-1994 have been obtained from Maddison (1995) and these series have been updated using the GGDC (Groningen Growth and Development Center) Database 2002. As indicator of real convergence, we use the differences of the per capita GDP of each of the 15 countries with respect to the US economy, used as the benchmark country. This indicator has been widely used in other empirical works based on convergence (e.g., St. Aubyn, 1999, Silverberg and Verspagen, 2001, etc.) [1].

The first thing that we do here is to peform the tests of Robinson (1994a) described in Section 2.1 to the individual series as well as to their differences with respect to the US. Denoting each of the the time series y_t, we employ throughout the model given by (1) and (3), with $z_t = (1,t)'$, $t \geq 1$, $z_t = (0,0)'$. Thus, under the null hypothesis H_o (2):

$$y_t \;=\; \beta_0 \;+\; \beta_1 t \;+\; x_t\,, \qquad t = 1, 2, \ldots \qquad (7)$$

$$(1 \;-\; L)^{d_o}\; x_t \;=\; u_t\,, \qquad t = 1, 2, \ldots . \qquad (8)$$

and we treat separately the cases $\beta_0 = \beta_1 = 0$ a priori; β_0 unknown and $\beta_1 = 0$ a priori; and β_0 and β_1 unknown, i.e., we consider respectively the cases of no regressors in the undifferenced regression (7), an intercept, and an intercept and a linear time trend. We will model the I(0) process u_t to be both white noise and to have parametric autocorrelation.

We start with the assumption that u_t in (8) is white noise. 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, we report test statistics not merely for the null $d_o = 1$ in (2) but for d_o = 0, (0.25), 2, thus including also a test for stationarity (d_o = 0.5) and for I(2) (d_o = 2), as well as other fractionally integrated possibilities.

[1] There are alternative measures for convergence in the literature. Strazicich, Lee and Day (2001), for example, use the differences of per capita GDP of each of the countries with an average of the analyzed economies as an indicator of convergence.

The test statistic reported across Table 1 (and also in Tables 2 – 4), is the one-sided one corresponding to $\hat{r}$ in (4), so that significantly positive values of this are consistent with orders of integration higher than d_o, whereas significantly negative ones are consistent with alternatives of form: $d < d_o$. A notable feature observed in Table 1(i), in which u_t is taken to be white noise (when the form of $\hat{r}$ significantly simplifies) and $\beta_o = \beta_1 = 0$ a priori, is the fact that we cannot reject the unit-root hypothesis in any of the countries, while in three of them (Finland, Germany and Italy) we cannot reject d = 1.25. However, in some of the countries, we observe also some lack of monotonic decrease of $\hat{r}$ as d_o increases. Such monotonicity is a characterisitc of any reasonable statistic, given correct specification and adequate sample size, because for example, we would wish that if H_o (2) is rejected with $d_o = 1$ against alternatives of form: H_a: d > 1, an even more significant result in this direction should be expected when $d_o = 0.75$ or $d_o = 0.50$ are tested. However, in the event of misspecification (which in this specialized model can be due to a departure from white noise in u_t, to y_t having a drift, or to both) monotonicity is not necessarily to be expected: frequently misspecification inflates both numerator and denominator of $\hat{r}$ to varying degrees, and thus affects $\hat{r}$ in a complicated way. Computing $\hat{r}$ for a range of d_o values is thus useful in revealing possible misspecification, though monotonicity is by no means necessarily strong evidence of correct specification.

(Insert Table 1 about here)

Tables 1(ii) and (iii) give results with, respectively, $\beta_1 = 0$ a priori (no time trend in the undifferenced regression) and both β_0 and β_1 unrestricted, still with white noise u_t. In every case in both tables, $\hat{r}$ is monotonic, and moreover, while there are sometimes large differences in the value of $\hat{r}$ across Tables 1(ii) and (iii) for the same series/d_o combination, the conclusions suggested by both seem very similar, that on the whole the extreme nonstatochastic trends are inappropriate. The most nonstationary series seem to be those corresponding to Belgium, Sweden and the UK, where d = 1 is rejected and d = 1.25 cannot be rejected. For the remaining countries the unit root null hypothesis cannot be rejected though in some countries (Canada, Finland, France, Germany and the US), H_o (2) cannot be rejected with $d_o = 1.25$.

In connection with the power properties of Robinson's (1994a) tests, it must be stressed that it is only in a local sense that they are optimal, and doubtless they could be bettered against nonlocal departures of interest by some point optimal procedure. In view of this, there is some satisfaction in the fact that d < 1 and d > 1.25 are always decisively rejected in Table 1. On the other hand, this significant result might be due in large part to un-accounted for I(0) autocorrelation in u_t, even bearing in mind the monotonicity of $\hat{\rho}$ in d_o achieved in Tables 1(ii) and (iii). Thus, we also fitted AR models to u_t. The results are not reported in this article though is important to stress that we observed a lack of monotonicity in $\hat{\rho}$ with respect to d_o in practically all series. This could be explained in terms of model misspecification as it was argued above. 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 case of using AR(1) disturbances.

In order to solve this problem, we have decided to use other less conventional 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 which the spectral density function is given by:

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2\sum_{r=1}^{m} \tau_r \cos(\lambda r)\right). \qquad (9)$$

The intuition behind this model is the following. Suppose that u_t follows an ARMA process of form

$$u_t = \sum_{r=1}^{p} \phi_r u_{t-r} + \varepsilon_t - \sum_{r=1}^{q} \theta_r \varepsilon_{t-r},$$

where ε_t is a white noise process and all zeros of $\phi(L)$ lying outside the unit circle and all zeros of $\theta(L)$ lying outside or on the unit circle. Clearly, the spectral density function of this process is then

$$f(\lambda ; \varphi) = \frac{\sigma^2}{2\pi} \left| \frac{1 - \sum_{r=1}^{q} \theta_r e^{ir\lambda}}{1 - \sum_{r=1}^{p} \phi_r e^{ir\lambda}} \right|^2, \qquad (10)$$

where φ corresponds to all the AR and MA coefficients and σ^2 is the variance of ε_t. Bloomfield (1973) showed that the logarithm of an estimated spectral density function is often found to be a fairly well-behaved function and can thus be approximated by a truncated Fourier series. He showed that (9) approximates (10) well where p and q are of small values, which usually happens in economics. Like the stationary AR(p) model, the Bloomfiled (1973) model has exponentially decaying autocorrelations and thus we can use a model like this for u_t in (8). Formulae for Newton-type iteration for estimating the τ_l are very simple (involving no matrix inversion), updating formulae when m is increased are also simple, and we can replace $\hat{A}$ below (4) 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 τ_j (unlike what happens in the AR case). The Bloomfield (1973) model, confounded with fractional integration has not been very much used in previous econometric models, (though the Bloomfield model itself is a well-known model in other disciplines, e.g., Beran, 1993), and one by-product of this work is its emergence as a credible alternative to the fractional ARIMAs which have become conventional in parametric modelling of long memory.[3]

(Insert Table 2 about here)

The results based on the Bloomfield (1973) exponential model (with m = 1) are displayed in Table 2. We see that monotonicity is achieved for all series and all values of d_o. Starting with the case of no regressors (Table 2(i)), we observe that the unit root null hypothesis cannot be rejected in any series except for Finland, H_o (2) being rejected in this case in favour of smaller orders of integration. We also observe that for some countries, the null cannot be rejected with d_o = 0.75 and d_o = 1.25. Including an intercept and a linear time trend, the results are similar and the non-rejection values of d take place when d_o is equal to 9.75, 1 and 1.25. The most nonstationary series appear to be Australia and Japan (d_o = 1 and 1.25) whereas the less nonstationary ones are Finland, Germany, the Netherlands and the US, with values of d smaller than 1 when an intercept and/or a linear trend is included.

In view of all this, we can conclude the analysis of these two tables by saying that unit root models are plausible ways of modelling these series, though fractional degrees of integration (with d smaller than or greater than 1) may also be plausible alternatives ways of modelling their behaviour.

(Insert Tables 3 and 4 about here)

Tables 3 and 4 correspond respectively to Tables 1 and 2 but based on the differences with respect to the US. Starting with the case of white noise disturbances (Table 3) we observe that most of the non-rejection values take place at d = 1 and 1.25, that is, the same values as in Table 1. The two exceptions here are Australia and Canada where

[3] Amongst the few empirical applications found in the literature are Gil-Alana and Robinson (1997), Velasco and Robinson (2000) and more recently Gil-Alana (2001c).

H_o (2) cannot be rejected with $d_o = 0.75$. Thus, the analysis of this table suggest that real convergence do not take place for most countries in this context of white noise disturbances. However, a very different picture is obtained in Table 4 where u_t is allowed to be weakly autocorrelated. Here, $d_o = 1.25$ is rejected in practically all cases, and the non-rejection values of d oscillate between 0.5 and 1. Comparing these results with those in Table 2, we generally observe a smaller degree of integration. Thus, for Canada, Denmark, France, the Netherlands, Sweden and the UK, H_o (2) cannot be rejected with $d_o = 0.5$, this hypothesis being rejected in favour of higher values of d in case of Table 2. In view of this, there is some evidence of real convergence for some of the countries.

In order to be a bit more precise about the appropriate order of integration of each series, we recompute the tests of Robinson (1994a), but this time for values of $d_o = 0$, (0.01), 2. Tables 5 and 6 report for each time series and each type of regressors, the confidence intervals of those values of d_o where H_o (2) cannot be rejected at the 95% significance level. Table 5 corresponds to the case of white noise u_t, while Table 6 reports the results based on Bloomfield (1973) disturbances. We mark in bold in the tables those intervals where the lowest and the highest values of each interval are smaller with the differenced series. Using white noise u_t, we observe smaller intervals in case of Austria, Australia, Canada, Finland, Germany, Japan and the UK. However, using the Bloomfield (1973) exponential spectral model for the disturbances, we observe at least one smaller interval for each series with the only exceptions of Finland and Germany.

(Insert Tables 5 – 8 about here)

Finally, Tables 7 and 8 reports again for each series and each type of regressors, the values of d_o (d_o^*) which produces the lowest statistic in absolute value across d_o. The most interesting feature observed here is that if u_t is autocorrelated (Table 8), the values of d_o^* are smaller with the differenced series in all cases with the only exception of Germany, where the values of d are higher in case of the undifferenced series.

Next, we perform the semiparametric procedure described in Section 3.2. Figure 1 reports the results based on the QMLE of Robinson (1995b), i.e., $\hat{d}_1$ given by (5) for a range of values of m from 50 to 100. Since the time series are clearly nonstationary, the analysis will be carried out based on the first differenced data, adding then 1 to the estimated values of d to obtain the proper orders of integration of the series. We see that for Austria, Australia, Canada, Gemany and the UK, the estimated values of d are strictly higher in case of the individual series. On the other hand, the values of d in Belgium, Denmark, France, Italy, the Netherlands and Norway are higher for the differenced data. Finally, Finland, Sweden and Japan present similar values in both cases. The results here are consistent with those in Tables 5 and 7 for the case of white noise disturbances, observing smaller orders of integration in these five countries and thus, supporting the real convergence hypothesis.

(Insert Figure 1 about here)

4. Concluding remarks

In this article we have examined the real convergence hypothesis by means of using fractionally integrated techniques. In particular, we have examined the order of integration of the log real GDP per capita series in Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Sweden and the UK as well as their differences with respect to the US which is used as a benchmark country. For this purpose we have used a parametric testing procedure due to Robinson (1994a) and a semiparametric estimation method (QMLE, Robinson, 1995b). We have used these procedures, firstly because of the distinguishing features that they make them particular relevant in comparison with other methods. Thus, Robinson's (1994a) tests allow us to consider unit and fractional root tests with no effect on its standard null limit distribution which is also unaffected by the inclusion of deterministic trends and of different types of I(0) disturbances. In addition, the tests are the most efficient ones when directed against the appropriate (fractional) alternatives. The reason for using the QMLE of Robinson (1995b) is based on its computational simplicity along with the fact that it just requires a single bandwidth parameter, unlike other procedures where a trimming number is also required. A FORTRAN code with the programs is available from the author upon request. Using the parametric procedure of Robinson (1994a), the results support the view that all them may be specified in terms of unit root models, though fractional degrees of integration, with d smaller than or greater than 1 may also be plausible in some cases. Performing the same tests on the differenced data, the results substantially vary depending on how we specify the I(0) disturbances. Thus, if they are white noise, we observe smaller degrees of integration, (and thus, evidence of real convergence) in the cases of Austria, Australia, Canada, Finland, Germany, Japan and the UK. However, if the disturbances are weakly autocorrelated, real convergence seems to be satisfied for all countries except for Germany. In view of this lack of robutness in the results depending on the structure on the disturbances, we also performed a semiparametric procedure of Robinson, namely, the quasi maximum likelihood estimation (QMLE, Robinson, 1995b) method. The results here were consistent with the parametric ones in Robinson (1994a) for the case of white noise disturbances, finding thus conclusive evidence of real convergence in Austria, Australia, Canada, Finland, Germany, Japan and the UK. For the remaining seven countries, (Belgium, Denmark, France, Italy, the Netherlands, Norway and Sweden), we find strong evidence against real convergence.

Several other lines of research are under progress which should prove relevant to the anlaysis of these and other macroeconomic and financial data. Multivariate versions of the tests of Robinson (1994a) are being developed and this would lead to an alternative approach to the study of cointegration. The Bloomfield model for the I(0) components is also being developed in a multivariate set-up. Other issues such as the potential presence of structural breaks on the data and the effect that this may have on the above results will be addressed in future papers.

References

Adenstedt, R.K., 1974, On large sample estimation for the mean of a stationary random sequence, Annals of Statistics 2, 259-272.

Barro, R., 1991, Economic growth in a cross section of countries, Quarterly Journal of Economics 106, 407-443.

Barro, R. and Sala-i-Martin, 1991, Convergence across states and regions, Brookings Papers of Economic Activity 1, 107-182.

Barro, R. and Sala-i-Martin, 1992, Convergence, Journal of Political Economy 100, 223-251.

Barro, R. and Sala-i-Martin, 1995, Economic Growth, McGraw Hill.

Baumol, W. J., 1986, Productivity growth, convergence, and welfare: what the long-run data show, American Economic Review 76, 1072-1085.

Beran, J., 1993, Fitting long memory models by generalized linear regressions, Biometrika 80, 817-822.

Bernard, A.B., 1991, Empirical implications of the convergence hypothesis, Working Paper, Center for Economic Policy Research, Stanford University.

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

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

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

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

Carlino, G.A. and Mills, L.O., 1993, Are U.S. regional incomes converging? A Time Series Analysis, Journal of Monetary Economics 32, 335-346.

Cellini, R. and Scorcu, A., 2000, Segmented stochastic convergence across the G-7 countries, Empirical Economics, 25, 463-474.

Chambers, M., 1998, Long memory and aggregation in macroeconomic time series, International Economic Review 39, 1053-1072.

Cogley, T., 1990, International evidence on the size of the random walk in output, Journal of Political Economy 98, 501-518.

Croczek-Georges, R. and B.B. Mandelbrot, 1995, A class of micropulses and anti-persistent fractional Brownian motion, Stochastic Processes and Their Applications 60, 1-18.

Dahlhaus, R., 1989, Efficient parameter estimation for self-similar process, Annals of Statistics, 17, 1749-1766.

De Long, J.B., 1988, Productivity growth, convergence and welfare: a comment, American Economic Review 78, 1138-1155.

Dolado, J.J., Gonzalo, J. and Mayoral, L. (2002a), The role of deterministic components in the fractional Dickey-Fuller test for unit roots, Journal of Econometrics, forthcoming.

Dolado, J.J., Gonzalo, J. and Mayoral, L. (2002b), A fractional Dickey-Fuller test for unit roots, Econometrica, forthcoming.

Dowrick, S. and Nguyen, D. T., 1989, OECD comparative economic growth 1950-1985: catch-up and convergence, American Economic Review 79, 1010-1030.

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

Gil-Alana, L.A., 1999, Testing fractional integration with monthly data, Economic Modelling 16, 613-629.

Gil-Alana, L.A., 2000, Mean reversion in the real exchange rates, Economics Letters 16, 285-288.

Gil-Alana, L.A., 2001a, Testing stochastic cycles in macroeconomic time series, Journal of Time Series Analysis 22, 411-430.

Gil-Alana, L.A., 2001b, Semiparametric estimation of the fractional differencing parameter in the UK unemployment, forthcoming in Computational Economics.

Gil-Alana, L.A., 2001c, An exponential spectral model for the UK unemployment, Journal of Forecasting 20, 329-340.

Gil-Alana, L.A., 2002, Comparisons between semiparametric procedures for estimating the fractional differencing parameter, Preprint.

Gil-Alana, L.A. and P.M. Robinson, 1997, Testing of unit roots and other nonstationary hypotheses in macroeconomic time series, Journal of Econometrics 80, 241-268.

Gil-Alana, L.A. and P.M. Robinson, 2001, Testing seasonal fractional integration in the UK and Japanese consumption and income, Journal of Applied Econometrics 16, 95-114.

Granger, C.W.J., 1980, Long memory relationships and the aggregation of dynamic models, Journal of Econometrics 14, 227-238.

Granger, C.W.J., 1981, Some properties of time series data and their use in econometric model specification, Journal of Econometrics 16, 121-130.

Granger, C.W.J. and R. Joyeux, 1980, An introduction to long memory time series and fractionally differencing, Journal of Time Series Analysis 1, 15-29.

Grier, K.B. and Tullock, G., 1989, An empirical analysis of cross-national economic growth, 1951-1980, Journal of Monetary Economics 24, 259-276.

Hosking, J.R.M., 1981, Modelling persistence in hydrological time series using fractional differencing, Water Resources Research 20, 1898-1908.

Kunsch, H., 1986, Discrimination between monotonic trends and long-range dependence, Journal of Applied Probability, 23, 1025-1030.

Lippi, M. and P. Zaffaroni, 1999, Contemporaneous aggregation of linear dynamic models in large economies, Manuscript, Research Department, Bank of Italy.

Lobato, I., 1999, A semiparametric two-step estimator for a multivariate long memory process, Journal of Econometrics, 73, 303-324.

Lucas, R., 1988, On the mechanics of economic development, Journal of Monetary Economics, 22, 3-41.

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

Mankiw, G., Romer, P. and Weil, D. N., 1992, A contribution to the empirics of economic growth, Quarterly Journal of Economics, 107, 407-437.

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

Greasly, D. and Oxley, 1997, Time-series based tests of the convergence hypothesis: some positive results, Economic Letters, 56, 143-147.

Parke, W.R., 1999, What is fractional integration?, The Review of Economics and Statistics 81, 632-638.

Robinson, P.M., 1978, Statistical inference for a random coefficient autoregressive model, Scandinavian Journal of Statistics 5, 163-168.

Robinson, P.M., 1994a, Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M., 1994b, Semiparametric analysis of long memory time series, Annals of Statistics, 22, 515-539.

Robinson, P.M., 1995a, Gaussian semiparametric estimation of long range dependence, Annals of Statistics 23, 1630-1661.

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

Romer, P., 1986, Increasing returns and long-run growth, Journal of Political Economy 94, 1002-1037.

Silverberg, G. and Verspagen, B. (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, Quaterly Journal of Economics 70, 65-94.

Sowell, F., 1992, Maximum likelihood estimation of stationary univariate fractionally integrated time series models, Journal of Econometrics, 53, 165-188.

St. Aubyn, M. (1999), Convergence across industrialised countries (1890-1989): new results using time series methods, Empirical Economics, 24, 23-44.

Strazicich, M.C., Lee, J. and Day, E., 2001, Are incomes converging among OECD countries? Time series evidence with two structural breaks, Working Paper, University of North Texas.

Taqqu, M.S., 1975, Weak convergence to fractional motion and to the Rosenblatt process, Z. Wahrscheinlichkeitstheorie verw. Geb. 31, 287-302.

Taqqu, M.S., W. Willinger and R. Sherman, 1997, Proof of a fundamental result in self-similar traffic modelling, Computer Communication Review 27, 5-23.

Velasco, C. and P.M. Robinson, 2000, Whittle pseudo-maximum likelihood estimation for nonstationary time series, Journal of the American Statistical Association 95, 1229-1243.

TABLE 1. Testing the order of integration with white noise disturbances

i): with no regressors									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	25.12	24.38	14.29	4.32	**-0.10**	-2.28	-3.54	-4.35	-4.89
Australia	25.47	25.64	12.54	4.53	**-0.40**	-3.00	-4.27	-4.95	-5.36
Belgium	25.24	27.07	15.49	5.16	**0.04**	-2.53	-3.87	-4.62	-5.10
Canada	25.61	25.28	15.01	4.05	**0.51**	-1.68	-3.16	-4.12	-4.75
Denmark	25.60	26.65	16.70	3.29	**-0.85**	-2.90	-4.03	-4.69	-5.12
Finland	26.32	26.37	23.30	10.35	**1.42**	**-1.24**	-2.60	-3.48	-4.09
France	25.62	25.56	15.85	5.22	**0.54**	-1.92	-3.36	-4.24	-4.79
Germany	25.33	24.31	13.37	4.54	**0.73**	**-1.45**	-2.85	-3.78	-4.41
Italy	25.94	26.20	20.93	7.82	**1.05**	**-1.60**	-3.02	-3.91	-4.52
Japan	23.26	22.76	18.81	8.50	**1.00**	-2.01	-3.43	-4.22	-4.70
The Netherlands	25.20	24.29	11.83	3.78	**-0.31**	-2.51	-3.72	-4.44	-4.91
Norway	26.13	26.86	25.28	10.46	**0.02**	-2.65	-3.83	-4.52	-4.97
Sweden	26.64	28.10	22.68	6.25	**0.39**	-2.24	-3.73	-4.58	-5.07
U.K.	25.17	25.77	11.66	4.52	**0.16**	-2.29	-3.63	-4.41	-4.92
U.S.	25.18	24.19	9.28	3.43	**0.07**	-2.15	-3.50	-4.33	-4.87
ii): with an intercept									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	25.12	22.20	15.31	4.95	**-0.09**	-2.26	-3.52	-4.34	-4.89
Australia	25.47	22.76	17.37	7.33	**0.16**	-2.60	-3.95	-4.73	-5.24
Belgium	25.24	22.92	18.78	10.10	1.85	**-1.30**	-2.79	-3.68	-4.26
Canada	25.61	22.72	17.10	6.90	**1.50**	**-0.94**	-2.60	-3.74	-4.51
Denmark	25.60	22.98	18.44	7.96	**-0.67**	-2.79	-3.76	-4.36	-4.75
Finland	26.32	24.09	20.23	10.90	**1.64**	**-1.09**	-2.42	-3.31	-3.93
France	25.62	22.92	17.13	6.91	**1.06**	**-1.46**	-2.92	-3.82	-4.41
Germany	25.33	22.24	15.47	5.86	**1.49**	**-0.59**	-1.98	-2.97	-3.68
Italy	25.94	23.85	19.88	10.22	1.99	**-1.09**	-2.64	-3.61	-4.28
Japan	23.26	21.21	17.32	8.52	**1.00**	-1.95	-3.37	-4.17	-4.66
The Netherlands	25.20	22.04	14.97	4.66	**-0.11**	-2.13	-3.30	-4.05	-4.56
Norway	26.13	23.97	20.63	12.79	**0.61**	-2.50	-3.63	-4.31	-4.76
Sweden	26.64	24.34	20.57	12.74	2.01	**-1.38**	-2.94	-3.87	-4.46
U.K.	25.17	22.46	17.65	9.10	2.41	**-0.12**	-1.69	-2.88	-3.78
U.S.	25.18	21.67	14.10	4.73	**1.10**	**-0.78**	-2.24	-3.33	-4.12
iii): with an intercept and a linear time trend									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	25.81	20.01	11.31	3.98	**-0.09**	-2.24	-3.51	-4.33	-4.89
Australia	27.42	23.16	14.96	5.80	**0.15**	-2.57	-3.95	-4.70	-5.18
Belgium	28.06	24.67	17.46	8.21	1.85	**-1.24**	-2.79	-3.68	-4.26
Canada	18.60	13.82	9.12	4.88	**1.48**	**-0.93**	-2.60	-3.73	-4.50
Denmark	25.07	19.20	11.01	3.57	**-0.70**	-2.73	-3.76	-4.36	-4.74
Finland	26.77	21.87	14.80	6.85	**1.61**	**-0.98**	-2.41	-3.31	-3.93
France	24.73	19.42	12.18	5.44	**1.07**	**-1.44**	-2.92	-3.83	-4.41
Germany	23.09	16.82	9.92	4.72	**1.48**	**-0.58**	-1.98	-2.97	-3.68
Italy	26.21	21.89	15.32	7.61	**1.97**	**-1.01**	-2.63	-3.64	-4.28
Japan	24.13	20.47	14.17	6.53	**0.99**	-1.99	-3.36	-4.15	-4.64
The Netherlands	24.27	18.21	10.12	3.58	**-0.12**	-2.12	-3.29	-4.05	-4.56
Norway	28.56	24.72	17.80	7.60	**-0.57**	-2.33	-3.61	-4.32	-4.77
Sweden	25.80	22.44	17.00	8.61	2.02	**-1.31**	-2.96	-3.88	-4.47
U.K.	27.05	22.34	14.55	7.01	2.46	**-0.04**	-1.66	-2.84	-3.74
U.S.	14.60	10.07	6.39	3.46	**1.09**	**-0.78**	-2.24	-3.32	-4.11

TABLE 2. Testing the order of integration with Bloomfield (1) disturbances									
i): with no regressors									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	12.60	12.26	6.58	**1.16**	**-1.13**	-2.29	-2.89	-3.27	-3.67
Australia	12.69	14.28	6.62	3.09	**0.42**	**-1.19**	-2.32	-3.05	-3.59
Belgium	12.65	13.95	7.58	2.45	**-0.10**	-1.71	-2.66	-3.19	-3.62
Canada	13.46	12.97	6.04	**0.22**	**-1.19**	-1.90	-2.55	-2.95	-3.38
Denmark	12.95	12.68	8.20	**1.42**	**-0.87**	-2.14	-2.90	-3.45	-3.82
Finland	13.59	12.73	8.54	2.56	-1.71	-2.88	-3.32	-3.69	-3.97
France	12.92	11.15	6.37	**1.32**	**-0.87**	-1.97	-2.60	-3.14	-3.56
Germany	12.62	9.86	4.23	**0.18**	**-1.52**	-2.46	-3.04	-3.49	-3.79
Italy	13.62	13.70	9.36	2.69	**-0.90**	-2.35	-3.03	-3.53	-3.81
Japan	11.86	11.28	8.79	4.00	**0.31**	**-1.50**	-2.35	-3.03	-3.51
The Netherlands	12.75	10.79	4.65	**0.99**	**-1.03**	-2.33	-3.03	-3.52	-3.92
Norway	13.63	13.50	12.25	5.62	**-0.46**	-2.21	-2.93	-3.44	-3.75
Sweden	14.17	15.20	11.43	2.85	**-0.03**	**-1.29**	-2.24	-2.81	-3.31
U.K.	13.06	13.28	5.00	**1.54**	**-0.55**	-2.02	-2.82	-3.37	-3.75
U.S.	12.93	11.64	3.01	**0.37**	**-1.00**	-2.01	-2.75	-3.30	-3.60
ii): with an intercept									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	12.60	10.78	6.95	1.74	**-1.12**	-2.25	-2.88	-3.24	-3.54
Australia	12.69	10.79	7.93	4.07	**0.28**	**-1.46**	-2.33	-2.97	-3.36
Belgium	12.65	10.41	7.74	2.95	**-0.85**	-2.44	-3.20	-3.71	-4.02
Canada	13.46	11.09	7.90	1.90	**-0.88**	-1.82	-2.40	-2.85	-3.22
Denmark	12.95	10.87	7.88	3.09	**-1.47**	-2.88	-3.48	-3.96	-4.25
Finland	13.59	11.59	8.88	2.55	-1.80	-3.01	-3.50	-3.82	-4.00
France	12.92	10.36	6.47	**1.24**	**-1.35**	-2.36	-2.94	-3.35	-3.70
Germany	12.62	10.03	5.28	**-0.23**	**-1.29**	-2.92	-3.43	-3.83	-4.09
Italy	13.62	11.93	9.28	3.74	**-0.56**	-2.32	-3.02	-3.50	-3.84
Japan	11.86	10.25	7.99	4.06	**0.16**	**-1.56**	-2.47	-3.10	-3.53
The Netherlands	12.75	9.94	5.66	**0.58**	**-1.88**	-2.81	-3.34	-3.71	-3.93
Norway	13.63	11.57	9.67	5.84	**-0.30**	-2.57	-3.20	-3.56	-3.86
Sweden	14.17	12.24	9.97	5.47	**-0.22**	-2.07	-2.92	-3.53	-3.89
U.K.	13.06	10.85	8.17	3.12	**-0.96**	-2.23	-2.77	-3.06	-3.34
U.S.	12.93	10.23	5.98	**-0.05**	-1.89	-2.42	-2.84	-3.21	-3.45
iii): with an intercept and a linear time trend									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	13.09	9.05	4.50	**1.00**	**-1.11**	-2.20	-2.86	-3.20	-3.57
Australia	15.35	12.46	7.74	3.32	**0.47**	**-1.38**	-2.34	-2.76	-3.12
Belgium	13.92	11.11	6.61	2.04	**-0.87**	-2.44	-3.18	-3.71	-4.01
Canada	7.46	4.49	2.19	**0.37**	**-0.90**	-1.81	-2.40	-2.84	-3.18
Denmark	11.49	7.96	3.81	**0.61**	**-0.54**	-2.71	-3.46	-3.96	-4.24
Finland	12.29	8.63	4.49	**0.65**	-1.74	-2.85	-3.47	-3.82	-4.02
France	10.80	7.18	3.47	**0.47**	**-1.36**	-2.32	-2.94	-3.36	-3.71
Germany	9.29	4.88	1.43	**-0.99**	-2.20	-2.90	-3.43	-3.83	-4.08
Italy	13.30	9.79	5.68	2.06	**-0.58**	-2.19	-3.00	-3.49	-3.84
Japan	12.49	9.61	6.18	2.67	**0.15**	**-1.42**	-2.39	-2.99	-3.38
The Netherlands	10.56	6.79	2.62	**-0.10**	-1.88	-2.78	-3.34	-3.71	-3.92
Norway	15.33	11.84	8.21	3.32	**-0.35**	-2.25	-3.09	-3.56	-3.88
Sweden	13.18	10.26	6.83	2.89	**-0.24**	-1.94	-2.95	-3.49	-3.92
U.K.	14.21	10.02	5.41	**1.34**	**-1.03**	-2.11	-2.71	-2.91	-3.28
U.S.	4.28	1.68	**0.03**	**-0.99**	-1.90	-2.42	-2.84	-3.20	-3.42

TABLE 3									
Testing the order of integration with respect to the US with white noise disturbances									
i): with no regressors									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	23.20	16.28	9.26	3.24	**-0.60**	-2.78	-4.04	-4.80	-5.28
Australia	25.06	19.11	9.94	2.65	**-1.32**	-3.34	-4.43	-5.06	-5.47
Belgium	23.25	15.97	9.85	5.43	2.27	**-0.01**	-1.68	-2.92	-3.83
Canada	22.35	17.93	10.36	3.04	**-1.25**	-3.33	-4.37	-4.97	-5.36
Denmark	15.40	12.56	8.67	4.74	**1.54**	**-0.82**	-2.48	-3.61	-4.37
Finland	25.45	20.42	13.14	5.56	**0.76**	-1.72	-3.13	-4.03	-4.64
France	18.47	13.52	8.89	4.81	1.72	**-0.49**	-2.07	-3.18	-3.95
Germany	20.25	15.44	10.36	5.25	**1.24**	**-1.37**	-2.96	-3.90	-4.48
Italy	22.56	18.23	12.28	5.98	**1.52**	**-1.10**	-2.69	-3.71	-4.39
Japan	22.71	18.75	12.51	5.12	**0.09**	-2.45	-3.76	-4.49	-4.93
The Netherlands	18.97	12.02	7.20	3.68	**1.07**	**-0.82**	-2.21	-3.21	-3.95
Norway	23.96	19.01	12.25	5.63	**1.36**	**-1.11**	-2.67	-3.71	-4.42
Sweden	23.47	16.27	9.05	4.27	**1.20**	**-0.91**	-2.43	-3.52	-4.29
U.K.	24.30	17.60	9.38	3.89	**0.50**	-1.70	-3.14	-4.08	-4.70
ii): with an intercept									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	23.20	16.98	9.32	3.20	**-0.57**	-2.73	-3.99	-4.76	-5.25
Australia	25.06	19.15	8.50	**1.27**	**-1.61**	-3.24	-4.24	-4.89	-5.33
Belgium	23.25	16.88	10.04	5.43	2.29	**0.02**	-1.65	-2.87	-3.79
Canada	22.35	15.29	6.11	**0.64**	-2.08	-3.60	-4.49	-5.05	-5.42
Denmark	15.40	11.44	7.75	4.47	**1.62**	**-0.66**	-2.35	-3.52	-4.35
Finland	25.45	20.20	11.73	5.10	**1.41**	**-0.87**	-2.44	-3.53	-4.29
France	18.47	13.37	8.60	4.79	1.87	**-0.30**	-1.91	-3.06	-3.88
Germany	20.25	15.43	10.09	5.17	**1.30**	**-1.31**	-2.92	-3.89	-4.48
Italy	22.56	17.50	11.04	5.56	1.80	**-0.61**	-2.22	-3.30	-4.06
Japan	22.71	20.09	14.05	6.03	**0.73**	-2.06	-3.55	-4.39	-4.89
The Netherlands	18.97	12.77	7.31	3.67	**1.08**	**-0.81**	-2.20	-3.21	-3.94
Norway	23.96	18.45	11.02	5.54	2.28	**0.04**	-1.65	-2.92	-3.83
Sweden	23.47	16.27	9.05	4.27	**1.20**	**-0.91**	-2.43	-3.52	-4.29
U.K.	24.30	17.92	8.73	3.28	**0.35**	-1.73	-3.19	-4.13	-4.75
iii): with an intercept and a linear time trend									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	23.12	17.02	9.40	3.21	**-0.57**	-2.73	-3.99	-4.76	-5.25
Australia	22.90	15.71	7.23	**1.41**	**-1.60**	-3.25	-4.24	-4.86	-5.28
Belgium	21.53	16.10	10.20	5.52	2.29	**0.01**	-1.65	-2.87	-3.78
Canada	14.13	9.24	4.47	**0.53**	-2.08	-3.60	-4.50	-5.05	-5.41
Denmark	14.06	10.74	7.55	4.44	**1.62**	**-0.66**	-2.35	-3.52	-4.31
Finland	20.17	14.58	9.34	4.77	**1.41**	**-0.86**	-2.44	-3.53	-4.29
France	18.28	13.23	8.58	4.79	1.87	**-0.30**	-1.91	-3.06	-3.88
Germany	20.12	15.27	10.05	5.17	**1.30**	**-1.31**	-2.92	-3.88	-4.47
Italy	21.18	15.97	10.43	5.48	1.80	**-0.62**	-2.22	-3.30	-4.06
Japan	22.08	18.09	12.11	5.57	**0.73**	-2.05	-3.54	-4.38	-4.89
The Netherlands	17.42	12.18	7.39	3.72	**1.08**	**-0.81**	-2.20	-3.21	-3.94
Norway	19.65	14.24	9.33	5.28	2.28	**0.04**	-1.65	-2.90	-3.82
Sweden	17.16	12.59	8.20	4.20	**1.20**	**-0.91**	-2.43	-3.52	-4.29
U.K.	17.78	12.51	7.45	3.36	**0.35**	-1.76	-3.19	-4.13	-4.75

TABLE 4

Testing the order of integration with respect to the US with Bloomfield (1) disturbances

	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
i): with no regressors									
Austria	11.27	6.92	3.82	**1.14**	**-0.55**	-1.67	-2.32	-2.87	-3.19
Australia	13.52	9.51	4.98	1.70	**-0.47**	-1.64	-2.52	-3.09	-3.52
Belgium	11.20	5.51	2.16	**0.09**	**-1.21**	-2.07	-2.62	-3.04	-3.29
Canada	10.92	8.65	5.17	2.09	**-0.38**	-2.00	-2.89	-3.43	-3.76
Denmark	4.76	3.14	**1.48**	**-0.14**	**-1.13**	-1.88	-2.53	-2.93	-3.28
Finland	12.44	9.03	5.13	**1.34**	**-0.93**	-2.16	-2.92	-3.30	-3.59
France	6.16	3.05	**0.91**	**-0.64**	-1.74	-2.39	-2.92	-3.33	-3.58
Germany	7.85	4.53	2.26	**0.39**	**-1.04**	-2.06	-2.85	-3.40	-3.88
Italy	9.89	7.18	3.92	**1.02**	**-0.93**	-2.10	-2.83	-3.27	-3.59
Japan	11.71	9.01	5.85	2.61	**0.31**	**-1.29**	-2.37	-3.03	-3.45
The Netherlands	6.75	2.57	**0.23**	**-1.27**	-2.12	-2.76	-3.21	-3.47	-3.79
Norway	11.18	7.76	3.99	**0.83**	**-1.00**	-2.11	-2.72	-3.13	-3.44
Sweden	11.08	7.81	3.71	**0.69**	**-1.25**	-2.35	-2.92	-3.29	-3.58
U.K.	11.55	6.86	2.41	**0.07**	**-1.16**	-2.10	-2.62	-3.13	-3.54
ii): with an intercept									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	11.27	7.64	3.71	**1.13**	**-0.67**	-1.71	-2.32	-2.85	-3.18
Australia	13.52	9.60	4.30	**0.14**	**-1.35**	-2.23	-2.88	-3.26	-3.58
Belgium	11.20	6.33	2.31	**-0.04**	**-1.29**	-2.13	-2.67	-3.08	-3.33
Canada	10.92	7.07	2.62	**0.02**	**-1.39**	-2.28	-2.93	-3.28	-3.57
Denmark	4.76	2.68	**0.77**	**-0.28**	**-1.28**	-1.88	-2.35	-2.87	-3.22
Finland	12.44	8.19	3.60	**0.24**	**-1.24**	-2.08	-2.71	-3.09	-3.40
France	6.16	3.29	**0.88**	**-0.64**	-1.76	-2.33	-2.85	-3.26	-3.52
Germany	7.85	4.72	2.26	**0.35**	**-0.96**	-1.94	-2.75	-3.34	-7.78
Italy	9.89	6.01	2.50	**0.12**	**-1.39**	-2.25	-2.97	-3.37	-3.68
Japan	11.71	10.00	6.68	2.85	**0.38**	**-1.11**	-2.04	-2.72	-3.17
The Netherlands	6.75	2.97	**0.27**	**-1.26**	-2.10	-2.74	-3.19	-3.45	-3.78
Norway	11.18	7.05	2.63	**-0.06**	**-1.31**	-2.12	-2.55	-3.01	-3.30
Sweden	11.08	6.15	2.12	**-0.16**	**-1.37**	-2.16	-2.69	-3.12	-3.39
U.K.	11.55	7.09	2.03	**-0.30**	**-1.27**	-2.04	-2.51	-2.98	-3.38
iii): with an intercept and a linear time trend									
	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
Austria	11.14	7.69	3.80	**1.15**	**-0.67**	-1.72	-2.32	-2.84	-3.16
Australia	11.55	7.30	3.33	**0.18**	**-1.35**	-2.26	-2.87	-3.15	-3.27
Belgium	9.50	5.60	2.63	**0.07**	**-1.29**	-2.14	-2.68	-3.07	-3.49
Canada	4.98	2.83	**1.33**	**-0.16**	**-1.39**	-2.28	-2.93	-3.28	-3.57
Denmark	3.91	2.23	**0.75**	**-0.31**	**-1.28**	-1.88	-2.35	-2.86	-3.19
Finland	8.29	4.67	2.02	**0.05**	**-1.25**	-2.08	-2.72	-3.09	-3.40
France	6.35	3.07	**0.86**	**-0.64**	-1.76	-2.33	-2.85	-3.26	-3.53
Germany	7.67	4.61	2.21	**0.34**	**-0.96**	-1.94	-2.75	-3.32	-3.80
Italy	8.69	5.25	2.28	**0.03**	**-1.39**	-2.25	-2.97	-3.37	-3.68
Japan	11.41	8.32	5.36	2.55	**0.38**	**-1.07**	-2.01	-2.67	-3.22
The Netherlands	5.72	2.52	**0.23**	**-1.21**	-3.10	-2.74	-3.19	-3.45	-3.78
Norway	7.38	4.41	1.72	**-0.13**	**-1.31**	-2.11	-2.55	-3.01	-3.29
Sweden	6.35	3.67	**1.51**	**-0.23**	**-1.37**	-2.16	-2.69	-3.12	-3.38
U.K.	6.79	3.55	**1.39**	**-0.25**	**-1.28**	-1.92	-2.51	-2.98	-3.38

TABLE 5						
Confidence intervals for the non-rejection values of d with white noise disturbances						
	Individual series			With respect to the US		
	No regressors	Intercept	Linear trend	No regressors	Intercept	Linear trend
Austria	[0.88 – 1.16]	[0.89 – 1.16]	[0.88 – 1.16]	**[0.84 – 1.10]**	**[0.84 – 1.10]**	**[0.84 – 1.10]**
Australia	[0.88 – 1.10]	[0.93 – 1.13]	[0.92 – 1.14]	**[0.80 – 1.02]**	**[0.73 – 1.00]**	**[0.74 – 1.00]**
Belgium	[0.91 – 1.14]	[1.02 – 1.29]	[1.02 – 1.30]	[1.07 – 1.49]	[1.08 – 1.49]	[1.08 – 1.49]
Canada	[0.92 – 1.24]	[0.98 – 1.34]	[0.98 – 1.34]	**[0.82 – 1.03]**	**[0.69 – 0.94]**	**[0.68 – 0.94]**
Denmark	[0.83 – 1.07]	[0.90 – 1.08]	[0.85 – 1.09]	[1.00 – 1.36]	[1.00 – 1.38]	[1.00 – 1.38]
Finland	[0.99 – 1.31]	[1.01 – 1.33]	[1.00 – 1.34]	**[0.95 – 1.23]**	**[0.98 – 1.33]**	**[0.98 – 1.34]**
France	[0.93 – 1.21]	[0.97 – 1.27]	[0.96 – 1.27]	[1.01 – 1.41]	[1.03 – 1.44]	[1.03 – 1.44]
Germany	[0.93 – 1.27]	[0.99 – 1.43]	[0.99 – 1.43]	[0.98 – 1.28]	**[0.98 – 1.29]**	**[0.98 – 1.29]**
Italy	[0.97 – 1.25]	[1.02 – 1.32]	[1.03 – 1.33]	[1.00 – 1.32]	[1.02 – 1.39]	[1.02 – 1.39]
Japan	[0.98 – 1.20]	[0.98 – 1.21]	[0.98 – 1.21]	**[0.91 – 1.14]**	**[0.95 – 1.20]**	**[0.95 – 1.20]**
Netherlands	[0.87 – 1.13]	[0.88 – 1.17]	[0.87 – 1.17]	[0.94 – 1.37]	[0.94 – 1.38]	[0.94 – 1.38]
Norway	[0.95 – 1.12]	[0.98 – 1.14]	[0.96 – 1.16]	[0.98 – 1.32]	[1.07 – 1.50]	[1.07 – 1.50]
Sweden	[0.94 – 1.17]	[1.01 – 1.28]	[1.02 – 1.28]	[0.95 – 1.27]	[0.97 – 1.36]	[0.97 – 1.36]
U.K.	[0.91 – 1.16]	[1.06 – 1.49]	[1.07 – 1.49]	[0.92 – 1.24]	**[0.90 – 1.23]**	**[0.90 – 1.23]**

TABLE 6						
Confidence intervals for the non-rejection values of d with Bloomfield (1) disturbances						
	Individual series			With respect to the US		
	No regressors	Intercept	Linear trend	No regressors	Intercept	Linear trend
Austria	[0.73 – 1.14]	[0.76 – 1.08]	[0.69 – 1.08]	**[0.69 – 1.14]**	[0.69 – 1.24]	[0.68 – 1.24]
Australia	[0.87 – 1.34]	[0.90 – 1.28]	[0.89 - 1.31]	**[0.76 – 1.24]**	**[0.63 – 1.05]**	**[0.61 - 1.05]**
Belgium	[0.83 – 1.22]	[0.83 – 1.08]	[0.79 – 1.11]	**[0.55 – 1.10]**	**[0.56 – 1.08]**	**[0.57 – 1.11]**
Canada	[0.66 – 1.16]	[0.78 – 1.20]	[0.57 – 1.20]	[0.79 – 1.16]	**[0.57 – 1.06]**	**[0.46 – 1.06]**
Denmark	[0.73 – 1.13]	[0.81 – 1.01]	[0.67 – 1.01]	**[0.48 – 1.13]**	[0.37 – 1.15]	[0.35 – 1.15]
Finland	[0.79 – 0.99]	[0.79 – 0.98]	[0.68 – 0.98]	[0.73 – 1.10]	[0.62 – 1.08]	[0.56 – 1.08]
France	[0.74 – 1.17]	[0.74 – 1.05]	[0.63 – 1.07]	**[0.43 – 0.98]**	**[0.40 – 0.99]**	**[0.41 – 0.99]**
Germany	[0.63 – 1.02]	[0.65 – 0.89]	[0.47 – 0.88]	[0.58 – 1.13]	[0.56 – 1.17]	[0.56 – 1.17]
Italy	[0.81 – 1.11]	[0.85 – 1.13]	[0.79 – 1.14]	**[0.70 – 1.10]**	**[0.58 – 1.04]**	**[0.56 – 1.04]**
Japan	[0.93 – 1.29]	[0.89 – 1.27]	[0.85 – 1.28]	**[0.84 – 1.29]**	[0.87 – 1.37]	[0.85 – 1.38]
Netherlands	[0.70 – 1.11]	[0.69 – 0.97]	[0.59 – 0.97]	**[0.32 – 0.87]**	**[0.36 – 0.86]**	**[0.34 – 0.86]**
Norway	[0.89 – 1.12]	[0.91 – 1.09]	[0.85 – 1.15]	**[0.69 – 1.12]**	**[0.58 – 1.09]**	**[0.51 – 1.10]**
Sweden	[0.83 – 1.34]	[0.90 – 1.16]	[0.85 – 1.19]	**[0.67 – 1.06]**	**[0.54 – 1.05]**	**[0.46 – 1.05]**
U.K.	[0.74 – 1.17]	[0.81 – 1.09]	[0.72 – 1.12]	**[0.57 – 1.13]**	[0.53 – 1.15]	[0.47 – 1.14]

TABLE 7						
Values of d which produces the lowest statistics in absolute value with white noise u_t						
	Individual series			With respect to the US		
	No regressors	Intercept	Linear trend	No regressors	Intercept	Linear trend
Austria	0.99	0.99	0.99	**0.95**	**0.95**	**0.95**
Australia	0.97	1.01	1.01	**0.90**	**0.84**	**0.85**
Belgium	1.00	1.12	1.13	1.25	1.25	1.25
Canada	1.05	1.14	1.14	**0.91**	**0.80**	**0.79**
Denmark	0.93	0.96	0.94	1.15	1.17	1.17
Finland	1.10	1.12	1.13	**1.06**	1.14	1.14
France	1.04	1.09	1.09	1.19	1.21	1.21
Germany	1.07	1.16	1.16	1.10	**1.11**	**1.11**
Italy	1.08	1.14	1.15	1.13	1.18	1.18
Japan	1.06	1.06	1.07	**1.01**	**1.05**	**1.05**
Netherlands	0.97	0.99	0.99	1.13	1.13	1.13
Norway	1.00	1.03	1.03	1.12	1.26	1.26
Sweden	1.03	1.12	1.13	1.07	1.13	1.13
U.K.	1.01	1.23	1.24	1.05	**1.04**	**1.04**

TABLE 8						
Values of d which produce the lowest statistic in absolute value with Bloomfield (1) u_t						
	Individual series			With respect to the US		
	No regressors	Intercept	Linear trend	No regressors	Intercept	Linear trend
Austria	0.86	0.87	0.84	**0.81**	**0.87**	**0.88**
Australia	1.06	1.03	1.04	**0.95**	**0.77**	**0.78**
Belgium	0.99	0.93	0.92	**0.76**	**0.74**	**0.77**
Canada	0.77	0.88	0.83	0.94	**0.75**	**0.71**
Denmark	0.88	0.88	0.82	**0.76**	**0.69**	**0.69**
Finland	0.87	0.87	0.80	**0.87**	**0.78**	**0.76**
France	0.88	0.83	0.79	**0.65**	**0.62**	**0.62**
Germany	0.77	0.72	0.63	0.80	0.79	0.80
Italy	0.91	0.94	0.93	**0.87**	**0.77**	**0.75**
Japan	1.03	1.03	1.03	**1.02**	**1.03**	**1.03**
Netherlands	0.86	0.79	0.74	**0.53**	**0.54**	**0.54**
Norway	0.97	0.98	0.97	**0.84**	**0.74**	**0.72**
Sweden	0.99	0.99	0.98	**0.81**	**0.81**	**0.70**
U.K.	0.91	0.90	0.87	**0.76**	**0.69**	**0.71**

FIGURE 1

QMLE of Robinson (1995b) based on the first differenced data for a range of values J=50, 100

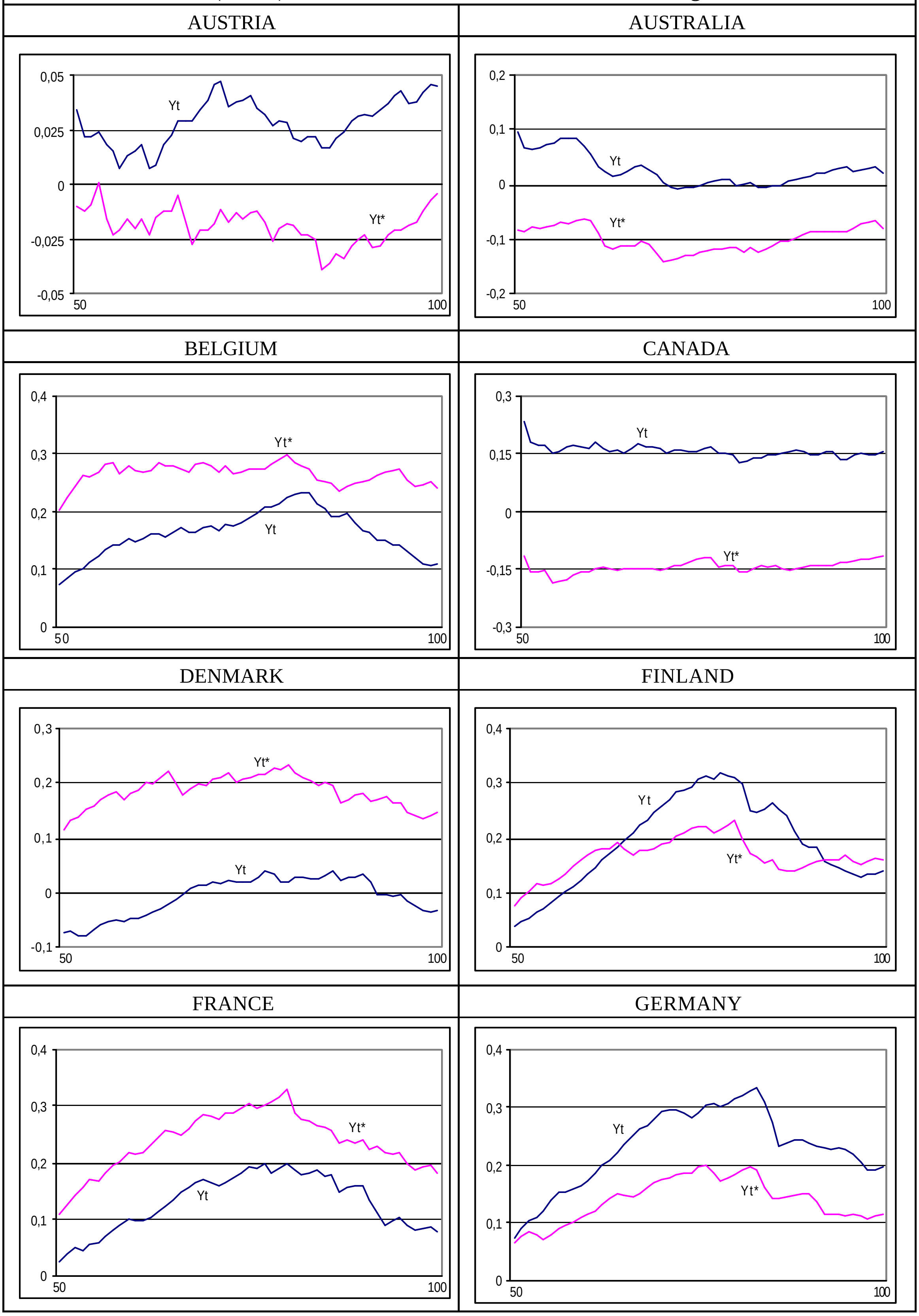
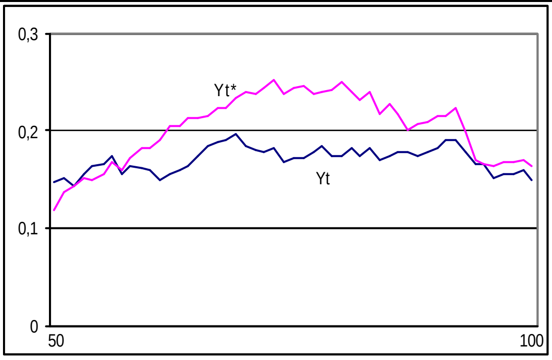


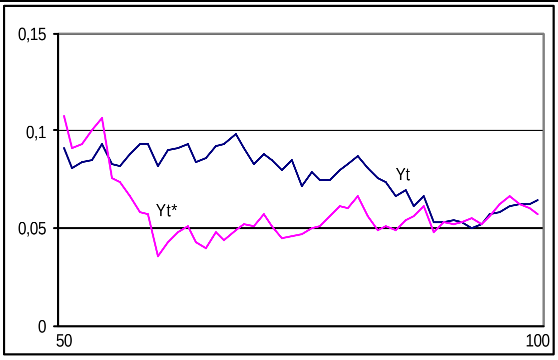
FIGURE 1 (cont.)

QMLE of Robinson (1995b) based on the first differenced data for a range of values J=50, 100

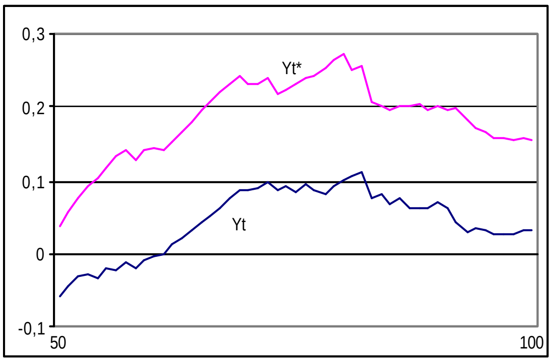
ITALY



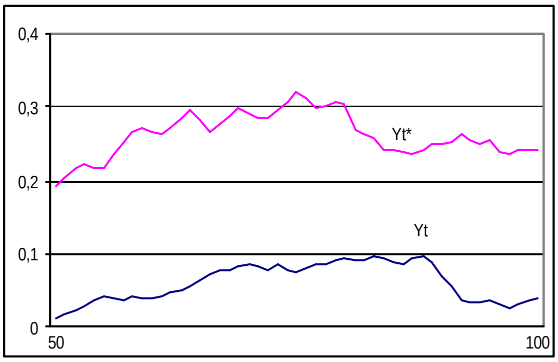
JAPAN



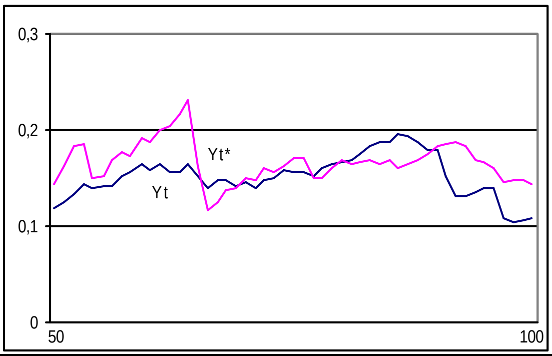
THE NETHERLANDS



NORWAY



SWEDEN



UNITED KINGDOM