HUMAN CAPITAL IN OECD COUNTRIES: TECHNICAL CHANGE, EFFICIENCY AND PRODUCTIVITY*

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Abstract

The aim of this paper is to analyse the role of human capital in the productivity gains of the OECD countries in the period 1965-90, breaking down the productivity gains into technical change and gains in efficiency. For this purpose we use both a stochastic frontier approach and a non-parametric approach (DEA) and calculate Malmquist indices of productivity. The results obtained indicate the existence of both a level effect (a higher level of human capital raises labour productivity) and a rate effect (a higher level of human capital affects positively the rate of technical change) associated with human capital. The differences among countries in endowments of human capital have worked against labour productivity convergence, since the richer countries, thanks to their greater endowment of human capital, have experienced higher rates of technical change.

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1. Introduction

The literature on the relationship between human capital and growth has a long tradition. Indeed, we can find a concern for this type of questions since the early 1960s with the birth of the theory of human capital. Schultz himself[1] clearly sets out how investment in human capital constitutes one of the main explanatory elements of economic growth. It is responsible, to a large extent, for the divergence observed between output growth and that of the quantity of productive factors used, giving rise to a qualitative improvement of the labour factor which increases its productive capacity and generates economic growth.

Persisting with this idea, investment in human capital was rapidly incorporated into the literature on growth starting with Solow's seminal study (1957). From then onwards, a succession of papers on growth accounting concerned themselves with quantifying the notable contribution to growth of investment in human capital. On the same lines, but using more sophisticated procedures and better information on the educational levels of the population and their impact on productivity, more recent papers have provided the same kind of results.

In general, the studies carried out so far analyse the importance of human capital by means of both the estimation of production functions, including as additional input a proxy variable of human capital, and the estimation of the effect of human capital on total factor productivity (TFP) estimated by the traditional non-parametric approach of index numbers. In the first case, the usual practice in economic literature has consisted of estimating average production functions (estimated by conventional regression methods) rather than genuine frontiers, assuming in consequence that all the units of production are efficient. Obviously the non-fulfilment of this assumption would affect the parameters estimated, and consequently the importance of human capital.

In the second case, the accounting estimation of TFP also incorporates the implicit assumption that all individuals are efficient, so TFP growth is interpreted as the movement of the frontier function (technical change). However, in the presence of technical or allocative inefficiency, the accounting estimation of TFP would also be biassed[2], therefore affecting the effect on TFP growth attributed to human capital in this sort of analysis.

In order to avoid such bias, it is necessary to use frontier techniques that consider the possible existence of inefficient behaviour. Such is the case in the papers by Färe et al. (1994), Taskin and Zaim (1997) and Maudos et al. (2000) on the analysis of TFP growth and its decomposition into technical change and efficiency gains in the OECD countries. In the three cases it is assumed that production is carried out using physical capital and labour exclusively, without considering the role of human capital.

Consequently, there are studies which, although they consider the importance of human capital as an additional productive factor, use non-frontier techniques that ignore inefficiency; and on the other hand there are studies which, although they use frontier techniques, do not include human capital as an additional productive factor. The only exception is the paper by Maudos et al. (1999) who confirm that the inclusion of human capital has a significant effect on the measurement of TFP.

This paper extend the results of Maudos et al. (1999) analysing the importance of human capital by means of frontier techniques considering at the same time its contribution as input (level effect) and as a factor determining the rate of technical change (rate effect). This avoids the possible bias deriving from non-incorporation of inefficiency and that deriving from the omission of a relevant input.

The paper is organised as follows. The second section reviews the role of human capital in economic growth, examining the existing empirical evidence. The third section offers a brief description of frontier techniques for measuring efficiency and productivity, commenting on the disadvantages inherent to their particular use. The fourth section describes the database used and presents the results relating to efficiency, technical change and productivity, and tests the significance of human capital as productive input. The fifth section analyses the effect of human capital as a determining factor of technical change and its effect on convergence. Finally the main conclusions of the paper are presented in section six.

2. The importance of human capital

The theoretical models have incorporated human capital as one of the determining factors of development. Thus, in the case of neo-classical growth models[3], the study by Mankiw, Romer and Weil (1992) offers the generalisation of the Solow model along this line, including a rate of investing in human capital, and offers evidence to confirm its positive contribution to growth, reconciling the empirical evidence with the neo-classical model of exogenous growth.

Apart from the neo-classical growth models, the endogenous growth models have also used human capital in their analyses. The central idea of some of these models[4] consists of generating the growth from the existence of non-diminishing returns on the accumulable factors. This property is sometimes established through externalities, thus maintaining the coherence with a context of perfect competition. The incorporation of an added type of capital (human capital) seems appropriate, especially if it is a factor to which positive externalities can be attributed, as for example in Lucas (1988).

Another type of models[5] derives endogenous growth as a result of the development of new ideas and new products. In Romer (1990) the existence of a sector of the economy dedicated to research and development is the mechanism through which sustained growth is reached, human capital being the most highly-qualified candidate for generator of this type of progress and, therefore, becoming a determinant of the economic growth rate. Indeed, human capital can not only drive innovation, but also contribute significantly to the imitation and adoption by one economy of the techniques previously developed by more advanced countries. This question is not new, this type of phenomena having already been analysed in Nelson and Phelps (1966) or Welch (1970).

To sum up, there exist varied theoretical arguments on which to base the idea that a greater endowment of human capital increases the rate of technical change by encouraging both innovation and the diffusion of technology and new products. Indeed, this diversity of mechanisms by means of which human capital can influence growth may explain to a large extent its success in the literature. This diversity is an aspect that requires more detailed reflection. Firstly, human capital may contribute to growth in a way analogous to any other factor of production such as the amount of labour or physical capital. In this sense, the higher the level of human capital, ceteris paribus, the greater the production. This is what we call a *level effect* of human capital as a consequence of which the growth of human capital will generate economic growth. This is the type of effects that are usually considered by the neo-classical growth models and there exists both positive[6] and negative[7] evidence.

Human capital may also contribute to technical change by driving both innovation and imitation. In this case, the economic growth rate itself will depend on the level of human capital. This is what we call the *rate effect* of human capital. Endogenous growth models, though not only they, emphasise these aspects. Kyriacou (1991) and Benhabib and Spiegel (1994) point out that this seems to be the channel through which human capital acts, the significance of the level effect being non-existent or debatable. The evidence offered by Barro and Lee (1994) and Engelbrecht (1997) indicates the existence of both types of effects. In general, the results seem to be sensitive to the specification employed, as well as to the indicator of human capital used[8].

Therefore, a higher level of human capital per worker will increase labour productivity for any given technology (*level effect*) and also the rate of technical change (*rate effect*).

3. Efficiency, technical change and productivity: techniques of measurement

The traditional approach to the analysis of productivity by means of non-frontier models, which includes both growth accounting approach (Solow, 1957; Denison, 1972; etc.), and the index number approach[9] (indices of Divisia, Törnqvist, etc.), incorporate the implied assumption that all individuals are efficient, so that the productivity growth is interpreted as movement of the frontier function (technical change). However, in the presence of inefficiency the estimation of technical progress would be biassed[10]. Furthermore, even in the absence of technical inefficiency, the accounting estimation of TFP growth would be a biassed estimation if the inputs shares used to aggregate inputs are not those that minimise cost, i.e. there is allocative inefficiency[11].

On the other hand, frontier approaches to the analysis of productivity take explicitly into account the possible inefficient behaviour of the units analysed, measuring as inefficiency the potential increase in the observed value of production, this being measured against the maximum technically achievable value defined by frontier of production or technology. In this study we use this frontier approach through both a parametric method (stochastic frontier approach, SFA) and a non-parametric method (DEA).

a) Parametric methods: Stochastic frontier approach (SFA)

The SFA was introduced simultaneously by Aigner et al. (1977) and Meeusen et al. (1977). This approach modifies the standard production function by assuming that inefficiency forms part of the error term. This compound error term, therefore, includes an inefficiency component and a purely random component that captures the effect of variables that are beyond the control of the production unit being analysed (weather, bad luck, etc.).

The basic stochastic production frontier model posits that the observed production of an economy deviates from the frontier as a consequence of random fluctuations (v_{it}) and of inefficiency (u_{it}). That is to say,

$$[\,1\,] \qquad LnY_{it}=LnF(X_{it},\beta)\cdot exp.(v_{it}-u_{it}) \qquad i=1,\ldots,N;\ t=1,\ldots,T$$

where Y_{it} is the observed production and X_{it} is the input vector of country i at time t, β is the vector of parameters to be estimated, and $LnF(X_{it}, \beta)$ is the logarithm of optimum output. The random error term v_{it} is assumed to be independent and identically distributed, and the term u_{it} is assumed to be distributed independently of v_{it}. The indicator of efficiency, obtained as the ratio of optimum output to observed output, is obtained as $exp(u_{it})$[12].

Since inefficiencies can only decrease production below the frontier, it is necessary to specify asymmetrical distributions for the inefficiency term. Usually, it is assumed that v_{it} is distributed as a normal with zero average and variance σ^2_v, and u_{it} as a half-normal, truncated normal, exponential, etc.

On the assumption that both components of the error term are distributed independently, the frontier function can be estimated by maximum likelihood, inefficiency being estimated on the basis of the residuals of the regression. More specifically, individual estimations of inefficiency can be obtained by using the distribution of the inefficiency term conditioned to the estimation of the compound error term (Greene, 1993).

Thus, the stochastic frontier approach has as its principal advantage the fact that it allows us to isolate the influence of factors other than efficiency. However, its disadvantages are that it is a parametric approach (it is necessary to impose *a priori* a particular functional form) and that it is necessary to specify distributional assumptions in order to separate the two components of the error term. Moreover, although in this approach the estimation of technical progress can be done easily by introducing time dummies or a trend, it has the disadvantage that technical change, calculated on the basis of the parameters estimated, is the same for all countries.

b) Non-parametric methods: Malmquist productivity index and DEA

The Malmquist productivity index allows changes in productivity to be broken down into changes in efficiency and technical change. If it is estimated using a non-parametric frontier model (data envelopment analysis, DEA), which is the most commonly used approach, it will not be necessary to impose any functional form on the data nor to make distributional assumptions for the inefficiency term, unlike the stochastic frontier approach. The main disadvantage of this approach is that the estimation of inefficiency may show an upward bias, capturing as inefficiency the influence of other factors, such as errors in data measurement, bad luck, weather, etc.

Following Shephard (1970) or Caves et al. (1982), the "distance function in outputs" of an individual in t relative to the technology of t (F^t) can be expressed as $D_0^t(x^t,y^t)=inf\{\vartheta^{t,t}:(x^t,y^t/\vartheta^{t,t})\in F^t\}$, where y^t is the vector of outputs, x^t the vector of inputs, and (F^t) the technology corresponding to period t. This function D_0^t is defined as the reciprocal of the maximum expansion to which it is necessary to subject the vector of outputs of period t (y^t), given the level of inputs (x^t), so that the observation stands at the frontier of period t. On the basis of the above concepts, the Malmquist productivity index based on outputs to analyze productive change between periods t and $t+1$, using the technology of period t as reference, is defined as

$$[2] \qquad M_o^t\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)}$$

$M_o^t>1$ indicates that the productivity of period $t+1$ is higher than that of period t, $M_o^t<1$ indicates that productivity has descended between periods t and $t+1$.

When we wish to analyze the productive change of a longer time series, the use of a fixed technology may cause problems the further we get from the base year (Moorsten, 1961). To attempt to solve these problems it is usual to calculate two indices based on pairs of consecutive years which take as base the technology of the two periods t and $t+1$, and to calculate the geometric mean of the two. Re-writing the geometric mean, it is possible to break down the Malmquist productivity index into the catching-up effect and technical change[13]:

$$[3] \qquad M_o\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)}\left[\left(\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}\right)\right]^{1/2}$$

The catching-up effect, or change in relative efficiency between periods t and $t+1$, is represented by the first ratio, which will be higher than unity if there has been an increase in efficiency. Similarly, the geometric mean of the two ratios between brackets measures the technical change, or movement of technology, between periods t and $t+1$.

4. Data and Results

The sample used for the estimation of the frontier production function consists of OECD countries in the period 1965-90 using the Summers and Heston database (Penn World Table, Mark 5.6)[14] and Barro and Lee (1993)[15]. The variables for each country are: 1) aggregated output measured by real Gross Domestic Product (GDP) (Y), expressed in international prices;

2) aggregated labour input (L) measured by total employment, computed from real GDP per worker; 3) total capital stock (K) calculated from the non-residential capital per worker; and 4) human capital stock (H) calculated as the number of schooling years completed by the occupied population obtained as a product of the average schooling years of the population over 25 years of age[16] (proxy of the per capita endowment of human capital (h)), and the number of workers.

The empirical studies on the importance of human capital in the explanation of differences in productivity between countries are usually based on the estimation of production functions, into which a proxy variable of human capital is introduced as well as labour and physical capital. In this sense, it is usual practice to use Cobb-Douglas production functions in which it is also usual to impose the assumption of constant returns to scale.

However, it is well-known that the assumption that the technology underlying the production function is of the Cobb-Douglas type has a restrictive effect. For this reason, in the SFA approach the strategy adopted in this paper is to estimate a more flexible (translogarithmic) production function which nests the Cobb-Douglas function as a particular case, which would be no more than a restricted case of the translog specification. This specification would be as follows:

$$\begin{aligned} [4] \qquad & LnY_{it} = \beta_0 + \beta_L LnL_{it} + \beta_K LnK_{it} + \beta_H LnH_{it} + \\ & (1/2)\beta_{LL} LnL_{it}^2 + (1/2)\beta_{KK} LnK_{it}^2 + (1/2)\beta_{HH} LnH_{it}^2 \\ & \beta_{LK} LnL_{it} LnK_{it} + \beta_{LH} LnL_{it} LnH_{it} + \beta_{KH} LnK_{it} LnH_{it} + \sum_{t=65}^{90} \lambda_t TE_t + v_{it} - u_{it} \end{aligned}$$

where Y=output (GDP), K=stock of physical capital, L=employment and H=stock of human capital (total number of person years of education emboid in those workers). In addition, time effects (*TE*) are introduced into the estimation to reflect the effects of technical change.

Columns (1) and (2) of table 1[17] show the results of the estimation of the equation with and without human capital using the SFA with a Cobb-Douglas specification. Comparison of the two models shows the importance of human capital in the explanation of the differences in labour productivity among the OECD countries, its elasticity (0.329) being similar to the elasticity of labour (0.309). Also it is not possible to reject the hypothesis of constant returns to scale in all the inputs. However, the results that appear in columns (3) and (4) show the specification bias inherent to the Cobb-Douglas function given the high significance both of the squares of the variables and of their crossed products[18], as well as the importance of human capital. More particularly, in model (4) human capital presents a statistically significant elasticity in the average values of the sample of 0.09 (t-ratio 2.704), this elasticity being much lower than that corresponding to the Cobb-Douglas specification.

>Insert Table 1 here<

Another outstanding feature is the increase in the importance of inefficiency in the explanation of the variance of the compound error term of the estimation. Thus, in the translog estimation practically all the variance of the error term ($\sigma^2_u+\sigma^2_v$) is explained by inefficiency, which shows the small bias that would be incurred in the event of using a deterministic approach.

Table 2 shows the average levels of efficiency of the OECD countries for the period as a whole, corresponding to the translog estimation with human capital (column 1) and without human capital (column 2). It is important to note, first, the existence of high levels of inefficiency in certain countries (Japan, Greece, Finland, etc), which shows the importance of not ignoring the differences in efficiency in the analysis of productivity gains. Second, there are substantial differences among countries, USA, the Netherlands and the UK being the most efficient OECD countries. Third, on occasions (in countries with low levels of human capital such as Italy, Portugal and Turkey) there are important differences between the efficiency estimated with human capital and without it, which shows the importance of incorporating it as an additional productive factor in the production function for the evaluation of efficiency[19].

>Insert Table 2 here<

In order to test empirically the significance of human capital in the DEA model the Banker[20] test was used, indicating that, similar to the parametric techniques, human capital is statistically significant[21]. For that reason, using the approach described in section 3 (Malmquist productivity indices), table 3 shows the growth rate of TFP and its breakdown into technical change and changes in efficiency of the OECD countries considering, as well as labour and physical capital, human capital given its importance as an additional productive factor (level effect)[22].

For the average of the countries considered, the results show different relationships during the period analysed (1965-1990), with respect both to the growth rate of TFP and to the importance of the sources of growth (technical change *vs* catching-up). Thus, while in the sub-periods of growth (1965-73) and recovery (1985-90) improvements occur in productivity (much greater in the latter sub-period), in the period of crisis (1973-85) hardly any improvement of productivity occurs. Furthermore, the relative importance of technical change and of gains in efficiency is variable in time, notably the relative importance of technical progress in the sub-period 1985-1990 (1.21%) and of efficiency gains in the sub-period 1965-1973.

By countries, important differences are again observed. Thus, in the case of Japan, the losses of productivity until 1985 are due both to losses of efficiency and to the absence of technical progress, even though productivity grew above the OECD average in the last sub-period, due both to the important gains in efficiency (1.105%) and to technical progress (1.51%).

Also outstanding is the behaviour of Canada, Belgium, Finland, France, Germany, Italy, Netherlands, Norway, Sweden and Australia which in all the sub-periods experienced important gains in productivity. Denmark and Iceland, on the contrary, experienced losses in all the sub-periods considered.

>Insert Table 3 here<

4. Human capital, technical change and convergence

As we have seen in the previous section, human capital is a relevant input in the OECD countries together with employment and physical capital. However, human capital is different from other inputs in some ways. It is reasonable to suppose that a positive relationship may exist between the endowment of human capital of an economy and its capacity to develop and incorporate new techniques, more complex and productive. Additionally, it is reasonable to suppose that the economies close to the technological frontier (more efficient) are those that devote more effort to innovate and that adopt those innovations with greatest ease.[23]

The breakdown of economic growth as above enables us to test those hypotheses in the case of the OECD countries, an estimation of technical change by countries being available. For this purpose, for a given period of time, we estimate equations such as:

[5] $$TC_i = \alpha + \gamma \cdot Ln(h_i) + \delta \cdot Ln(INEF_i) + e_i$$

where TC_i is the average annual rate of technical change for country *i*, *h* the average endowment of human capital per worker of the period in economy *i*, $INEF_i$ average inefficiency of *i*, and *e* a disturbance term.

Column 1 of table 4 offers the estimated effect of human capital on technical change over the whole period. Overall, human capital has driven the average rate of technical change to a significant extent. The estimated coefficient of 0.0082 means that an additional 100% of human capital leads to a rise of 0.082% in the average rate of technical change, a variation that, accumulated over the period 1965-1990, would imply an increase of more than 20% in total factor productivity (TFP). Also, the countries furthest from the technological frontier (less efficient) seem to experience lower rates of technical change, as indicated by the negative values estimated for δ.

>Insert Table 4 here<

However, the influence of human capital does not seem to have maintained the same intensity over the whole of the period analysed, as can be appreciated in the other columns of table 4. The figures were especially relevant during the sub-period of growth 1965-1973 (0.0125) although they decreased somewhat during the period of crisis 1973-1985 (0.0087), being statistically significant nevertheless in both cases. If the initial intensity had been maintained, 100% more human capital would have meant 36% more productivity due to greater technical progress. On the other hand, in the last sub-period there does not seem to be any significant relationship between human capital and technical change.

Although there is evidence of skilled-biased technical change for the US and some other countries in the last period, that fact is not general. A recent paper, Trostel, Walker and Wolley (2002), shows that the world wide rate of return to schooling declined slightly over the period 1985-95. An increasing problem of overeducation in some countries could explain this paradoxical result for the last period.

The importance of human capital as a determining factor of technical change allows us to understand better the pattern of slow convergence followed by the OECD countries, the more developed countries having experienced higher rates of technical change thanks to their greater endowments of human capital. To illustrate this matter, and following Serrano (1999) and Maudos et al. (2000), we will apply the classical analytical method of absolute beta-convergence analysis by means of regressions[24], as:

[6] $$\hat{y}_i = a_y + b_y \cdot Ln(y_{0i}) + u_{yi}$$

[7] $$\hat{T}C_i = a_{TC} + b_{TC}\cdot Ln(y_{0i}) + u_{TCi}$$

[8] $$\hat{T}C_i^h = a_h + b_h\cdot Ln(y_{0i}) + u_{hi}$$

[9] $$\hat{T}C_i^r = a_r + b_r\cdot Ln(y_{0i}) + u_{ri}$$

where $\hat{y}_i$ is the average rate of growth of labour productivity of country i from 0 to T, $\hat{T}C_i$ the average rate of technical change, $\hat{T}C_i^h$ the rate of technical change explained by the endowment of human capital obtained from the results of Table 5, and $\hat{T}C_i^r$ the residual rate of technical change not explained by human capital $\left(\hat{T}C_i^r = \hat{T}C_i - \hat{T}C_i^h\right)$.

Thus b_y is the rate of total labour productivity convergence and b_{TC} the rate of convergence attributable to technical change. The latter is due to the effect of the endowment of human capital on technical change (b_h) and to residual technical change (b_r)[25].

Table 5 offers the results for the period 1965-90 and for the sub-periods 1965-73, 1973-85 and 1985-90. In column 1 we can observe convergence in the levels of labour productivity over the whole period. Its cumulative magnitude (-1.77%) and its time pattern agree with the results habitually offered by the literature (see Barro and Sala-i-Martin, 1995). Thus, convergence was more intense in the period 1965-73 (-2.85%) than during the crisis of 1973-85 (-1.04%) and recovered again in the final sub-period (-3.03%).

>Insert Table 5 here>

The effect of technical change is shown in column 2. The results indicate that, contrary to the results obtained in other papers (Dowrick and Nguyen, 1989; Dollar and Wolff, 1994; Bernard and Jones, 1996b or Wolff, 1991), technical change was a systematic and significant source of divergence[26]. Both in the period as a whole and in each of the sub-periods considered, the countries with highest initial productivity experienced greater relative technical change. Thus, the effect over the period as a whole was +0.91%, being somewhat higher in the sub-period 1965-73 (+1.83%), and less during the sub-period 1973-85 (+0.83%), the effect becoming not significant during sub-period 1985-90 (+0.21%). This result seems reasonable if it is considered that it is the most developed countries that make the innovations. This means that they are the first to adopt them, and also that technical progress is adapted to the characteristics of this type of economy. For all these reasons technical progress benefits especially the more developed countries in the short term.

Examining column 3, we can see that human capital has generated a significant divergence by means of its effect on technical change (+0.51%). In fact this effect represents more than half the divergence that we have attributed to technical change. Technical change not explained by human capital, according to the results of column 4, is at the limits of significance. Examining the sub-periods in which there was a significant relationship between human capital and technical change, we find similar situations. Thus, during the sub-period 1965-1973, the divergent contribution of the rate effect of human capital (+0.85%) is significant and represents 40% of the divergence attributable to technical change. Finally in the period of crisis 1973-1985 that effect continues to be significant an remains at similar levels (+0.68%), being solely responsible for the fact that technical change generates divergence, as the specific value offered by the residual effect is very low and not significant.

To sum up, human capital seems to have had a positive contribution to the growth of the OECD countries, since as well as being an important input of the productive process (level effect) it also drove technical change (rate effect) even though the latter effect sees to have greatly weakened towards the end of the period. Indeed the rate of growth followed by these countries is in large part determined by this effect. The differences with respect to endowments of human capital have led to divergent rates of technical change, and therefore less intensive convergence[27].

5. Conclusions

The studies made so far have analysed the importance of human capital both by means of the estimation of production functions that include human capital as an additional productive factor and by means of the estimation of the effect of human capital on TFP, the latter being estimated by the traditional non-parametric approach of index numbers.

However, in both cases it is implicitly assumed that all the units of production (in our case countries) are efficient, so that technical progress is identified with productivity gains. However, in the presence of inefficiency the estimation of TFP will be biassed, thus affecting the possible effect of human capital on TFP.

This study has confirmed the importance of human capital in productivity growth in the OECD, explicitly incorporating into the analysis the importance of efficiency as a source of variation in TFP other than technical progress.

The results for the period 1965-1990 show the existence of both a level effect (human capital is an additional input in the production function) and a rate effect (human capital fosters technical change) associated with human capital. Thus, the estimation of a stochastic translog production function shows a statistically significant product elasticity of human capital and non-parametric techniques confirm its significance as input.

The results show that human capital has significantly driven the rate of technical change, its magnitude being especially important in the period of growth 1965-1973. This phenomenon, together with the fact that human capital was greater in the countries that were initially richer, implies that human capital has been a significant source of divergence.

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Table 1: Stochastic production function

	Model 1		*Model 2*		*Model 3*		*Model 4*	
	C-D without H		**C-D with H**		**Translog without H**		**Translog with H**	
	Param.	**t-student**	**Param.**	**t-student**	**Param.**	**t-student**	**Param.**	**t-student**
Constant	19.9140	543.06	19.8650	734.46	20.0700	468.39	20.0160	639.90
Ln*K*	0.5600	39.98	0.3715	17.02	0.4574	18.10	0.4115	14.10
Ln*L*	0.4468	29.37	0.3090	26.57	0.5887	23.08	0.6394	23.74
Ln*H*			0.3294	12.45			0.0887	2.57
LnK^2					-0.3636	-7.38	-0.4961	-7.12
LnL^2					-0.4464	-8.04	-0.5428	-8.44
LnH^2							-1.0968	-4.97
Ln*L**Ln*K*					0.4141	8.22	0.5305	8.00
Ln*L**LnH							-0.4624	-4.31
LnH*Ln*K*							0.4611	4.44
σ^2_u / σ^2_v	2.9260	4.99	5.5791	3.80	89.0590	0.23	46.6690	0.51
$\sigma^2_u + \sigma^2_v$	0.2979	16.91	0.2901	19.66	0.2610	26.94	0.2433	29.90
N. obs.	598		598		598		598	
Log-lik.	150.4574		228.8128		356.8233		402.8102	
σ^2_v	0.0093		0.0026		0.0000		0.0000	
σ^2_u	0.0795		0.0816		0.0681		0.0592	

Table 2: Efficiency levels (SFA): 1965-90

	With human capital	***Without human capital***
Canada	1.070	1.073
USA	1.043	1.063
Japan	1.728	1.695
Austria	1.171	1.195
Belgium	1.142	1.146
Denmark	1.237	1.275
Finland	1.480	1.473
France	1.117	1.195
Germany	1.385	1.402
Greece	1.644	1.656
Iceland	1.160	1.174
Ireland	1.330	1.344
Italy	1.136	1.215
Netherlands	1.036	1.039
Norway	1.275	1.368
Portugal	1.122	1.270
Spain	1.080	1.119
Sweden	1.157	1.156
Switzerland	1.109	1.157
Turkey	1.357	1.455
UK	1.069	1.067
Australia	1.128	1.136
New Zealand	1.081	1.113
Mean	**1.204**	**1.236**

Note: Values higher than unity imply that the country is technically inefficient; the higher the index, the greater the inefficiency.

Table 3: Malmquist index decomposition. Average annual growth (%)

	Efficiency Change				*Technical Change*				*Malmquist Index*			
	1965-90	**1965-73**	**1973-85**	**1985-90**	**1965-90**	**1965-73**	**1973-85**	**1985-90**	**1965-90**	**1965-73**	**1973-85**	**1985-90**
Canada	0.415	-0.043	0.878	0.038	1.046	1.245	0.658	1.661	1.461	1.201	1.535	1.700
USA	0.000	0.000	0.000	0.000	0.103	0.127	-0.177	0.736	0.103	0.127	-0.177	0.736
Japan	0.041	-0.342	-0.147	1.105	-0.528	-2.205	-0.259	1.507	-0.487	-2.546	-0.406	2.612
Austria	-0.731	-1.754	-0.381	0.067	0.784	0.868	0.227	1.987	0.053	-0.885	-0.154	2.054
Belgium	1.062	1.810	0.626	0.909	0.552	0.313	0.181	1.827	1.614	2.123	0.807	2.736
Denmark	-0.279	-0.858	0.352	-0.866	-0.541	-1.371	-0.474	0.624	-0.820	-2.228	-0.122	-0.242
Finland	1.406	1.611	1.488	0.880	0.586	1.053	-0.204	1.736	1.992	2.664	1.284	2.616
France	0.001	0.477	-0.269	-0.115	1.168	1.863	0.323	2.083	1.168	2.340	0.054	1.968
Germany	0.893	1.395	1.115	-0.442	0.461	0.366	-0.049	1.839	1.355	1.761	1.066	1.397
Greece	0.496	1.415	-0.077	0.400	-0.393	-0.615	-0.502	0.225	0.103	0.800	-0.580	0.625
Iceland	-0.201	0.131	0.000	-1.212	-0.584	-0.864	-0.226	-0.997	-0.785	-0.733	-0.226	-2.209
Ireland	0.810	0.159	-0.047	3.909	-0.208	-0.958	0.192	0.033	0.602	-0.799	0.144	3.942
Italy	0.826	1.451	0.753	0.000	0.677	0.730	0.345	1.389	1.503	2.181	1.098	1.389
Netherlands	-0.214	-0.580	-0.022	-0.089	0.537	0.634	0.203	1.184	0.323	0.054	0.181	1.095
Norway	0.284	-1.568	2.417	-1.869	1.084	2.247	-0.052	1.948	1.368	0.678	2.365	0.079
Portugal	0.568	1.775	-0.422	1.014	-0.078	-0.245	-1.414	3.396	0.490	1.530	-1.836	4.410
Spain	-0.279	0.000	-0.742	0.387	-0.671	-0.752	-1.143	0.594	-0.950	-0.752	-1.886	0.980
Sweden	-0.096	-0.458	0.291	-0.448	0.644	0.958	-0.007	1.704	0.548	0.500	0.284	1.256
Switzerland	-0.091	0.000	-0.255	0.155	1.025	2.522	-0.304	1.821	0.934	2.522	-0.559	1.976
Turkey	0.267	1.118	-0.906	1.720	-1.354	-2.814	-1.175	0.551	-1.087	-1.695	-2.082	2.271
UK	0.000	-0.086	-0.476	1.279	-0.269	-0.815	0.221	-0.575	-0.269	-0.901	-0.254	0.704
Australia	0.471	0.618	0.911	-0.819	0.838	1.593	-0.009	1.661	1.309	2.211	0.902	0.842
New Zealand	-0.629	0.280	-0.937	-1.342	0.100	-0.019	-0.141	0.871	-0.528	0.261	-1.078	-0.472
MEAN	**0.218**	**0.285**	**0.180**	**0.203**	**0.216**	**0.168**	**-0.165**	**1.209**	**0.435**	**0.453**	**0.016**	**1.412**

Table 4: Effect of human capital on technical change

Period	*1965-90*	*1965-73*	*1973-85*	*1985-90*
Ln(h)	0.0082	0.0125	0.0087	-0.4548
	(2.237)	(2.003)	(3.842)	(-0.515)
Ln(INEF)	-0.0174	-0.0222	-0.0073	-0.0109
	(-2.048)	(-1.326)	(-1.634)	(-0.764)
R^2	0.288	0.172	0.426	0.053

Note: Heteroscedastic consistent t-ratio in parentheses.

NOTES

[1] See Schultz (1962).
[2] See a more detailed exposition in Grosskopf (1993).
[3] Established on the basis of the contributions by Solow (1956) and Swan (1956).
[4] For example, Romer (1986) or Lucas (1988).
[5] See, for example, Romer (1987 and 1990).
[6] See Baumol, Blackman and Wolff (1989), Barro (1991), Mankiw, Romer and Weil (1992), Lichtenberg (1994), Barro and Lee (1994) and Murthy and Chien (1997).
[7] See Kyriacou (1991), Benhabib and Spiegel (1994) or Nonneman and Vanhoudt (1996).
[8] In general the use of the percentage of individuals with secondary school complete offers results more favorable to the effect of human capital than that of other educational levels or that of school enrollment rates.
[9] See among others Baumol (1986), Baumol and Wolff (1988), Abramovitz (1986, 1990 and 1994), Bernard and Jones (1996a and b), Dollar and Wolff (1994) and Wolff (1991).
[10] Note that there are two possible sources of inefficiency: the first is technical inefficiency (i.e. production below the frontier), and the second is allocative inefficiency. Allocative inefficiency would be reflected in the shares used to aggregate inputs.
[11] See a more detailed exposition in Grosskopf (1993).
[12] Values higher than unity imply that the country is technically inefficient; the higher the efficiency index the greater the inefficiency.
[13] For additional details of this decomposition see, for example, Färe, Grosskopf, Norris and Zhongyang (1994). Alternative decompositions to this traditional decomposition have been discussed by Färe, Grosskopf and Lovell (1994), Grifell and Lovell (1995), Ray and Desli (1997), Färe et al. (1997a,b), etc.
[14] This is an updated version of Summers and Heston (1991).
[15] The sample used consists of Canada, USA, Japan, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK, Australia and New Zealand. Luxemboug is excluded because of lack of data on human capital.
[16] Barro and Lee (1993) only offer this datum every five years. The intermediate years have been estimated by interpolation.
[17] The results correspond to the model in which the inefficiency component is distributed as a half-normal, the results being similar in the truncated-normal and exponential models.
[18] The test value of the Cobb-Douglas specification (model 3) against translog (model 4) distributed according to a Chi-squared with 6 degrees of freedom, is equal to 222.9, so the Cobb-Douglas specification is rejected.
[19] Unlike the practice adopted in the studies by Färe et al. (1994), Fecher and Perelman (1995) and Taskin and Zaim (1997).
[20] Banker (1996) proposes several tests to evaluate the significance of the variables introduced into the DEA models, on the basis of their asymtotic properties. Among others, Banker (1996) proposed tests to evaluate the significance of a variable Z introduced into the model. The tests are based on the comparison of a basic model that includes the inputs (X) and the outputs (Y) with a model that also includes the variable being tested (Z). If the inefficiency is distributed as a half-normal, the test is distributed as an F:

$$T_{HN} = \sum_{j=1}^{N}\left[\vartheta_j\left(X_j;Y_j\right)-1\right]^2 \Big/ \sum_{j=1}^{N}\left[\vartheta_j\left(X_j,Z_j;Y_j\right)-1\right]^2 \sim F_{N,N}$$

[21] The probability of rejection of the null hypothesis is 5.54E-8. This result is robust at other alternative distributions of the inefficiency term.
[22] See also Maudos et al. (1999).
[23] The idea is that, given the level of human capital, technical change (not TFP growth that includes efficiency gains) will be faster for economies close to the frontier. This is true although, of course, that distance is dependent on human capital.
[24] We have used OLS although these equations could be related. However, SURE and OLS are equivalent when the set of explanatory variables is the same as in this case.
[25] It is easy to prove that $b_{TC}= b_b+ b_r$
[26] This result is compatible with the convergence in labour productivity over the period because physical capital per worker grew faster in the countries with lowest initial productivity.
[27] Because the possible presence of outliers in the sample may affect the results obtained, their robustness is tested as follows. Firstly, the decomposition of the Malmquist productivity index was re-calculated *n* times, omitting each time one individual of the sample. Secondly, on the basis of the results, equations [12] to [16] were re-estimated recursively *n* times. On the basis of the results of this operation, the existence of outliers was tested by comparing the parameters estimated in the sample that contains the *n* individuals and the samples with *n-1* individuals by means of a test of equality among them (see Pindyck and Rubinfeld, 1991). The results show that the conclusions obtained from the sample as a whole (that human capital positively affects technical progress and generates divergence during the period 65-90 and the sub-periods 65-73 and 73-85) are qualitatively robust to the exclusion of any of the individuals of the sample.