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Productivity growth and convergence in the European Union*

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Abstract This paper analyses the determinants of labour productivity in the European Union (EU) area and examines the extent to which convergence in output per worker is occurring among Member States (plus Norway) using a recursive common trends analysis and non-parametric kernel density methods. Data Envelopment Analysis (DEA) is used to construct the best practice EU production frontier and compute a Malmquist index of total factor productivity (TFP) and its decomposition to the factors that affect productivity for each country. We consider a pent-partite decomposition of the growth in labour productivity in terms of (i) pure technological change (ii) input biased technical change (iii) efficiency change (iv) growth in human capital and (v) (physical) capital accumulation. This decomposition enables us to gain more insight on patterns of productivity growth for a cross section of countries as well as isolate the individual factor contributions to (or lack of) convergence and common trends for output per worker in the EU area. The use of human capital as an additional input in the description of technology has a small effect in the overall productivity measures but leads to a substantial fall in the contribution of capital accumulation to growth in output per worker for our sample of countries. Furthermore, there is evidence to suggest that the market reforms of the post 1980 period are likely to have induced considerable change in input prices and factor mix which in turn is reflected in input bias. This is evident from the pattern of the shift in the frontier of technology over time and the underlying trends in the components of technological change. Cross section regression analysis suggests that although there appears to be overall convergence in output per worker in the sample of countries, the input bias component of technological change is a source of divergence. Evidence on increasing convergence among the EU countries is also provided via an analysis of the distribution dynamics of output per worker. Non-parametric methods are used to determine the number of modes in the productivity distribution over time. The evidence suggests that the distribution of output per worker in the EU area has changed

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from bimodal (twin-peak) to unimodal over time. A recursive common stochastic trends analysis provides further evidence of increased convergence in output per worker among groups (convergence 'clubs') of European countries. In particular, the recursive tests show that a common stochastic trend was driving output per worker for the group of small northern European economies (Belgium, Denmark, Luxembourg, Netherlands and Sweden) by the 1990s. Similarly, increased convergence trends were detected for two more groups (1) Greece, Ireland and Portugal and (2) France, Germany and the UK. However, time series tests fail to support the hypothesis that the EU area is a single convergence club.

JEL Classification D24, O47

Keywords Distance function · Malmquist index · DEA · TFP · Productivity convergence

Introduction

This paper investigates relative labour productivity trends among member states of the European Union plus Norway.[1] It endeavours to shed light on two important and inter-related issues facing EU policymakers: (1) assessing convergence in output per worker among member states and (2) identifying its underlying trend components. Both of these issues impact greatly on the policy authority's ability to assess correctly the potential growth rate of real output and evaluate the effect of policy on economic performance across member states. It is thus important for the policymaker to distinguish between measured productivity changes and sustainable productivity changes (largely driven by technological change) as well as to assess the degree to which technology adoption and diffusion contributes to a productivity catch-up. Clearly, such measures of technological change and diffusion should be free of substantial measurement bias. Measurement bias problems are often the result of a number of restrictive assumptions made about the type of technology or market structure that underlie the development of a productivity index (e.g., Cobb-Douglas technology, Hicks neutrality, perfect competition). The increasingly volatile behaviour of productivity in recent times has further complicated the task of disentangling permanent from temporary shifts in measured productivity, thus making observed historical patterns an increasingly poor guide of sustainable productivity trends. Furthermore, a study of productivity convergence requires a benchmark country (or group of countries) to set a standard against which individual countries are compared to. This in turn requires an appropriate framework (e.g., an encompassing frontier production technology) to form a basis on which an analysis of the convergence process can be conducted.

Research in cross-country growth performance comparisons has intensified in recent years. Particular attention has been given to the questions of (1) convergence in per capita (or per worker) output levels and growth rates across groups of countries and (2) the type of variables that serve as empirical determinants of economic growth (see Baumol et al. 1994; Barro and Sala-I-Martin 1995; Durlauf and Quah 1998; for a survey of the literature). Much of the earlier work on tests of the convergence hypothesis used cross sections (and sometimes panel data) to run regressions of real per capita output growth rates on the initial period per capita output level and possibly other country specific determinants of long-run growth. In this approach, known as β-convergence, the convergence hypothesis involves testing that the coefficient of the output variable is less than zero, namely that countries with lower initial per capita income are expected to grow faster than countries with higher per capita income. Such an approach, aside from the obvious requirement of a large cross-sectional sample size, has been criticised on various grounds including the classical regression fallacy argument (see Friedman 1992, Quah 1993). An alternative approach, and sufficient condition for β-convergence, known as σ-convergence, examines whether the dispersion of the (log) productivity distribution for a cross section of countries diminishes over time. While decreasing values of σ can be viewed as evidence towards convergence, it is the case that this type of analysis is not on its own accord sufficient to establish convergence. The basic shortcoming with these cross-sectional approaches to testing the convergence hypothesis is that either they ignore intra-distribution dynamics or confound short-run transitional dynamics and long-run steady-state behaviour (see Bernard and Durlauf 1995; Bianchi 1997). Most

[1] The inclusion of Norway is justified on at least two grounds (1) its proximity and close ties with EU countries and (2) our interest to see if there are any discernible patterns of difference in productivity performance (and its underlying determinants) between Norway and similar EU Member States, especially Sweden.

of the recent work uses time series methods based on unit roots and cointegration analysis to carry out tests of convergence. In this context per capita output of different countries can fail to converge only if the permanent components driving this variable are distinct (Bernard and Durlauf 1995).

The Bernard and Durlauf definition of (asymptotically perfect) convergence is fairly strong. It requires that the (log) per capita (or per worker) output levels of different countries will be expected to ultimately become equal independently of their current and past levels (see Hobijn and Franses 2000). In fact, Baumol et al. (1994) have argued that once countries are relatively close to each other the process of convergence is likely to come to an end. In this situation, differences in (log) per capita output levels among pairs of countries will be expected to ultimately become level stationary instead of zero mean stationary. This is the definition of asymptotically relative convergence used by Hobijn and Franses (2000). Convergence of growth rates, a weaker condition, will require that the first difference of these (log) per capita output differentials is zero mean stationary. Note that growth rate convergence is a necessary but not a sufficient condition for the expected long-run distribution of (log) output per capita to converge asymptotically into a stable non-degenerate distribution (Jones 1997). A necessary and sufficient condition for such a result to be achieved is provided by means of an asymptotically perfect or relative convergence in the output variable. To achieve convergence in multivariate per capita output in a group of k countries, there is a requirement that the $(k-1)$ pairs of per capita output differentials are zero mean or level stationary, i.e., they are linked by $(k-1)$ cointegration vectors and are driven by one common trend.

In most practical situations with a large number of countries and relatively short horizons it will be difficult to ascertain the required convergence results through the use of cointegration methods. It is thus of interest to an analysis of growth and convergence in the EU context to focus on the degree of integration in labour productivity among clusters of countries over time. This can be analysed within the framework of common stochastic trends that drive the non-stationary behaviour of the individual series. More specifically, increased integration will be taken to imply that the number of cointegrating relations that link the individual series is increasing over time and therefore the non-stationary behaviour of the individual series is correspondingly driven by a decreasing number of common stochastic trends.

The methodology used in this study to assess the degree of convergence in output per worker is based on the cointegration analysis of Johansen (1988, 1991) and Hansen and Johansen (1999). It recognises that labour productivity is generally a non-stationary time series and convergence is a gradual process. If two or more non-stationary series are not cointegrated, they cannot converge. Thus cointegration of a group of non-stationary series is a necessary condition for convergence (Bernard and Durlauf 1995). Note that standard cointegration analysis is not adequate to carry out testing of the process of convergence.[2] This is because convergence is a gradual process and tests which do not account for the time-varying nature of the underlying data generation process may be biased towards rejecting convergence (see Durlauf and Quah 1999; Rangvid and Sorensen 2001). The recursive approach used to test stock market integration by Rangvid (2001) is employed here to study the timing of the convergence process in output per worker.

This study comprises an in depth investigation into the process of convergence in labour productivity. It starts with a cross-sectional analysis of convergence. Standard regression analysis is complemented by an analysis of the evolution of the cross-country distribution of labour productivity in terms of its components as in Kumar and Russell (2002) and Henderson et al. (2002). We turn next to investigate convergence and common trends using time series cointegration methods.

The novelty of the proposed productivity measurement and analysis approach derives from a decomposition of the growth in labour productivity in terms of (a) technical change (b) efficiency change and (c) capital accumulation. In particular, DEA is used to construct the best practice production frontier for a sample of European Union countries (plus Norway), and compute Malmquist productivity indexes and their decomposition into the underlying productivity components for

[2] As Bernard and Durlauf (1996) point out standard cointegration tests of convergence assume that economies are near steady-state equilibria while cross-sectional tests assume that the economies are in a transitional state. Initial conditions (and shocks) are important in the latter but not the former case. A time-varying parameter framework is therefore general enough to encompass most tests of convergence considered in the literature (see Hall et al. 1997).

each country.[3] Using this information we are able to assess the individual contribution of the various components to the convergence in labour productivity.

We would expect that the economic liberalisation programmes that were implemented at various degrees and intensity in the EU area over the last two decades in conjunction with further progress in EU market integration would trickle-down into better productivity performance via a positive effect in the efficiency component. In turn, these productivity improvements should lead to improved convergence performance. We would also expect that major micro- and macro-economic reform programmes are likely to alter relative movements in the production frontier over time in the input and output direction. In other words, it is likely that Hicks-neutral technical change may not be a good description of technology in this situation. In line with this argument, we propose to decompose technical change in an output bias, an input bias and a (pure) magnitude component. In addition, we recognise that the absence of a quality adjustment in the labour input may bias the TFP measures to the extent that this factor is correlated with the other components of the Malmquist index (see Henderson and Russell 2001). We adopt the Hall and Jones (1999) approach which uses a human capital-augmented labour measure in the production function where the efficiency of a unit of labour is driven by the recently updated estimates of returns to investment in education reported by Psacharopoulos and Patrinos (2002).

This paper is organised as follows. Section 'The productivity index' describes the index used in this study to measure productivity. Productivity results along with results for β- and σ-type of convergence tests are presented in Section 'Productivity results'. An analysis of integration trends within groups of countries (convergence 'clubs') is presented in Section 'Recursive convergence tests'. Concluding remarks are given in Section 'Conclusion'.

The productivity index

This section describes the index used in this study to measure productivity. A detailed exposition of this approach is provided in Färe et al. (1994). The index is defined in terms of output distance functions. These functions measure the ray distance between a given output vector and maximal potential output. This maximal output belongs to the boundary of the reference or frontier technology. We start by explaining how the frontier is constructed from data in our case.

At each time period $t = 1, \ldots, T$ there are $k = 1, \ldots, 16$ countries that use two inputs $\mathbf{x}^{k,t} = (X_{1k}, X_{2k})$ to produce a single output $\mathbf{y}^{k,t} = (Y_k)$. From these observations an overall EU area production technology is constructed for each time period. Rather than specifying and estimating a specific production function we choose to construct the technologies non-parametrically using activity analysis.[4] This technique is also known as Data Envelopment Analysis (DEA) (see Charnes et al. 1978).

For a given period t, the constant returns to scale (CRS) frontier technology is

$$S^t_{\mathrm{CRS}} = \{(x^t, y^t) : \sum_{k=1}^{\mathrm{K}} z_k y^t_k \geq y^t, \sum_{k=1}^{\mathrm{K}} z_k x^t_{nk} \leq x^t_n,$$
$$n = 1, 2, z_k \geq 0, \quad k = 1, \ldots, 16\} \qquad (1)$$

In this formulation output levels may be less than or equal to linear combinations of observed output, that is, output is freely disposable. Input levels may be greater or equal to linear combinations of observed input, that is, producers may freely dispose of inputs as well. The intensity variables, z_k, indicate at what intensity a particular activity (or observation) may be employed in production. They are only required to be non-negative, thus they form the convex cone of the data. The convexity implies that convex combinations of observed inputs and outputs are hypothetically feasible. The technology being a cone is equivalent to constant returns to

[3] An additional reason for the inclusion of Norway is that it helps achieve in a technical sense a more balanced frontier in that it is closer than any other European country to Luxembourg in terms of labour productivity performance.

[4] We are not imposing a specific production function on each country with identical parameters (e.g., fixed input elasticities). Our technology is much more general than a typical parametric production function. We are merely taking the observed data, constructing the frontier from the observed data, and using that frontier as a benchmark. We do not require competitive behaviour or other assumptions about market structure, rather we impose minimal regularity conditions (disposability of inputs and outputs, for example). We define technical change as shifts in the frontier between t and $t + 1$, which we feel is consistent with the received notions of technical change. We note that data measurement problems will affect our measure of technical change, as they would for any of the techniques used to measure TFP or technical change.

scale. The upper boundary of this set represents the best practice frontier.

Relative to a frontier technology S^t, one may define the corresponding output distance function for country k as

$$D_0^t(x^{k',t}, y^{k',t}) = \min\left\{\theta : \left(x^{k',t}, \frac{y^{k',t}}{\theta}\right) \in S^t\right\}$$
$$= \left[\max\left\{\theta : (x^{k',t}, \theta y^{k',t}) \in \ S^t\right\}\right]^{-1}$$
$$= [F_o{}^t(x^{k',t}, y^{k',t})]^{-1} \quad (2)$$

(see Shephard 1970; Färe 1988 for details). In (2) $F_o^t(.)$ denotes the Farrell (1957) output-oriented measure of technical efficiency. Thus (2) shows that the distance function and the Farrell technical efficiency measure are reciprocals. This fact is important, since we decompose our productivity index into two components: one measuring efficiency change and another measuring technical change.[5] This index has become known as the Malmquist index. It was introduced as a theoretical index by Caves et al. (1982) who named it the (output-based) Malmquist productivity index after Sten Malmquist who had earlier shown how to construct quantity indexes as ratios of distance functions (see Malmquist 1953).

Following Färe et al. (1989) the Malmquist productivity change index (M) is defined as

$$M_0(k', t, t+1) = \left[\frac{D_0^t(x^{k',t+1}, y^{k',t+1})}{D_0^t, (x^{k',t}, y^{k',t})} \frac{D_0^{t+1}(x^{k',t+1}, y^{k',t+1})}{D_0^{t+1}(x^{k',t}, y^{k',t})}\right]^{1/2} \quad (3)$$

An important feature of the Färe et al. (1989) version of the Malmquist index (3) is that it can be decomposed into two independent components, namely

$$\text{Efficiency Change} = \text{ECH} = \frac{D_0^t(x^{k',t+1}, y^{k',t+1})}{D_0^t(x^{k',t}, y^{k',t})} \quad (4)$$

and

$$\text{Technological Change} = \text{TCH} = \left[\frac{D_0^t(x^{k',t+1}, y^{k',t+1}) D_0^t(x^{k',t}, y^{k',t})}{D_0^{t+1}, (x^{k',t+1}, y^{k',t+1}) D_0^{t+1}(x^{k',t}, y^{k',t})}\right]^{1/2} \quad (5)$$

Thus (3) can be written as

$$M_0(k', t, t+1) = \text{MALM} = \text{ECH} * \text{TCH} \quad (6)$$

and for each country $k' = 1, \ldots, 16$, time paths of productivity, efficiency and technical change can be calculated.

Before we show how the indexes are computed, Fig. 1 is used to illustrate expression (6), the productivity index and its components. For the diagram, we assume that one input is used to produce one output, and that the reference technologies satisfy constant returns to scale.[6] There are two observations, (x^t, y^t) and (x^{t+1}, y^{t+1}), respectively. Note that (x^{t+1}, y^{t+1}) is not feasible at period t. However, $(x^t, y^t) \in S_{\text{CRS}}^{t+1}$ indicates that technical progress has occurred.

The indices can be illustrated as distances on the output axis. We then obtain the change efficiency as the ratio of the distance of the period $t+1$ observation relative to its frontier to the period t observation from its frontier as

$$\text{ECH} = \frac{\text{Od}}{\text{Of}}\frac{\text{Ob}}{\text{Oa}} \quad (4')$$

The technical change part equals the geometric average of the shift in the frontier in the output direction from period t to period $t+1$ evaluated at points (x^{t+1}, y^{t+1}) and (x^t, y^t), respectively,

$$\text{TCH} = \left(\frac{\text{Of}}{\text{Oe}}\frac{\text{Oc}}{\text{Ob}}\right)^{\frac{1}{2}} \quad (5')$$

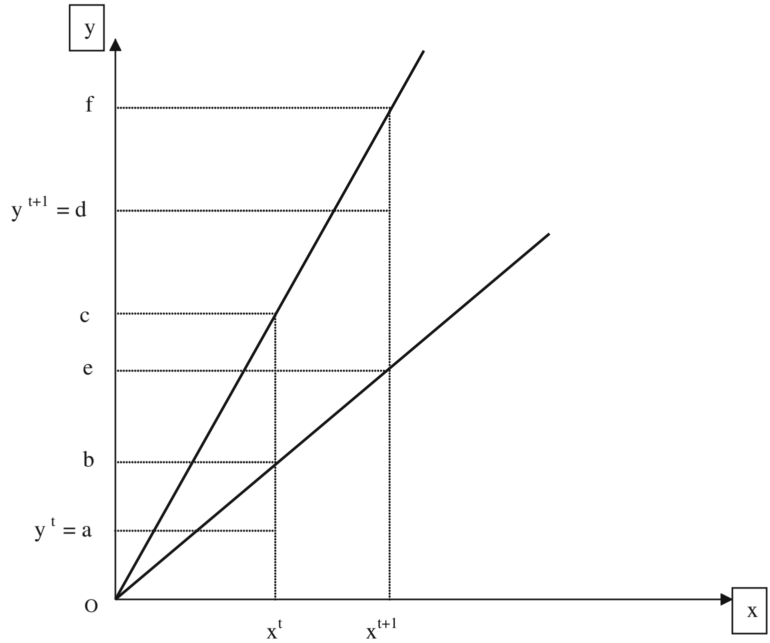
and hence the productivity change is

$$\text{MALM} = \frac{\text{Od}}{\text{Oa}}\left(\frac{\text{Ob}}{\text{Oe}}\frac{\text{Oc}}{\text{Of}}\right)^{\frac{1}{2}} \quad (6')$$

[5] Each country is compared to its previous year's performance (relative to the frontier derived from realised data). For example, if a country does not change its inputs and outputs from t to $t+1$, then it will have no change in productivity as we measure it. On the other hand, if the frontier shifted from t to $t+1$, then there was technical change as we define it (i.e. a shift in the frontier), but this particular country did not shift the frontier, rather it is now farther from the frontier. These 'barriers' or 'sluggish adjustment' to technology adoption will be a source of cross-country per capita income differences not accounted for by factor endowments. Note that there may be offsetting efficiency change and technical change, i.e., we allow for deviations from the frontier, and we allow the frontier to change over time.

[6] In our case with one output and two inputs, labour and (physical) capital, the simplest way to illustrate this under a CRS technology is by letting y = output to labour ratio and x = capital to labour ratio in Fig. 1.

Fig. 1 The productivity index



Following Kumar and Russell (2002) we can also decompose the relative change in the output to labour ratio (y) between periods t and $t+1$ under CRS into (i) a change in efficiency; (ii) technological change; and (iii) change in the capital to labour ratio (KCH) given by:

$$(y_k^{t+1}/y_k^t) = \left(\frac{Od}{Of}\frac{Ob}{Oa}\right)\left(\frac{Of}{Oe}\frac{Oc}{Ob}\right)^{1/2}\left(\frac{Oe}{Ob}\frac{Of}{Oc}\right)^{\frac{1}{2}}$$
$$= \mathrm{ECH} * \mathrm{TCH} * \mathrm{KCH} \qquad (7)$$

where the capital deepening component (KCH) is measured by the geometric average of the movement in the output direction of the capital to labour ratio (x) along the period t frontier (corresponding to the change from x^t to x^{t+1}) to the respective movement along the period $t+1$ frontier.[7]

The productivity index and its components are all constructed from distance functions. We note that there are two mixed period distance functions, namely $D^{t+1}(x^t, y^t)$ and $D^t(x^{t+1}, y^{t+1})$, that are involved in the computation of the Malmquist productivity index. Therefore, we need to compute a total of four distance functions in order to estimate the productivity of country k' between t and $t+1$. For a given country k', we can calculate the reciprocal of the distance function $D^t(x^{t+1}, y^{t+1})$ as the solution to the following linear programming problem:

$$|D_0^t(x^{k',t+1}, y^{k',t+1}|\mathrm{CRS}\,)\rfloor^{-1} = \max\theta \text{ s.t.}$$
$$\sum_{k=1}^{K} z_k y_k^t \geq \theta y_k^{t+1}, \qquad (8)$$
$$\sum_{k=1}^{K} z_k y_{\mathrm{nk}}^t \leq x_{\mathrm{nk}}^{t+1}, \quad n = 1, 2; \quad z_k \geq 0,$$
$$k = 1, \ldots, 16$$

where the input and output data are from period $t+1$ while the technology is constructed from data at period t, that is, the linear programming problem is a mixed period problem. The three remaining distance functions required by (3) can be similarly computed. Note that if we substitute the (k', t) observation with $(k', t+1)$ then (8) becomes the usual Farrell efficiency problem.

We calculate the Malmquist index and its components under the CRS technology. Fluctuations in productivity may be due to variation in capacity utilisation and differences in the structure of each country which will be reflected in changes in the efficiency compo-

[7] Note that labour productivity growth and its components in (7) may be stated in terms of efficiency units of labour. Thus the change in output per worker can be decomposed into the growth of output per effective labour and the growth of human capital which in turn implies that a human growth component can be added to the labour productivity growth decomposition (see Henderson and Russell 2001). We construct the technology frontier with and without an adjustment for human capital.

nent. This follows from the fact that observations are compared to the best practice frontier.

Improvements in productivity yield Malmquist index values greater than unity. Deterioration in performance over time is associated with a Malmquist index less than unity. (Deterioration in performance may also represent diminishing returns in applying capital and labour to a third unspecified and non-reproducible factor, for example, a fall in TFP may occur in fishing when capital and labour are applied to a fixed fishing ground (see Chapple 1994).) The same interpretation applies to the values taken by the components of the overall TFP index. Improvements in the efficiency component yield index values greater than one and are considered to be evidence of catching up (to the frontier). Values of the technical change component greater than one are considered to be evidence of technical progress. While the product of the efficiency and technical change components must, by definition, equal the Malmquist index, those components may be moving in opposite directions.

Note that if technology exhibits joint input and output neutrality then the whole technical change effect is expressed either as the output or as the input change. However, in the absence of joint neutrality, we must consider the possibility of both input and output biased technical change. Therefore, we can decompose the technical change component into an output biased (OBTCH), an input biased (IBTCH), and a magnitude component (MTCH), as in Färe and Grosskopf (1996).

$$
\begin{aligned}
&\text{Technological Change} = \\
&\text{TCH} \\
&= \left[\frac{D_0^t(x^{k',t+1}, y^{k',t+1}) D_0^{k',t+1}(x^{k',t+1}, y^{k',t})}{D_0^{t+1}, (x^{k',t+1}, y^{k',t+1}) D_0^t(x^{k',t+1}, y^{k',t})} \right]^{1/2} \\
&\quad * \left[\frac{D_0^{t+1}(x^{k',t}, y^{k',t}) D_0^t(x^{k',t+1}, y^{k',t})}{D_0^t, (x^{k',t}, y^{k',t}) D_0^{t+1}(x^{k',t+1}, y^{k',t})} \right]^{1/2} \\
&\quad * \frac{D_0^t(x^{k',t}, y^{k',t})}{D_0^{t+1}(x^{k',t}, y^{k',t})} \\
&= \text{OBTCH} * \text{IBTCH} * \text{MTCH} \qquad (9)
\end{aligned}
$$

Note that the output biased component (the first quantity in the brackets) is the square root of two Malmquist output indexes, one for period t technology and one for period $t+1$. In this study, the technology produces only one output, thus OBTCH=1. This follows from (9) and the property that the output distance function is homogeneous of degree +1 in output. The first ratio in IBTCH (the expression in the second bracket of (9)) measures the shift in technology between periods t and $t+1$ evaluated at the input–output vector observed in period t. The second ratio in the input bias term measures the same shift in technology evaluated at the input–output vector observed in period $t+1$. Note that in both these ratios output does not change, it is at the level observed in period t. Thus the only change is in the input vector. If there is technical change — a shift in the technology frontier — that change will be input biased if the product of these two terms does not equal unity. Under joint neutrality, the magnitude component equals the technical change component, i.e., the quantity in the second bracket of (9) is the inverse of that in the first bracket. In our case, this implies that the input bias term is equal to unity and the shift in technology is parallel (neutral).

Productivity results

We calculate productivity growth and its components for a sample of 16 countries (EU Member States plus Norway) over the period from 1965 to 1998. The output (real GDP), labour and most capital series are from the Heston and Summers PWT5.6 and the provisional PWT6.0. Estimates of capital stock for the period 1991–1998 were constructed using the investment series contained in PWT6.0. As in Henderson and Russell (2001) human capital enters the technology as a multiplicative augmentation of raw labour. Following Hall and Jones (1999) the human capital-augmentation factor is the exponential of a piecewise linear function $\Phi(S)$ of the average years of schooling (S) of the adult population. This function represents the relative efficiency of a unit of labour with S years of schooling and its derivative $\Phi'(S)$ is a measure of the return to schooling. We use recently updated estimates of returns to investment in education by Psacharopoulos and Patrinos (2002) to obtain values for the slope coefficients (weights) of the $\Phi(S)$ function. We consider both fixed and variable weights for each level of schooling across the different countries. Data for the different levels of schooling (educational attainment) for each country are from Barro and Lee (2000). Note that the standard specification of technology with no adjustment for human capital assumes that $\Phi(S) = 0$ for all S.

The approach outlined in Section The productivity index constructs a best practice frontier from the

Table 1 Efficiency indexes

	Without human capital			Without human capital		
	1965	1990	1998	1965	1990	1998
AUT	0.84	0.83	0.65	0.84	0.78	0.66
BEL	0.88	0.95	0.76	0.79	0.89	0.77
DNK	0.90	0.80	0.62	0.81	0.72	0.60
FIN	0.64	0.70	0.66	0.64	0.64	0.63
FRA	0.87	0.90	0.76	0.88	0.87	0.78
GRE	0.60	0.73	0.55	0.65	0.71	0.56
IRL	0.76	0.91	1.00	0.73	0.89	1.00
ITA	0.77	1.00	0.83	0.81	1.00	0.89
LUX	1.00	1.00	1.00	0.96	1.00	1.00
NLD	1.00	0.99	0.77	1.00	0.93	0.77
NOR	0.76	0.73	0.61	0.96	0.76	0.68
PRT	0.90	1.00	0.63	0.90	1.00	0.70
ESP	1.00	0.90	0.76	1.00	0.92	0.81
SWE	0.91	0.78	0.66	0.85	0.70	0.61
GBR	1.00	1.00	0.81	0.99	0.97	0.81
GER	0.81	0.71	0.55	0.75	0.66	0.54
Mean	0.85	0.87	0.73	0.85	0.84	0.74
(Std. Dev.)	(0.12)	(0.11)	(0.13)	(0.11)	(0.12)	(0.14)

data. In particular, it constructs an aggregate frontier for the overall EU region and individual countries are compared to that frontier.[8] In this context, i.e., where we have one output for each country, the output distance function is equivalent to a frontier production function.

Table 1 reports the estimates of the efficiency levels for each country in the sample over three select periods, 1965, 1990 and 1998. The first three columns list the efficiency indexes obtained from a technology without human capital adjustment and the last three columns are the corresponding figures when human capital enters the production process. Overall the incorporation of human capital does not appear to make much of an impact on the efficiency scores across the sample of countries. Some countries, like Italy, Norway, Portugal and Spain benefit from the human capital adjustment, while others, like Belgium, Denmark, Finland and Sweden move further away from the frontier when an adjustment is made for the efficiency of labour. The mean efficiency scores remain largely the same in 1965 and 1990 at about 85% but drop off considerably to about 74% efficiency in 1998 indifferently if the technology includes or excludes human capital. This is, of course, far from a desirable trend and it may be attributed to problems that EU area countries faced in the 1990s, in part related to exchange rate misalignments, institutional features (e.g., rigidities in product and labour market regulation) and accelerated economic convergence or monetary unification (e.g., stability and growth pact) pressures.[9]

[8] Note that the frontier is defined in terms of the 'best practice' of those countries in the sample and therefore performance measures are relative. Different productivity measures are likely to obtain in relation to different groupings of countries. The choice of a grouping should be dictated by the object of the study. For example, one may question the suitability of a potentially transferable technology or whether an 'appropriate technology' fits equally well a diverse group of countries. While we recognise this, we still choose to construct a frontier for the whole EU area, noting that each country is compared to the frontier segment with the same input mix. As the capital to labour ratio changes across countries, output per worker may also change (see the production frontiers in Fig. 3). In essence, our modelling of technology is flexible enough to capture both the 'barriers' to technology adoption (distance to the frontier) view featured in traditional development-accounting studies and the 'appropriate technology' (movement along the frontier) interpretations of technology and output differences (see Caselli and Coleman 2003). Also, note that in our approach a different technology may apply in different years. A similar approach but in a parametric setting is adopted by Hultberg et al. (1999). As in Hultberg et al. we allow for the possibility that countries may overtake each other during the transition to their steady state.

[9] Note that the presence of Luxembourg exacerbates the drop in efficiency in 1998 to 73% on average (see Fig. 3). Average efficiency for a sample without Luxembourg is 83% in 1998. There is not as much difference in average efficiency measured with and without Luxembourg in 1990 (87% and 90%, respectively). Germany and Sweden are the worst affected countries while there is no change in relative efficiency for Belgium, Italy, Portugal and the UK by the presence of Luxembourg in the sample in 1998.

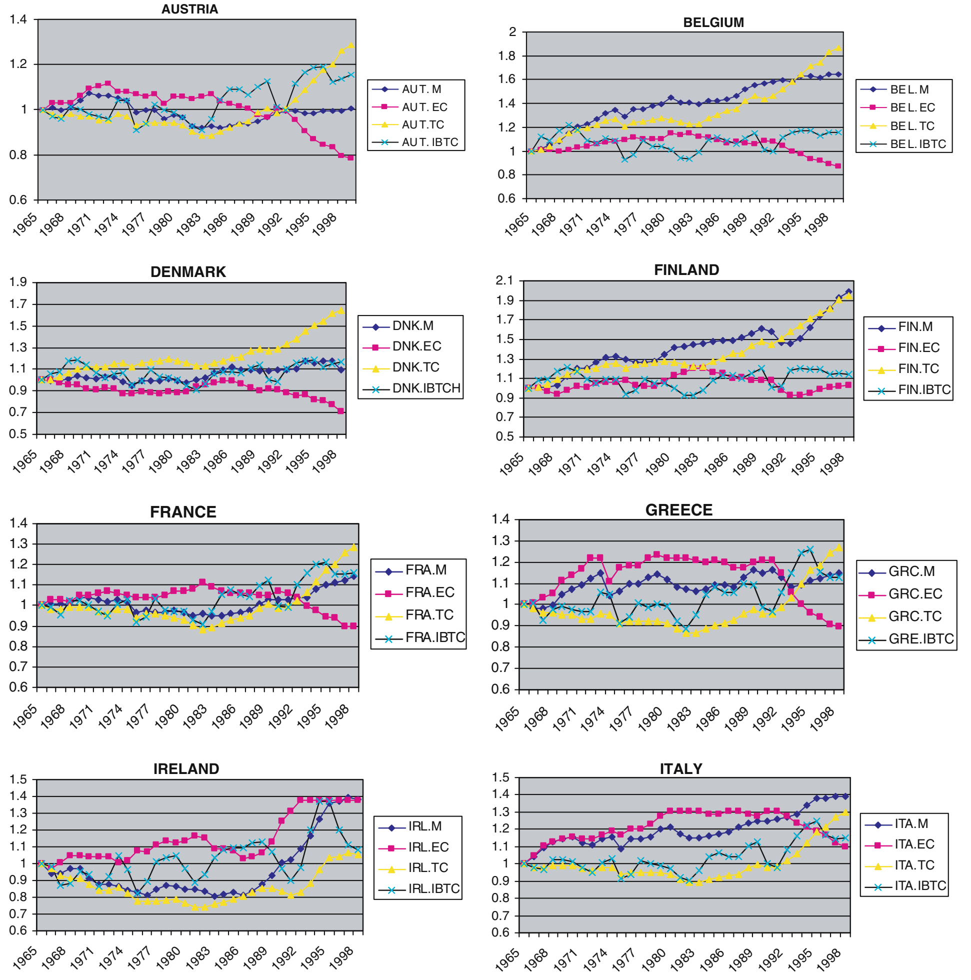


Fig. 2 The TFP productivity index (M) and its components (EC, TC, IBTC)

Luxembourg is the only country that is featured most frequently on the technological frontier. The UK appears to have moved below the frontier when the efficiency of the labour force is taken into account in 1965 and 1990. This appears to be consistent with available evidence on lower levels of UK manpower skills and productivity performance relative to Continental Europe (see Prais 1995; Crafts and O'Mahoney 2001; O'Mahoney 2002).[10] Note that the UK dropped-off the frontier in 1998 even when human capital is not taken into account. In fact, UK efficiency levels started to steadily decline below the frontier from 1992 onwards at the same time that Ireland reached the frontier and has remained on it since then (see Fig. 2). This may, in part, reflect lags in the diffusion of new technologies which exacerbated on-going problems arising from a widening gap on innovations (e.g., R&D spending) with other countries (see O'Mahoney 2002).

It may seem at first glance puzzling that Portugal, the poorest of the EU countries, should appear on the frontier in 1990. Indeed, our results indicate that Portugal was on the frontier in the entire period 1969 through 1982 and again in 1989 through 1991 but dropped-off sharply from there in the last part of the sample period. Portugal is the country with the lowest capitalisation in the EU and is represented by the left-most point in the production frontiers of Fig. 3. To the extent that we have correctly identified the frontier of technology at low values of the capital to labour ratio, the

[10] UK labour productivity was only better than Greece and Portugal and about the same with Spain in 1998 and only better than Greece and Sweden and about the same with Denmark in 1998 when measured in terms of labour efficiency units.

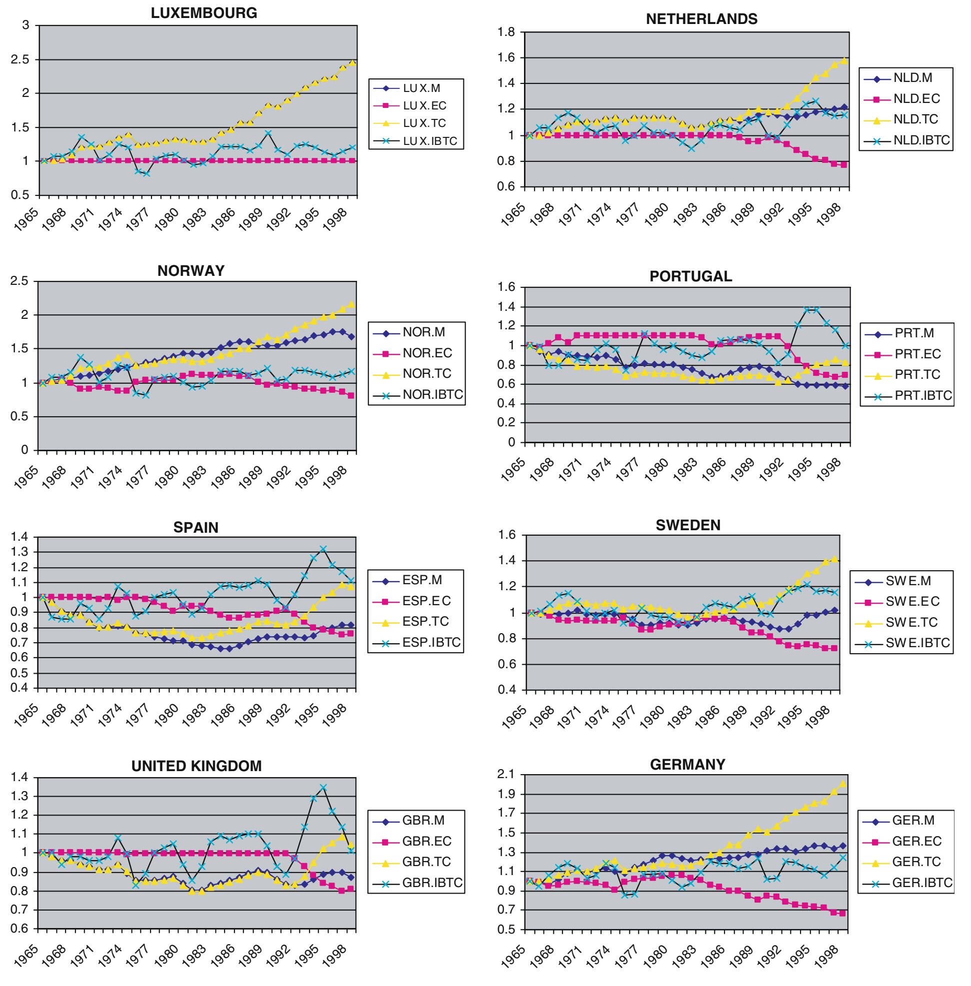


Fig. 2 Continued

presence of a relatively poor and undercapitalised country on the frontier does not necessarily imply that it cannot make efficient use of its resources (see Kumar and Russell 2002, for a similar argument). It may be the case that as Portugal closed the capital intensity gap with other EU countries in the 1990s, it lacked ability to utilise its new resource mix efficiently. This observation appears to be consistent with the 'appropriate technology' arguments put forth by Caselli and Coleman (2003), namely, countries with different factor endowments may use their abundant factor more efficiently than countries which are relatively less abundant in that factor. Note that Portugal is closer to the frontier in 1998 when an adjustment for the efficiency of labour is made. Nevertheless, it seems plausible that attempts by labour abundant countries like Portugal to adopt a more capital intensive technology, perhaps as a result of the economic convergence and monetary unification pressures, may come at a high resource utilisation cost. These costs will be even higher in situations where countries like Portugal face, for various reasons, significant barriers to technology adoption.[11]

Table 2 gives a summary description of the average TFP performance of each country over the period 1965–1998 as well as the sub-period 1965–1990. Since the productivity index is based on discrete time, each

[11] It is likely that Portugal's labour market, one of the most rigid in the EU, imposes higher costs of adjustment and therefore exacerbates the problems firms face with adopting or developing new technology (see Scarpetta et al. 2002). In the 1965–1998 period the capital to labour ratio in Portugal increased by five-fold while output per worker increased at about half this rate. Contrast this with the case of Ireland where the output productivity outpaced the rate of capital productivity over the same period.

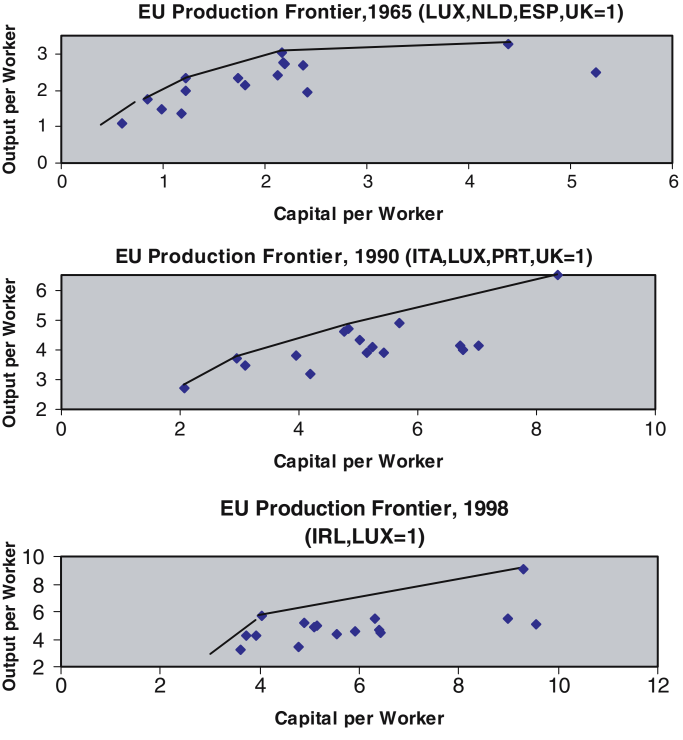


Fig. 3 Production frontiers (EU-15 & Norway) without human capital

country will have an index for every pair of years. Recall that index values greater (less) than one denote improvements (deterioration) in the relevant performance.[12]

The MALM figures at the bottom of Table 2 indicate that the overall average TFP productivity growth without (with) human capital adjustment was 0.532 (0.284) percent in the period 1965–1990 and 0.636 (0.419) percent in the period 1965–1998, respectively.[13] On average, that growth was due to technical change of 0.419 (0.32) percent in 1965–1990 and 1.13 (0.857) percent in 1965–1998 rather than improvements in efficiency. The latter is estimated at 0.112 (−0.035) percent in 1965–1990 and −0.488 (−0.435) percent in 1965–1998. Luxembourg and Finland stand out as the countries with the best productivity record at just over 2% on average over the sample period. Portugal has the worst record. In addition, our estimates show negative growth on average for Spain and the UK. The UK TCH figures are remarkably low but consistent with the evidence on relative trends in the UK innovation record, as measured by the ratio of R&D to the level of output, discussed above (see O'Mahoney 2002). The efficiency change component of TFP growth is negative for most countries. Ireland is the only notable exception. Technical change is the driving force of TFP growth for most countries. The best technological change performance is estimated for Belgium, Finland, Luxembourg and Germany.

The time paths of the (cumulative) productivity index and its components for the 16 countries are given in Fig. 2. There is no adjustment for human capital in the indexes. It is clear that there is positive trend (TCH) productivity for all countries but Portugal. The importance of the input bias (IBTCH) component of technological change is quite noticeable for most countries after the mid-1980s, particularly so for Ireland, Portugal and Germany. This result may have important policy conse-

[12] Productivity results with a human capital adjustment are shown in the second row of each country cell in Table 2. We only report figures for schooling levels with fixed weights across the different countries.

[13] These figures are geometric average rates of change. For example, the cumulative TFP and ECH index values for Austria are estimated to be 1.0047 and 0.7865, respectively, in 1998 (see Fig. 2). This gives average index values of 1.00032 and 0.992748 or average growth rates of 0.032 and −0.725%, respectively, during the 1965–1998 period. The overall mean figures shown at the bottom of Table 2 are the geometric averages of the individual 16 country mean values.

Table 2 Average annual productivity changes (%)*

	1965–1990			1965–1998		
Country	MALM	ECH	TCH	MALM	ECH	TCH
Austria	−0.039	0.019	−0.058	0.032	−0.725	0.762
	0.222	−0.275	0.498	0.211	−0.729	0.947
Belgium	1.805	0.348	1.452	1.492	−0.414	1.913
	1.344	0.535	0.805	1.187	0.005	1.181
Denmark	0.591	−0.348	0.943	0.471	−1.039	1.525
	−0.447	−0.470	0.022	−0.309	−0.917	0.613
Finland	1.815	0.318	1.492	2.130	0.095	2.033
	1.314	0.015	1.299	1.575	−0.041	1.617
France	0.213	0.270	−0.057	0.441	−0.318	0.762
	0.231	−0.061	0.293	0.404	−0.353	0.760
Greece	0.581	0.759	−0.177	0.396	−0.329	0.727
	0.893	0.431	0.459	0.526	−0.354	0.883
Ireland	0.179	0.899	−0.713	1.136	0.978	0.157
	−0.531	0.728	−1.249	0.529	0.906	−0.374
Italy	0.967	1.064	−0.095	1.072	0.280	0.791
	1.403	0.825	0.573	1.321	0.284	1.034
Luxembourg	2.389	0.000	2.389	2.744	0.000	2.744
	2.055	0.128	1.924	2.430	0.097	2.330
Netherlands	0.577	−0.084	0.662	0.585	−0.802	1.398
	0.042	−0.249	0.292	0.039	−0.802	0.847
Norway	1.904	−0.094	2.000	1.687	−0.657	2.360
	1.098	−0.884	2.000	1.355	−1.010	2.389
Portugal	−1.219	0.363	−1.577	−1.698	−1.127	−0.578
	−1.138	0.363	−1.496	−1.454	−0.815	−0.645
Spain	−1.128	−0.374	−0.756	−0.622	−0.839	0.222
	−0.871	−0.245	−0.627	−0.407	−0.553	0.147
Sweden	−0.406	−0.667	0.262	0.056	−0.999	1.065
	−0.857	−0.798	−0.059	−0.486	−1.031	0.551
UK	−0.630	0.000	−0.630	−0.520	−0.648	0.129
	−0.799	−0.113	−0.686	−0.713	−0.645	−0.069
W Germany	1.000	−0.656	1.666	0.873	−1.235	2.135
	0.663	−0.477	1.145	0.563	−0.981	1.560
Mean 1	1.075	−0.064	1.140	1.145	−0.568	1.723
	0.592	−0.251	0.845	0.746	−0.554	1.307
Mean 2	−0.400	0.411	−0.807	−0.203	−0.332	0.130
	−0.415	0.319	−0.731	−0.205	−0.206	0.001
Mean 3	0.385	0.167	0.217	0.465	−0.482	0.952
	0.371	0.042	0.329	0.391	−0.425	0.820
Overall Mean	0.532	0.112	0.419	0.636	−0.488	1.130
	0.284	−0.035	0.320	0.419	−0.435	0.857

Mean 1= Austria, Belgium, Denmark, Finland, Luxembourg, Netherlands, Norway, Sweden
Mean 2= Greece, Ireland, Portugal, Spain
Mean 3= France, Italy, United Kingdom, West Germany
*First (second) line numbers in each country cell are measures without (with) human capital

quences. For example, input biased technological growth has significant implications for the behaviour of the real exchange rate (the price of non-tradeables relative to tradeables) in a Balassa–Samuelson model.

Figure 3 shows how individual countries fare towards the empirically constructed production frontiers in 1965, 1990 and 1998, respectively. It becomes evident from an inspection of the three production frontiers that the vertical shifts in the frontier over time in the $x - y$ (capital per worker-output per worker) space are not proportional, that is, technological change is non-neutral. There also appears to be an implosion of the frontiers in the low capital-labour ratios area which either can be interpreted

Table 3 Contribution to growth in output per worker 1965–1998

Country	Y/L 1965	Y/L 1998	Y/LChange(%)	EffChg(%)	TechChg(%)	Kaccum(%)	Haccum(%)
Austria	19743.54	46945.59	137.78	−21.35	28.48	135.31	
				−21.45	36.50	92.68	15.10
Belgium	26816.12	54640.12	103.76	−12.79	86.91	24.99	
				0.18	47.33	27.63	8.16
Denmark	27131.71	44928.80	65.60	−29.15	64.80	41.83	
				−26.21	22.36	67.45	9.53
Finland	19547.56	45463.33	132.58	3.18	94.31	16.01	
				−1.34	69.76	0.57	38.08
France	23430.20	48347.08	106.35	−9.99	28.46	78.45	
				−11.03	28.40	50.01	20.41
Greece	13703.64	33907.24	147.43	−10.30	27.01	117.20	
				−11.05	33.66	59.91	30.14
Ireland	14920.85	56908.57	281.40	37.89	5.30	162.68	
				34.69	−11.62	164.92	20.95
Italy	21366.33	51796.01	142.42	9.66	29.67	70.48	
				9.82	40.43	33.28	17.94
Luxembourg	32714.09	91087.58	178.44	0.00	144.35	13.95	
				3.26	113.88	8.14	16.58
Netherlands	30216.58	49291.52	63.13	−23.33	58.11	34.56	
				−23.33	32.11	22.83	31.11
Norway	24717.67	54490.77	120.45	−19.55	115.91	26.92	
				−28.46	117.96	3.45	36.67
Portugal	10914.93	32058.80	193.72	−31.20	−17.40	416.88	
				−23.66	−19.22	275.35	26.88
Spain	17404.40	42220.48	142.59	−24.28	7.50	198.01	
				−16.73	4.96	112.99	30.31
Sweden	27567.55	43873.49	59.15	−28.20	41.86	56.26	
				−28.97	19.86	42.15	31.50
UK	23389.42	42565.72	81.99	−19.32	4.35	116.16	
				−19.22	−2.24	96.13	17.51
W Germany	24194.80	50428.02	108.43	−33.65	100.80	56.43	
				−27.77	66.65	54.96	11.74
Mean	22361.21	49309.57	129.07	−13.27	51.28	97.88	
	(5870.33)*	(12665.03)*	(54.63)	−11.95	37.55	69.53	22.66

* Numbers in brackets are standard deviations

as evidence of technological regression or more likely as efficiency declines. The latter will be possible if the DEA constructed frontier is below the true frontier of technology.

Table 3 reports the results of decomposing labour productivity growth into (i) efficiency change (ii) technical change and (iii) the change in the capital to labour ratio, both with and without human capital. The evidence provided in Table 3 indicates that capital accumulation has been the main driving force of labour productivity growth in the EU area. Technical progress has also made an important contribution whereas the effect of efficiency is largely negative. Finland, Italy and mainly Ireland are the countries where changes in technical efficiency have made a positive contribution to the growth in output per worker. Germany's poor efficiency record is quite notable. Technical change has been the main contribution to growth in labour productivity for Belgium, Luxembourg, Netherlands, Finland and Norway. In contrast to the evidence shown in Tables 1 (efficiency measures) and 2 (TFP measures), here we see some differences, especially in the role of capital deepening on productivity growth, when we include human capital (generally reducing its contribution to productivity growth). In particular, for Finland, France, Greece, Italy and Norway we find that human capital substantially lowers the contribution of physical capital accumulation to the growth process and considerably lessens the negative effect of efficiency to growth for Belgium, Portugal and Spain.[14]

[14] Yet it is puzzling to explain why efficiency has become worse over time for the majority of the countries, especially during a period where regulatory reforms have made their economies

Table 4 Convergence in output per worker 1965–1998

	Output/worker	Efficiency	Technical change	Capital accum
Coeff	−3.72	−0.684	2.601	−5.640
t	(4.53)	(2.18)	(3.57)	(6.98)
R^2	0.379	−0.027	0.455	0.647

System $R^2 = 0.723$

Table 4 reports the results of tests for convergence using cross-section data. The regression results of Table 4 suggest that technological change was a significant source of divergence in the sense that countries with higher initial productivity experienced greater rates of technological change relative to countries with low levels of initial labour productivity.[15] Further analysis indicates that the positive sign of the TCH coefficient is due to the effect of input biased technical change. The net magnitude component of technological change is negatively and significantly related to initial output per worker. The slope coefficient in the change in efficiency equation is negative but quite small. Note the sum of the change in efficiency plus the technical change coefficients is positive which implies that TFP growth had an adverse effect on convergence in output per worker over the sample period. This result contradicts those reported in earlier studies (e.g., Dowrick and Nguyen 1989; Bernard and Jones 1996) but is consistent with the findings of Maudos et al. (2000). However, the negative coefficient of the output per worker variable in the first column of Table 4 suggests overall convergence in labour productivity for our sample of countries. A major contributing factor to convergence in output per worker is capital accumulation as the results of the last column in Table 4 indicate.[16]

The evidence from the cross-section regression results in support of the convergence hypothesis should be treated with caution. For example, it is possible that there could be a negative correlation between growth and initial output per worker for a group of countries that diverge in situations where the marginal product of capital is diminishing (see Bernard and Durlauf 1992). Durlauf (2000) also emphasises the spurious nature of evidence in favour of convergence that fails to consider the properties of cross-country regressions. In addition, Quah (1996, 1997) has argued that convergence analysis solely relying on the first moments of a distribution cannot adequately address convergence issues. Thus, to gain a broader perspective on convergence trends and productivity and efficiency gains a non-parametric kernel-based method is used to estimate the distribution of output per worker and its efficiency component at different time periods. These distributions, essentially smoothed histograms of productivity and efficiency levels for the cross-section of countries, are

more market friendly. A possible explanation is that the transition costs of these reforms have been relatively high and have varied across countries as a result of differences in the initial regulatory environment, the pace and extent of their reform programmes. Using evidence from sectoral data, Färe et al. (2004) find that sectoral contributions to aggregate productivity growth for OECD countries is predominantly driven by within sector effects with very little contribution emerging from sectoral shifts (the 'in-between' static or dynamic effects resulting from higher or above average productivity industries gaining employment shares or low productivity industries loosing shares). The dynamic effects are negative for most countries and the same applies to the static effects in the 1990s. These effects may be attributed to diverging reform patterns associated with institutional rigidities or other country specific factors. The notable difference is Ireland which shows relatively strong 'in between' effects consistent with an effective process of economic restructuring.

15 The results of Table 3 are Seemingly Unrelated Regression estimates where the dependent variables are the average rate of growth in labour productivity and each of its three components, respectively, and the independent variable is the (log) initial productivity level. The restriction that the sum of the slope coefficients of the regressions in columns (2)–(4) is equal to the slope coefficient of the regression in column (1) is imposed.

16 The lack of technology convergence may, in part, be attributed to differences in the composition of aggregate output across EU countries, especially in the tradables sector where specialisation and product heterogeneity may mitigate the effects of technology diffusion across national borders. These mitigating effects are likely to become more pronounced during a transition period when the forces of deregulation and market integration increase input mix response to relative factor movements albeit at varying degrees across member states. This is consistent with our finding; namely, it is input biased technological change that underpins technology divergence. It is also worth noting the conceptual difference in the measurement of technical change compared to other studies which assume neutral technical progress and no inefficiency; our measure of technical change relates to how the frontier is shifting at different input mixes. The identity of the frontier may be changing over time and is determined by only a small subset of countries in our sample.

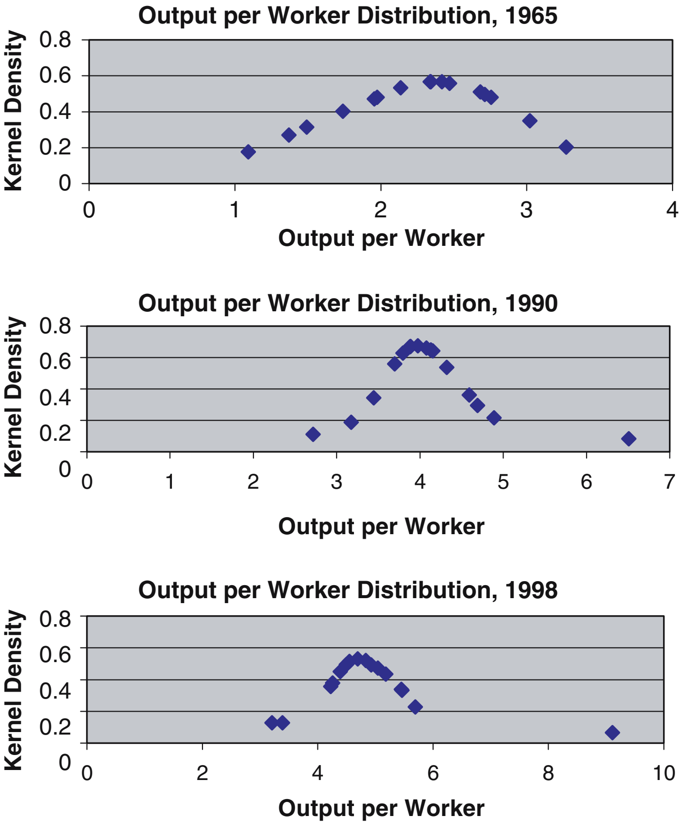


Fig. 4 Output per worker distribution of 1965, 1990 and 1998

shown in Fig. 4. The small sample size problems for kernel estimation should be noted. There is evidence to suggest an improvement in the productivity on average over time marked by the steady increases in the mean of the distribution in the three periods. Further, the shift of the probability mass towards the mean between 1965 and 1990 is evidence suggestive of improved convergence during this period.[17] There is no clear evidence to suggest that more progress in productivity convergence took place between 1990 and 1998. Figure 5 gives no indication that the economies are moving closer to the production frontier over time.

Formal evidence in determining the number of modes in the empirical distribution is given in Fig. 6. The approach used is the SiZer (significance of zero) test of Chaudhuri and Marron (1997). This is a graphical test made up of two parts: (1) a family of empirical kernel distributions associated with a different bandwidth and (2) the SiZer map exhibiting the significance of zero crossings (see Henderson et al. 2002, for more details). From the change in the number of modes, we can see if and when productivity in the EU converges to a unimodal distribution. The black curve in the top graph is for a large bandwidth, so the kernel distribution is smoother. The light (white) curve corresponds to a smaller bandwidth, so the kernel estimate of the distribution looks less smooth. This produces more modes in the kernel estimate of the productivity distribution which may be regarded as a spurious artefact of the sampling process (see Henderson et al. 2002). The SiZer map shows which features of the family of distributions are statistically significant for a given bandwidth.

The dark grey shade on the left in the SiZer map indicates a significant increase in the kernel distribution, the medium grey shade on the right means there

[17] Note that convergence in distribution or σ-convergence provides evidence of convergence but it does not necessarily support the convergence hypothesis as it does not address the issue of β-convergence, namely, that lower income per capita (or per worker) countries will catch-up with the rich countries through the process of technology transfer or through higher (marginal) capital productivity. It does not also address the issue of mobility patterns or intra-distribution dynamics (see Bianchi 1997). For example, countries like Denmark, Sweden or the UK have moved over time from above to below the mean whereas others like Ireland started low but moved above the mean (see Table 3).

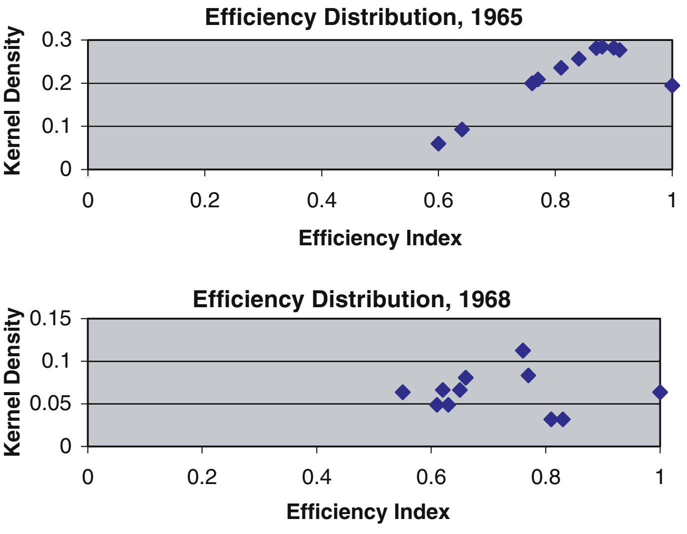


Fig. 5 Efficiency distribution of 1965 and 1998

is a decrease in the kernel, and the light grey shade area in the middle shows there is a maximum (turning) point in the kernel. Thus significant modes have a dark grey region on the left and a medium grey region on the right. Owing to the small number of cross-sectional units (countries) in our sample, there is no clear indication from the SiZer map whether there are significant changes in the number of modes of the productivity distribution over time.[18] Nonetheless, it appears from inspection of the empirical kernel estimates given by the black curves that from 1960 to 2000 the distribution of output per worker has shifted from bimodal to unimodal, thus providing further evidence in support of the convergence hypothesis.[19]

Recursive convergence tests

There is no clear evidence from the empirical kernel estimates shown in Fig. 6, depending on the size of the bandwidth parameter, as to whether the EU countries can be considered as part of one or more convergence groups or 'clubs'. Furthermore, we have already argued that σ-convergence cannot be viewed on its own accord as evidence of convergence. In this section we use the recursive approach of Rangvid (2001) to analyse the convergence process. The idea is that an increasing number of cointegration relationships in output per worker for different countries may be regarded as an indicator of a process of closer integration. The recursive estimation method employed is based on Hansen and Johansen (1999). It is a forward recursion procedure, and the parameters of the model are estimated based on a sub-sample covering $t = 1, \ldots, T_0$. The recursive formulas are used to update the parameter values stepwise from T_0 to the full sample value (T). The time paths of the estimated parameters are presented graphically. There are two procedures, the 'Z-representation' and the 'R-representation' in this recursive estimation. In the Z-representation all parameters are estimated recursively whereas the R-representation is based upon the concentrated likelihood function (the short-run parameters are concentrated out).

A vector error correction model (VECM) for the k log output per worker variables (y), may be written as

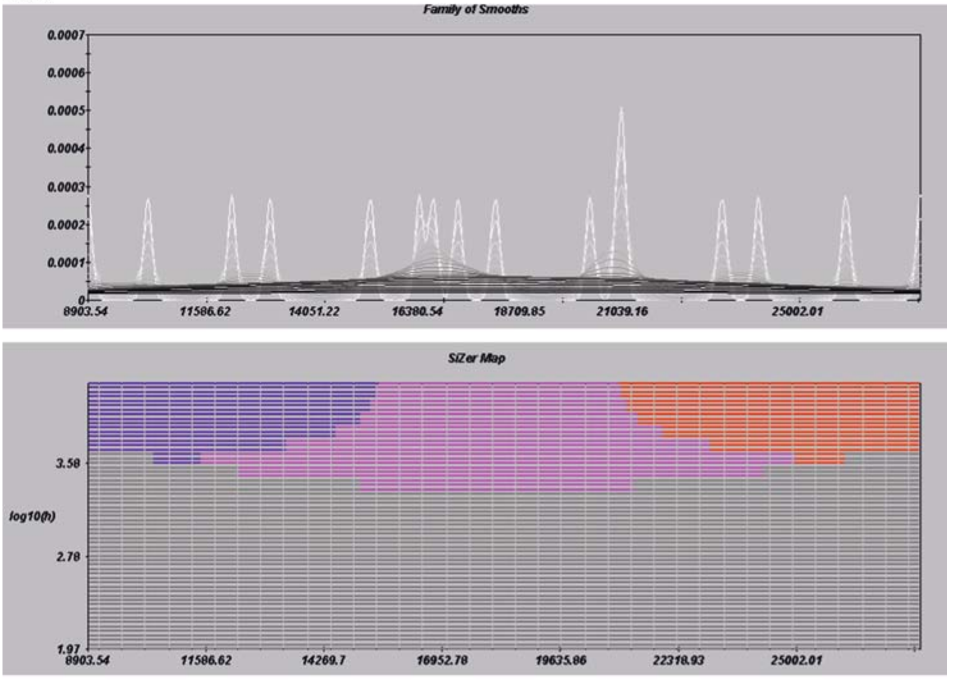
$$\Delta y_t = c + \sum_{i=1}^{l} \Gamma_i \Delta y_{t-l} + \Pi y_{t-1} + \varepsilon_t$$

where c is a constant, Γ is the short-run dynamics matrix, Π is the long-run impact matrix summarising all the long-run info in the y process and whose rank (r) determines the number of stationary linear combinations (cointegrating vectors) of y_t. The vector ε_t is *i.i.d* with N(0, Σ). The matrix Π can be of full rank.

[18] The results are fairly robust indifferently of whether we look at output per worker, its log transformation or we consider a relative output per worker measure.

[19] Kernel estimates indicate that the input biased technological change distribution exhibits a variable number of 1–3 modes over time whereas the net magnitude component distribution appears to have converged to a single mode.

1960



1965

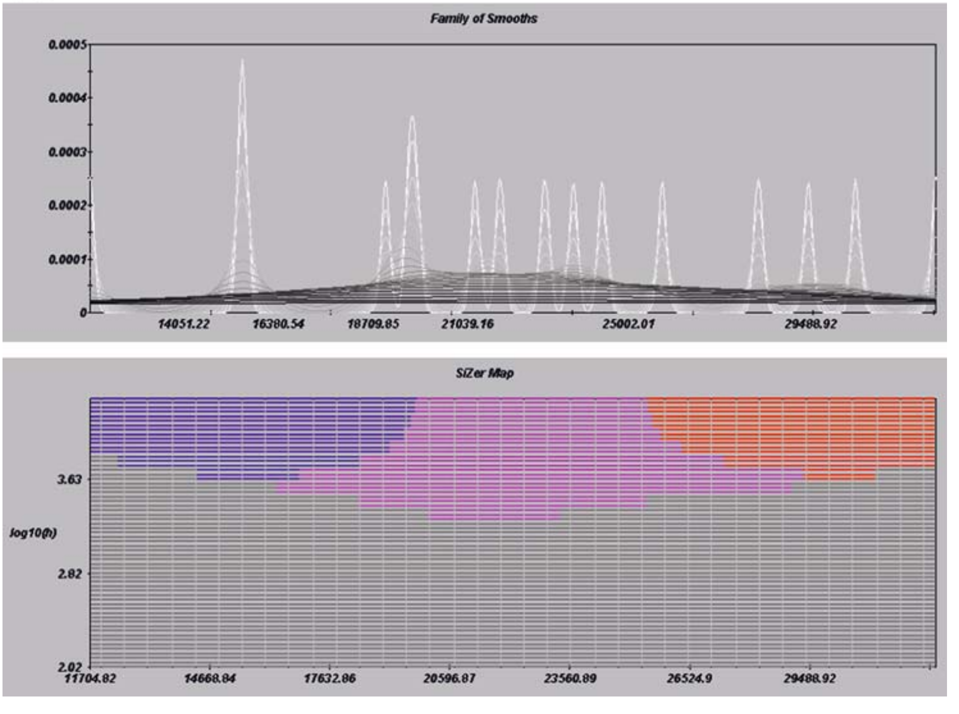
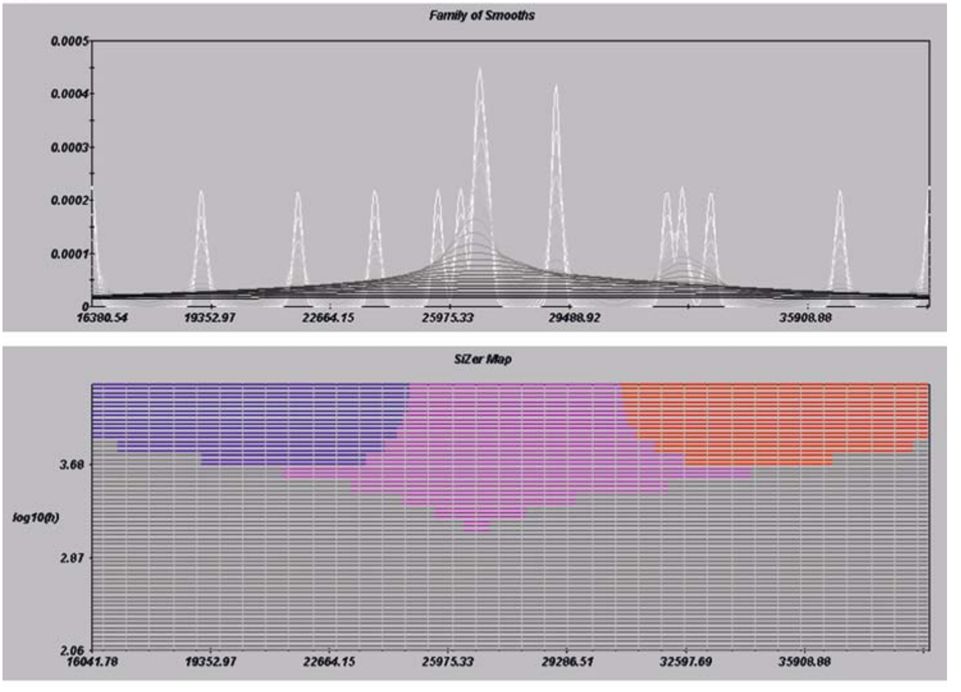


Fig. 6 SiZer tests GDP per worker (EU-15 & Norway)

1970



1975

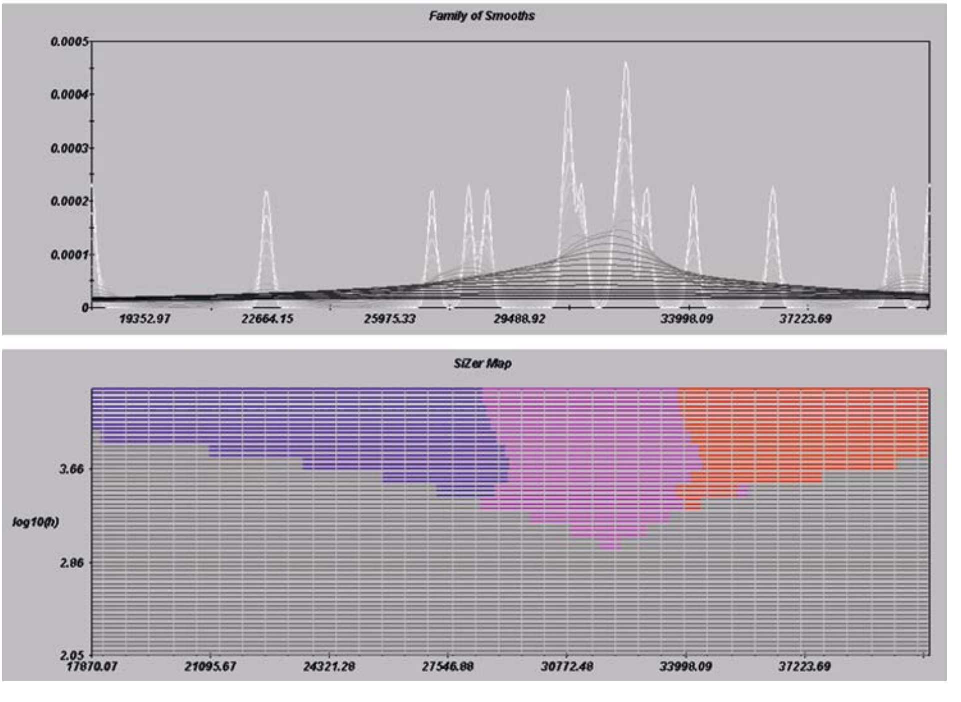
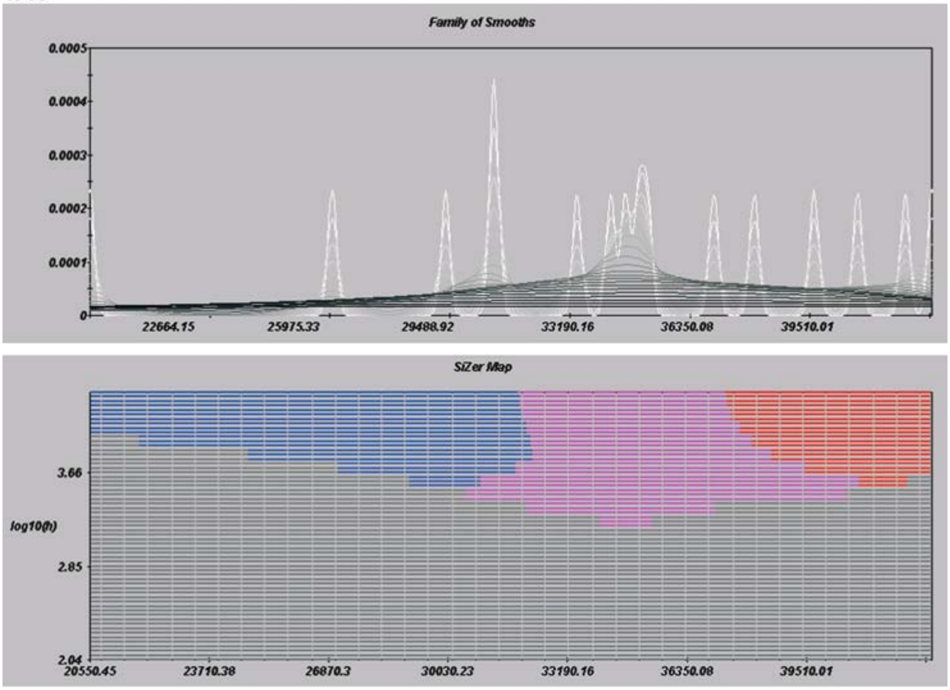


Fig. 6 Continued

1980



1985

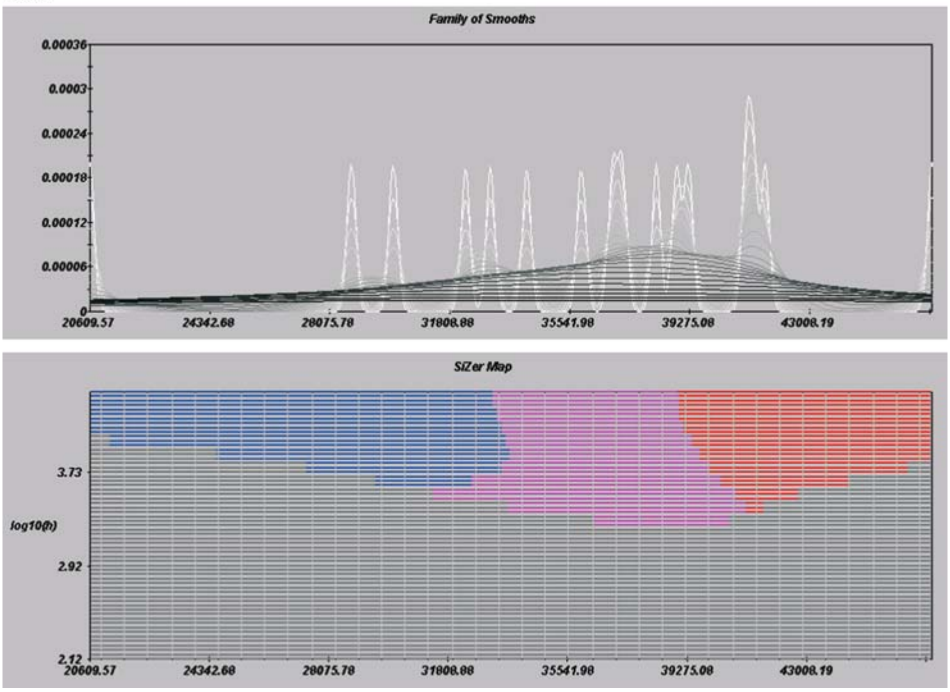
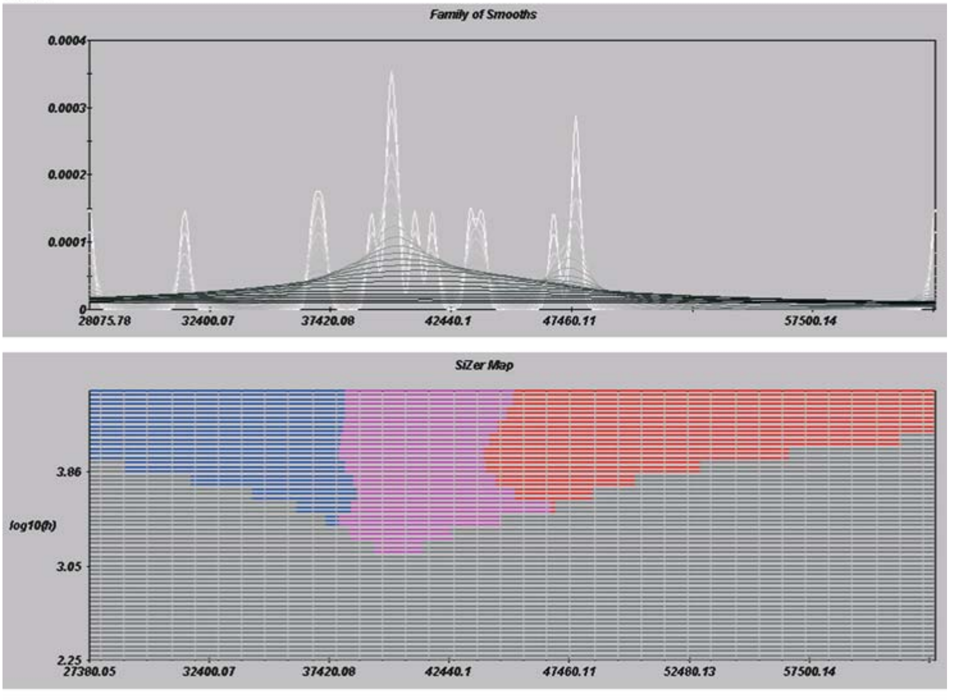


Fig. 6 Continued

1990



1995

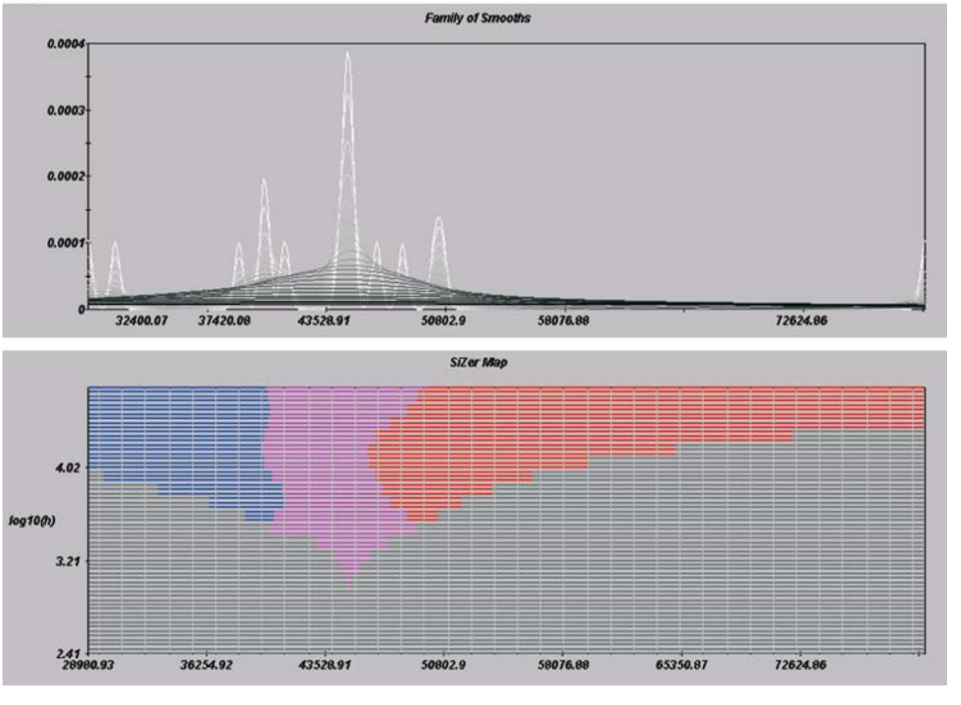


Fig. 6 Continued

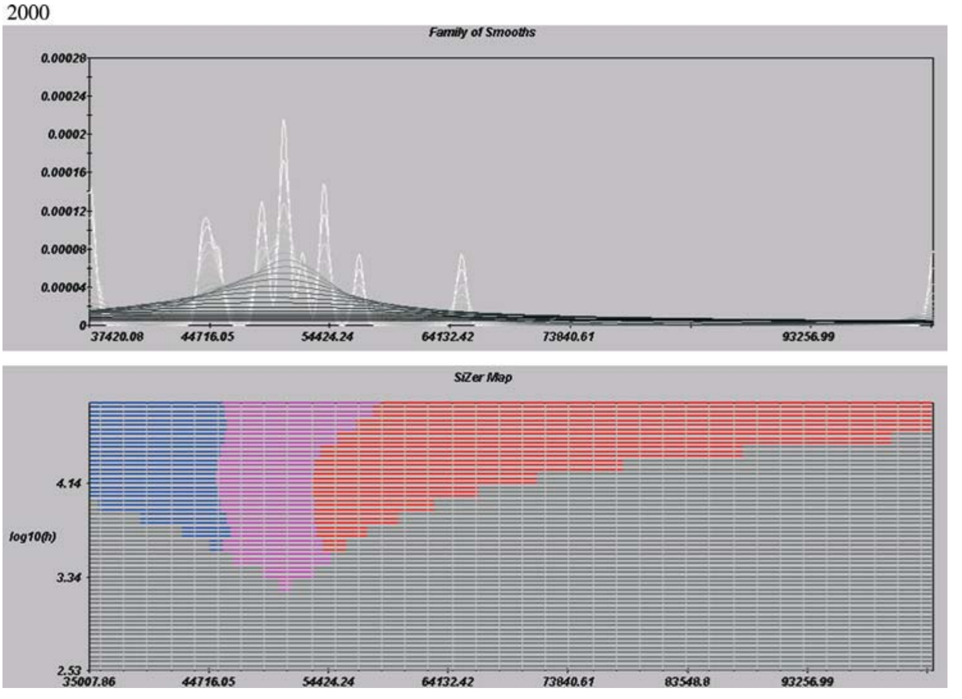


Fig. 6 Continued

In this case, the assumed stationarity of the error item requires that the levels of the process y_t are themselves stationary, implying there is no stochastic trends in the series, contrary to the original $I(1)$ specification. Π could also be of rank zero, which indicates there are no stationary long-run relations among the elements of y_t. For $0 < r < k$, there exist r cointegration vectors. In this case, Π can be factorized as $\alpha\beta$', where both α and β are full rank $k \times r$ matrices. This model reflects a dynamic equilibrium relation, in which the expression $\beta' y_{t-1}$ represents the extent to which the system deviates from long-run equilibrium. The series are integrated together over time by the long-run relations in β' (the r columns of β are the cointegration vectors). The elements of α are the error-correction parameters which account for the speed of adjustment towards long-run equilibrium (the ith row of α tells us how important each of these r vectors are to the dynamics of the ith productivity series).

Let $Z_{0t} = \Delta y_t$, $Z_{1t} = y_{t-1}$, $Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-l+1}, 1)$, $\Pi = \alpha\beta'$ and stack the parameters $((\Gamma_1, \ldots, \Gamma_{l-1})$ in Γ. The model can then be formulated as

$$Z_{0t} = \alpha\beta' Z_{1t} + \Gamma Z_{2t} + \varepsilon_t \quad t = 1, \ldots, T.$$

In the 'Z-representation' all the parameters of the VECM are re-estimated during the recursions that involve a reduced rank regression of Z_{0t} on Z_{1t} corrected for Z_{2t}. The residuals R_{0t} and R_{1t} of these regressions are given by:

$$R_{0t} = Z_{0t} - M_{02}M_{22}^{-1}Z_{2t},$$

$$R_{1t} = Z_{1t} - M_{12}M_{22}^{-1}Z_{2t},$$

$$\tilde{\varepsilon}_t = \varepsilon_t - M_{\varepsilon 2}M_{22}^{-1}Z_{2t},$$

where $M_{ij} = T^{-1}\sum_{t=1}^{T} Z_{it}Z'_{jt}$,

$$M_{\varepsilon j} = T^{-1}\sum_{t=1}^{T} \varepsilon_t Z'_{jt}, \quad i, j = 0, 1, 2.$$

In the 'R-representation' the short-run parameters are fixed to their full sample values (the parameter Γ has been concentrated out) and only the long-run parameters are re-estimated via the regression,

$$R_{0t} = \alpha\beta' R_{1t} + \tilde{\varepsilon}_t, \quad t = 1, \ldots, T.$$

Then define the product moment matrices by

$$S_{ij} = T^{-1}\sum_{t=1}^{T} R_{it}R'_{jt}, \quad i, j = 0, 1$$

The maximum likelihood estimator of β using the full sample is found by solving for the eigenvalues of the equation:

$$|\lambda S_{11} - S_{10}S_{00}^{-1}S_{01}| = 0$$

which gives the k eigenvalues, $1 > \hat{\lambda}_1 > \cdots > \hat{\lambda}_k > 0$ and the corresponding eigenvectors $\hat{V} = (\hat{v}_1, \ldots, \hat{v}_k)$ normalized such that $\hat{V}'S_{11}\hat{V} = I$. The eigenvalues $\hat{\lambda}_i$ correspond to the squared canonical correlations between the 'levels' residuals and the 'difference' residuals, as defined above. The eigenvectors $\hat{v}_i$ are the maximum likelihood estimators of $\beta = (\hat{v}_1, \ldots, \hat{v}_r)$.

Johansen (1988, 1991) propose two methods for testing for the number of cointegration vectors: the Trace test and Maximal Eigenvalue test. The Trace test is a likelihood ratio test for maximum r cointegration vectors against the alternative of k vectors.

$$\text{Trace} = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\lambda}_i),$$

where $\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_k$ are the $(k-r)$ smallest eigenvalues of the squared canonical correlations as described above.

The *Maximal Eigenvalues* test has an identical null hypothesis, while the alternative is $r + 1$ cointegration vectors.

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1})$$

where $\hat{\lambda}_{r+1}$ is the largest eigenvalue as defined above. Both tests have a non-standard asymptotic distribution (see Johansen 1988, 1991).

Hansen and Johansen (1999) show that in the recursive cointegration analysis the $k - r$ smallest eigenvalues $\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_k$ of the product moment matrices defined above will converge to zero while the r largest eigenvalues $1 > \hat{\lambda}_1 > \cdots > \hat{\lambda}_r > 0$ converge towards the solution of the equation

$$|\lambda\beta' S_{11}\beta - \beta' S_{10}S_{00}^{-1}S_{01}\beta| = 0$$

where $\beta' S_{11}\beta$ and S_{oo} are the asymptotic variances of $\beta' R_{1t}$ and R_{0t}, respectively, and $\beta' S_{10}$ is the asymptotic covariance matrix for $\beta' R_{1t}$ and R_{0t}. The eigenvectors $\hat{V} = (\hat{v}_1, \ldots, \hat{v}_k)$ are normalized by $\hat{V}'S_{11}\hat{V} = I$. The trace test is a likelihood ratio test for a maximum r cointegration vectors against the alternative of k vectors (see Johansen 1988, 1991). Its test statistic is in the same form as the cointegration rank test statistic given above for the full sample:

$$\text{Trace}_j = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\lambda}_i), \quad j = 1, 2, \ldots, k - 1$$

where again the $(k-r)$ smallest eigenvalues $\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_k$ are used for the computation of the test statistic. Non-constancy of the estimates of α_i and β_i will be reflected in the recursively updated time path of the eigenvalues $\hat{\lambda}_i$. It is expected that that time path of Trace_j will be upward sloping for $j \leq r$ (as the cointegration rank does not change throughout the sample period) and constant for $j > r$.

Each of the recursive likelihood ratio test statistics is scaled by the 90% quantile of the asymptotic (trace) distribution. Our interest is on the time paths of these statistics. For a given t, the rank r can be identified as the number of these paths with values that exceed unity. Note that convergence should show up in an increasing number of cointegrating vectors being accepted as significant. Convergence and declining common stochastic trends may result from stationarity of the relevant time series or the relevant time series being increasingly driven by the same shocks. Note that finding one common trend at sample end should not be interpreted as a perfectly converged system because shocks to individual series would still have permanent effects (see Rangvid and Sorensen 2001).

Tables 5–9 present test statistics for five different groupings of the 16 countries in our sample over the period 1965–1998 using ordinary (full-sample), recursive and rolling sample cointegration methods.[20] We use the recursive tests to study the dynamics of convergence for the full sample of observations, whereas the rolling tests are used to investigate the degree of

[20] The groups (relative convergence clubs) were chosen using the cluster algorithm of Hobijn and Franses (2000). This is a two part (endogenous) process where countries in the sample are clustered to obtain asymptotically perfect (zero mean stationary differences in log output per worker) and relative (level or stationary differences in log output per worker) convergence clubs. The algorithm uses a multivariate generalisation of the Kwiatkowski et al. (1992) (KPSS) unit root test to test the (zero mean and level) stationary null hypotheses against the non-convergence alternative of a stochastic trend (unit root) or deterministic trend plus a non-zero intercept hypotheses. The outcome of the clustering procedure (number and composition of convergence clubs) appears to be robust to the choice of the bandwidth parameter of the Bartlett window used in the construction of the test statistics and is independent of the ordering of the individual country series. The number of convergence clubs is probably larger than what one would expect to find for an area operating under formal convergence protocols like the EU but it is consistent with the study Hobijn and Franses (2000) who also report a large number of clubs, particularly for industrialised countries. It is also consistent with the multi-modal (low bandwidth white line) kernel estimates in Fig. 6.

Table 5 Cointegration analysis

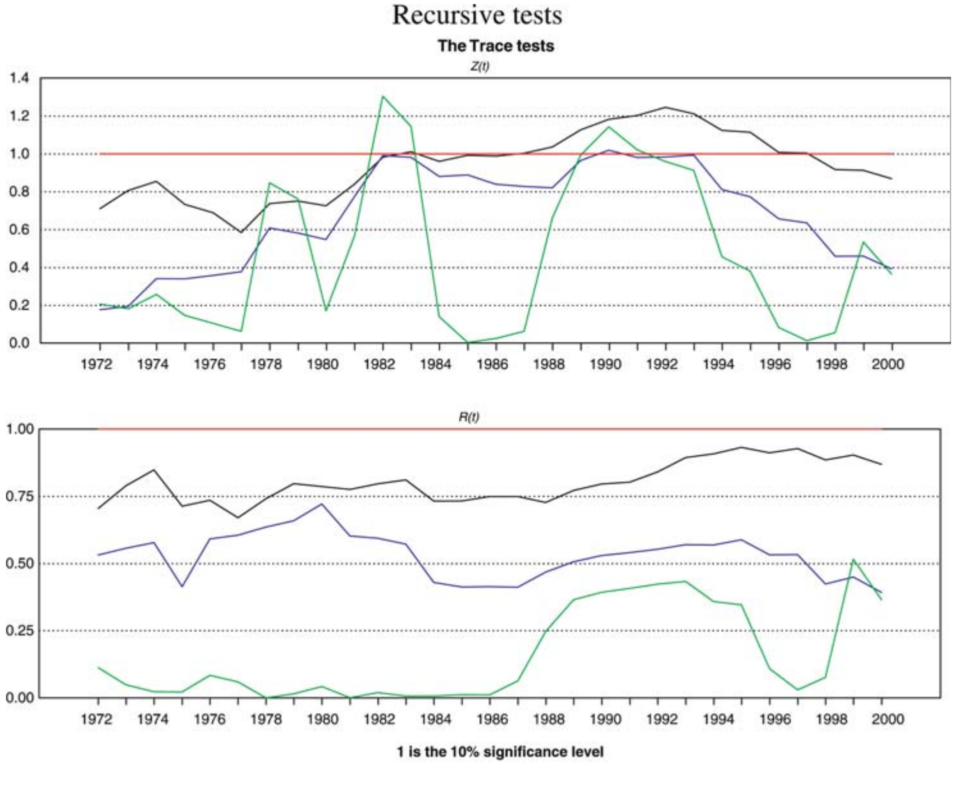
(Group 1) Endogeneous series:
AUT ITA NOR

Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) ANALYSIS

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.3419	17.99	23.22	0	3	13.39	26.70
0.0938	4.23	5.22	1	2	10.60	13.31
0.0227	0.99	0.99	2	1	2.71	2.71

LR test of pairwise (1, −1) differences; $\chi^2(1) = 1.14$; p-value $= 0.29$



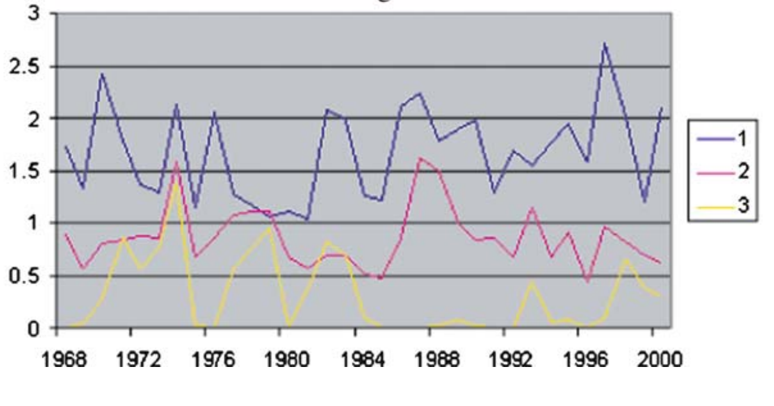


Table 6 Cointegration analysis

(Group 2) Endogeneous series:

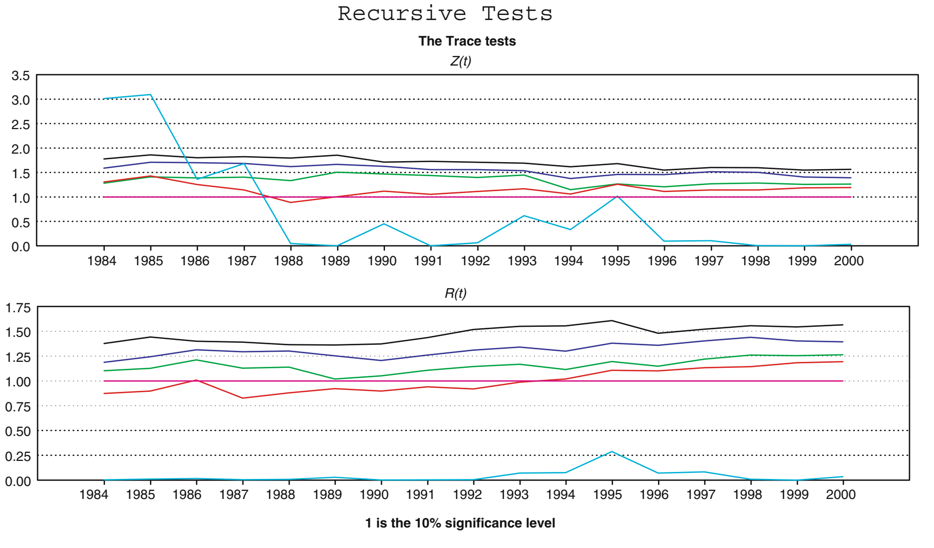
BEL	DNK	LUX	NLD	SWE

Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) Analysis

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.6073	40.19	101.31	0	5	20.90	64.74
0.4710	27.38	61.11	1	4	17.14	43.84
0.3397	17.85	33.73	2	3	13.39	26.70
0.3074	15.79	15.88	3	2	10.60	13.31
0.0021	0.09	0.09	4	1	2.71	2.71

LR test of pairwise $(1, -1)$ differences; $\chi^2(4) = 25.02$; p-value $= 0.00$



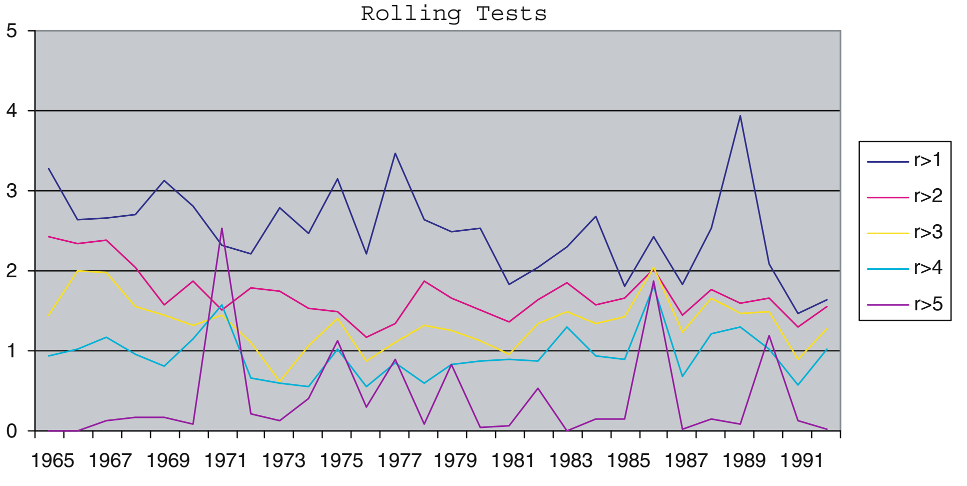


Table 7 Cointegration analysis

(Group 3) Endogeneous series:

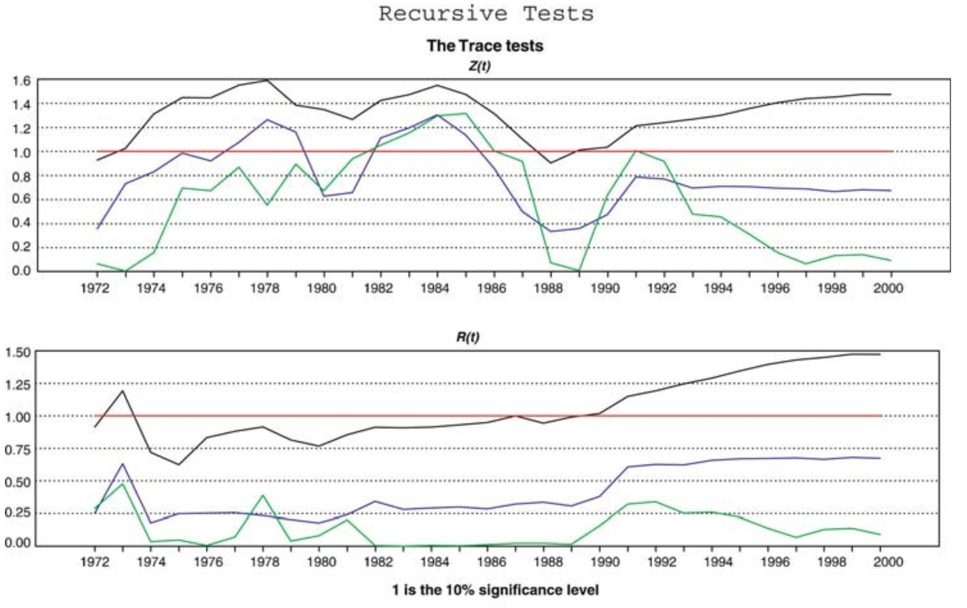
FRA	GER	UK

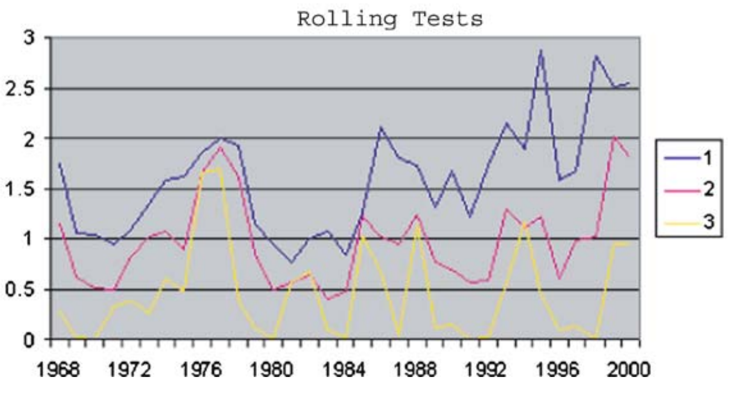
Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) Analysis

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.5066	30.38	39.34	0	3	13.39	26.70
0.1834	8.71	8.96	1	2	10.60	13.31
0.0057	0.25	0.25	2	1	2.71	2.71

LR test of pairwise $(1, -1)$ differences; $\chi^2(1) = 0.93$; p-value $= 0.34$





convergence (e.g., the periods where convergence is strongest or weakest) during different sub-samples of the full sample (see Rangvid and Sorensen 2001). In addition, the use of rolling tests provides a means by which we can assess the robustness of the recursive test results.

The test results suggest that there is possibly one cointegration vector and therefore two common stochastic trends that drive (log) output per worker for Group 1 countries (Austria, Italy and Norway). The fluctuations around the critical values in the top time path of the trace test based on the 'Z-represen-

Table 8 Cointegration analysis

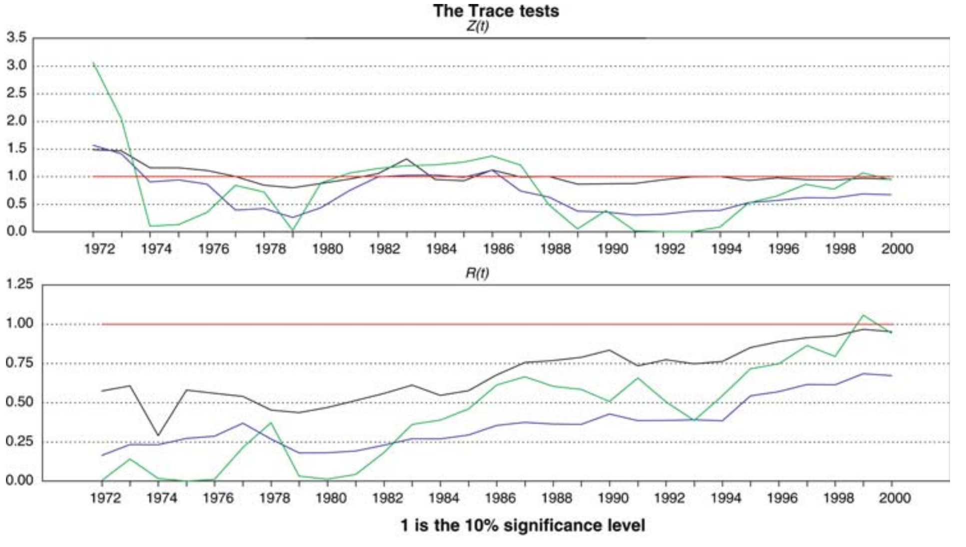
(Group 4) Endogeneous series:
GRC IRL PRT

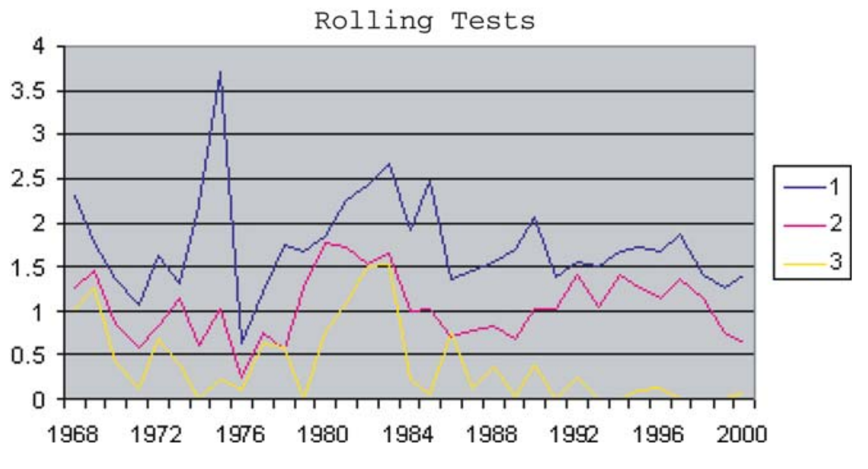
Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) Analysis

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.3182	16.47	25.41	0	3	13.39	26.70
0.1381	6.39	8.94	1	2	10.60	13.31
0.0576	2.55	2.55	2	1	2.71	2.71

LR test of pairwise (1, −1) differences; $\chi^2(1) = 9.97$; p-value $= 0.00$





tation' in Table 5 provide mixed evidence on convergence trends for Austria, Italy and Norway. The top path of the 'R-representation' is upward sloping which may be consistent with a rank of one, $r = 1$, for the three country model over the full sample, but it is positioned below the critical value even at the end of the sample period. The (log) labour productivity series for the Group 2 countries (Belgium, Denmark, Luxembourg, Netherlands and Sweden) are driven by one common trend. The time paths of the trace statistics

Table 9 Cointegration analysis

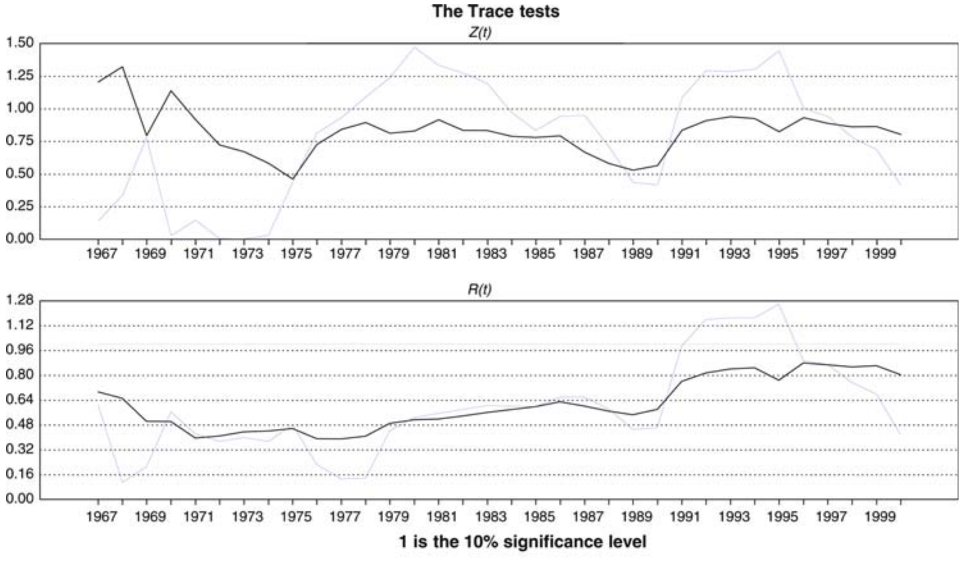
(Group 5) Endogeneous series:
FIN ESP

Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) Analysis

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.1997	9.58	10.70	0	2	10.60	13.31
0.0259	1.13	1.13	1	1	2.71	2.71

LR test of pairwise $(1,-1)$ differences; $\chi^2(1) = 4.38$; p-value $= 0.04$



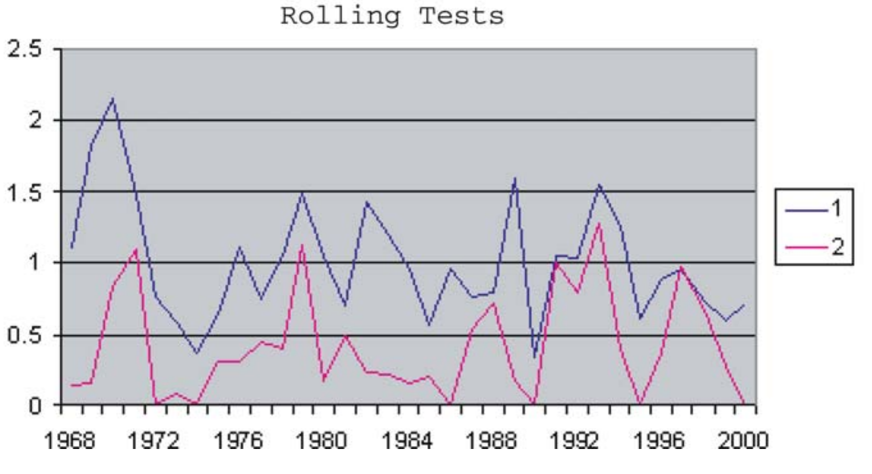


Table 10 (Original EU countries) Cointegration analysis

(Group 6) Endogeneous series:

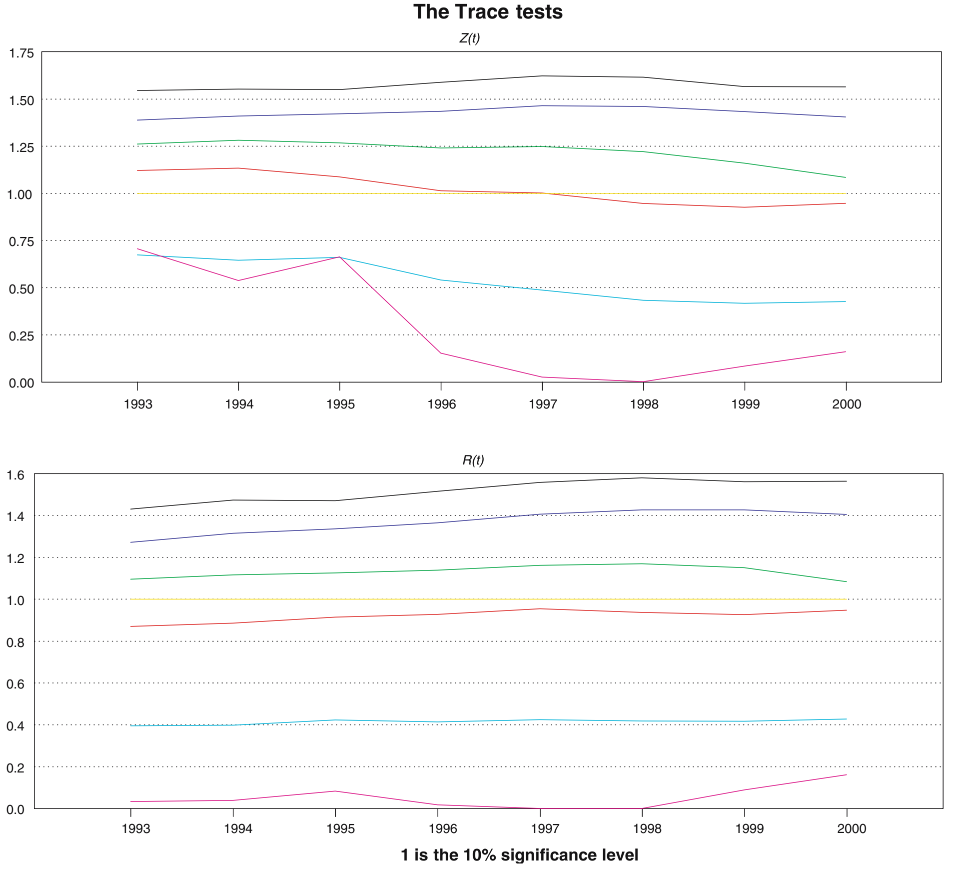
BEL	FRA	LUX	ITA	NLD	GER	

Effective sample: 1958 to 2000
Lag(s) in VAR-model: 2

I(1) Analysis

Eigenv.	L-max	Trace	H0:r	$k-r$	L-max90	Trace90
0.6790	48.86	139.82	0	6	24.63	89.37
0.6355	43.40	90.96	1	5	20.90	64.74
0.4039	22.25	47.56	2	4	17.14	43.84
0.3663	19.62	25.31	3	3	13.39	26.70
0.1150	5.25	5.69	4	2	10.60	13.31
0.0102	0.44	0.44	5	1	2.71	2.71

Test convergence restrictions: LR test of pairwise $(1, -1)$ differences; $\chi^2(3) = 3.24$; p-value $= 0.36$



show evidence of increased convergence after 1993 (see Table 6). The Group 3 countries (France, Germany and UK) are driven by two common trends. The recursive tests of Table 7 show convergence in (log) output per worker occurred after 1990. Labour productivity for Group 4 countries (Greece, Ireland and Portugal) is also driven by two common trends. The time path of the 'R-representation' trace statistics indicates increased convergence towards the end of the sample period.

The evidence for Group 5 (Finland and Spain) countries is much less clear cut. However, it seems possible that this group is driven by one common trend (see Table 9) although it appears that this trend is a lot weaker in the second half of the 1990s. Table 10 presents convergence results for the group of the original six EU Member States (Group 6). There appears to be three common trends driving output per worker in this group. The evidence of increased convergence in labour productivity among groups of EU countries corroborates the results presented in Fig. 4–6 for the dynamics of the distribution of labour productivity across the sample of 16 countries. This should probably come as no surprise, as the concept of stochastic trends and cointegration is closely related to the dynamics of the underlying distributions. Indeed, as Hobijn and Franses (2000) point out, asymptotically perfect and relative convergence imply that the cross-country (log) per capita income (or labour productivity) distribution settles down to a stable non-degenerate distribution. For all the groupings of countries considered above, there was no evidence to suggest asymptotically perfect convergence in multivariate output in the sense of Bernard and Durlauf (1995). However, asymptotically relative convergence in the sense of Hobijn and Franses (2000) was attained for countries in Groups 1, 3 and 6 (see the χ^2 test results in Tables 5, 7, 10).[21]

Conclusion

In this paper we investigate whether convergence has occurred in the EU area over the last four decades. We look at convergence in terms of productivity convergence, where we include human and physical capital as factors of production. We find that human capital plays a fairly minor role; calculations of productivity with and without human capital are not very different.

However, since we use frontier methods, we can isolate sources of productivity growth including shifts in the frontier of technology (including input bias), capital deepening and catching up to the frontier. Here we see some differences in the role of capital deepening when we include human capital (generally reducing its contribution to productivity growth).

Generally speaking, labor and multifactor productivity improved for most of the countries in our sample. Portugal showed dramatic improvements (largely due to capital deepening) until the 1990s, when it started a sharp decline. Nevertheless it moved from about half in 1965 to two-thirds of the EU average in 1998. On the other hand, Sweden and Denmark moved from well above average in 1965 to below average by 1998. Ireland showed the most dramatic productivity improvements in the sample.

It is not clear whether efficiency (the transfer and diffusion of technology) matters more as in the case of Ireland rather than technological change as in the case of Finland in closing the gaps. On the other hand, a poor record of efficiency has proved detrimental in pushing Denmark, Sweden and the UK below the EU productivity average. It is always intriguing to explain why countries that have access to the same technology, close trade, investment and other economic relations differ in their ability to innovate and adopt new technology. An answer may be found in the individual country regulatory and institutional environment.

A recent OECD study (Scarpetta et al. 2002) reports that stringent product market regulation, either in the form of direct state control of economic activities, barriers to private entrepreneurial activity (e.g., access to markets, resource consents and business compliance costs) or barriers to international trade and investment, have a negative effect on multifactor productivity which appears to be greater the further a given country is from the technology leader. Scarpetta et al. argue that such regulations have the effect of reducing competitiveness, technology spillovers and the entry of new high-tech firms and therefore hinder both innovation and the adoption of existing technologies. These issues warrant further investigation in future research.

Our cross-section and time series convergence results are broadly consistent; the cross-section results support convergence in principle, although when we take advantage of our decomposition of productivity

[21] Note that the number and composition of clusters (convergence clubs) are determined by the Hobijn and Franses (2000) algorithm which uses the KPSS unit root test. The cointegration results reported here use the Johansen method. This allows us to assess the degree of integration of ‘club’ members over time and also the robustness of the KPSS results. We also experimented with an alternative method of assessing convergence proposed by Haldane and Hall (1991). This method uses a Kalman filter to estimate time-varying models of productivity differentials. The (log) productivity differential between Germany and each of the other 14 European countries (excluding UK) was regressed on the relative (log) productivity of Germany to UK. The convergence assumption is that the time-path of the slope coefficient in each regression should tend to zero. The results are indicative of increased convergence of Austria, Belgium, Finland, Greece, Ireland, Italy, Spain and Sweden with respect to Germany.

into technical change, capital deepening and catch-up, we find that technical change (especially input biased technical change) is a source of divergence. Nevertheless, capital deepening especially dominates this effect overall. Non-parametric kernel-based estimates of output per worker and efficiency levels suggest that most convergence took place between 1965 and 1990. We also implement SiZer tests to determine the number of modes in the distributions, but probably due to the small sample size, find no significant changes over this time period, although the empirical kernel estimates suggest a shift from bimodal to unimodal.

To provide further evidence we turn to time series evidence; we use ordinary, rolling sample and recursive cointegration methods to analyse trends in output per worker. We use the recursive tests to study the dynamics of convergence for the full sample of observations, whereas the rolling tests are used to investigate the degree of convergence (e.g., the periods where convergence is strongest or weakest) during different subsamples of the full sample. Here we find evidence of convergence 'clubs'; for example Belgium, Denmark, Luxembourg, the Netherlands and Sweden have one common stochastic trend. However, time series tests fail to support the hypothesis that the EU area is a single convergence club.

We included Norway—a non-EU country—in our analysis. It is an interesting comparison to find that Norway does not differ significantly in any obvious way from the EU member countries. This finding may have to do with the fact that three of these countries, Austria, Finland and Sweden, only joined in 1996. In the case of Norway and Finland, we find that technical change is the main force driving their growth in output per worker whereas changes in capital per worker play a minor role, especially when we account for the role of human capital in the production process. In contrast, Sweden has a more modest labour and TFP growth record owed to a slower rate of technical progress and a larger contribution of capital accumulation to growth in output per worker than Norway and Finland.

Convergence and declining common stochastic trends may result from the stationarity of the relevant time series or the relevant time series being increasingly driven by the same shocks. The evidence presented in this paper indicates that across the EU area markedly different pattern of shocks continue to prevail which in turn place increasing pressures on the sustainability of the EU stability and growth pact. The recent suspension of the fiscal rules of the pact is a testament to this pressure.

We conclude that by the end of the 20th century the EU was not a single convergence club. Is it likely to become one? Given the expansion of the EU to the East, that seems unlikely. In fact, our results raise the question—will these new members form their own convergence club or will they cluster with say, Portugal and Greece?

References

Barro RJ, Lee J-W (2000) International data on educational attainment: updates and implications. Center for International Development Working Paper 42, Cambridge, MA

Barro RJ, Sala-I-Martin X (1995) Economic growth. McGraw-Hill, New York

Baumol WJ, Nelson RR, Wolff EN (1994) Convergence in productivity: cross national studies and historical evidence. Oxford University Press, New York

Bernard AB, Durlauf SN (1996) Interpreting tests for the convergence hypothesis. J. Econometrics 91:161–173

Bernard AB, Durlauf SN (1995) Convergence in international output. J. Appl. Econometrics 10:97–108

Bernard AB, Jones CI (1996) Productivity across industries and countries: time series theory and evidence. Rev. Eco. Statist., 78:135–146

Bianchi M (1997) Testing for convergence: evidence from non-parametric multimodality tests. J. Appl. Econometrics 12:393–409

Caselli F, Coleman II WJ (2003) The world technology frontier. unpublished paper, Harvard University

Caves D, Christensen L. Diewert WE (1982) The economic theory of index numbers and the measurement of input, output and productivity. Econometrica 50:1390–1414

Chapple S (1994) Searching for the Heffalump? An exploration into sectoral growth and productivity in new zealand. New Zealand Institute of Economic Research Working Paper 94/10

Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur. J. Operat. Res. 2:429–444

Chaudhuri P, Marron JS (1997) SiZer for exploration of structures in curves. North Carolina Institute of Statistics Mimeo Series #2355

Crafts N, O'Mahoney M (2001) A perspective on UK productivity performance. Fiscal Stud 22(3): 271–306

Dowrick S, Nguyen D (1989) OECD comparative economic growth 1950–85: catch up and convergence. Am. Econ. Rev. 79(5):1010–1030

Durlauf SN (2000) Econometric analysis of the study of economic growth: a sceptical perspective. mimeo, Department of Economics, University of Wisconsin

Durlauf SN, Quah DT (1998) The new empirics of economic growth. NBER Working Paper Series 6422. In: Handbook of Macroeconomics. Taylor J, Woodford M (eds.) North Holland, Amsterdam, forthcoming

Färe R (1988) Fundamentals of production theory. Springer-Verlag, Heidelberg
Färe R, Grosskopf S (1996) Intertemporal production frontiers: with dynamic DEA. Kluwer Academic Publishers, Boston
Färe R, Grosskopf S, Lindgren B, Roos P (1989) Productivity developments in swedish hospitals: a malmquist output index approach. In: Data envelopment analysis: theory, methodology and applications. Charnes A, Cooper WW, Lewin A, Seiford L (eds.) Quorum Books
Färe R, Grosskopf S, Margaritis D (2004) Cross-country comparisons of sectoral productivity performance and the role of policy: a study of OECD countries. Asia-Pacific Productivity Conference, University of Queensland, Brisbane
Färe R, Grosskopf S, Norris M, Zhang Z (1994) Productivity growth, technical progress, and efficiency change in industrialized countries. Am. Econ. Rev. 84(1):66–83
Farrell MJ (1957) The measurement of productive efficiency. J. Roy. Statist. Soc. A 120 (Part 3):253–281
Friedman M (1992) Do old fallacies ever die? J. Econ. Literature 30:2129–2132
Haldane AG, Hall SG (1991) Sterling's relationship with the dollar and the deutschemark: 1976–1989, Econ. J. 101:436–443
Hall RE, Jones CI (1999) Why do some countries produce so much more output per worker than others? Quart. J. Econ. 114:83–116
Hall SG, Robertson D, Wickens MR (1997) Measuring economic convergence. Int. J. Financial Econ. 2:131–143
Hansen H, Johansen S (1999) Some tests for parameter constancy in cointegrated VAR-Models. Econometrics J. 2:306–333
Henderson DJ, Russell RR (2001) Human Capital and Convergence: A Production Function-Frontier Approach. Unpublished Paper, University of California, Riverside
Henderson DJ, Attar PK, Russell RR (2002) Modality tests for use in applied econometrics: application to macroeconomic convergence. Unpublished Paper, University of California, Riverside
Hobijn B, Franses PH (2000) Asymptotically perfect and relative convergence of productivity. J. Appl. Econometrics 15:59–81
Hultberg PT, Nadiri MI, Sickles RC (1999) An international comparison of technology adoption and efficiency: a dynamic panel model. Annals d'Economie et de Statistique 55–56:449–474
Johansen S (1988) Statistical analysis of cointegration vectors. J. Econom. Dynamics Control 12:231–254
Johansen S (1991) Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 59:1511–1580
Jones CI (1997) On the evolution of the world income distribution. J. Econ. Perspect. 11(3):19–36
Kumar S, Russell RR (2002) Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. Am. Econ. Rev. 92(3): 527–548
Kwiatkowski D, Phillips PCB, Schmidt P, Shin Y (1992) Testing the null hypothesis of stationarity against the alternative of a unit root. J. Econometrics 54:159–178
Malmquist S (1953) Index numbers and indifference curves. Trabajos de Estatistica 4(1):209–242
Maudos J, Pastor JM, Serrano L (2000) Convergence in OECD countries: technical change, efficiency and productivity. Appl. Econ. 32:757–765
O'Mahoney M (2002) Productivity and convergence in the EU. Nat. Instit. Econ. Rev. 180(April):72–82
Prais SJ (1995) Productivity, Education and training – an international perspective. Cambridge, Cambridge University Press
Quah D (1993) Galton's fallacy and tests of the convergence hypothesis. Scand. J. Econ. 95(4):424–443
Quah D (1996) Twin peaks: growth and convergence in models of distribution dynamics. Econ. J. 106:1045–1055
Quah D (1997) Empirics for growth and distribution: stratification, polarization, and convergence clubs. J. Econ. Growth 2:27–59
Rangvid J (2001) Increasing convergence among European stock markets? A recursive common stochastic trends analysis. Econ. Lett. 71:383–389
Rangvid J, Sorensen C (2001) Convergence in the ERM and declining numbers of common stochastic trends. Unpublished Paper, Copenhagen Business School
Scarpetta S, Hemmings P, Tressel T, Woo J (2002) The role of policy and institutions for productivity and firm dynamics: evidence from micro and industry data. OECD Working Paper No. 329
Shephard RW (1970) Theory of cost and production functions. Princeton University Press, Princeton, NJ