View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Research Papers in Economics

EUROPEAN ECONOMY

EUROPEAN COMMISSION
DIRECTORATE-GENERAL FOR ECONOMIC AND FINANCIAL AFFAIRS

ECONOMIC PAPERS

ISSN 1725-3187
http://europa.eu.int/comm/economy_finance

N° 199 February 2004

Innovations, technological specialisation and economic growth in the EU

by
Andre Jungmittag

European Institute for International Economic Relations

Economic Papers are written by the Staff of the Directorate-General for Economic and Financial Affairs, or by experts working in association with them. The "Papers" are intended to increase awareness of the technical work being done by the staff and to seek comments and suggestions for further analyses. Views expressed represent exclusively the positions of the author and do not necessarily correspond to those of the European Commission. Comments and enquiries should be addressed to the:

European Commission
Directorate-General for Economic and Financial Affairs
Publications
BU1 - -1/180
B - 1049 Brussels, Belgium

ECFIN/74/04-EN

ISBN 92-894-5964-6

KC-AI-04-199-EN-C

©European Communities, 2004

Innovations, Technological Specialisation and Economic Growth in the EU*

Andre Jungmittag
Macroeconomic Theory and Policy, University of Wuppertal and
European Institute for International Economic Relations

November 3, 2003

Abstract

The paper analyses the effects of innovations, technological specialisation and technology diffusion on economic growth and convergence of the EU countries from 1969 to 1998. The empirical analysis is based on a panel data model, which enables us, on the one hand, to assess the impacts of these three factors as well as of the usual production factors on long-term economic growth, and, on the other hand, to calculate their partial contributions to β- and σ-convergence of labour productivities within the EU. The results show that besides capital accumulation, transferable technical knowledge is a driving force of growth for catching-up EU countries, while it is the level of Ricardian technological specialisation for advanced EU countries. Furthermore, technology diffusion is a main driving force for the convergence of labour productivities, while different levels of Ricardian technological specialisation slow down convergence.

*This paper was prepared while the author was a Visiting Fellow at the Directorate General for Economic and Financial Affairs, EU Commission. I gratefully acknowledge the stimulating research atmosphere at DG ECFIN and would like to thank Werner Röger and Klaus Wälde for helpful comments.

Contents

1 Introduction

Although the growth enhancing effects of technological change and innovations had been known for some time, it took several decades to attract the interest of researchers to study technical change. This lack of interest may be explained in part by complex procedures ruling science and technology and the unknown mechanisms translating innovations into broad-based economic effects.

Besides the general innovativeness of a country, its technological specialisation might also affect its economic performance. Based on new growth theory, we can differentiate between two kinds of specialisation: Smithian specialisation and Ricardian specialisation (Dowrick, 1997; Dalum/Laursen/Verspagen, 1999). Smithian specialisation leads to 'learning-by-doing' effects and increasing returns to scale, independent of the technological areas in which countries are specialised. Ricardian specialisation, on the other hand, concerns the qualitative character of a country's technological specialisation, because countries specialised in technological areas with opportunities for higher rates of productivity growth might be in a better position to achieve fast overall growth. Furthermore, technologically backward countries can catch up by imitating technologies from other countries. This paper aims at assessing empirically in a consistent manner the impact of these three facets of technological progress on economic growth and convergence of output per worker within the EU.

To this end, I estimate different versions of a growth model that captures innovations, technology diffusion and the different kinds of technological specialisation in an augmented technical progress function. The model is based on panel data for 14 EU countries from 1969 to 1998 and allows also for unobserved country effects. Patents granted at the US Patent and Trademark Office are used as an indicator for commercially relevant innovations and to calculate measures of Smithian and Ricardian technological specialisation. The calculations of measures of the Ricardian specialisation are based on the high-technology list developed at the Fraunhofer Institute for Systems and Innovation Research, which enables us to differentiate between leading-edge technologies, high-level technologies and a remaining group of low technologies. The superior models, i.e. the models with the most appropriate indicators of technological specialisation, are then used to assess the effects of innovations, technology diffusion and technological specialisation as well as the impact of the usual production factors on long-term economic growth of the EU countries. Furthermore, a simple transformation of the empirical growth model enables us to calculate the partial contributions of these factors to β- and σ-convergence of output per worker within the EU.

The paper proceeds in four parts. Section 2 deals with some theoretical issues concerning the links between innovations, technological specialisation and economic growth. A description of the methodology applied in the empirical analysis follows in section 3. In this context, some data issues especially with regard to the calculation of patent stocks and specialisation measures are also considered. Section 4 contains the empirical results and finally, in section 5 some conclusions are presented.

2 Innovations, Specialisation and Growth: Theoretical Issues

In spite of their dissimilarities in the theoretical foundation and the concrete design, the numerous approaches in neoclassical growth theory, evolutionary economics and a central branch of new growth theory show the common quintessence that technical progress and innovations are important driving forces of economic growth (Aghion/Howitt, 1998). However, with regard to technological specialisation the conclusions are not unambiguous. One branch of new growth theory, following Romer (1986) and Lucas (1988), emphasizes the importance of 'learning-by-doing' effects and increasing returns to scale, independent of the technological areas, in which countries are specialised. From this viewpoint, Smithian specialisation matters to growth. Another branch of new growth theory, following Romer (1990) and Grossman/Helpman (1991), concludes on the basis of so-called 'R&D-models of growth' that the qualitative character of a country's specialisation is decisive, because countries specialised in technological areas with opportunities for higher rates of productivity growth might be in a better position to achieve fast overall growth. From this viewpoint Ricardian specialisation matters to growth, because positive spillovers emerge mainly in R&D-intensive technologies and industries.

Both viewpoints of specialisation can also be found in evolutionary economics. One branch, based on the variation-selection principle, emphasizes the importance of Smithian specialisation by concluding that specialisation advantages emerge "regardless of the particular sectors in which individual countries concentrate their efforts; in other words, for advanced countries being specialized appears to be even more important than choosing the 'right' fields" (Archibugi/ Pianta, 1992). The other branch, inspired by the post-Keynesian tradition, takes a neo-Schumpeterian view and argues that Ricardian specialisation matters to growth because of differential income elasticities between activities (e.g. Dalum/Laursen/Verspagen, 1999). This view adds a demand-side related argument to the supply-side related argument of new growth theory.

Neoclassical growth theory, on the other hand, first of all emphasizes that decreasing marginal productivity of capital drives convergence of per capita incomes and labour productivities. This might be the reason why in cross-country growth analyses usually identical exogenous rates of technical change are assumed. A classical example for this approach is the influential analysis in Mankiw/Romer/ Weil (1992) which has been reproduced – in spite of all criticism – many times. As a consequence, differences in growth rates of per capita income or labor productivity stem mainly from differences in capital accumulation, because differences in national innovation capabilities are assumed away in explaining both relative output levels and growth rates, and therefore economic convergence. To the extent that these capabilities, i.e. the adoption and accumulation of technologies, are important for convergence, a large part of the empirical literature to date is misguided (Bernard/Jones, 1996).

Following Bernard/Jones (1996), I will elaborate this argument within the context of the Solow growth model. The aggregate production function of a country n is given by

$$Y_n = K_n^{\alpha_n} (A_n L_n)^{1-\alpha_n} \Rightarrow \frac{Y_n}{L_n} = A_n^{1-\alpha_n} \left(\frac{K_n}{L_n}\right)^{\alpha_n}, \tag{1}$$

where Y_n represents the output, A_n the level of labour-augmenting technical progress, K_n the capital employed and L_n the amount of labour. The partial production elasticity α_n as well as A_n are allowed to vary across countries. For the sake of simplicity, I assume that these variations are caused by differences in aggregate innovation capabilities and perhaps different technological specialisations.

As usual, net capital accumulation is a constant fraction of output, i.e.

$$\dot{K}_n = s_n Y_n - \delta_n K_n, \tag{2}$$

while convergence of national innovation capabilities as a catching-up process requires that the accumulation of labor-augmenting technology be faster, the larger the gap towards the technologically leading country is. Hence, a simple assumption for the growth rate of technology is

$$g_{A_n} = \frac{\dot{A}_n}{A_n} = \xi_n \frac{A_w}{A_n}, \tag{3}$$

where ξ_n represents the ability of a country to reduce the technological gap. Furthermore, it is assumed that the level of technology in the leading country A_w grows exogenously at a rate $g \equiv \xi_w$. Solving this differential equation yields the steady state technology ratios

$$\frac{A_n}{A_w} = \frac{\xi_n}{\xi_w}. \tag{4}$$

In this framework, steady state growth rates of output per capita and capital per capita for each country as usual equal the growth of the labor-augmenting technology in the technologically leading country:

$$g_{\left(\frac{Y_n}{L_n}\right)} = g_{\left(\frac{K_n}{L_n}\right)} = g_{A_n} = g, \tag{5}$$

but the relative steady state levels of output per capita depend not only on saving rates s_n, depreciation rates δ_n and population growth rates p_n, but also on the abilities of countries to reduce the technological gap towards the leading country and on the aggregate partial production elasticities, namely

$$\frac{\left(\dfrac{Y_n}{L_n}\right)^*}{\left(\dfrac{Y_w}{L_w}\right)^*} = \frac{\xi_n}{\xi_w} \frac{\left(\dfrac{s_n}{p_n + g + \delta_n}\right)^{\frac{\alpha_n}{1-\alpha_n}}}{\left(\dfrac{s_w}{p_w + g + \delta_w}\right)^{\frac{\alpha_w}{1-\alpha_w}}}. \tag{6}$$

Thus, in a world with technologies varying across countries, convergence of per capita incomes and labor productivities will only occur if there is a converging development of national innovation capabilities. Otherwise, countries will only converge to their own steady states.

3 Methodology and Data Issues

For the empirical analysis, the approach developed by de la Fuente (2002) for the analysis of convergence between the Spanish regions has been taken up and modified as well as augmented. This modification allows us to assess the effects of innovations, technological specialisation and technology diffusion as well as the impact of the usual production factors labour and capital on economic growth and convergence within the EU. Furthermore, data issues are discussed in this section.

3.1 The Empirical Model

The starting point for the derivation of the empirical model is an augmented Cobb-Douglas production function

$$Y_{nt} = A_{nt} K_{nt}^{\alpha} L_{nt}^{\beta} P_{nt}^{\gamma} S_{nt}^{\delta}, \tag{7}$$

where P_{nt} represents the patent stock and S_{nt} the technological specialisation of EU-country n in the period t.[1] The interplay of A_{nt}, P_{nt} and S_{nt} could be interpreted as a technical progress function: A_{nt} measures the level of – at the moment still – exogenous technical progress, which will be partly endogenized in the further course of specification of the empirical model, while P_{nt}^{γ} and S_{nt}^{δ} reflect

[1] The following presentation leans on de la Fuente (2002), but the Cobb-Douglas production function is – additionally to the presentation in de la Fuente (2002) – extended to include the patent stock and a measure of technological specialisation. Furthermore de la Fuente (2002) assumes labour-augmenting Harrod-neutral technical progress, while I assume Hicks-neutral technical Progress for the sake of a slightly simpler parametrisation of the underlying model. However, in the case of a Cobb-Douglas production function and also for the empirical model derived from it, the different kinds of technical progress have no impact on the parameters to be estimated.

the degree of efficiency due to the stock of results of R&D activities (innovations) and technological specialisation. In logarithmic form the production function can be written as

$$y_{nt} = a_{nt} + \alpha k_{nt} + \beta l_{nt} + \gamma p_{nt} + \delta s_{nt}, \tag{8}$$

where lower case letters denote logarithms. Taking first differences gives growth rates as

$$\Delta y_{nt} = \Delta a_{nt} + \alpha \Delta k_{nt} + \beta \Delta l_{nt} + \gamma \Delta p_{nt} + \delta \Delta s_{nt}, \tag{9}$$

where Δ is the difference operator.

For the log level of – at the moment still – exogenous technical progress a_{nt} it is assumed that it consists of an index of transferable technical knowledge b_{nt} and of a temporally fixed country-specific effect r_n, which takes into account e.g. different geographic conditions or endowments of natural resources. Hence

$$a_{nt} = b_{nt} + r_n. \tag{10}$$

Next, the transferable part of technical knowledge is endogenized as a function of the patent stock, technological specialisation and the technological gap between the respective country and the EU average. To this end, it is written as

$$b_{nt} = b_t + \tilde{b}_{nt}, \tag{11}$$

where $b_t = (1/N)\sum_{n=1}^{N} b_{nt}$ is the EU average of b_{nt} and $\tilde{b}_{nt} = b_{nt} - b_t$ the technological distance between EU country n and the EU average. Let the average (log) level of transferable technical knowledge b_t continue being exogenous and it depends on e.g. the technological gap between the EU and other technologically leading countries. For its change, i.e. the average rate of technical progress, it is assumed that it can be approximated for the considered period of time by a constant g and a trend t, therefore

$$\Delta b_t = g + ct. \tag{12}$$

The change of the technological distance between EU country n and the EU average depends, on the one hand, on the difference between its log patent stock and the EU average at the end of the previous period ($\tilde{p}_{nt-1} = p_{nt-1} - p_{t-1}$ with $p_{t-1} = (1/N)\sum_{n=1}^{N} p_{nt-1}$) as well as on its relative specialisation with regard to the EU average at the end of the previous period ($\tilde{s}_{nt-1} = s_{nt-1} - s_{t-1}$ with $s_{t-1} = (1/N)\sum_{n=1}^{N} s_{nt-1}$), and, on the other hand, on its technological distance $\tilde{b}_{nt-1}$ to the EU average in the previous period. Adding furthermore an identically independently distributed error term u_{nt} gives

$$\Delta\tilde{b}_{nt-1} = \epsilon\tilde{p}_{nt-1} + \zeta\tilde{s}_{nt-1} - \eta\tilde{b}_{nt-1} + u_{nt}. \tag{13}$$

If technologies actually diffuse from one EU country to another, it can be expected that the coefficient η is negative, i.e. ceteris paribus the rate of technical progress is higher the more technologically backward a country is.

In order to obtain a feasible empirical model, $\tilde{b}_{nt-1}$ has to be depicted by observable variables. Substituting to this end (10) into (8), taking into account the time lag and solving for b_{nt-1} gives

$$b_{nt-1} = y_{nt-1} - \alpha k_{nt-1} - \beta l_{nt-1} - \gamma p_{nt-1} - \delta s_{nt-1} - r_n. \tag{14}$$

Analogously, we get for the EU average

$$b_{t-1} = y_{t-1} - \alpha k_{t-1} - \beta l_{t-1} - \gamma p_{t-1} - \delta s_{t-1} - r. \tag{15}$$

Subtracting (15) from (14) yields

$$\tilde{b}_{nt-1} = b_{nt-1} - b_{t-1} = \tilde{y}_{nt-1} - \alpha \tilde{k}_{nt-1} - \beta \tilde{l}_{nt-1} - \gamma \tilde{p}_{nt-1} - \delta \tilde{s}_{nt-1} - \tilde{r}_n, \tag{16}$$

where variables marked with tildes represent deviations from the EU average, so is $\tilde{r}_n = r_n - r$ with $r = (1/N)\sum_{n=1}^{N} r_n$, too.

Substituting (12), (13) and (16) into (9) gives the feasible empirical model

$$\begin{aligned} \Delta y_{nt} \;=\;& g + \eta \tilde{r}_v + ct + \alpha \Delta k_{nt} + \beta \Delta l_{nt} + \gamma \Delta p_{nt} + \delta \Delta s_{nt} + \epsilon \tilde{p}_{nt-1} + \zeta \tilde{s}_{nt-1} \\ & -\eta \left(\tilde{y}_{nt-1} - \alpha \tilde{k}_{nt-1} - \beta \tilde{l}_{nt-1} - \gamma \tilde{p}_{nt-1} - \delta \tilde{s}_{nt-1} - \sum_{\substack{n=1; \\ n \neq v}}^{N} \theta_n DC_n \right) \\ & + u_{nt}, \end{aligned} \tag{17}$$

where the index v denotes a reference country and the coefficient of the n-th country dummy DC_n is $\theta_n = \tilde{r}_n - \tilde{r}_v$. Austria is used as reference country in all estimations because it is relatively close to the hypothetical EU average country. The model can be estimated by nonlinear least squares.

3.2 Decomposition of Growth and Convergence Measures

The estimation results from the empirical model can be used, on the one hand, in the line of the usual growth accounting to put down the long-term economic growth of the individual EU countries to its different sources: capital, labour, innovations, specialisation and transferable technical knowledge. On the other hand, due to relative simple transformations of the empirical model, the measures of σ- and β-convergence of labour productivities within the EU can be decomposed into additive components, which capture the contributions of the just mentioned sources. For that I again fall back on a methodology proposed by de la Fuente (2002), which he labels as “partial convergence analysis”.

Assuming that the sum of the partial production elasticities of capital and labour equals unity, the growth rate of labour productivity of EU country n can be written according to (17) as

$$\begin{aligned}\Delta y_{nt} - \Delta l_{nt} &= g + \eta \tilde{r}_v + ct + \alpha\left(\Delta k_{nt} - \Delta l_{nt}\right) + \gamma \Delta p_{nt} + \delta \Delta s_{nt} + \epsilon \tilde{p}_{nt-1} \\ &\quad + \zeta \tilde{s}_{nt-1} - \eta \left(\tilde{y}_{nt-1} - \alpha \tilde{k}_{nt-1} - \beta \tilde{l}_{nt-1} - \gamma \tilde{p}_{nt-1} - \delta \tilde{s}_{nt-1} \right. \\ &\quad \left. - \sum_{\substack{n=1;\\ n\neq v}}^{N} \theta_n DC_n \right) + u_{nt}. \end{aligned} \tag{18}$$

Again, it is useful to relate the log labour productivities of the individual countries to the average of the EU countries. This average of log labour productivities which can be interpreted as the value for a hypothetical country that has average log factor and patent stocks as well as an average specialisation, is

$$\Delta y_t - \Delta l_t = g + \eta \tilde{r}_v + ct + \alpha\left(\Delta k_t - \Delta l_t\right) + \gamma \Delta p_t + \delta \Delta s_t + \eta\theta + u_t, \tag{19}$$

where θ is the average of θ_n, $n \neq v$. Subtracting (19) from (18) gives the change of relative labour productivity Δq_{nt} of EU country n as

$$\begin{aligned}\Delta q_{nt} &= \alpha\left(\Delta \tilde{k}_{nt} - \Delta \tilde{l}_{nt}\right) + \gamma \Delta \tilde{p}_{nt} + \delta \Delta \tilde{s}_{nt} + \epsilon \tilde{p}_{nt-1} + \zeta \tilde{s}_{nt-1} \\ &\quad - \eta \left(\tilde{y}_{nt} - \alpha \tilde{k}_{nt-1} - \beta \tilde{l}_{nt-1} - \gamma \tilde{p}_{nt-1} - \delta \tilde{s}_{nt-1} + \theta - \sum_{\substack{n=1;\\ n\neq v}}^{N} \theta_n DC_n \right) \\ &\quad + u_{nt} - u_t. \end{aligned} \tag{20}$$

Thus, change of relative labour productivity of EU country n is the weighted sum of its factor and patent stock and its specialisation as well as their rates of change, with all variables measured as deviations from the EU average.

For the sake of a concise presentation of the further procedure, a simplification of the notation is helpful. Let g_{qrn} denote the average annual contribution of the r-th component to the change of relative labour productivity $\overline{\Delta q_{nt}}$. Here, the contribution of capital-deepening $\alpha(\Delta \tilde{k}_{nt} - \Delta \tilde{l}_{nt})$ can be divided into $\alpha \Delta \tilde{k}_{nt} + (-\alpha \Delta \tilde{l}_{nt})$, where the first part of the term represents the contribution of the growth rate of the capital stock and the second part the contribution of a change in employment.

The decomposition of the measure of σ-convergence – the standard deviation of relative log labour productivities – can be carried out by calculating those standard deviations at the end of observation period which would arise if changes of relative labour productivities would be caused by just one component, while the changes of the other components would equal zero. To this end, the hypothetical log level of relative labour productivity at the end of the observation period (q^r_{n1998}) is calculated for each EU country n, which would result from a sole change of the r-th component, therefore

$$q^r_{n1998} = q_{n1968} + g_{qrn}T, \tag{21}$$

where $T = 1998 - 1968$ is the length of the observation period. Subsequently the standard deviation of these hypothetical levels of relative labour productivities can be calculated across all n EU countries. The comparison of this number with the standard deviation of relative labour productivities in the initial year (q_{n1968}) provides an approximate measure of how σ-convergence has been affected by the r-th component. It is only an approximate measure since the changes induced by the various components will generally not add up exactly to the total change of the standard deviation because the covariances of the individual components generally will not equal zero (de la Fuente, 2002).

By contrast, the measure of β-convergence can be decomposed exactly. As usual, the total extent of β-convergence can be estimated by a cross-section regression

$$\overline{\Delta q_n} = \alpha + \beta q_{n1968} + v_n. \tag{22}$$

Since $\overline{\Delta q_n} = \sum_{r=1}^{R} g_{qrn}$, the estimates of the coefficients α_r and β_r from R regressions

$$g_{qrn} = \alpha_r + \beta_r q_{n1968} + v_{rn} \tag{23}$$

add up exactly to the estimates of the coefficients α and β from (22). Thus $\hat{\beta}_r$ is a measure of the contribution of the r-th component to total β-convergence.

3.3 Data Issues

Before the results of the econometric estimations will be presented, some issues with regard to data used should be discussed. The output data are real GDP in 1990 PPP-US-$, which are taken from the data base of the Groningen Growth and Development Centre. Domestic civil employment numbers are from the AMECO data base of the DG ECFIN of the European Commission. This source also contains real net capital stocks with 1995 as the base year in million Euro (for the members of the European Monetary Union) or in national currencies (for the other EU countries). These data were converted into 1990 PPP-US-$ to achieve comparability with the GDP data. Furthermore, for these variables the unique level shift in 1991 due to German unification was eliminated from the time series for Germany.

The patent stocks of the EU countries were calculated from the patents granted to these countries at the US Patent and Trademark Office. With regard to the calculation of patent stocks from patents granted, two opposite opinions predominate in the literature. In the one line of the literature, the view is taken that the economically relevant life time of a patent is much longer than its legal life. Thus Andersen/Walsh (1998), Cantwell/Andersen (1996), Cantwell/Piscitello (2000) and Fai (1999) calculate patent stocks by accumulating patents over a thirty-year period and assume thereby a linear depreciation function as in vintage capital models, i.e. the current number of patents is weighted with 1, those of the previous periods with factors from 29/30 to 1/30. They justify their assumption with the hint that new technical knowledge is partly embodied in new equipment or devices, which have an average life span of 30 years. Zachariadis (2000), who calculates patent stocks using the perpetual inventory method with a depreciation rate of 7 per cent, argues similarly by pointing out that his rate would correspond with this century's average annual rate of technological obsolescence estimated by Caballero/Jaffe (1993).

In the other line of the literature, the opinion is held that the economically relevant life span of a patent is much shorter than its legally possible life.[2] As evidence for it, among other things, the analysis of Mansfield/Schwartz/Wagner (1981) is quoted, which shows that 60 per cent of all patents are invented at most 4 years ago. Therefore many authors use a depreciation rate of 15 per cent in their calculations of patent stocks by means of the perpetual inventory method, which implies a average life of $6.\bar{6}$ years (e.g. Chen/Ho/Ik et al., 2002; Gambardella/Torrisi, 2000; Hall/Jaffe/Trajtenberg, 2001 and Lach, 1995). Other authors use even higher depreciation rates of 20 per cent (e.g. Agrawal/Henderson, 2001 and Henderson/Cockburn, 1996) or 30 per cent (e.g. Blundell/Griffith/Van Reenen, 1998; Cockburn/Griliches, 1988 and Dushnitsky/Lenox, 2002).

I also assume a depreciation rate $\mu = 0.15$ for the calculation of patent stocks, but the problem of calculating a initial stock is avoided by following the suggestion of Heeley/Khorana/Matusik (2000) to confine the depreciation of the patent stock to a period lasting only several years.[3] Here, a six year period is used, such that

[2] Some authors steer a middle but theoretically not convincing course by calculating the patent stock in such a manner that the explanatory power of this variable is maximized. So Bosworth/Wharton/Greenhalgh (2000) assume that the patent stock evolves proportionally to the number of patents granted, thus $P_t = \beta P_t^{granted}$, whereas β is quasi-estimated within the model because $P_t^{granted}$ is used as a proxy variable for the patent stock. This implies that patents granted grow with a constant rate g, such that $\beta = 1/\left[1-(g-\mu)\right]$, where μ is the depreciation rate. Koleda/Le Mouël (1998), on the other hand, use all depreciation rates from 0 to 100 per cent in 1 per cent intervals and choose that rate which provides the best estimation results for the total factor productivity to patent relation of different industries in each case. They yield depreciation rates from 1 per cent for intermediate goods to 41 per cent for private services.

[3] Assuming that the number of annual patents granted evolved in the past with the same average rate g like in the observation period, an initial stock may be calculated as $P_{n0} = P_{n0}^{granted}\left[(1+g)/(\mu+g)\right]$, but for several EU countries the number of patents granted is zero in the first available year 1963, especially when patents granted in the area of leading-edge or high-level technology are considered. Referring to the fact that at high depreciation rates, patents granted far in the past have only little impact on the patent stock, some authors avoid

Table 1: Concordance between ISIC2 and SIC for the R&D-intensive industries

ISIC2	Description	SIC (USPTO sequence number)
	Leading-edge technology	
3522	Drugs and medicines	14
3825	Office and computing machinery	27
3832	Radio, TV and communication equipment	42+43
3845 (and partly 3829)	Aircraft, guided missiles and space vehicles	47, 54
	High-level technology	
351+352 (without 3522)	Chemicals ex. drugs	6-9, 11-13
382 (without 3825)	Non-electrical machinery (ex. office and computing machinery)	23-26, 29-32
383 (without 3832)	Electrical machinery (ex. radio, TV, communication equipment)	35+36, 38-40
3843	Motor vehicles	46
3841+3842+3844+3849	Other transport equipment	49-53
385	Professional goods	55

the patent stock P_{nt} is given by

$$P_{nt} = \sum_{\tau=t-5}^{t} (1-\mu)^{(t-\tau)} P_{n\tau}^{granted}, \tag{24}$$

where $P_{nt}^{granted}$ is the number of US patents granted to EU country n in year t.[4]

These patent stocks are also used to calculate measures of specialisation. For these calculations, I differentiate – as already mentioned – between Ricardian specialisation, which concerns the qualitative character of a country‘s technological specialisation, and Smithian specialisation, which leads to ‘learning-by-doing’ effects and increasing returns to scale, independent of the technological areas, in which countries are specialised.

As measures of Ricardian specialisation, the patent stock share in the area of the entire R&D-intensive technology as well as those in the areas of leading-

this problem by using the first available observation of patents granted as initial stock (e.g. Blundell/Griffith/Van Reenen, 1998 and Dushnitsky/Lenox, 2002).

[4] Those authors using the first available observation of patents granted as the initial stock basically apply a very similar approach, namely $P_{nt} = \sum_{\tau=t-t_0}^{t} (1-\mu)^{(t-\tau)} P_{n\tau}^{erteilt}$, except that they put down every further patent stock vintage to an additional vintage of patents granted.

edge and high-level technology were used. The assignment of industries to these areas is based on the high-technology list developed at the Fraunhofer Institute for Systems and Innovation Research, which is displayed in Table 1 (cf. Grupp/Jungmittag/Legler et al., 2000). In order to use this list based on ISIC2 for a classification of US patents, I developed a concordance to the US classification (SIC from 1972) to which each US patent is originally assigned.

It can be shown easily that the log patent share of a technological area adjusted to the EU average equals the national log relative patent share $\log RPS_{mn}$ adjusted to the EU average log relative patent share $\frac{1}{N}\sum_{n=1}^{N}(\log RPA_{mn})$. For the patents of a technological area m ($m =$ R&D-intensive technology, leading edge or high-level technology), it holds namely:

$$\log\left(\frac{P_{mn}}{\sum\limits_{m=1}^{M}P_{mn}}\right)-\frac{1}{N}\sum_{n=1}^{N}\left(\log\left(\frac{P_{mn}}{\sum\limits_{m=1}^{M}P_{mn}}\right)\right)$$

$$=\log\left(\frac{\frac{\frac{P_{mn}}{\sum\limits_{m=1}^{M}P_{mn}}}{\sum\limits_{n=1}^{N}P_{mn}}}{\sum\limits_{m=1}^{M}\sum\limits_{n=1}^{N}P_{mn}}\right)-\frac{1}{N}\sum_{j=1}^{N}\left(\log\left(\frac{\frac{\frac{P_{mn}}{\sum\limits_{m=1}^{M}P_{mn}}}{\sum\limits_{n=1}^{N}P_{mn}}}{\sum\limits_{m=1}^{M}\sum\limits_{n=1}^{N}P_{mn}}\right)\right)$$

$$=\log RPS_{mn}-\frac{1}{N}\sum_{n=1}^{N}(\log RPS_{mn}) \tag{25}$$

For the analysis of the impact of Smithian specialisation, standardized diversity indices

$$D_n=\left(1-\sum_{m=1}^{M}\sigma_{mn}^2\right)/\left(1-1/M\right)$$

were calculated, where σ_{mn} is the patent share of sector m in the EU country n. Here, $M = 42$ sectors according to the SIC classification were included.

GDP data are available for 14 EU countries (excluding Luxemburg) and because taking into account a six year period for the calculation of patent stocks, patent stock data are available from 1968 to 1998. Since a further year is needed for taking first differences, a total of 420 observations is used for the empirical analysis.

4 Empirical Results

4.1 Estimation Results

In the first step, the empirical model considering technological specialisation in the entire R&D-intensive area was estimated in three variants (Table 2). In the first variant (model 1), no restrictions were imposed on the model. The estimates of the production elasticities of the factors capital and labour (α and β) show the usual magnitude. At the same time, the null hypothesis of a F-test that their sum equals 1 cannot be rejected on the usual levels of significance. Furthermore, there is a significant positive growth effect of an increase of the patent stock. The estimate of this elasticity γ is rather similar to those of other analyses (e.g. Jungmittag/Blind/Grupp, 1999 and Jungmittag/Welfens, 2002). However, the relative level of the patent stock (ϵ) has no significant impact on economic growth. For the Ricardian specialisation in the entire R&D-intensive area, the effects are inverted. The change of specialisation (δ) has no significant effect on growth, while the relative level of specialisation (ζ) shows a highly significant positive impact. The coefficient that captures technology diffusion (η) is at a significance level below 1 per cent different from zero and indicates a moderate rate of diffusion (6.3 per cent per year). Moreover, a F-test shows that the country-specific fixed effects are different from zero.

In model 2, the non-rejected null hypothesis that the sum of the production elasticities of the factors capital and labour equals 1 is taken into account explicitly. This hardly has any effect on the other parameters of the model. Additionally, the non-significant variables are removed in model 3. This leads to a slight increase of the estimate of the coefficient of the level effect of technological specialisation, while the estimate of the rate of technology diffusion decreases slightly.

In the second step, technological specialisation in the area of leading-edge technology is taken into account instead of specialisation in the area of the entire R&D-intensive technology (Table 3). In this case, an increase in the patent stock also has a positive effect on economic growth in the most general specification (model 4). However, the null hypothesis that the relative level of specialisation has no impact on growth cannot be rejected at a significance level of 10 per cent. Furthermore, the influence of the relative level of the patent stock and of the change of technological specialisation is again not different from zero at the usual levels of significance. The null hypothesis, that the sum of the production elasticities of capital and labour is zero, cannot be rejected either. The opposite holds for the null hypothesis with regard to fixed country-effects.

Explicitly taking into account the restriction concerning the production elasticities of capital and labour again hardly changes the estimation results (model 5). However, if the clearly non-significant variables are removed from the model, the positive impact of the relative level of specialisation in the area of leading-

Table 2: Estimation results considering specialisation in R&D-intensive technology

	Model 1		Model 2		Model 3	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
$g+\eta\tilde{r}_v$	0.0502	$3.08^{a)}$	0.0449	3.18	0.0469	3.45
c	-0.0004	-2.48	-0.0004	-2.60	-0.0004	-2.71
α	0.3068	2.47	0.3751	5.54	0.3662	5.48
β	0.6191	9.14	[0.6249]		[0.6338]	
γ	0.0371	2.52	0.0349	2.50	0.0358	2.54
δ	0.0057	0.23	0.0082	0.33		
ϵ	0.0075	1.27	0.0076	1.30		
ζ	0.0399	2.07	0.0401	2.07	0.0448	2.49
η	0.0632	2.86	0.0576	2.71	0.0512	2.37
$R^2_{adj.}$	0.3778		0.3786		0.3769	
$\alpha=\beta$	$0.4292^{b)}$	$0.51^{c)}$				
$\sum\theta_n=0$	$4.5575^{b)}$	$0.00^{c)}$	$3.9335^{b)}$	$0.00^{c)}$	$3.1155^{b)}$	$0.00^{c)}$

$^{a)}$ White's heteroskedasticity-consistent estimators of the variance matrix are used to calculate t-statistics.

$^{b)}$ F-value

$^{c)}$ Level of significance

edge technology is statistically highly significant (model 6), while the estimates of the other coefficients remain largely unchanged. Particularly as well by taking into account this kind of specialisation, the rate of technology diffusion is around 6 per cent per year.

When specialisation in the area of high-level technology is included, the relative level of the patent stock is also initially in the most general specification beside the rate of change of the patent stock – at a significance level of 10 per cent – different from zero (model 7 in Table 4). On the other hand, the two specialisation variables do not show the slightest significance. Restricting the sum of the production elasticities of capital and labour to zero again hardly has any influence on the other parameters (model 8). However, if the non-significant variables are removed from the model, the relative level of the patent stock also loses significance, so that we come to a model which includes – besides capital, labour and exogenous technical progress – only the change of the patent stock. In this specification, the estimate of the rate of technology diffusion also is distinctly lower (4 per cent).

In the last step, the standardized diversity index as a measure of absolute Smithian specialisation is included in the model (Table 5). The two coefficients for the change (δ) and the relative level (ζ) of this measure of specialisation show in the most general specification (model 10) a negative value which implies that

Table 3: Estimation results considering specialisation in leading-edge technology

	Model 4		Model 5		Model 6	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
$g + \eta\tilde{r}_v$	0.0425	2.70$^{a)}$	0.0402	2.86	0.0427	3.17
c	-0.0003	-1.96	-0.0003	-2.19	-0.0003	-2.28
α	0.3770	3.01	0.4074	5.90	0.4097	5.90
β	0.5906	8.51	[0.5926]		[0.5903]	
γ	0.0353	2.46	0.0345	2.51	0.0339	2.47
δ	-0.0077	-1.07	0.0075	-1.06		
ϵ	0.0039	0.61	0.0038	0.59		
ζ	0.0103	1.54	0.0105	1.61	0.0133	2.35
η	0.0619	2.65	0.0595	2.66	0.0604	2.71
$R^2_{adj.}$	0.3820		0.3834		0.3838	
$\alpha = \beta$	0.0814$^{b)}$	0.78$^{c)}$				
$\sum \theta_n = 0$	4.4531$^{b)}$	0.00$^{c)}$	4.1842$^{b)}$	0.00$^{c)}$	4.3280$^{b)}$	0.00$^{c)}$

$^{a)}$ White's heteroskedasticity-consistent estimators of the variance matrix are used to calculate t-statistics.

$^{b)}$ F-value

$^{c)}$ Level of significance

Table 4: Estimation results considering specialisation in high-level technology

	Model 7		Model 8		Model 9	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
$g + \eta\tilde{r}_v$	0.0452	2.74$^{a)}$	0.0395	2.78	0.0416	3.00
c	-0.0004	-2.34	-0.0003	-2.41	-0.0004	-2.51
α	0.3214	2.51	0.3900	5.55	0.3843	5.34
β	0.6061	8.64	[0.6100]		[0.6157]	
γ	0.0352	2.37	0.0331	2.34	0.0321	2.24
δ	0.0030	0.13	0.0043	0.18		
ϵ	0.0103	1.71	0.0104	1.73		
ζ	0.0015	0.09	0.0012	0.08		
η	0.0586	2.56	0.0520	2.37	0.0408	1.83
$R^2_{adj.}$	0.3670		0.3679		0.3638	
$\alpha = \beta$	0.3920$^{b)}$	0.53$^{c)}$				
$\sum \theta_n = 0$	3.6893$^{b)}$	0.00$^{c)}$	3.2210$^{b)}$	0.00$^{c)}$	1.8804$^{b)}$	0.03$^{c)}$

$^{a)}$ White's heteroskedasticity-consistent estimators of the variance matrix are used to calculate t-statistics.

$^{b)}$ F-value

$^{c)}$ Level of significance

Table 5: Estimation results considering Smithian technological specialisation

	Model 10		Model 11		Model 12	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
$g+\eta\tilde{r}_v$	0.0427	2.56$^{a)}$	0.0395	2.76		
c	-0.0004	-2.11	-0.0003	-2.33	see model 9	
α	0.3757	2.89	0.4142	5.66		
β	0.5830	7.97	[0.5858]			
γ	0.0341	2.35	0.0330	2.39		
δ	-0.2470	-1.48	-0.2537	-1.53		
ϵ	0.0114	1.90	0.0114	1.91		
ζ	-0.1865	-1.59	-0.1896	-1.62		
η	0.0542	2.44	0.0510	2.35		
$R^2_{adj.}$	0.3746		0.3759			
$\alpha=\beta$	0.1298$^{b)}$	0.72$^{c)}$				
$\sum\theta_n=0$	3.3289$^{b)}$	0.00$^{c)}$	2.9945$^{b)}$	0.00$^{c)}$		

$^{a)}$ White's heteroskedasticity-consistent estimators of the variance matrix are used to calculate t-statistics.

$^{b)}$ F-value

$^{c)}$ Level of significance

a low specialisation of this kind has a negative effect on economic growth. But they are only slightly above a significance level of 10 per cent different from zero (12.65 per cent for δ and 10.51 per cent for ζ). At the same time, the level effect of the patent stock is at a significance level of 5.64 per cent different from zero for the first time. However, since countries with a relative large patent stock often show a low degree of Smithian specialisation, a certain degree of intercorrelations among these variables can be expected. This suspicion is confirmed when at a time one of these three variables is eliminated from the model. Then the two others clearly lose significance. Therefore, it can be assumed that the impact of a low Smithian specialisation is not robust, so that we finally end up again with a model without specialisation variables (model 12 = model 9).

The country-specific fixed effects are in all models highly significantly different from zero. This result shows that there are long-term productivity differentials between the EU countries which cannot be explained by the variables in the models. The normalized country-specific effects, i.e. their average is exactly one after adding the fixed effect for Austria, are displayed in Figure 1. In the model without specialisation variables (model 9), Ireland shows the largest positive difference in long-term productivity relative to the EU average with 18.7 per cent, followed by Belgium, Spain and France. At the lower end Germany, Sweden, Great Britain and particularly Greece with -39.6 per cent can be found. The standard deviation of the unexplained long-term productivity differentials is

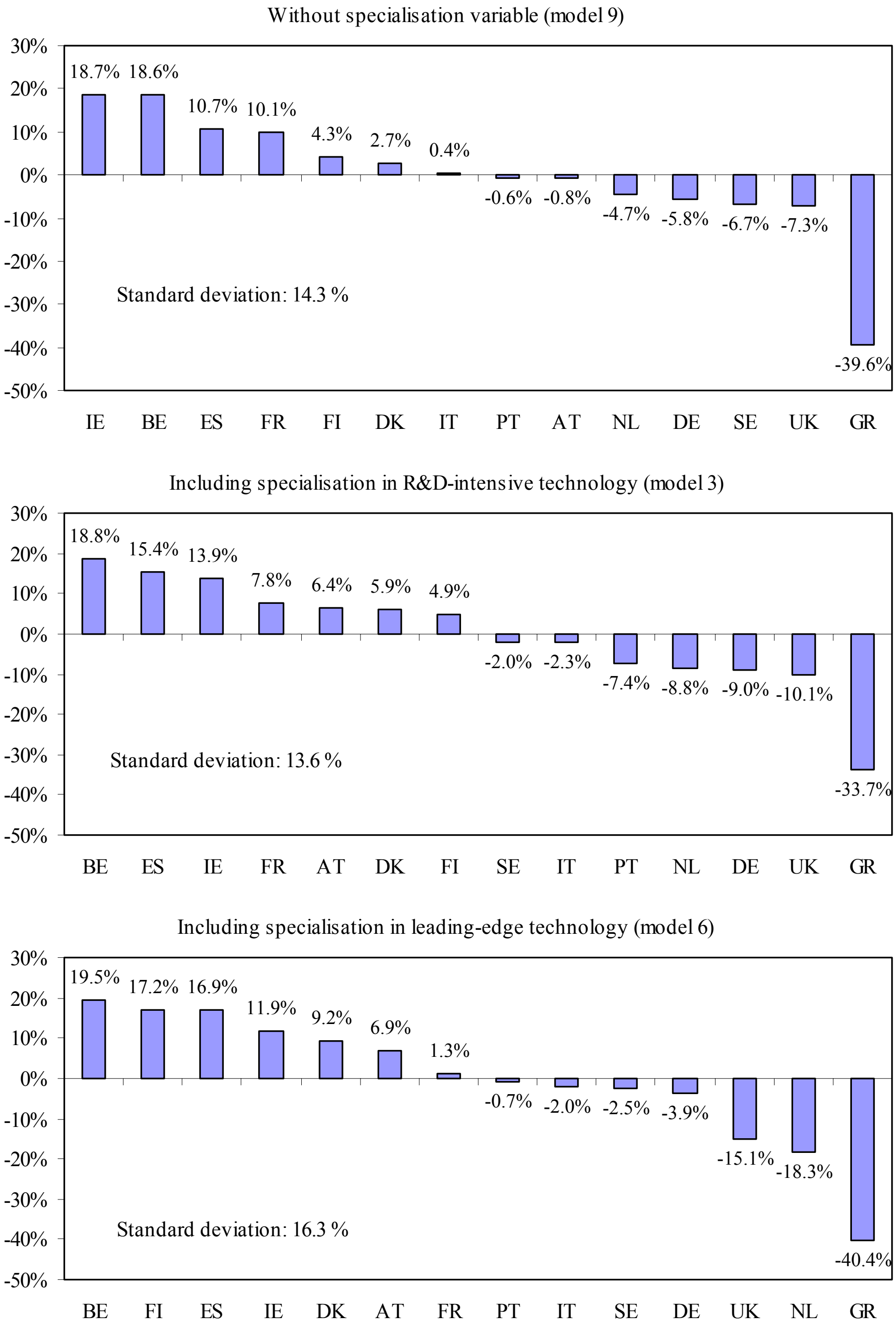

Figure 1: Unexplained long-term productivity differences within the EU

14.6 per cent. It decreases to 13.6 per cent, when the specialisation in the area of entire R&D-intensive technology is included in the model (model 3). At the upper end the same countries as before are located in a slightly changed order, while at the lower end Sweden is replaced by the Netherlands in the group of the last four countries. If specialisation in the area of leading-edge technology is taken into account (model 6), the standard deviation increases distinctly to 16.3 per cent, with mainly a rise in the range while those countries with unexplained small below-average productivity differentials approach the average. In the group of the four countries with the largest positive unexplained productivity differentials, Finland replaces France, while there is only an internal change of ranks within the group of the last four countries with the largest negative unexplained productivity differentials. Altogether, however, the ranking of unexplained long-term productivity differentials is rather stable. The rank correlation coefficient between the unexplained differences in model 9 and either model 3 or 6 is in both cases equal to 0.886 and between the unexplained differences in model 3 and 6 equal to 0.877. Of course this result also shows that a certain scope for the further search for the determinants of long-term productivity differentials within the EU remains.

4.2 Results of the Growth Decompositions

Based on the models capturing specialisation either in the area of the entire R&D-intensive technology (model 3) or in the area of leading-edge technology (model 6), the average annual GDP growth of EU countries from 1969 to 1998 can be decomposed into its various components. In the period under consideration, Ireland shows the highest average annual growth with 4.63 per cent, followed by the four other initially lagging countries Portugal, Spain, Greece and Finland, whose growth rates were between 3.60 and 3.09 per cent (Table 6). Austria, the Netherlands, France, Belgium and Italy form the medium group with growth rates above 2.5 per cent. Denmark, Great Britain, Germany and Sweden with growth rates between 2.26 and 2.00 per cent are to be found in the last group.

Within the group with high average annual GDP growth, Finland, Spain and Ireland saw relatively high growth contributions from transferable technical knowledge (between 57.6 and 46.0 per cent), measured by the term $\hat{g} + \hat{c}\bar{t} - \hat{\eta}\,(\cdot)$. In contrast, this contribution is comparatively small for Greece and Portugal with 33.3 and 34.3 per cent. At the same time, the growth contribution of capital is relatively small for Ireland and Finland at 31.5 per cent, mediocre for Portugal and Spain, and very high for Greece with 51.0 per cent. Moreover, Ireland, Greece and Portugal show a comparatively high contribution of labour to GDP growth (between 15.7 and 14.1 percent), while this contribution is rather small in the case of Spain and Finland (6.2 and 4.8 per cent). In this group, Finland profits above all from the growth of its patent stock, followed by Ireland and Spain with a clear margin. In comparison, the contributions of this component as expected are very small in the case of Greece and Portugal. The relative level of specialisation in the area of the entire R&D-intensive technology shows a slightly negative impact

Table 6: Decomposition of average annual growth of GDP from 1969 to 1998 considering specialisation in R&D-intensive technology

Country	$\overline{\Delta y_n}$ (%)	Percentage contribution to average annual growth $\hat{g}+\hat{c}\bar{t}-\hat{\eta}(\cdot)$	$\hat{\alpha}\overline{\Delta k_n}$	$(1-\hat{\alpha})\,\overline{\Delta l_n}$	$\hat{\gamma}\overline{\Delta p_n}$	$\hat{\zeta}\overline{\tilde{s}_n^{R\&D}}$
IE	4.63	46.0	31.5	15.7	5.9	0.9
PT	3.60	34.3	41.0	14.1	2.0	8.7
ES	3.32	53.7	43.1	6.2	5.2	-8.2
GR	3.13	33.3	51.0	15.6	3.1	-3.0
FI	3.09	57.6	31.5	4.8	11.0	-4.9
AT	2.93	49.1	42.3	15.8	4.0	-11.1
NL	2.78	23.3	36.0	28.0	2.9	9.8
FR	2.63	41.8	39.9	10.8	3.7	3.7
BE	2.62	49.1	38.8	7.2	5.1	-0.3
IT	2.54	40.6	43.7	4.0	5.3	6.5
DK	2.26	51.0	33.8	14.7	5.9	-5.4
UK	2.21	53.9	33.0	8.6	0.5	4.0
DE	2.19	29.2	45.8	10.3	4.3	10.4
SE	2.00	65.7	35.8	6.6	3.3	-11.5

for Greece, Finland and Spain, while it is negligible or slightly positive in the case of Ireland and Portugal.

Within the second group, above all the Netherlands are striking, for which a very small relative contribution of transferable technical knowledge (23.3 per cent) can be observed at the same time as a very large relative contribution of labour growth (28.0 per cent) to GDP growth. This development is accompanied by moderate contributions of capital and the patent stock (36.0 and 2.9 per cent) as well as a distinct contribution of the relative technological specialisation to GDP growth. In comparison, the contributions of transferable technical knowledge are clearly higher for the other countries of this group, with values between 49.1 (Austria and Belgium) and 40.6 per cent (France). The same also holds to a lesser degree for the contributions of capital and patent stocks to growth. With regard to the contributions of technological specialisation, however, no clear-cut picture evolves. France and Italy profit slightly from their relative specialisation in the area of R&D-intensive technology (3.7 and 6.5 per cent), while this contribution is negligible for Belgium and clearly negative for Austria (-11,1 per cent).

Within the last group of EU countries with relatively low GDP growth, three countries show either high or very high relative contributions of transferable technical knowledge to growth (Denmark and Great Britain with 51.0 and 53.9 per cent as well as Sweden with 65.7 per cent). At the same time, these countries experienced relatively small contributions of capital growth to GDP growth. Moreover, Denmark realized a distinct contribution of employment growth to

GDP growth, while the contribution of this component is moderate in the case of Great Britain and Sweden. The growth of the patent stock is a contributing factor in two of these three countries (Denmark and Sweden), with 5.9 and 3.3 per cent on average to economic growth; in the case of Great Britain this influence is negligible. Finally, Great Britain profits comparatively moderately from its relative specialisation in the area of the entire R&D-intensive technology, while this contribution is clearly negative for Denmark and Sweden which bring up the rear within the EU with -11.5 per cent.

Germany takes a special position within this group, but partly also within the EU as a whole. Its relative contribution of transferable technical knowledge only amounts to 29.2 per cent. This value is only undercut by the Netherlands. At the same time it shows the highest relative contribution of specialisation in the area of the entire R&D-intensive technology to growthwith 10.4 per cent. The picture is completed by relatively high contributions of capital and labour (45.8 and 10.3 per cent) as well as by an average contribution of patent stock growth.

When the growth decomposition is based on the model capturing specialisation in the area of leading-edge technology, all countries – of course without changing the ranking – have slightly higher contributions of capital to GDP growth and the contributions of labour and patent stocks are a little bit smaller (Table 7). However, there are distinct shiftings of the contributions of transferable technical knowledge and of the relative level of technological specialisation. Within the group of heavily growing, initially lagging countries more than 80 per cent of Finland's average annual GDP growth can be ascribed to transferable technical knowledge, while with -30.7 per cent it experienced a high negative contribution of its relative specialisation in the area of leading-edge technology. Spain also experienced a negative contribution of its specialisation (-14.8 per cent) and at the same time a high positive contribution of transferable technical knowledge. The contributions of the latter component are more moderate for Ireland and Portugal (44.6 and 36.8 per cent), for which, furthermore, the effects of their relative specialisation in the area of leading-edge technology are negligible. The case of Greece is different. It experienced only a small relative contribution of transferable technical knowledge (with 20.2 per cent the penultimate position within the EU) and a moderate contribution of its technological specialisation (5.4 per cent).[5]

Within the second group, especially the Netherlands and in a less pronounced form also France are striking, because they have either no or only a small contribution of transferable technical knowledge and, at the same time, either a very or strongly distinct contribution of their relative specialisation in the area of leading-edge technology. In comparison, the contribution of transferable technical

[5]With regard to the interpretation of Greece's technological specialisation, a certain degree of caution is required due to its small patent stocks, especially in the area of leading-edge technology.

Table 7: Decomposition of average annual growth of GDP from 1969 to 1998 considering specialisation in leading-edge technology

Country	$\overline{\Delta y_n}$ (%)	Percentage contribution to average annual growth $\hat{g} + \hat{c}\bar{t} - \hat{\eta}(\cdot)$	$\hat{\alpha}\overline{\Delta k_n}$	$(1-\hat{\alpha})\,\overline{\Delta l_n}$	$\hat{\gamma}\overline{\Delta p_n}$	$\hat{\zeta}\overline{\tilde{s}_n^{LE}}$
IE	4.63	44.6	35.2	14.6	5.6	0.0
PT	3.60	38.8	45.8	13.1	1.8	0.5
ES	3.32	55.9	48.2	5.7	4.9	-14.8
GR	3.13	20.2	57.0	14.5	2.9	5.4
FI	3.09	80.7	35.2	4.5	10.4	-30.7
AT	2.93	47.8	47.3	14.7	3.7	-13.6
NL	2.78	-4.8	40.2	26.0	2.8	35.7
FR	2.63	21.2	44.6	10.1	3.5	20.6
BE	2.62	48.0	43.4	6.7	4.9	-2.9
IT	2.54	37.8	48.8	3.7	5.0	4.8
DK	2.26	54.3	37.7	13.6	5.6	-11.3
UK	2.21	33.3	36.8	8.0	0.5	21.3
DE	2.19	34.7	51.2	9.6	4.1	0.5
SE	2.00	58.2	40.0	6.2	3.1	-7.5

knowledge is much higher in the case of Italy, with at the same time a moderate contribution of its specialisation to GDP growth. Finally, a very high share of growth can be ascribed to transferable technical knowledge in the case of Austria and Belgium, while their specialisations in the area of leading-edge technology contributed either strongly or slightly negatively to their growth performance.

Among the four countries of the last group with relatively low average annual growth rates, a very large part of growth can be attributed to transferable technical knowledge in the case of Denmark and Sweden (54.3 and 58.2 per cent). Moreover, both countries experienced losses of growth by -11.3 and -7.5 per cent respectively due to their specialisation. In contrast, Great Britain and Germany profit only to a modest extent from transferable technical knowledge with 33.3 and 34.7 per cent. They differ, however, to a large extent with regard to the contribution of their relative technological specialisation to growth, which is negligible in the case of Germany, while Great Britain comes second within the EU with 21.3 per cent.

In summary, it may be noticed that on the one hand, growth of capital stocks and transferable technical knowledge provided the most important contributions to long-term GDP growth in the EU during the period from 1969 to 1998. However, the contributions of the other components (changes in employment and patent stocks as well as the relative levels of technological specialisation) cannot be neglected. On the other hand, a glance at the decomposition results already shows the opposite tendency of the contributions of transferable techni-

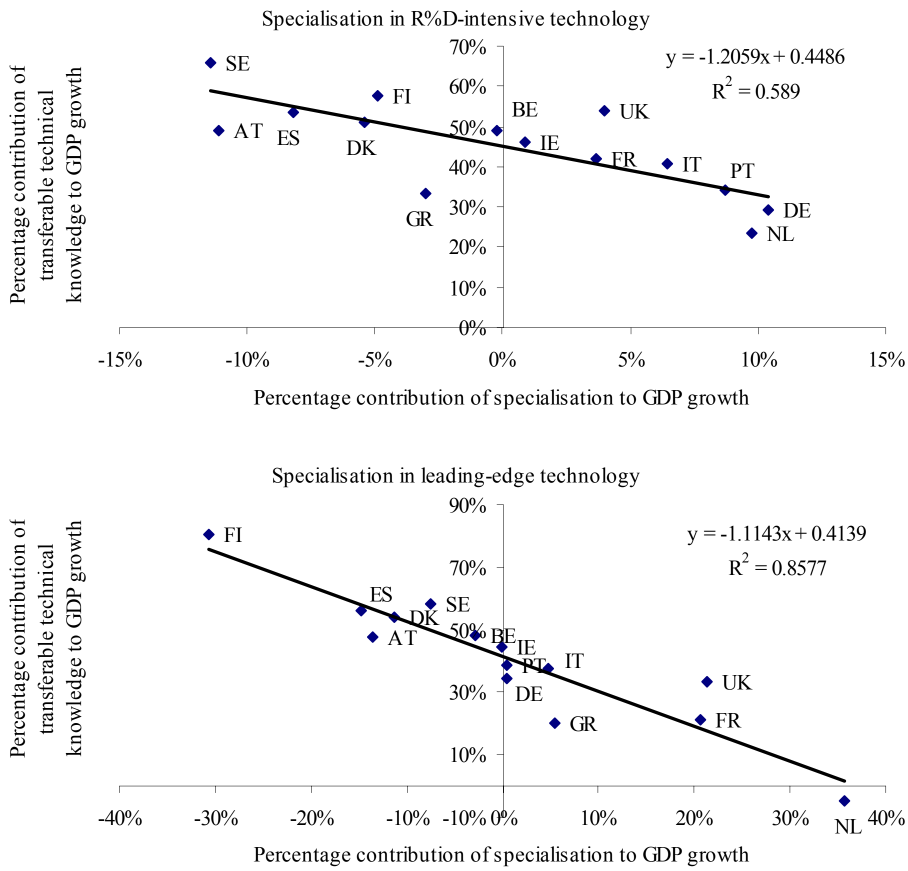

Figure 2: Correlations between contributions of transferable technical knowledge and technological specialisation to GDP growth

cal knowledge and technological specialisation to GDP growth. This impression is confirmed, when both components are plotted against each other in a scatter diagram (Figure 2). Considering specialisation in the area of the entire R&D-intensive technology, the R^2 is 0.589 and we have a highly significant negative relationship at a level of one per cent. If alternatively specialisation in the area of leading-edge technology is considered, the R^2 increases to 0.858. This result indicates that some of the countries negatively specialized in the entire R&D-intensive technology or – even more pronounced – in leading-edge technology managed in the past to achieve high relative contributions to growth due to technology transfer and imitation. Therefore, it can be assumed that especially for those countries which catched-up strongly within the EU, increases of efficiency enabled by technology transfer and imitation are an important preliminary stage to an own innovation capability in the R&D-intensive area.

4.3 Results of the Convergence Decompositions

The starting point of the decomposition of σ- and β-convergence is the calculation of the labour productivities in the initial year of the observation period 1968 and of their average annual changes until 1998 as well as the decomposition of the latter into the components of the empirical model. The results of this exercise on the basis of the model with specialisation in the entire R&D-intensive technology are displayed in Table 8. With regard to the initial level of labour productivity in 1968, Germany was clearly in the first place with a value of about 34 per cent above the (hypothetical) EU average. France (21.77 per cent) and Belgium (21.31 per cent) followed with a clear margin. An additional six countries also show an above-average initial level (from the Netherlands with 19.75 per cent to Austria with 1.59 per cent). Finland, Ireland and the three South European countries were clearly below the average, with Portugal (-54.72 per cent) far behind.

If average annual changes of relative labour productivity are considered, countries being initially positioned above-average – with the exception of Belgium and Italy – show negative values, while initially backward countries show positive rates of change, which were highest for Ireland (1.17 per cent) and lowest for Greece (0.05 per cent). Thus, a broad majority of the EU countries show a more or less distinct tendency towards the average of log labour productivities.[6]

With the exception of Austria, the contributions of changes of the capital stock are negative for all countries with initially above-average labour productivities, which partly explains the tendency of labour productivities towards the EU average. These were most pronounced for Sweden, Great Britain and Denmark. On the other hand, four of the five initially lagging countries (except Finland) show a clearly positive contribution of relative capital stock growth. In contrast, the impact of changes in relative employment is rather heterogeneous. Among the initially above-average countries they contribute to an approach towards the average in the case of the Netherlands and Austria. The results are similar with an opposite sign for the initially backward countries. In the case of Finland and Spain changes of relative employment support the tendency towards the average, while they act as a brake in the case of Ireland, Greece and Portugal.

For six of the nine initially above-average countries, changes of relative patent stocks contribute to the tendency towards the EU average labour productivity, while their contributions are negligible in the case of Belgium, Denmark and Italy. Among the initially backward countries, Finland and Ireland – as well as to a modest extent Spain – profit from an improvement of their relative positions with regard to patent stocks. In contrast, for Greece and Portugal, this component counteracts the slight (Greece) or stronger (Portugal) tendency towards the EU average of labour productivities.

[6]However, it cannot be excluded that there is not only a tendency towards the average, but that in the long-term some initially backward countries will top the average, while some initially leading countries will fall back below the average.

Table 8: Decomposition of relative labour productivity growth from 1969 to 1998 considering specialisation in R&D-intensive technology

Country	q_{n1968}	$\overline{\Delta q_n}$	$\hat{\alpha}\overline{\Delta\tilde{k}_n}$	$-\hat{\alpha}\overline{\Delta\tilde{l}_n}$	$\hat{\gamma}\overline{\Delta\tilde{p}_n}$	$\hat{\zeta}\overline{\tilde{s}}_n^{R\&D}$	$-\hat{\eta}\,(\cdot)$
				(per cent)			
DE	33.91	-0.48	-0.11	0.07	-0.04	0.23	-0.63
FR	21.77	-0.14	-0.06	0.03	-0.03	0.10	-0.17
BE	21.31	0.00	-0.10	0.09	0.00	-0.01	0.01
NL	19.75	-0.76	-0.11	-0.25	-0.05	0.27	-0.62
DK	17.76	-0.57	-0.35	0.01	0.00	-0.12	-0.11
IT	16.36	0.06	0.00	0.14	0.00	0.16	-0.24
SE	14.23	-0.53	-0.40	0.12	-0.06	-0.23	0.04
UK	9.83	-0.41	-0.38	0.09	-0.12	0.09	-0.08
AT	1.59	-0.11	0.13	-0.07	-0.01	-0.33	0.17
FI	-15.69	0.55	-0.14	0.11	0.21	-0.15	0.51
ES	-20.03	0.68	0.32	0.08	0.04	-0.27	0.51
IE	-28.74	1.17	0.35	-0.22	0.14	0.04	0.86
GR	-37.34	0.05	0.49	-0.09	-0.03	-0.09	-0.23
PT	-54.72	0.48	0.36	-0.10	-0.06	0.31	-0.04

The impact of relative technological specialisation varies rather considerably. Among the countries with initially above-average labour productivity, it alleviates the decrease in relative levels of labour productivity in the case of the Netherlands and Germany as well as – to a smaller extent – also in the case of Italy, France and Great Britain, while it supports this process in the other four countries. The picture is similarly heterogeneous for the initially lagging countries. The influence of technology diffusion is generally a mirror image of the impact of technological specialisation, so that among the initially advanced countries it provides the highest contribution to the approach towards the average in the case of Germany and the Netherlands. Among the initially backward countries, Ireland, Finland and Spain profit from very high contributions of technology diffusion to the growth of their relative levels of labour productivity. On the other hand, a negative contribution in the case of Greece takes prime responsibility for its small tendency towards the average.

Alternatively taking into consideration specialisation in the area of leading-edge technology leads mainly to a shift of the contributions of technological specialisation and technology diffusion to the changes of relative labour productivity, without changing their total contribution to a greater extent (Table 9). Among the countries with above-average initial levels, the comparatively highly positive specialisation in the area of leading-edge technology reduces the tendency towards the EU average in the case of the Netherlands, France and Great Britain. Technology diffusion works against this, such that the sum of both effects is pos-

Table 9: Decomposition of relative labour productivity growth from 1969 to 1998 considering specialisation in leading-edge technology

Country	q_{n1968}	$\overline{\Delta q_n}$	$\hat{\alpha}\overline{\Delta\tilde{k}_n}$	$-\hat{\alpha}\overline{\Delta\tilde{l}_n}$	$\hat{\gamma}\overline{\Delta\tilde{p}_n}$	$\hat{\zeta}\overline{\tilde{s}_n^{LE}}$	$-\hat{\eta}\left(\cdot\right)$
				(in %)			
DE	33.91	-0.48	-0.12	0.07	-0.03	0.01	-0.41
FR	21.77	-0.14	-0.07	0.04	-0.03	0.54	-0.61
BE	21.31	0.00	-0.11	0.10	0.00	-0.08	0.09
NL	19.75	-0.76	-0.13	-0.28	-0.05	0.99	-1.30
DK	17.76	-0.57	-0.39	0.01	0.00	-0.25	0.06
IT	16.36	0.06	0.00	0.15	0.00	0.12	-0.21
SE	14.23	-0.53	-0.44	0.13	-0.06	-0.15	-0.01
UK	9.83	-0.41	-0.43	0.10	-0.11	0.47	-0.43
AT	1.59	-0.11	0.15	-0.08	-0.01	-0.40	0.23
FI	-15.69	0.55	-0.15	0.12	0.20	-0.95	1.33
ES	-20.03	0.68	0.36	0.09	0.04	-0.49	0.69
IE	-28.74	1.17	0.39	-0.25	0.14	0.00	0.89
GR	-37.34	0.05	0.55	-0.10	-0.03	0.17	-0.54
PT	-54.72	0.48	0.40	-0.11	-0.06	0.02	0.23

itive only for Great Britain. Compared to specialisation in the area of the entire R&D-intensive technology, the positive contributions of technological specialisation decrease particularly in the case of Germany and to a lesser extent in the case of Italy, while the amount of negative contributions increase in the case of Belgium, Denmark and Austria. Only for Sweden is the amount of the negative contribution a little bit lower. The changes in contributions of technology diffusion are almost a mirror image of the changes in contributions of specialisation. For Denmark, the Netherlands and Sweden, the sum of these components is now slightly higher, so that the tendency towards the average diminishes a bit.

Among the five countries with labour productivities below the EU average in 1968, the trade-off between growth contributions of technological specialisation and technology diffusion increases in favour of the latter in the case of Finland and Spain and to a lesser extent in the case of Portugal. The opposite occurs in the case of Greece, where the contribution of technology diffusion to relative growth decreases further, while the contribution of specialisation moves into the positive zone.[7] Due to its negligible contributions of the specialisation in the entire R&D-intensive technology as well as in leading-edge technology, there hardly is any change in the high contribution of technology diffusion to growth for Ireland.

Based on these figures, the decomposition of σ- and β-convergence within the

[7] As already mentioned in footnote 5, a certain degree of caution is required with regard to the interpretation of Greece's technological specialisation because of its small patent stocks, especially in the area of leading-edge technology.

Table 10: Decomposition of σ-convergence of labour productivities within the EU considering technological specialisation

	Standard deviation of relative labour productivities						
		R&D-intensive			Leading-edge technology		
	1968	1998	%Δ	% total	1998	%Δ	% total
Actual	0.2662	0.1764	-33.74		0.1764	-33.74	
Without level shift DE 1991	0.2662	0.1852	-30.45	100	0.1852	-30.45	100
Growth due only change in:							
capital	0.2662	0.2072	-22.17	72.81	0.2015	-24.30	79.81
labour	0.2662	0.2825	6.09	-20.02	0.2847	6.92	-22.73
capital/labour	0.2662	0.2207	-17.09	56.14	0.2165	-18.69	61.38
patents	0.2662	0.2600	-2.34	7.69	0.2603	-2.24	7.35
specialisation	0.2662	0.2780	4.43	-14.53	0.3361	26.23	-86.15
technology diffusion	0.2662	0.2270	-14.73	48.39	0.2470	-7.22	23.73

EU can be carried out. With regard to σ-convergence, the standard deviation of the relative labour productivities of the 14 considered EU countries was 0.2662 in 1968 (Table 10). Until 1998 it actually decreased by 33.74 per cent to 0.1764, while a decrease of 30.45 per cent to 0.1852 has to be assumed when the unique level shift due to German unification is eliminated. Since this was done with the data of the empirical model, this adjusted measure of σ-convergence is also the basis of the decomposition.

Obviously the development of capital stocks provided the largest contribution to σ-convergence in the thirty-year period until 1998. If growth in this period had been caused only by changes in capital stocks, the standard deviation would have decreased by 22.17 per cent to 0.2072 based on the empirical model considering specialisation in the area of the entire R&D-intensive technology, that is 72.81 per cent of the total decline. When the model considering specialisation in the area of leading-edge technology is used, the share in the total decline is even slightly higher at 79.81 per cent. On the other hand, the standard deviation would have increased by 6.09 and 6.92 per cent respectively if growth had been caused only by changes of employment. Altogether, capital deepening would have contributed 56.14 per cent (taking into account specialisation in the area of the entire R&D-intensive technology) and 61.38 per cent (taking into account specialisation in the area of leading-edge technology) to the total decline of the standard deviation of relative labour productivities respectively.

If growth of labour productivities had been caused solely by changes of patent stocks, the decline of the standard deviation would have been rather small with

7.69 and 7.35 per cent respectively of the total decline. The effect of specialisation in the area of the entire R&D-intensive technology is moderately negative – the standard deviation would have increased by 4.43 per cent – and the effect of specialisation in leading-edge technology is strongly negative – the standard deviation would have been increased by 26.23 per cent. Finally, technology diffusion provides an important contribution to the reduction of the standard deviation. Its sole consideration on the basis of the model with specialisation in the area of the entire R&D-intensive technology would have reduced the standard deviation by 14.73 per cent, which is a contribution of 48.39 per cent to total σ-convergence. When the model with specialisation in the area of leading-edge technology is used, the hypothetical reduction is only 7.22 per cent, thus 23.73 per cent of total σ-convergence.

The estimate of β is 0.0151, which implies a rate of absolute β-convergence $\lambda = 0.02011$ within the EU from 1969 to 1998, since $\lambda = (-1/T)\left[\ln\left(1 - \beta T\right)\right]$ (Table 11). This value is very similar to the ubiquitous 2 per cent which is ascertained in various cross-section studies of convergence (e.g. Barro/Sala-i-Martin, 1991 and Sala-i-Martin, 1996). The contribution of the factor capital to the estimate of β amounts to 55.32 per cent on the basis of the model with technological specialisation in the entire R&D-intensive area and to 61.89 per cent on the basis of the model with specialisation in leading-edge technology. Changes of employment, on the other hand, slowed down β-convergence slightly, such that the contribution of capital deepening was between 43.67 and 48.87 per cent, depending on the model used.

The contributions of patent stocks and technological specialisation are not significantly different from zero, but the magnitude of the estimate for the contribution of specialisation in the area of leading-edge technology points to a considerable convergence impeding effect. The contribution of technology diffusion is almost as large as the contribution of capital in the model with specialisation in the area of the entire R&D-intensive technology, and it is even higher in the model with specialisation in the area of leading-edge technology. Therefore, convergence of capital stocks per person employed and technology diffusion are the important driving forces of absolute β-convergence.

Since Greece and Portugal still have a special position within the EU, it was assumed by introducing a dummy variable for these two countries that they and the rest of the EU would converge to different steady states. This dummy variable is highly significant and the estimate of β rises to 0.258, which implies a conditional convergence rate of 4.96 per cent (the lower panel of Table 11). In the case of such a conditional convergence, the contribution of capital reduces distinctly to either 28.34 per cent (when specialisation in the area of the entire R&D-intensive technology is considered) or 31.71 per cent (when specialisation in the area of leading-edge technology is considered). Altogether, capital deepening is then responsible for only one-fifth to one-quarter of the total estimate of the convergence parameter.

Table 11: Decomposition of β-convergence of labour productivities within the EU considering technological specialisation

	Absolute β-convergence							
	R&D-intensive technology				Leading-edge technology			
	$\hat{\beta}$	t-value	R^2	%	$\hat{\beta}$	t-value	R^2	%
Total	-0.0151	-3.34$^{a)}$	0.53	100	-0.0151	-3.34	0.53	100
Contribution of change in:								
capital	-0.0083	-5.10	0.59	55.32	-0.0093	-5.10	0.59	61.89
labour	0.0018	1.74	0.14	-11.64	0.0020	1.74	0.14	-13.03
capital/labour	-0.0066	-3.83	0.47	43.67	-0.0074	-3.83	0.47	48.87
patents	-0.0009	-0.97	0.08	6.13	-0.0009	-0.97	0.08	5.80
specialisation	0.0006	0.23	0.01	-4.08	0.0051	1.25	0.08	-33.85
technology diffusion	-0.0082	-1.67	0.28	54.28	-0.0119	-1.82	0.22	79.19
	Conditional β-convergence (GR, PT and the rest of the EU)							
	R&D-intensive technology				Leading-edge technology			
	$\hat{\beta}$	t-value	R^2	%	$\hat{\beta}$	t-value	R^2	%
Total	-0.0258	-6.46	0.76	100	-0.0258	-6.46	0.76	100
Contribution of change in:								
capital	-0.0073	-2.53	0.60	28.34	-0.0082	-2.53	0.60	31.71
labour	0.0015	0.65	0.14	-5.82	0.0017	0.65	0.14	-6.52
capital/labour	-0.0058	-2.01	0.48	22.52	-0.0065	-2.01	0.48	25.19
patents	-0.0032	-3.26	0.51	12.26	-0.0030	-3.26	0.51	11.60
specialisation	0.0041	1.45	0.18	-15.80	0.0134	1.80	0.27	-51.66
technology diffusion	-0.0209	-10.01	0.86	81.03	-0.0297	-4.73	0.65	114.87

$^{a)}$ White's heteroskedasticity-consistent estimators of the variance matrix are used to calculate t-statistics.

The contribution of the development of patent stocks is now highly significantly different from zero and constitutes about 12 per cent of the total estimate of β, independent of the specification of the empirical model. With regard to technological specialisation, at least specialisation in the area of leading-edge technology is now at a level of 10 per cent significantly different from zero. At this magnitude, it prevents a 51.66 per cent higher estimate of β. Thus the different degrees of relative specialisation in the area of leading-edge technology are an important obstacle for conditional β-convergence within the EU. On the other hand, with contributions of either 81 or 115 per cent, technology diffusion is to a even larger extent the driving force of convergence of labour productivities in this specification of the convergence regressions, however, towards two different steady states.

5 Summary and Conclusions

The empirical analysis of the impact of innovations, technological specialisation and technology diffusion on economic growth and convergence of the EU countries from 1969 to 1998 provided some clear-cut results. Innovations measured by the growth rates of the patent stocks of the EU countries foster economic growth. With regard to specialisation, there is only little empirical evidence that technological Smithian specialisation is conducive to economic growth within the EU. In contrast, the level of relative technological specialisation in the area of R&D-intensive industries and especially in the area of leading-edge industries contributes significantly to economic growth within the EU. Moreover, the estimations suggest a moderate rate of technology diffusion, depending on the specification of the empirical model between 5 and 6 per cent per year.

The growth decomposition showed that besides capital accumulation, technology diffusion is a driving force for growth of catching-up countries within the EU, while it is the level of relative Ricardian technological specialisation for initially leading EU countries. Furthermore, the decomposition of measures of σ- and β-convergence reveals that technology diffusion is also a main driving force – at least as important as capital accumulation – of the convergence of labour productivities within the EU, while different levels of relative Ricardian technological specialisation slow down convergence. The relative growth of the patent stock, however, only contributes significantly to β-convergence if conditional convergence (Greece and Portugal against the rest of the world) is considered.

In accordance with Dalum/Villumsen (1996), it can be concluded on the basis of the empirical results, that a sole specialisation in leading-edge technology is probably no panacea for a "paradise on earth". However, it is also obvious from the empirical results that processes of structural change towards R&D-intensive industries should be supported by policy, because countries which were successful in this process also experienced higher growth opportunities in the recent past. Furthermore, national as well as EU policy should support cross-border technology diffusion and knowledge spillovers. Especially with regard to the catching-up but still backward countries within the EU, it might be necessary to promote these countries through a selective EU research and technology policy, so that they succeed in setting up efficient national innovation systems and, at the same time, participate in a gradually emerging European innovation system.

References

Aghion, P./Howitt, P. (1998), Endogenous Growth Theory, Cambridge (MA), London.

Agrawal, A./Henderson, R. (2001), Putting Patents in Context: Exploring Knowledge Transfer from MIT, Working Paper Queen's University and MIT Sloan School.

Anderson, B./Walsh, V. (1998), Co-evolution of Technological Systems, Blurring of Industry Boundaries and Broadening of Competencies in the Chemical Industry, Paper presented at 1998 DRUID Summer Conference, 9-11 June, Bornholm.

Archibugi, D./Pianta, M. (1992), The Technological Specialisation of Advanced Countries, A Report to the EEC on International Science and Technology Activities, Dordrecht/Boston/London.

Barro, R. J./Sala-i-Martin, X. (1991), Convergence across States and Regions, in: Brookings Papers on Economic Activity, 107 - 182.

Bernard, A. B./Jones, C. I. (1996), Technology and Convergence, in: The Economic Journal 106, 1037 - 1044.

Blundell, R./Griffith, R./Van Renen, J. (1998), Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms, Working Paper University College London and Institute for Fiscal Studies.

Bosworth, D./Wharton, A./Greenhalgh, C. (2000), Intangible Assets and the Market Value of UK Companies: Evidence from Fixed Effects Models, Working Paper No. 2 Oxford Intellectual Property Research Centre at St. Peter's College.

Caballero, R./Jaffe, A. (1993), How High are the Giant's Shoulders, NBER Working Paper No. 4370.

Cantwell, J. A./Anderson, B. (1996), A Statistical Analysis of Corporate Technological Leadership Historically, in: Economics of Innovation and New Technology 4, 211 - 234.

Cantwell, J. A./Piscitello, L. (2000), Accumulating Technological Competence - Its Changing Impact on Corporate Diversification and Internationalisation, Working Paper University of Reading.

Chen, S. S./Ho, K. W./Ik, K. H. et al. (2002), How Does Strategic Competition Affect Firm Values? A Study of New Product Announcements, in: Financial Management, 5 - 22.

Cockburn, I./Griliches, Z. (1988), Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents, in: American Economic Review 78, 419 - 423.

Dalum, B./Laursen, K./Verspagen, B. (1999), Does Specialization Matter for Growth, in: Industrial and Corporate Change 8, 267 - 288.

Dalum, B./Villumsen, G. (1996), Are OECD Export Specialisation Patterns 'Sticky'? Relations to the Convergence-Divergence Debate, DRUID Working Paper No. 96-3, Aalborg University.

de la Fuente, A. (2002), On the Sources of Convergence: A Close Look at the Spanish Regions, in: European Economic Review 46, 569 - 599.

Dowrick, S. (1997), Innovation and Growth: Implications of the New Theory and Evidence, in: Fagerberg, J./Lundberg, L./Hansson, P. et al. (eds.), Technology and International Trade, Cheltenham.

Dushnitsky, G./Lenox, M. J. (2002), Corporate Venture Capital and Incumbent Firm Innovation Rates, Working Paper Stern School of Business, New York University.

Fai, F. (1999), The Evolution of Corporate Technological Diversification 1930-90: An Investigation into the Concept of Technological Relatedness, Communication to the European Meeting on Applied Evolutionary Economics, 7-9 June, Grenoble.

Gambardella, A./Torrisi, S. (2000), The Economic Value of Knowledge and Interfirm Technological Linkages: An Investigation of Science-Based Firms, Paper prepared for the Dynacom TSER Project (Contract No. SOE1-CT97-1078).

Grossman, G./Helpman, E. (1991), Innovation and Growth in a Global Economy, Cambridge (MA).

Grupp, H./Jungmittag, A./Legler, H. et al. (2000), Hochtechnologie 2000 – Neudefinition der Hochtechnologie für die Berichterstattung zur technologischen Leistungsfähigkeit Deutschlands, Karlsruhe/Hannover.

Hall, B. H./Jaffe, A./Trajtenberg, M. (2001), Market Value and Patent Citations: A First Look, Working Paper Department of Economics, UC Berkeley.

Heeley, M. B./Khorana, A./Matusik, S. F. (2000), Underpricing and the Long-run Financial Performance of IPOs: Information Asymmetry and Firm Incentive Capability, in: Reynolds, P. D. (ed.), Frontiers of Entrepreneurship Research – Proceedings of the 19th Annual Entrepreneurship Research Conference 1999, Babson College.

Henderson, R./Cockburn, I. (1996), Scale, Scope and Spillovers: The Determinants of Research Productivity in Drug Discovery, in: Rand Journal of Economics 27, 32 - 59.

Jungmittag, A./Blind, K./Grupp, H. (1999), Innovation, Standardisation and the Long-Term Production Function - A Cointegration Analysis for Germany, 1960-1996, in: Zeitschrift für Wirtschafts- und Sozialwissenschaften 119, 205-222.

Jungmittag, A./Welfens, P. J. J. (2002), Telecommunications, Innovations and the Long-term Production Function: Theoretical Aspects and a Cointegration Analysis for West Germany 1960 – 1990, in: Audretsch, D./Welfens, P. J. J. (eds.), The New Economy and Economic Growth in Europe and the US, Berlin et al., 99 – 127.

Koleda, G./Le Mouël, P. (1998), Explaining Technical Progress by Patent Statistics: An Empirical Study of the French Case, Paper prepared for the conference "The Economics of Science and Technology: Micro-Fundations and Policy, 5-6 June, University of Urbino.

Lach, S. (1995), Patents and Productivity Growth at the Industry Level: A First Look, in: Economics Letters 49, 101 - 108.

Lucas, R. E. (1988), On the Mechanics of Economic Development, in: Journal of Monetary Economics 22, 3 - 42.

Mankiw, N. G./Romer, D. /Weil, D. N. (1992), A Contribution to the Empirics of Economic Growth, in: The Quarterly Journal of Economics 107, 407 - 438.

Mansfield, E./Schwartz, M./Wagner, S. (1981), Imitation Costs and Patents: An Empirical Study, in: The Economic Journal 91, 907 - 918.

Romer, P. M. (1986), Increasing Returns and Long-run Growth, in: Journal of Political Economy 94, 1002 - 1037.

Romer, P. M. (1990), Endogenous Technological Change, in: Journal of Political Economy 98, S71-S102.

Sala-i-Martin, X. (1996), Regional Cohesion: Evidence and Theories of Regional Growth and Convergence, in: European Economic Review 40, 1325 - 1352.

Zachariadis, M. (2000), R&D-induced Growth? Evidence from the U.S. Manufacturing Sector, Working Paper Department of Economics, LSU, Baton Rouge, LA.