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ABSTRACT

Convergence and Cycles in the Euro Zone

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JEL Classification: C32 and O40
Keywords: balanced growth, error correction mechanism, Kalman filter, signal extraction, stochastic trend and unobserved components

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Convergence and Cycles in the Euro-Zone

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March 4, 2003

Abstract

Multivariate unobserved components (structural) time series models are fitted to annual post-war observations on real income per capita in countries in the Euro-zone. The aim is to establish stylised facts about convergence as it relates both to long-run income levels and to cycles. The analysis is based on a new model in which convergence components are combined with a common trend and similar cycles. These convergence components are formulated as a second-order error correction mechanism which ensures that the extracted components change smoothly thereby giving a clearer decomposition into long-run movements and cycles.

KEYWORDS: Balanced growth, error correction mechanism, Kalman filter, signal extraction, stochastic trend, unobserved components.

JEL classification: C32, O40.

1 Introduction

Minimising income inequality across its members has long been a declared objective of the European Union. In particular, promoting convergence of income in levels (or at least the conditions for that to be obtained) has been the justification for the establishment first, of Structural Funds (the largest of which the European Regional Development Fund established in 1975) and, more recently (1993), of the Cohesion

Fund. The latter is specifically directed at poorer countries (Greece, Ireland, Portugal and Spain) and was set up with the purpose of making compatible the EMU budgetary discipline requirements and the continued infrastructure investment requirements in these countries, which the EU deems as necessary for convergence to take place. As Boldrin and Canova (2001) point out, what this implies about the view underlying EU policies is that deepening economic and monetary integration, by itself, leads to divergence of income levels across Europe; see also Martin (2000). However, this view stands at odds with neo-classical growth theories. As economic and monetary integration deepens and free movement of goods, people and capital becomes a reality across Europe, the preconditions for such theories are more likely to be met. As such, the theoretical prediction would be one of convergence not divergence.

Which view is correct is not only of theoretical interest but also has important policy implications. If the EU view is correct, the creation of EMU means that incentives for structural adjustment are needed for catching up to take place.[1] Given the loss of national monetary policies and the strict budgetary requirements limiting national public spending, European-wide redistribution would be the only option. Indeed, a substantial part of EU's resources is already directed at sustaining cohesion: Boldrin and Canova (2000) find that, over the 1986-1999 period, it is close to 8% of the Community's GDP.

Given such vast policy implications, the need to verify the validity of the underlying premise is obvious. Stylised facts on growth and convergence are needed to answer questions such as: are Euro-zone economies converging to a single steady state distribution or are they clustering around different states? Were they diverging before the establishment of Structural and Cohesion funds? Is there any visible effect of the latter on the growth dynamics of poorer countries?

However the fact remains that the existing literature on European convergence - mirroring the situation throughout the entire growth empirics literature- has reached

[1] The Delors Report of 1989 makes this clear, stating that with deeper integration 'transport costs and economies of scale would tend to favor a shift in economic activity away from less developed regions (...) to the highly developed areas (...). The economic and monetary union would have to encourage and guide structural adjustment which would help poorer regions catch up with the wealthier ones'.

no agreement on what the European record really is. This stems mainly from the use of different methods; see Durlauf and Quah (1999) for a review and criticism of the empirical literature. Thus while the early cross-sectional approach of Barro and Sala-i-Martin (1992) concluded in favour of absolute but slow convergence in Europe, panel models with fixed effects have suggested very fast convergence towards different steady states. Finally, following the time-series/cointegration approach proposed in Bernard and Durlauf (1995, 1996), Tsionas (2000) applies a battery of unit-root/stationarity tests to conclude that both divergence and convergence are possible: 'the results are mixed and depend critically on the type of test employed'.

As we have argued elsewhere (see Harvey and Carvalho (2002) and Carvalho and Harvey (2002)) we believe that rather than adding yet another set of regressors or testing in a vacuum, presenting the stylised facts on growth and convergence is of more value both for the development of meaningful theories and for policy decisions. This response is in line with the growing dissatisfaction on the current state of growth empirics and Durlauf's (2001, p 68) call for econometrics to 'clarify how empirical workers should elucidate data patterns and draw inferences concerning growth'. The aim of the present paper is to establish stylised facts about convergence in Euro-zone countries both with respect to long-run income levels and to cycles. Distinguishing trends from cyclical movements is essential to an effective study of convergence. The analysis is based on a new multivariate unobserved components model in which convergence components are combined with a common trend and similar cycles. These convergence components are formulated as a second-order error correction mechanism which ensures that the extracted components change smoothly thereby giving a clearer decomposition into long-run movements and cycles. Furthermore the second-order mechanism is able to capture temporary divergence, something that is a feature of the Euro-zone data. Because the cross-section is relatively small, we are able to properly account for the cross-correlations across regions. The statistical treatment of the model is based on the state space form. Parameters are estimated by maximum likelihood and components are extracted by the Kalman filter and associated smoother.

The plan of the paper is as follows. In section 2 we review the main ideas of structural time series models and show how a multivariate model handles balanced growth. Section 3 sets out the convergence model. Following the preliminary analysis of trends in per capita income in the Euro-zone countries in section 4, this model is fitted to two groups in section 5. The growth paths of the two groups are then compared. Section 6 examines the evidence for convergence in cycles. Section 7 assesses the extent to which unit root and co-integration tests can provide meanigful evidence on convergence, while section 8 concludes.

2 Structural Time Series Models and Balanced Growth

2.1 Univariate models

The *local linear trend* model for a set of observations, $y_t, t = 1,..,T$, consists of a stochastic trend and an irregular component, that is

$$y_t = \mu_t + \varepsilon_t, \qquad t = 1, ..., T, \tag{1}$$

where the trend, μ_t, receives shocks to both its level and slope so

$$\begin{array}{rcll} \mu_t & = & \mu_{t-1} + \beta_{t-1} + \eta_t, & \eta_t \sim NID(0, \sigma_\eta^2), \\ \beta_t & = & \beta_{t-1} + \zeta_t, & \zeta_t \sim NID(0, \sigma_\zeta^2), \end{array} \tag{2}$$

where the irregular, level and slope disturbances, ε_t,η_t and ζ_t, respectively, are mutually independent and the notation $NID\left(0, \sigma^2\right)$ denotes normally and independently distributed with mean zero and variance σ^2. If both variances σ_η^2 and σ_ζ^2 are zero, the trend is deterministic. When only σ_ζ^2 is zero, the slope is fixed and the trend reduces to a random walk with drift. Allowing σ_ζ^2 to be positive, but setting σ_η^2 to zero gives an integrated random walk trend, which when estimated tends to be relatively smooth. The model is often referred to as the '*smooth trend*' model.

The statistical treatment of unobserved component models is based on the state space form (SSF). Once a model has been put in SSF, the Kalman filter yields estimators of the components based on current and past observations. Signal extraction refers to estimation of components based on all the information in the sample. It is based on smoothing recursions which run backwards from the last observation[2]. Predictions are made by extending the Kalman filter forward. Root mean square errors (RMSEs) can be computed for all estimators and prediction or confidence intervals constructed.

The unknown variance parameters are estimated by constructing a likelihood function from the one-step ahead prediction errors, or innovations, produced by the Kalman filter. The likelihood function is maximized by an iterative procedure. The calculations can be done with the STAMP package of Koopman et al (2000). Once estimated, the fit of the model can be checked using standard time series diagnostics such as tests for residual serial correlation.

Distinguishing a long-term trend and from short-term movements is important. Short-term movements may be captured by adding a serially correlated stationary component, ψ_t, to the model. Thus

$$y_t = \mu_t + \psi_t + \varepsilon_t, \quad t = 1, ..., T \tag{3}$$

An autoregressive process is often used for ψ_t. Another possibility is the stochastic cycle

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}, \quad t = 1, ..., T, \tag{4}$$

where λ_c is frequency in radians and κ_t and κ_t^* are two mutually independent white noise disturbances with zero means and common variance σ_κ^2. The period corresponding to λ_c is $2\pi/\lambda_c$. For $0 \leq \rho < 1$, the process ψ_t is stationary with zero mean and variance $\sigma_\psi^2 = \sigma_\kappa^2/(1-\rho^2)$; see Harvey (1989, p60). The reduced form is an $ARMA(2, 1)$ process in which the autoregressive part has complex roots. The complex root restriction together with the smooth trend restriction often allows a clearer separation into trend and cycle.

[2]In a smooth trend model with a signal-noise ratio, $\sigma_\zeta^2/\sigma_\varepsilon^2$, of 1/1600, the extracted trend corresponds to the trend obtained by the Hodrick-Prescott (HP) filter for quarterly data.

2.2 Multivariate models

Suppose we have N time series. Define the vector $\mathbf{y}_t = (y_{1t}, .., y_{Nt})'$ and similarly for $\boldsymbol{\mu}_t, \boldsymbol{\psi}_t$ and $\boldsymbol{\varepsilon}_t$. Then a multivariate UC model may be set up as

$$\mathbf{y}_t = \boldsymbol{\mu}_t + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon), \quad t = 1, ..., T, \tag{5}$$

where $\boldsymbol{\Sigma}_\varepsilon$ is an $N \times N$ positive semi-definite matrix. The trend is

$$\begin{aligned} \boldsymbol{\mu}_t &= \boldsymbol{\mu}_{t-1} + \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_\eta) \\ \boldsymbol{\beta}_t &= \boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t, \qquad \boldsymbol{\zeta}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_\zeta), \end{aligned} \tag{6}$$

With $\boldsymbol{\Sigma}_\eta = 0$, we get the smooth trend model. With $\boldsymbol{\Sigma}_\zeta = 0$, we get the random walk plus drift.

The *similar cycle* model, introduced by Harvey and Koopman (1997) is

$$\begin{bmatrix} \boldsymbol{\psi}_t \\ \\ \boldsymbol{\psi}_t^* \end{bmatrix} = \begin{bmatrix} \rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \otimes \mathbf{I}_N \end{bmatrix} \begin{bmatrix} \boldsymbol{\psi}_{t-1} \\ \\ \boldsymbol{\psi}_{t-1}^* \end{bmatrix} + \begin{bmatrix} \boldsymbol{\kappa}_t \\ \\ \boldsymbol{\kappa}_t^* \end{bmatrix}, \quad t = 1, ..., T, \tag{7}$$

where $\boldsymbol{\psi}_t$ and $\boldsymbol{\psi}_t^*$ are $N \times 1$ vectors and $\boldsymbol{\kappa}_t$ and $\boldsymbol{\kappa}_t^*$ are $N \times 1$ vectors of the disturbances such that

$$E(\boldsymbol{\kappa}_t \boldsymbol{\kappa}_t') = E(\boldsymbol{\kappa}_t^* \boldsymbol{\kappa}_t^{*'}) = \boldsymbol{\Sigma}_\kappa, \quad E(\boldsymbol{\kappa}_t \boldsymbol{\kappa}_t^{*'}) = \mathbf{0}, \tag{8}$$

where $\boldsymbol{\Sigma}_\kappa$ is an $N \times N$ covariance matrix. The model allows the disturbances to be correlated across the series. Because the damping factor and the frequency, ρ and λ_c, are the same in all series, the cycles in the different series have similar properties; in particular their movements are centred around the same period. This seems eminently reasonable if the cyclical movements all arise from a similar source such as an underlying business cycle. Furthermore, the restriction means that it is often easier to separate out trend and cycle movements when several series are jointly estimated.

The common cycle model of Vahid and Engle (1993) assumes perfect correlation between cycles. This is a very strong restriction. The recent paper by Carlino and Sill (2001) uses the methodology of Vahid and Engle (1993) to decompose series on US regions into common trends and common cycles. In Carvalho and Harvey (2002) we explain why we do not find the resulting cycles particularly plausible.

2.3 Stability and balanced growth

The *balanced growth* UC model is a special case of (5):

$$\mathbf{y}_t = \mathbf{i}\mu_t + \boldsymbol{\alpha} + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \ , \qquad t = 1, ..., T, \tag{9}$$

where μ_t is a univariate local linear trend, $\mathbf{i}$ is a vector of ones, and $\boldsymbol{\alpha}$ is an $N \times 1$ vector of constants. If μ_t is initialised with a diffuse prior, then $\boldsymbol{\alpha}$ must be subject to a constraint so it contains only $N-1$ free parameters, for example there may be one zero entry. Note that although the levels may be different, the slopes are the same, irrespective of whether they are fixed or stochastic.

A balanced growth model implies that the series have a stable relationship over time. This means that there is a full rank $(N-1) \times N$ matrix, $\mathbf{D}$, with no null columns and the property that $\mathbf{Di} = \mathbf{0}$, thereby rendering $\mathbf{Dy}_t$ jointly stationary. In other words it removes the common trend, μ_t. The rows of $\mathbf{D}$ may be termed *balanced growth co-integrating vectors.* Typically each row will contain a one, a minus one and zeroes elsewhere. For example, one country may be used as a benchmark.

3 Convergence models

The multivariate convergence model proposed by Carvalho and Harvey (2002) is

$$\mathbf{y}_t \quad = \quad \boldsymbol{\alpha} + \beta \mathbf{i} t + \boldsymbol{\mu}_t + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, ..., T \tag{10}$$

with $\boldsymbol{\alpha}'\mathbf{i} = 0$ and

$$\boldsymbol{\mu}_t = \boldsymbol{\Phi}\boldsymbol{\mu}_{t-1} + \boldsymbol{\eta}_t, \qquad Var(\boldsymbol{\eta}_t) = \boldsymbol{\Sigma}_\eta \tag{11}$$

or

$$\Delta\boldsymbol{\mu}_t = (\boldsymbol{\Phi} - \mathbf{I})\boldsymbol{\mu}_{t-1} + \boldsymbol{\eta}_t.$$

Each row of $\boldsymbol{\Phi}$ sums to unity, $\boldsymbol{\Phi}\mathbf{i} = \mathbf{i}$. Thus setting λ to one in $(\boldsymbol{\Phi} - \lambda\mathbf{I})\mathbf{i} = \mathbf{0}$, shows that $\boldsymbol{\Phi}$ has an eigenvalue of one with a corresponding eigenvector consisting of ones.

The other roots of $\mathbf{\Phi}$ are obtained by solving $|\mathbf{\Phi}-\lambda\mathbf{I}|=0$; they should have modulus less than one for convergence.

If we write

$$\overline{\boldsymbol{\phi}}'\Delta\boldsymbol{\mu}_t=\overline{\boldsymbol{\phi}}'(\mathbf{\Phi}-\mathbf{I})\boldsymbol{\mu}_{t-1}+\overline{\boldsymbol{\phi}}'\boldsymbol{\eta}_t$$

it is clear that the $N\times 1$ vector of weights, $\overline{\boldsymbol{\phi}}$, which gives a random walk must be such that $\overline{\boldsymbol{\phi}}'(\mathbf{\Phi}-\mathbf{I})=\mathbf{0}'$. Since the roots of $\mathbf{\Phi}'$ are the same as those of $\mathbf{\Phi}$, it follows from writing $(\mathbf{\Phi}'-\mathbf{I})\overline{\boldsymbol{\phi}}=\mathbf{0}$ that $\overline{\boldsymbol{\phi}}$ is the eigenvector of $\mathbf{\Phi}'$ corresponding to its unit root. This random walk, $\overline{\mu}_{\phi t}=\overline{\boldsymbol{\phi}}'\boldsymbol{\mu}_t$, *is a common trend in the sense that it yields the common growth path to which all the economies converge.* This is because $\lim_{j\rightarrow\infty}\mathbf{\Phi}^j=\mathbf{i}\overline{\boldsymbol{\phi}}'$; the proof follows along the same lines as that for a well-known result on ergodic Markov chains as given, for example, in Hamilton (1994, p681). The common trend for the observations is a random walk with drift, β, and with $\boldsymbol{\alpha}'\overline{\boldsymbol{\phi}}=0$ each element of $\boldsymbol{\alpha}$ is a deviation from the common trend.

The *homogeneous* model has $\mathbf{\Phi}=\phi\mathbf{I}+(1-\phi)\mathbf{i}\overline{\boldsymbol{\phi}}'$, where $\mathbf{i}$ is an $N\times 1$ vector of ones, ϕ is a scalar convergence parameter and $\overline{\boldsymbol{\phi}}$ is an $N\times 1$ vector of parameters with the property that $\overline{\boldsymbol{\phi}}'\mathbf{i}=1$. It is straightforward to confirm that $\overline{\boldsymbol{\phi}}$ is the eigenvector of $\mathbf{\Phi}'$ corresponding to the unit root. The convergence parameter and the elements of $\overline{\boldsymbol{\phi}}$, denoted $\overline{\phi}_i, i=1,...,N$ are estimated by maximum likelihood in the usual way by using the Kalman filter; the trend components are initialised with a diffuse prior. It is assumed that $|\phi|\leq 1$, with $\phi=1$ indicating no convergence. The $\overline{\phi}_i$ parameters are constrained to lie between zero and one and to sum to one by maximising the log-likelihood with respect to N unconstrained parameters, a_i, that are linked to the $\overline{\phi}_i's$ by the equations $\overline{\phi}_i=a_i^2/\sum a_i^2, i=1,..,N.$

Each trend can be decomposed into the common trend and a convergence component. The vector of convergence components is

$$\begin{aligned}\boldsymbol{\mu}_t^{\dagger} &= \boldsymbol{\mu}_t-\mathbf{i}\overline{\mu}_{\phi t}\\ &= \mathbf{\Phi}\boldsymbol{\mu}_{t-1}-\mathbf{i}\overline{\mu}_{\phi t-1}+\boldsymbol{\eta}_t-\mathbf{i}\overline{\eta}_{\phi t}=\phi(\mathbf{I}-\mathbf{i}\overline{\boldsymbol{\phi}}')\boldsymbol{\mu}_{t-1}+\boldsymbol{\eta}_t-\mathbf{i}\overline{\eta}_{\phi t}\end{aligned}$$

so

$$\boldsymbol{\mu}_t^{\dagger}=\phi\boldsymbol{\mu}_{t-1}^{\dagger}+\boldsymbol{\eta}_t^{\dagger},\qquad t=1,...,T.$$

where $\boldsymbol{\eta}_t^{\dagger} = \boldsymbol{\eta}_t - \mathbf{i}\overline{\eta}_{\phi t}$. Writing

$$\Delta\boldsymbol{\mu}_t^{\dagger} = (\phi - 1)\boldsymbol{\mu}_{t-1}^{\dagger} + \boldsymbol{\eta}_t^{\dagger}, \tag{12}$$

shows that each relative growth rate depends on the gap between the series in question and the common trend. Substituting into (10) gives

$$\mathbf{y}_t = \boldsymbol{\alpha} + \beta\mathbf{i}t + \mathbf{i}\overline{\mu}_{\phi t} + \boldsymbol{\mu}_t^{\dagger} + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, ..., T$$

Once convergence has taken place, the model is of the form (9), but with an additional stationary component $\boldsymbol{\mu}_t^{\dagger}$.

The smooth convergence model is

$$\mathbf{y}_t = \boldsymbol{\alpha} + \boldsymbol{\mu}_t + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, ..., T \tag{13}$$

with $\boldsymbol{\alpha}'\mathbf{i} = 0$ and

$$\begin{aligned} \boldsymbol{\mu}_t &= \boldsymbol{\Phi}\boldsymbol{\mu}_{t-1} + \boldsymbol{\beta}_{t-1} \\ \boldsymbol{\beta}_t &= \boldsymbol{\Phi}\boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t \end{aligned}$$

The forecasts converge to those of a smooth common trend, but in doing so they may exhibit temporary divergence; see Harvey and Carvalho (2002).

In scalar notation the homogeneous model can be expressed in terms of the common trend, $\overline{\mu}_{\phi,t}$, and convergence processes, $\mu_{it}^{\dagger} = \mu_{it} - \overline{\mu}_{\phi,t}, i = 1, ..., N$, by writing

$$y_{it} = \alpha_i + \overline{\mu}_{\phi,t} + \mu_{it}^{\dagger} + \psi_{it} + \varepsilon_{it}, \quad i = 1, ..., N, \tag{14}$$

where $\Sigma\alpha_i = 0$ and

$$\mu_{it}^{\dagger} = \phi\mu_{i,t-1}^{\dagger} + \beta_{it}^{\dagger}, \quad i = 1, ..., N, \qquad |\phi| < 1 \tag{15}$$

$$\beta_{it}^{\dagger} = \phi\beta_{i,t-1}^{\dagger} + \eta_{it}^{\dagger}, \tag{16}$$

where the initial conditions, $\mu_{i0}^{\dagger}, i = 1, .., N - 1$, are fixed and

$$\begin{aligned} \overline{\mu}_{\phi t} &= \phi\overline{\mu}_{\phi t-1} + \overline{\beta}_{\phi t-1} \\ \overline{\beta}_{\phi t} &= \phi\overline{\beta}_{\phi,t-1} + \overline{\eta}_{\phi t}. \end{aligned}$$

Note that the $N-th$ series (or indeed any series) can be constructed from the others as

$$\mu_{Nt}^{\dagger} = -\overline{\phi}_N^{-1} \sum_{i=1}^{N-1} \overline{\phi}_i \mu_{it}^{\dagger} \quad with \quad \overline{\phi}_N = 1 - \sum_{i=1}^{N-1} \overline{\phi}_i.$$

and similarly for $\beta_{Nt}^{\dagger}$.

4 Stylised facts on trends and convergence in Euro-zone Countries

In this section we use the multivariate model of sub-section 2.2 to display the stylised facts concerning trends and convergence in real per capita incomes in eleven Euro-zone countries: Austria (AU), Belgium (BE), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IR), Italy (IT), Netherlands (NE) Portugal (PO) and Spain (SP). Out of the present membership of the Euro-area, only Luxembourg is not included as no data are available.

4.1 Data and estimation

Data were obtained from the GGDC Total Economy Database, 2002, at the University of Groningen and the Conference Board [3]. All series are expressed in 1990 US dollars converted at 'Geary-Khamis' purchasing power parities and log-transformed. Figure 1 shows annual observations from 1950 to 1997. The German data refers to West Germany. After 1997 data is only available for Germany as a whole and this is why we concentrated our analysis on the period up to that point.

Estimation of all the new model was done using program routines written in the `OX 3.0` language (Doornik, 1999) with use being made of the SSfPack package for state space algorithms of Koopman, Shephard and Doornik (1999). Some of the more standard models were estimated using the STAMP package of Koopman et al (2000). All parameters were estimated by maximum likelihood as described in Section 2 and variances are reported multiplied by 10^5. The estimated covariance matrices

[3] For full description of the dataset refer to http://www.eco.rug.nl/ggdc

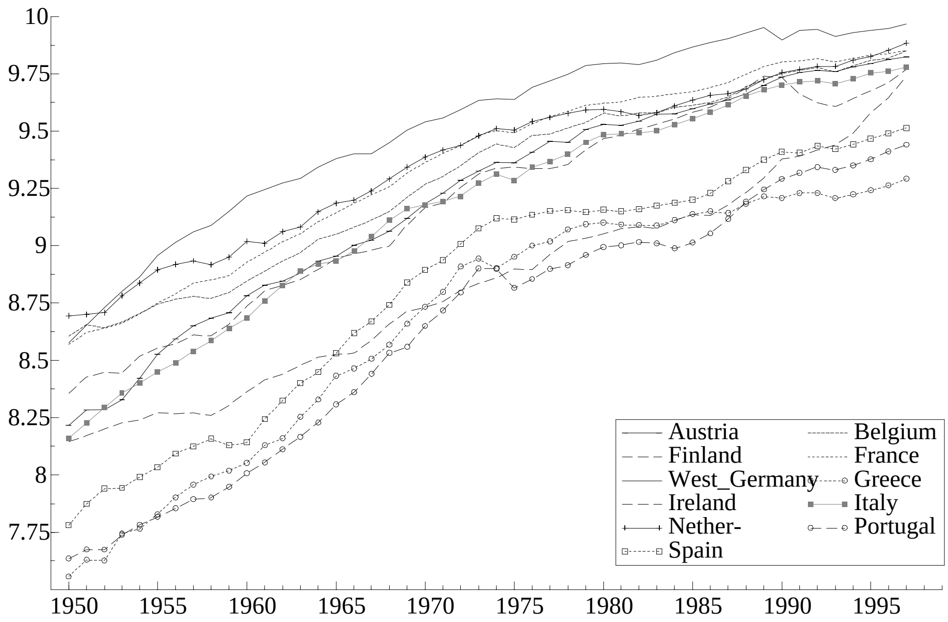

Figure 1: Annual series (1950-1997) for Euro-area countries.

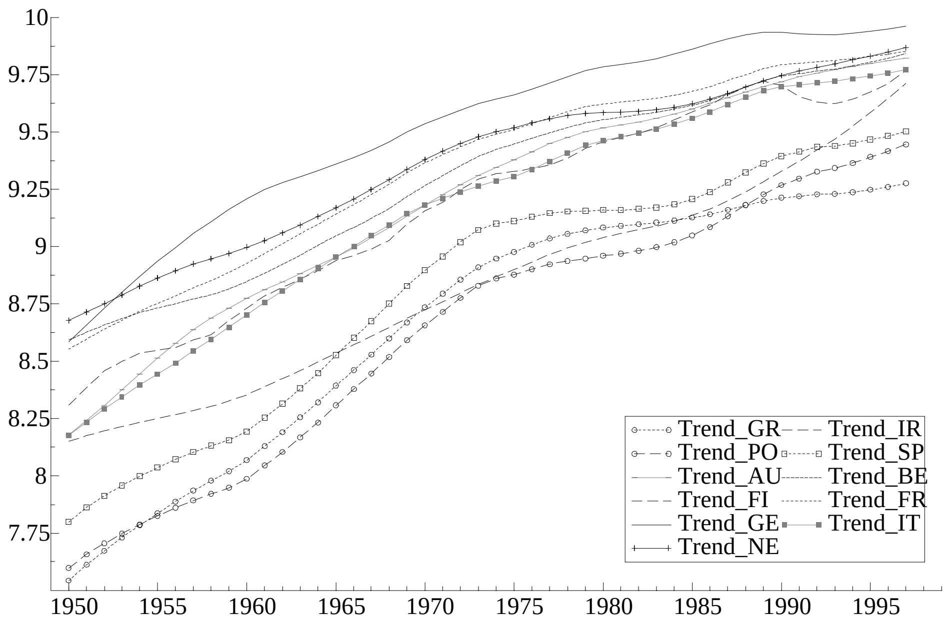

Figure 2: Smooth trends for Euro-zone countries.

are reported by showing the variances on the main diagonal while the entries above contain the cross-correlations. The components shown in the figures are extracted by the state-space smoothing algorithm. Comparisons with US regions refer to the results in Carvalho and Harvey (2002).

4.2 Trend growth and income inequality

Figure 2 shows the trends, $\widetilde{\mu}_{it|T}$, obtained by fitting a simple multivariate smooth trend plus cycle model. These slowly changing trends indicate the long-run movements from which we can start to assess any tendencies towards convergence or divergence.

The first point to note is the existence of subgroups, or clusters, within the Eurozone: a high-income group, consisting of traditional core countries (GR, FR, BE, NE), together with some peripheral countries (IT, AU, FI), and a low income group made up of poorer peripheral countries (PT, SP, GR). The outlier is Ireland, which cannot be labeled with certainty as a member of either group given its growth dynamics. Otherwise, this subgrouping is well defined and remarkably stable throughout the second half of the twentieth century. The three poorest and the seven richest countries in 1950 still had that status at the end of the nineties.

The second point to note is that the extracted trends clearly show the three distinct epochs of economic growth: 1950-1972; 1973-1979 and 1980-1997. These standard subdivisions in post-war European economic history correspond to the 'Golden Age', the shocks of the 1970s and the ensuing period of stabilisation and restructuring; see Crafts and Toniolo (1996). Table 1 below documents the average trend growth rates for each of the Euro-zone countries and for each subgoups..

	1950-1997	**1950-1972**	**1973-1979**	**1980-1997**
Austria	3.57%	5.10%	3.35%	1.80%
Belgium	2.70%	3.51%	2.71%	1.70%
Finland	3.19%	4.38%	2.65%	1.94%
France	2.81%	4.09%	2.54%	1.36%
Germany	3.00%	4.71%	2.51%	1.09%
Greece	3.79%	6.15%	3.12%	1.15%
Ireland	3.38%	2.99%	3.21%	3.93%
Italy	3.47%	4.94%	2.95%	1.86%
Netherlands	2.57%	3.57%	1.90%	1.62%
Portugal	4.03%	5.51%	2.49%	2.81%
Spain	3.72%	5.72%	1.99%	1.95%
7 richest, average	3.04%	4.33%	2.66%	1.63%
3 poorest, average	3.85%	5.79%	2.53%	1.97%

Table 1: Average trend growth rates for Euro-zone countries.

Taking the information in Figure 2 and Table 1 together, it is clear that: 1) the poorest subgroup has, over the entire period, a higher trend growth rate; 2) this higher average trend growth rate is a product of the strong catching-up process during the Golden Age[4]. These two facts largely explain the findings in cross-sectional

[4]Calculations by the authors show that this catching-up process is largely limited to the 60s.

studies, such as Sala-i-Martin (1996), supporting β-convergence in Europe throughout the post-war period and its absence from the 1970s onwards. Table 1 also sheds some light on (limited) mobility in income per-capita ranking within each group. Thus, for example Austria's and Portugal's superior growth performance leads to their overtaking of Finland and Greece respectively. On the other hand, Ireland's idiosyncratic behaviour is singled out: it is both the only country to miss out on the Golden Age and the best achiever over the 1980-1997 period.

Further insights on the evolution of income inequality across the Euro-zone can be gained by the plotting the cross-sectional standard deviation of the smoothed trend components, $SD(\widetilde{\mu}_{it|T})$. This is done in Figure 3, where we also plot the analogous series for the 8 US Census regions, as well as those of subgroups both within Europe and US.

Some interesting facts arise from Figure 3. The first is that overall Euro-zone trend dispersion (solid line) has in the last half-century. As was clear from the analysis of Table 1, this is mainly the result of the Golden Age period. One important factor is trade liberalisation process, set in motion in the 1960s both within the EEC and EFTA and between the two organisations; see Ben-David (1993). However the fact remains that, by the end of the nineties, inequality across the Euro-zone was still above that of the US regions (dotted line) in the 1950s.

The analysis of inequality within the two subgroups in Europe allows us to qualify the last statement. From Figure 3, it is clear that inequality within the groups is much lower than it is overall. In particular, inequality within the high-income group (box line) has been falling steadily and since the mid-eighties it has been below that of the US regions. Within the low-income group, inequality in the 1950s was relatively low and no downward trend can be observed in the data. Nevertheless, it is still the case that relative to the US benchmark, inequality within both groups of countries is not very different.

During the 50s the high income group actually grows faster due to the high growth rates of Austria, Germany and Italy, i.e. reconstruction efforts still appear to matter in explaining the 1950s relative performance.

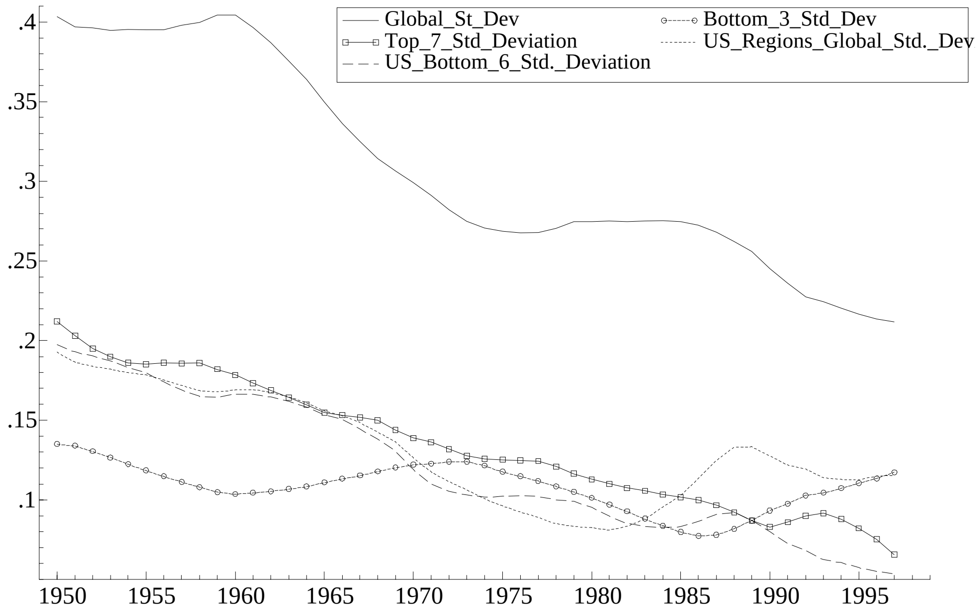

Figure 3: Evolution of global and subgroup cross-sectional standard deviations in Euro-zone and US.

4.3 Convergence and multiple steady states

The preliminary investigation of stylised facts on trend growth in within current Euro-zone countries indicates the existence of two convergence clubs[5], plus Ireland. If this is the case, convergence tests and models based on the assumption of a common growth path will be inadequate and could lead to misleading inferences being drawn. What we need to do is to investigate the case for absolute convergence within the two groups and relative convergence between the groups.

5 Fitting convergence models

Based on the analysis of the previous section, we proceed by fitting convergence models, as described in section 3, to the rich and poor subgroups rather than to the Euro-zone as a whole. Recall that this specification not only allows us to separate trends and cycles but also separates out the long-run balanced growth path from the transitional (converging) national dynamics, thus permitting a characterisation of convergence stylised facts. The results reported are for the homogeneous model with smooth convergence, (13), and absolute convergence, that is $\alpha_i = 0, i = 1, ..., N$. We analyse each sub-group in turn.

5.1 High-Income Group

Figure 4 below displays the estimated common trend, $\overline{\mu}_{\phi,t}$, together with the estimated trends for each country while figure 5 shows the smoothed estimates of the convergence components, $\mu^{\dagger}_{i,t}$, for the seven Euro-zone high-income countries [AU, BE, FI, FR, GE, IT, NE].

[5] Durlauf and Johnson (1995) identify four different regimes (determined by initial conditions) in the Summers-Heston dataset. They find that these regimes are associated with different aggregate production functions and hence, the assumption of a common long-run growth path is untenable. Their partition of the eleven Euro-zone countries is the same as the one noted in the previous sub-section. Thus, Greece, Portugal, Spain (and Ireland) are classified as intermediate-output countries with high literacy rates while the remaining seven are included in the high-output group.

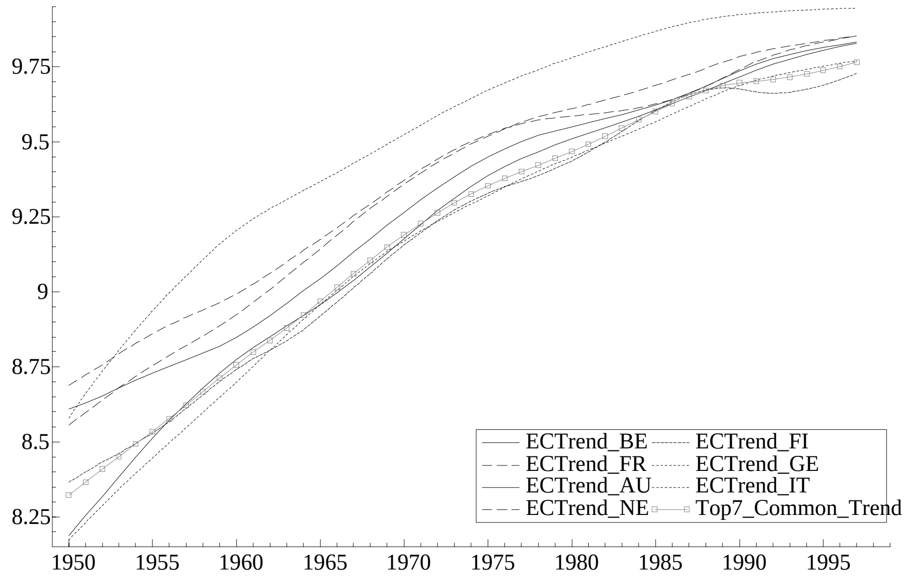

Figure 4: Converging Trends and Balanced Growth Path for the High Income Group.

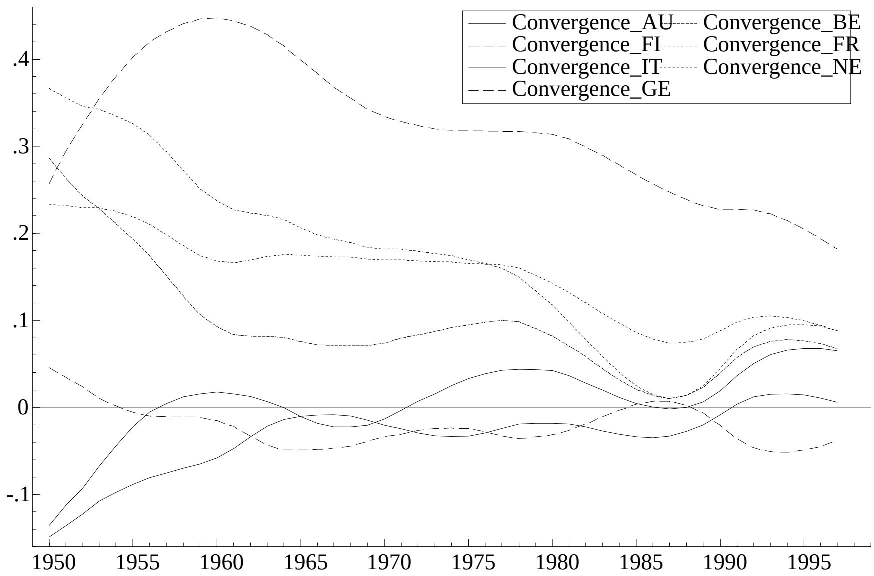

Figure 5: Convergence Components for High-Income Group

The convergence parameter, ϕ, was estimated[6] as 0.938 while the common trend weights, $\overline{\phi}_i$, are given by:

$\overline{\phi}_{AU}$	$\overline{\phi}_{BE}$	$\overline{\phi}_{FI}$	$\overline{\phi}_{FR}$	$\overline{\phi}_{GE}$	$\overline{\phi}_{IT}$	$\overline{\phi}_{NE}$
0.01	0.06	0.45	0.02	0.03	0.40	0.03

The within-group convergence is shown in figures 4 and 5, with all seven countries significantly narrowing their gap towards the common balanced growth path. The large weights assigned to Finland and Italy in constructing the common trend means that the future growth path depends primarily on extrapolating the trends in these two countries. In other words these two relatively poorer countries within the high-income group act as benchmarks to which all the other high-income countries converge. This may seem surprising at first. Why doesn't Germany dominate, for example? A glance at figure 4 gives the answer. The German growth rate has been gradually slowing down, particularly after re-unification, and at the end of the sample the trend is almost flat. If we were to extrapolate there would be almost no growth.

The convergence components are not monotonic over time and so the fact that the model allows a degree of divergence is important. During the 1950s and early 60s at least two distinct type of dynamics should be singled out. One is dominated by the strong effects of reconstruction in Austria, Italy and Germany and the other by relatively slower adjustment in France, Belgium and the Netherlands; further details can be found in Crafts and Toniolo (1996) and the references therein. In contrast the late 1960s and 1970s appear to bring a halt in the convergence process across the entire high-income group. This process is resumed in the 1980s before and again slowing down in the 1990s.

Further insights on cross national correlations can be gained by analysing the variance-covariance matrix of the converging trends, $\widetilde{\mathbf{\Sigma}}_\zeta$. Two subgroups, with relatively high, positive within-correlations and relatively low (or negative) across-correlations appear to emerge. On the one hand a group formed by Belgium, France, Netherlands and, to a smaller extent, Italy and on the other hand, a group formed by Austria, Germany and possibly Finland.

[6]The convergence parameter in a first-order error correction model, (12), will typically be higher.

$$\left[\begin{array}{ccccccc} 1.80 & 0.31 & 0.15 & -0.03 & 0.49 & -0.48 & 0.48 \\ & 1.22 & -0.19 & 0.83 & -0.63 & 0.09 & 0.94 \\ & & 8.15 & 0.18 & 0.57 & 0.03 & -0.26 \\ & & & .86 & -0.60 & 0.48 & 0.70 \\ & & & & .48 & -0.36 & -0.47 \\ & & & & & 1.06 & 0.15 \\ & & & & & & 2.23 \end{array}\right] \begin{array}{c} AU \\ BE \\ FI \\ FR \\ GE \\ IT \\ NE \end{array}$$

The forecasts of the convergence components will tend to zero as the lead time goes to infinity. The second-order ECM allows some divergence before convergence eventually takes place; see the model fitted to the US and Japan in Harvey and Carvalho (2002). In figure 5 all the convergence components are pointing in the direction of zero and a straightforward extrapolation suggests that the economies will be close to convergence after about ten years.

5.2 Low-Income Group

We now turn to the converging dynamics within the low income group [GR, PO, SP]. Ireland is excluded due to its idiosyncratic behaviour: it is difficult to classify it as a low income country given its position both at the beginning and end of the sample[7]. Figures 6 and 7 below present the common trend and convergence components respectively.

The convergence parameter was estimated as $\phi = 0.937$, and the common trend weights, $\overline{\phi}_i$ given by:

$\overline{\phi}_{GR}$	$\overline{\phi}_{PO}$	$\overline{\phi}_{SP}$
0.48	0.36	0.17

The sign of the convergence parameter is consistent with within-group convergence and similar in magnitude to the high-income group. The cross-correlations in the covariance matrix of the converging trends, $\widetilde{\boldsymbol{\Sigma}}_{\zeta}$ are shown below.

[7] Taking the Irish performance after the end of our sample (1997) only serves to confirm this assumption as the gap between Ireland and the three low income countries grows even larger.

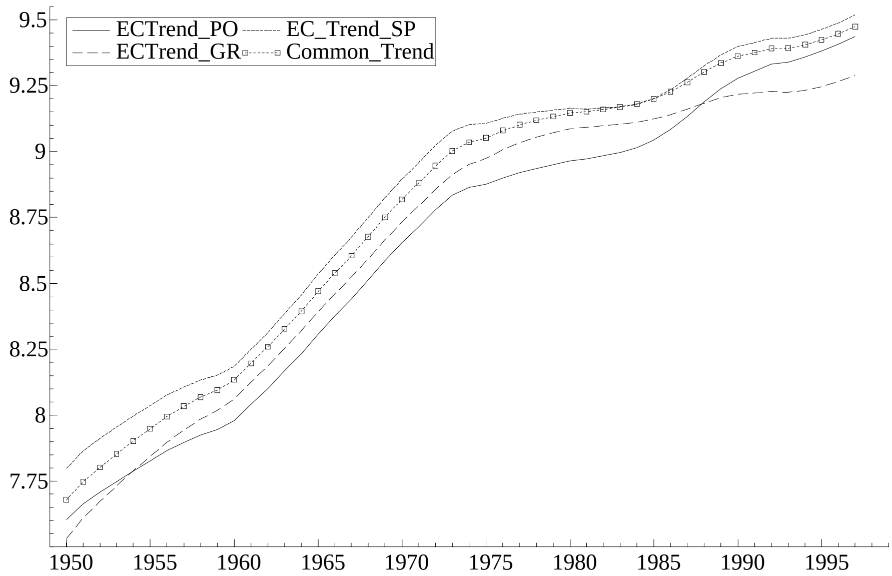

Figure 6: Common Trend and Converging Trends for Low-Income Group.

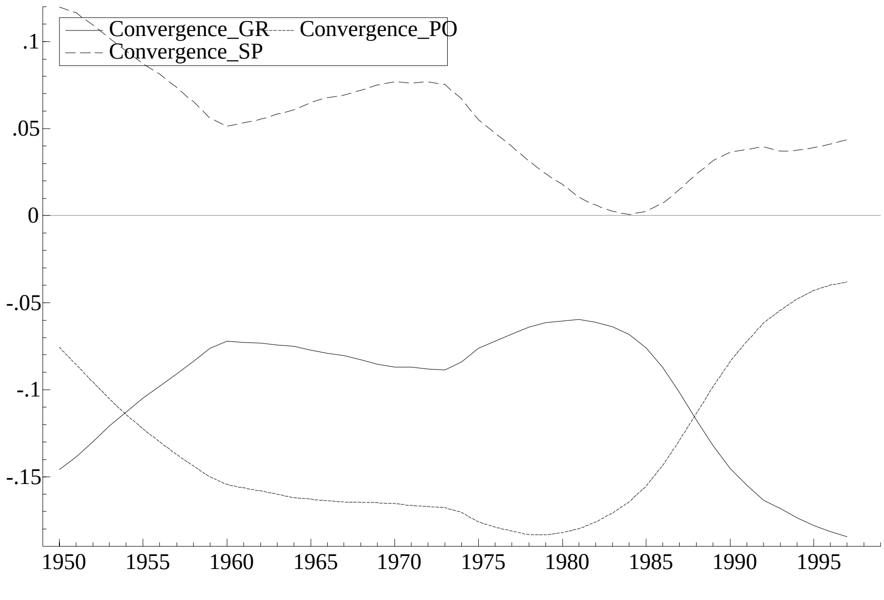

Figure 7: Convergence Components for Low Income Group.

$$\begin{array}{c} \begin{bmatrix} 10.0 & 0.89 & 0.95 \\ & 17.5 & 0.99 \\ & & 22.8 \end{bmatrix} \end{array} \begin{array}{c} GR \\ PO \\ SP \end{array}$$

All the pairwise correlations are greater than the BE-FR correlation, the largest in the high-income group. The magnitude of the convergence components is smaller and more stable for these three low income countries. However, figure 7 illustrates the point that a relatively stable cross-sectional standard deviation does not necessarily imply that there are no intra-distribution dynamics; see Quah (1996) and Durlauf and Quah (1999). Thus, Greece and Portugal alternate their ranking over the sample period: Greece starts off as the poorest economy, rapidly overtakes Portugal, but is subsequently overtaken by Portugal in the 1980s. Indeed the main conclusion to be drawn from the plots of the convergence components is that since that mid-eighties the gap between Spain and Portugal has narrowed considerably, while Greece has diverged. This throws some doubt on the coherence of the group.

5.3 Divergence or relative convergence in the Euro-zone?

Having characterised the within-group convergence dynamics we now proceed with a between groups analysis. The key question is whether the common trends estimated for each group indicate relative convergence. In order to investigate this issue, a bivariate convergence model is fitted to the two common trends. Since we are dealing with extracted trends, $\widetilde{\mu}_{it}$, the aim is to perform the decomposition:

$$\widetilde{\mu}_{it} = \widetilde{\alpha}_i + \widetilde{\overline{\mu}}_{\phi,t} + \widetilde{\mu}_{it}^{\dagger}, \quad i = LI, HI \tag{17}$$

with $\overline{\mu}_{\phi,t}$ and $\mu_{it}^{\dagger}$ defined as in (14) and LI and HI denoting low income and high income, respectively

When the model is fitted with no restrictions on ϕ_{LI} and ϕ_{HI}, the estimate of ϕ_{HI} is zero, indicating that the high-income trend can be treated as benchmark. Table 2 below shows the parameter estimates for the absolute and relative convergence versions of this benchmark model. It is convenient to standardise the intercepts in the relative convergence model by setting $\widetilde{\alpha}_{HI} = 0$; there is then absolute convergence when $\widetilde{\alpha}_{LI} = 0$.

		Absolute		Relative	
	Hyperparameters	**LI**	**HI**	**LI**	**HI**
Convergence	$\sigma^2_\zeta(\times 10^5)$	6.85	.54	6.51	.54
	$\widetilde{\phi}$	0.939		0.916	
Gap	$\widetilde{\alpha}_{LI}$	$0(fixed)$		-0.337 (0.168)	
Fit	$\log L$	366.56		367.92	

Table 2: Estimates for bivariate convergence model fitted to smoothed trends.

Two main points should be noted from table 2. First, the estimate of ϕ is less than one and so is consistent with convergence of the low-income trend towards the high income trend. Second, the estimate of α_{LI} is negative and its 't-statistic' is statistically significant[8] at the 5% level. This implies that the trend forecasts of the low income countries are converging to a growth path, $\widetilde{\mu}_{HI,t} + \widetilde{\alpha}_{LI}$, that is parallel to that of the high income countries but lies below it. Figure 8 shows a plot of $\widetilde{\mu}_{HI,t} + \widetilde{\alpha}$, labelled 'common trend', together with the two group common trends. The convergence component, $\widetilde{\mu}^{\dagger}_{LI,t} = \widetilde{\mu}_{LI,t} - (\widetilde{\mu}_{HI,t} + \alpha)$, is shown in figure 9. It can be seen that relative convergence had taken place by the early seventies. The gap appears to be permanent and the long-run implication is that each of the low income countries will have a per capita income that is almost 30% below that in the high income group.

6 Cycles

The other aspect of convergence concerns cycles. In order to investigate this issue we looked at the five core economies of France, Germany, Belgium, Netherlands and Italy to see to what extent the business cycle movements had converged. All of these countries are in the rich group. We have excluded Austria and Finland as they are relatively recent entrants into the EC. Fitting a multivariate STM to the five series

[8]The LR statistic is not significant however. Since a good deal of the variation has been removed by smoothing, tests of significance should only be regarded as giving a rough indication of the underlying situation.

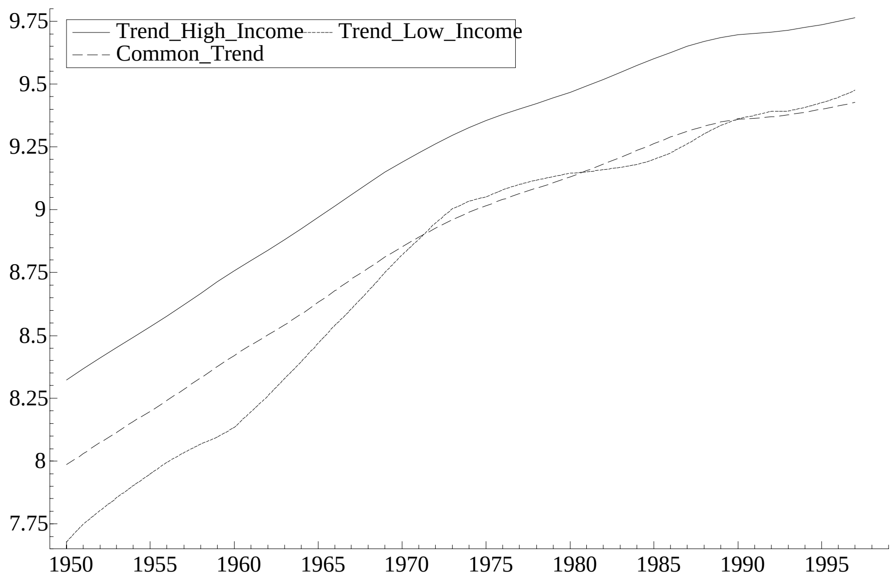

Figure 8: Common trend and trends for Low Income and High Income Group.

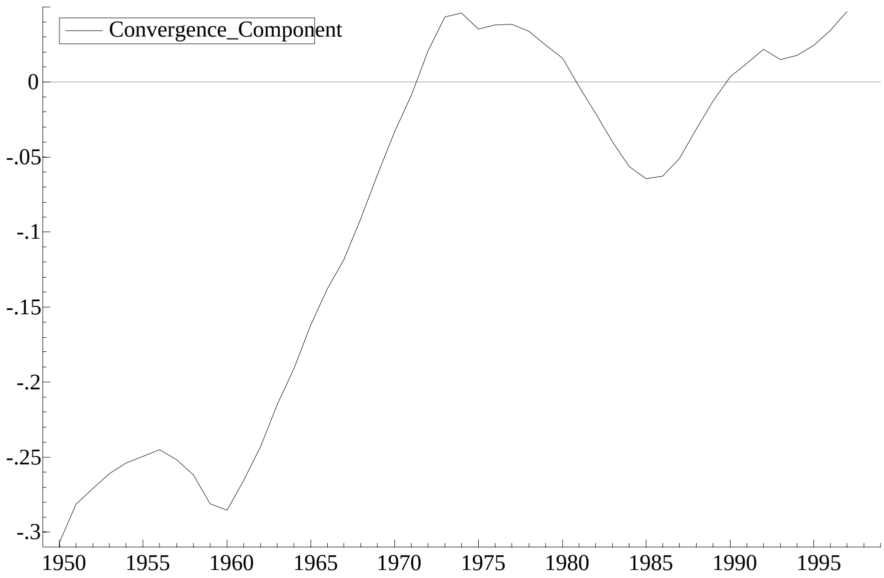

Figure 9: Convergence component for Low Income group.

using the STAMP package of Koopman et al (2000) gave very similar results to fitting the convergence model reported in sub-section 5.1 and it is quite adequate for the purposes of extracting cycles. The model consisted of smooth trends, similar cycles and irregular components.

Focussing attention on the cycle, the estimates of the damping factor, ρ, and the period were found to be 0.87 and 7.86 years respectively. The variances and cross-correlations are shown below.

BE	15.1	.75	.79	.55	.28
FR		12.2	.78	.45	.34
GE			24.8	.72	.35
NE				25.6	.26
IT					31.6

In our study of US regions we performed a principal components analysis on the correlation matrix and showed that the biggest component accounted for over 90% of

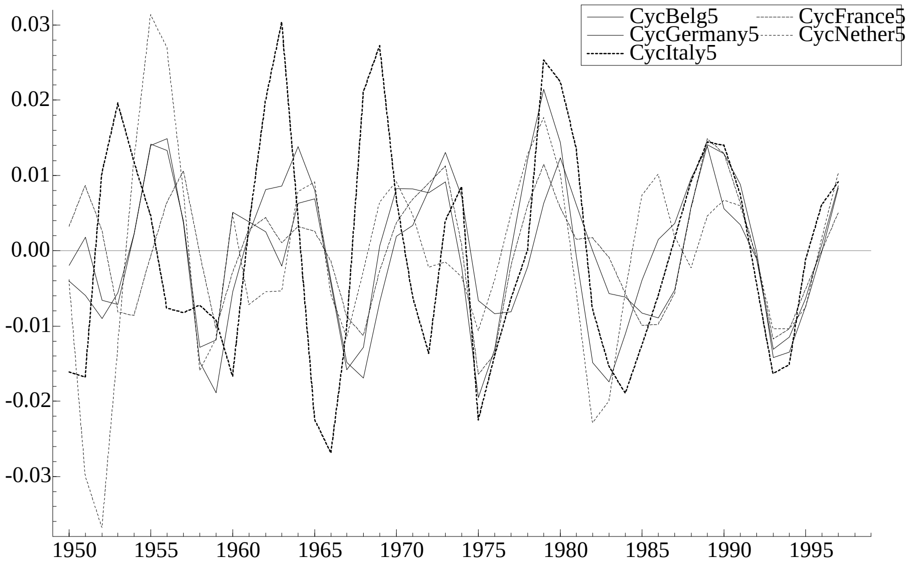

Figure 10: Cycles extracted from five core countries

the variation. This was not surprising in view of the fact that the majority of pairwise correlations were greater that 0.9. The issue here is somewhat different in that our interest is on the extent to which the cycles have come closer together. Figure 10 shows the smoothed estimates of the cycles. While the dispersion at the beginning is quite large, the cycles are almost perfectly co-ordinated by the end of the 1990s. Figure 11, which plots the standard deviation of the five cycles over time, tells the same story.

As part of the convergence process, the cycle cross-correlations may well have changed over time so the figures above have to be regarded as averages in some sense. Estimating the model over the period starting in 1970 gave estimates of ρ and the period equal to 0.90 and 5.90 years respectively. As can be seen below, the cross-correlations are much bigger.

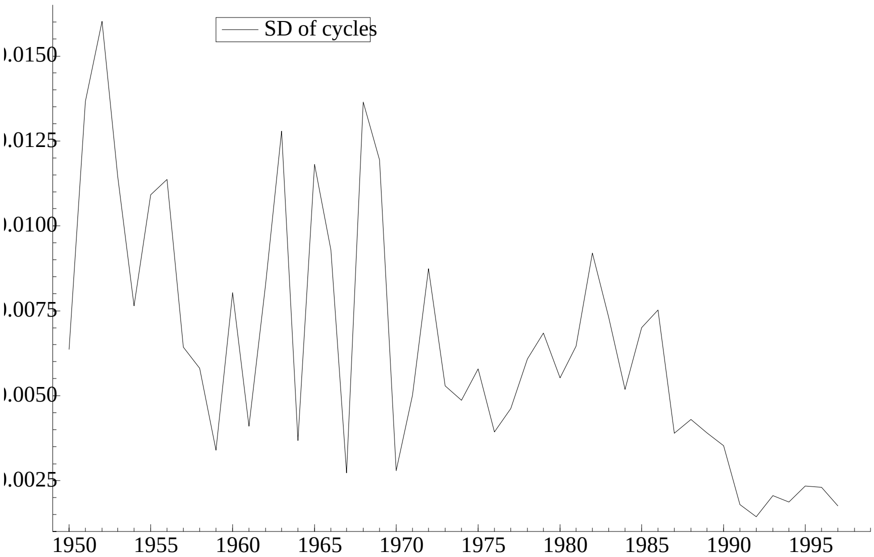

Figure 11: Standard deviation of cycles extracted from five core countries

BE	29.8	.88	.64	.78	70
FR		19.1	.78	.86	.69
GE			9.5	.75	.55
NE				25.1	.53
IT					23.7

As it stands, the cycle model does a good job of picking up the convergence, but if it were to be used to generate converging cycles, it would have to incorporate a mechanism that allowed the cross-correlations to tend gradually towards unity.

The same model was also fitted to three poorer countries, Greece, Portugal and Spain. The damping factor and the period were found to be 0.81 and 7.29 years, while the cycle variances and cross-correlations are

GR	22.3	.43	.20
PO		67.8	.05
SP			23.7

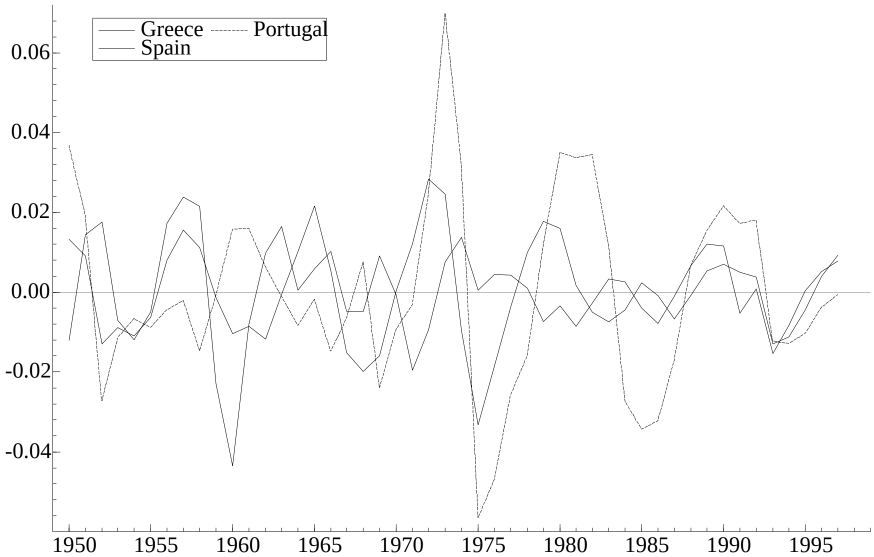

Figure 12: Cycles for Greece, Portugal and Spain

The relatively low value of ρ indicates that the cycles are not particularly well-defined. This is especially true of Spain. The low correlations between Spain and the other two countries indicates little coherence. Portugal's cycles are quite pronounced, with the variance being three times what it is in most countries. The cycles are shown in figure 11. Despite the low coherence in the period as a whole, it can be seen that they are converging towards the end of the period, with a pattern not dissimilar to that in the core group.

Finally a cycle was extracted for Ireland by modelling it jointly with Germany. This gave a moderately high correlation of 0.79 but with Ireland having a much larger variance of 49.6 ($\times 10^{-5}$). The extracted cycles are shown in figure 12. The most striking feature is the higher amplitude of the Irish cycle, even in recent years.

7 Testing re-visited

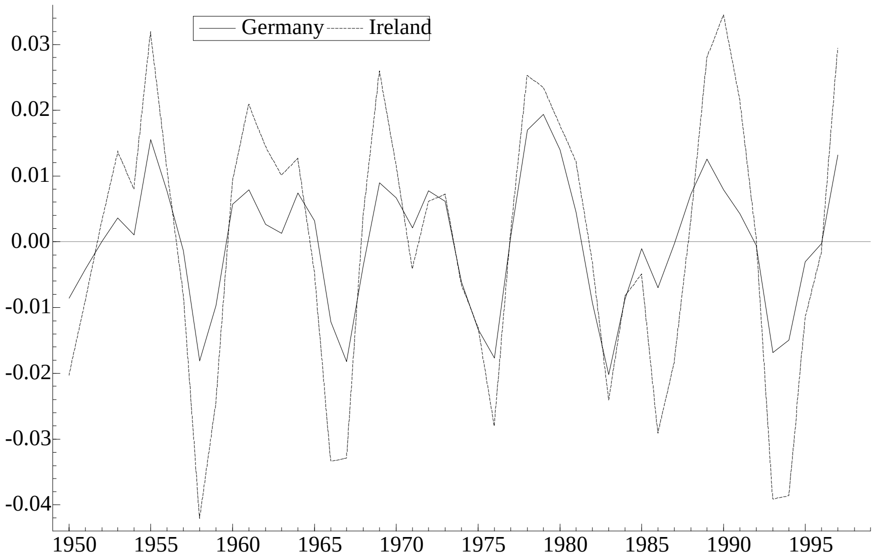

Figure 13: Cycles for Ireland and Germany

As was noted earlier, standard unit root tests give a confused message with regard to convergence. This section examines some of the issues in testing for convergence in the light of the descriptive results of the last two sections. In doing so we draw on the recent investigation by Harvey and Bates (2003).

The first point to note is that the standard augmented Dickey-Fuller (ADF) test, with a constant included, has very low power. This can be illustrated by applying the test to the series on The Netherlands minus Italy. A graph shows very clear convergence. In 1950 the difference (in logs) between the two series was 0.534, corresponding to The Netherlands having a per capita income 1.7 times that of Italy, while in 1997, the gap was 0.105, corresponding to a ratio of 1.11. Yet the ADF test fails to reject. For example, with one lagged first difference[9], the $t-$statistic is -2.14, as against a 10% critical value of -2.60. This is despite the fact, that, an initial value away from the mean actually helps to increase power. If the constant is dropped from the ADF

[9]The result is relatively insensitive to the number of lags. For example with three lags $t = -2.41$. (These additional lags are not statistically significant at the 10% level.)

regression, as is appropriate for a test of absolute convergence, then, with one lag, the $t-$statistic is -2.52, as against a 5% critical value of -1.96. Thus dropping the constant leads to a rejection of the null of no convergence at the 5% level of significance. The t-statistic is not quite significant at the 1% level, but if the information in all five core countries is pooled by forming a set of four contrasts with Italy, the multivariate homogeneous Dickey-Fuller t-test, studied in Harvey and Bates (2003), shows a very strong rejection[10]. Taking the observations from 1960 (since there is some divergence before 1960, although not between The Netherlands and Italy); the $t-$statistic, with one lag, is -3.04 while the 1% critical value (for $T = 100$) is -2.58. If all seven rich countries are considered, the rejection is even stronger as the $t-$statistic is -4.27. On the other hand if the constant is included, even the multivariate tests are unable to reject at the 10% level.[11] Note that because the test takes account of cross-correlations between the series, it is invariant to the choice of benchmark.

Testing in the low income group gives a less clear picture, as one might expect from the earlier analysis. Pairwise tests are unable to reject the null of no convergence, even with the constant excluded, and pooling the data does not help[12].

The trace likelihood ratio test of Johansen (1988) may be used, as in Bernard and Durlauf (1995), to try to detect the number of co-integrating relationships and hence the number of clubs. However, the test is likely to have low power and hence to indicate too many clubs. For example with the five core countries, again from 1960, the test, based on a model with an unrestricted constant[13] and two (p) lags, cannot

[10] A LR test of the null hypothesis that the four contrasts are nonstationary is unable to reject at the 5% level of significance; whether or not intercepts are included makes no difference to the conclusion. Such a result is consistent with the simulations in Harvey and Bates (2003), which indicate that the LR test can have very low power relative to the multivariate homogeneous Dickey-Fuller t-test.

[11] For 5 and 7 countries the t-statistics were -2.26 and -2.25 respectively. The 10% critical values - from table 3 of Harvey and Bates(2003) are -3.73 and -4.26 respectively.

[12] The t–statistic, with no constant, for Greece-Spain with one lag is only -0.069, while Portugal-Spain is -0.924 and -1.070 if a constant is added.

[13] This is appropriate (except possibly for $R = N - 1$) since the series are assumed to have drifts but no time trends in the co-integrating relationships. It could be argued that if clubs exhibit absolute convergence then constants should be excluded from the co-integrating relationships but

reject the null hypothesis of five common trends, against the alternative that there are fewer, at the 5% level of significance when the degrees of freedom correction is used. In other words it indicates that there is no co-integration and no convergence clubs (with more than one member). With no degrees of freedom correction, four trends cannot be rejected. The results, obtained from the PcFIML program of Doornik and Hendry (2000), are shown in the table below; R is the number of co-integrating vectors so $5 - R$ is the number of (common) trends. The max test, not shown in the table, could not reject five trends even without the degrees of freedom correction.

R	T	$T - Np$	5% cv
0	70.57*	52.00	68.5
1	42.79	31.53	47.2
2	19.74	14.54	29.7
3	8.56	6.31	15.4
4	0.11	0.08	3.8

Table 3 Trace LR statistic for co-integration with $(T - Np\ )$ and without (T) degrees of freedom correction.

* indicates a rejection at the 5% level of significance.

8 Conclusion

Preliminary analysis from fitting a multivariate structural time series model to the eleven Euro-zone countries indicates two possible convergence clubs, one a high income group, consisting of the five core economies plus Austria and Finland, and a low income group, made up of Spain, Greece and Portugal. Ireland seems to follow its own growth path. The multivariate convergence model is successful in separating trends from cycles and capturing the absolute convergence in the two groups. The evidence for convergence in the second group is less compelling, but the assumption of a single common trend is not unreasonable. The groups themselves appear to have converged in the relative sense. If this is correct, the implication is that the average

this is not a standard constraint.

per capita income in the poor group will remain almost 30% below that of the high group.

The cycles in the core high income group show a remarkable coherence in recent years, with the group standard deviation having fallen dramatically. There is less coherence in the poor group, though again there is evidence of a movement towards the same cycle as the rich group in recent years.

From the methodological point of view, the series illustrate the futility of trying to infer anything about convergence using Dickey-Fuller tests with constant included. However, it is possible to sensibly test against absolute convergence by dropping the constant and additional power is gained by pooling the information in several converging series. The likelihood ratio tests for co-integration appear to be of little use as a means of detecting the number of convergence clubs.

ACKNOWLEDGEMENTS

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