TECHNOLOGY, KNOWLEDGE SPILLOVERS AND CHANGES IN SKILL STRUCTURE*

Hugo Hollanders

Maastricht Economic Research Institute on Innovation and Technology
Maastricht University
P.O. Box 616
6200 MD Maastricht
h.hollanders@merit.unimaas.nl
http://meritbbs.unimaas.nl/hollanders/

Bas ter Weel

Maastricht Economic Research Institute on Innovation and Technology
Maastricht University
P.O. Box 616
6200 MD Maastricht
b.terweel@merit.unimaas.nl
http://meritbbs.unimaas.nl/staff/bas/terweel.html

Abstract

This paper investigates and compares the changes in skill structure in six OECD countries (Finland, France, Germany, Japan, the United Kingdom and the United States) in the period 1975-1995 using new OECD data on employment by skill level and type. For all countries evidence is found that technical change is skill-biased in the sense that it favors high-skilled labor. In particular white-collar high-skilled workers have profited from recent technical change. However, rather than employees literally working on R&D it are workers who supervise and use the implemented parts of the advancements of R&D that profit from increased R&D efforts. In addition, the results are extended by stressing the importance of knowledge spillovers on changes in employment shares between high-skilled and low-skilled workers.

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1. Introduction

There is little doubt that the structure of wages and employment has shifted in many countries over the last decade, thereby adversely affecting relatively unskilled workers. Many authors have attributed this shift to the impact of new technologies, such as information and communication technologies (ICTs). Indeed, the way to apply a particular technology is fully part of that specific piece of technology: human skills are essential and important complementary assets to implement, maintain, adapt to and use new physically embodied technology. From this perspective, as noted recently by Acemoglu (1998) and Goldin and Katz (1998), and already initiated by an early contribution of Griliches (1969), human capital and technology are two faces of the same coin, two non-separable aspects of wealth accumulation. Bresnahan (1999) goes one step beyond this observation and provides a framework of the impact of ICTs on white-collar work which goes far toward explaining the timing, form and locus of recent labor market changes.

This idea is closely related to the debate on skill-biased technical change (SBTC) and wage inequality, which centers around the observation that technical change has favored wages and employment opportunities of relatively skilled workers at the expense of relatively unskilled workers.[1] In this regard, Machin and Van Reenen (1998) are among the first to adopt an international approach to investigate the relationship between changes in skill structure and wages and employment in seven OECD countries in the period 1973-

[1] See for example, Bound and Johnson (1992); Katz and Murphy (1992); Juhn, Murphy, and Pierce (1993); Berman, Bound, and Griliches (1994); Doms, Dunne, and Troske (1997); Autor, Katz, and Krueger (1998); Bartel and Sicherman (1999); and Katz (1999) for United States evidence. Autor, Katz and Krueger (1998) also provide a summary of the evidence found so far and a supply-demand framework.

1989.[2] They conclude for all seven countries that there have been shifts in relative labor demand in favor of skilled workers, stressing the international nature of SBTC. Using a newly constructed data set they observe skill upgrading in all seven countries, but also dramatic changes in the wage structure in favor of high-skilled labor, particularly in the United Kingdom and the United States.

However, Machin and Van Reenen explain the dramatic sectoral increase in the earnings of high-skilled workers relative to low-skilled workers that took place during the 1970s and 1980s by dividing their data into "production" and "non-production" workers. Although the distinction between "production" and "non-production" workers is highly correlated with the share of educated workers across industries both in levels and cross section, this is a highly crude measure to define "unskilled" and "skilled" labor, because it underestimates the concept of SBTC in two respects. First, not all production workers are unskilled, e.g., many skilled "blue-collar" workers are classified as production workers. Second, not all non-production workers are skilled, e.g., clerks, service workers and shop and market sales workers are relatively unskilled "white-collar" workers.

In this paper we will focus on a more comprehensive distinction made on the basis of four types of labor: white-collar and blue-collar high-skilled and low-skilled workers.[3] This will enable us not only to make a distinction between blue and white-collar workers, but also between high and low-skilled workers. It is important to make this distinction

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[2] See also Card, Kramarz and Lemieux (1996) for a comparison of the United States, Canada and France; and Berman, Bound and Machin (1998) for a study on several OECD countries in the period 1970-1992.

[3] Like Machin and Van Reenen (1998) and Berman, Bound and Machin (1998) we study the change in sectoral skill-composition rather than studying this change between sectors. See for example, Haskel and Slaughter (1998); and Bartel and Sicherman (1999} for studies regarding the between component. Given our level of aggregation, we would provide an incomplete picture of the situation if we would study between sector components of SBTC; since the higher the level of aggregation, the lower by definition the between sector bias; e.g. Sanders and Ter Weel (1999).

because the results of our research indicate that white-collar high-skilled workers, such as legislators, senior officials, managers and other professionals, have profited most from recent technical change, a result already established in many studies using data on individual workers but never shown on an international manufacturing sector level.[4]

Another problem in the SBTC-literature is the measurement of technology and technical change. Among the several sources of technical change that have been proposed R&D is among the most popular measures. The reason to choose R&D is that it is a directly observable indicator, which can be relatively easy correlated with the degree of skill-upgrading and for which data are readily available. We adopt here a perspective in which R&D intensities in manufacturing are considered as a measure of technology. However, "the level of knowledge in any one sector or industry not only is derived from own research and development investments but also is affected by the knowledge borrowed or stolen from other sectors or industries." (Griliches, 1979, p. 100). This means, that the productivity of one sector or industry will depend not only on its own R&D expenditures but also on the effort put in R&D in other sectors or industries.

Most studies to measure technology neglect to a large extent such "spillovers" from one sector to another, which are the result of the public-good nature of R&D and the increasing difficulties to appropriate innovative success.[5] Machin and Van Reenen only consider a brief section based on a spillover study by Coe and Helpman (1995). The results

[4] See Chennells and Van Reenen (1999) and Sanders and Ter Weel (1999) for an overview of more than one hundred studies on SBTC.

[5] Bartel and Sicherman (1999) also carry out a study on SBTC (for the United States) taking the following five measures of technical change: (i) total factor productivity; (ii) the ratio of investment in computers to total investments; (iii) the ratio of R&D funds to net sales; (iv) the number of patents used in a particular sector; and (v) the ratio of scientific and engineering employment to total employment. However, these authors too neglect spillovers.

from adopting their approach are statistically insignificant for the United Kingdom and the United States and significant for the smaller Scandinavian (Denmark and Sweden) economies and Japan. These results potentially suggest that spillovers may play an important role in explaining SBTC, because both technology-creating and technology-absorbing manufacturing sectors may be affected in some way by innovations and new technologies.

In this paper we adopt a more elaborate method to measure spillovers, first suggested by Putnam and Evenson (1994) and Verspagen (1997b). Besides using R&D and a wide spectrum of bilateral trade flows, this method also uses patent citations to examine the flows of "knowledge" between 22 manufacturing sectors in six OECD countries (Finland, France, Germany, Japan, the United Kingdom and the United States) from 1975 to 1995. According to this analysis, spillovers are important determinants in explaining the change in the employment shares of high-skilled workers. Particularly high-technology sectors significantly profit from spillovers from other sectors.

The plan of the paper is as follows. Section 2 describes the construction of the data set. Section 3 outlines the econometric approach, tracks down spillovers and tests a modified version of the model suggested by Machin and Van Reenen using the new skill data and knowledge spillovers. Section 4 concludes.

2. Data Description and Construction

We draw on a number of data sources to construct the industry-level panel data we use in our empirical model. The data are all compiled by the OECD and hence relatively easily comparable. First, we use the Standardized Analytical Database (STAN) (OECD, 1998c) for data on investment and value added in all six countries. Second, we use the Business Enterprise R&D database (ANBERD/ANRSE) (OECD, 1999) for R&D information. Third, the Bilateral Trade Database (BTD) (OECD, 1998a) for international trade data is applied in our spillover analysis.[6] Finally, we included data on skill decomposition from the OECD secretariat, an OECD document (OECD, 1998b) and a paper by Colecchia and Papaconstantinou (1996). We divide the manufacturing workforce into four categories: white-collar high and low-skilled and blue-collar high and low-skilled labor. In addition, data from the ANBERD/ANRSE database are available on employment shares of scientists and engineers (S&Es). We use this class of workers as a particular white-collar high-skilled employment group.[7]

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[6] See Machin and Van Reenen pp. 1217-1219 and their Data Appendix (pp. 1240-1244) for a more detailed discussion of the OECD databases STAN, ANBERD and BTD.

[7] In terms of data on skills, Machin and Van Reenen have drawn on the United Nations Industrial Statistics Database (UNISD) which includes, up to 1991 in some countries, data on wage costs and the number of production and non-production workers by industry. The key data are reported in terms of “employees” and “operatives”. “Operatives” are taken to be the production workers. However, this distinction is made mainly to divide the per industry workforce into white-collar (employees) and blue-collar (operatives) workers rather than to divide them in terms of high-skilled and low-skilled workers. The distinction between production and non-production workers is far from accurate as a measure to distinguish high-skilled and low-skilled labor. In addition, recent (post-1991) data are not available as the UN stopped collecting disaggregated data in 1993 and changed UNISD into UNIDO. We thank Stephen Machin for clarification on this particular point. He explained that when the UN moved from Vienna to New York, the abbreviation of the United Nations Industrial Statistics Database was changed from UNISD into UNIDO. At the same time they stopped making the distinction between production and non-production workers. Finally, although the UNISD database contains information similar to the OECD data, it differs in the sense that the OECD data is derived from sample information subsequently calibrated by national accounts, whereas the UN data reports survey results. This may lead to differences in combining the OECD and UNISD data as a result of country-specific definitions.

We proceed in the following manner: industries are grouped on the basis of their R&D intensity in the OECD area as a whole, defined as the ratio of business-enterprise R&D to value added, resulting in high, medium and low-technology groups. The data appendix at the end of this paper provides detailed information on the classification of industries in the classes defined above.

Due to the absence of information on wage shares, we use employment data to observe the occurrence of SBTC. This approach is justified by Machin and Van Reenen, who report: "(w)e have (...) estimated employment share equations that reveal broadly supportive results" (p.1230). In addition, their Appendix I proves this statement statistically. In the next section we econometrically explore our data.

3. Empirical Model of Knowledge Spillovers, Changes in Skill Structure and Technology

A. Econometric Approach

Given the restrictions of the data used to estimate the presence of SBTC, the rationale of the econometric procedure is to test whether a change in the employment share of high-skilled workers can be attributed to traditional factors (capital and income) or specific technology variables (R&D intensity and spillovers). Following the simple restricted variable translog cost function introduced by Christensen, Jorgenson and Lau (1973) and used by Machin and Van Reenen, and defining industries as *i*, countries as *j* and years as *t*, we can obtain such an analysis by defining inter-industry differences, *SHARE*, as the share of high-skilled employment in total employment[8]

$$\textbf{(1)} \qquad SHARE_{jt} = \varphi_j + \alpha_j \log(K_{ijt}) + \beta_j \log(Y_{ijt}) + \gamma_j (TECH_{ijt}),$$

where *K* is the quasi-fixed capital stock, *Y* is value added, and *TECH* is a measure of the stock of technology.[9] This stock of technology consists of three R&D variables: own R&D effort and two indirect R&D stocks, which are made explicit in equation (4) and (5). The definition of *TECH* rests on the approach first suggested by Griliches and Mairesse (1984) in a micro-level study to examine the effects of R&D on productivity.

[8] Adams (1999) provides the derivation of this type of cost function. The system of equations (1) is often tested in a seemingly unrelated regression because it assumes the right-hand side of the equations to be independent of the error terms.

[9] Note that the translog cost function is restricted in terms of the capital stock. The capital stock is assumed to be quasi fixed in our setup because data on capital cost are not available at sector level. This means that our time series do not take into account the possible fluctuations. However, equation (6) introduces a dummy variable which captures such effects.

The capital and own R&D stock are determined using the perpetual inventory method as

(2) $$K_t = (1-\phi)K_{t-1} + I_{Kt}$$

and

(3) $$RD_t = (1-\chi)RD_{t-1} + I_{RDt},$$

where ϕ and χ are the depreciation rates with respect to the capital and own R&D stock, respectively, and I_{Kt} and I_{RDt} equal the (annual) investments in both stocks.[10]

To construct an estimate of the industry R&D spillovers, Jaffe (1986) and (1988) has introduced a technical similarity method, which measures for each firm the available pool of outside R&D, with the R&D of other firms being weighted inversely to their estimated technical distance from each others research results.[11] Here we apply a similar method proposed by Verspagen (1997b) to measure so-called "knowledge" spillovers.[12] This matrix is built using data from the European Patent Office (EPO), which assigns each patented invention to a single technology class, and one or several supplementary

[10] The initial capital and knowledge stocks are defined in the following manner $K_0 = (I_{K1})/(\phi + 0.05)$ and $RD_0 = (I_{RD1})/(\chi + 0.05)$. This is in line with the definitions suggested by Griliches (1980). With regard to the capital stock we take into account a depreciation rate of 5%, and with respect to the knowledge stock we consider a depreciation rate of 15%, which is also applied by Adams (1999).

[11] Griliches (1992) contains a discussion of notorious difficulties in tracking down spillovers.

[12] The construction of the matrix used here can be compared to Scherer's technology flow tables (Scherer, 1982) and to the one known as the Yale matrix constructed by Putnam and Evenson (1994) and applied by Kortum and Putnam (1997). However, the Yale matrix is aimed at measuring rent spillovers, while the matrix we use is aimed at measuring "knowledge" spillovers. The other two matrices of Verspagen are aimed at (i) measuring rent spillovers, as in Griliches (1979); and (ii) measuring spillovers on the basis of patent citation information using data from the United States Patent Office (USPO), as in Putnam and Evenson (1994).

technology classes.[13] A concordance scheme between the technical classes and industries assigns both the technology class and the supplementary technology class to an industry. The technology class is taken as an indicator of the industry that generates the knowledge, and the supplementary technology class is taken as an indicator of a spillover-receiving firm.

This matrix is used to construct "indirect R&D stocks" by summing R&D performed by firms in different sectors and different countries, which enables us to measure the extent to which a sector profits from R&D efforts in another sector. This is a more rigorous approach than the one applied in Coe and Helpman (1995), because we assume a more advanced weighting scheme for sectoral technology linkages; these linkages are based on the data compiled from the EPO data. Their analysis is also modified here, because the matrix is used in such a way that it is able to capture inter-sectoral spillovers, while import shares capture the international extent and distribution of spillovers. Coe and Helpman use implicitly equal fixed weights for both measures by not splitting them in these two components.[14]

The domestic indirect knowledge stock (*IRD*) for industry *i* is defined, as in Verspagen (1997a), as

$$IRD_{it} = \sum_{k} \omega_{ik} RD_{kt} (1 - m_{kt}) \tag{4}$$

and the foreign knowledge stock (*IRF*) for the same sector is defined as

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[13] The indirect knowledge stocks are constructed using the EPO matrix, which can be obtained from the Data Appendix.

[14] Keller (1998) also provides a critical assessment of the findings of Coe and Helpman (1995). He finds that it is doubtful that patterns of international trade by themselves are important in driving R&D spillovers.

$$IRF_{it} = \sum_{f=1,\ldots,F} \sum_{k} \omega_{ik} RD_{fkt} s_{fkt} m_{kt}. \quad \textbf{(5)}$$

In equations (4) and (5) ω_{ik} is defined as the part of R&D performed by sector k that spills over to sector i and m_k is the import share of sector k.[15] In (5) F is the number of trading partners that are taken into consideration, in this case thirteen.[16] The variable labeled s_{fk} gives us the import share of sector k from country f. The import-weight m is taken as an indicator of the degree of interaction between the countries involved, which is likely to have an impact in terms of to what extent spillovers flow between countries.

Finally, we time difference equation (1) to sweep out the correlated industry-specific fixed effects. The stochastic form of the estimating equation is then

$$\textbf{(6)} \quad \begin{aligned} \Delta SHARE_{jt} &= \alpha_j \Delta \log(K_{ijt}) + \beta_j \Delta \log(Y_{ijt}) \\ &+ \gamma_j \Delta(RD/Y)_{ijt} + \delta_j \Delta(IRD/Y)_{ijt-1} + \zeta_j \Delta(IRF/Y)_{ijt-1} + \eta_{jt} D_{jt} + u_{ijt}, \end{aligned}$$

with Δ being a difference operator and u a random error term. In comparison with equation (1), (6) uses the change in *RD/Y*, *IRD/Y* and *IRF/Y* as the variable measuring the change in the technology stock, i.e., $\Delta(TECH)$. In this specification, *IRD/Y* and *IRF/Y*, composed in equations (4) and (5), measure the change in "indirect R&D effort" or spillovers. Notice also that a country-specific time dummy D_{jt} is included, which captures exogenous shocks. Finally, the way in which the R&D stocks are constructed assumes that R&D becomes effective immediately, whereas in general R&D effort becomes effective only after a certain

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[15] It is important to note that the diagonal of the matrix with respect to the calculation of the domestic knowledge stock is put at zero to exclude the problem of multicollinearity, i.e., $\omega_{jj} = 0$. See Van Meijl (1995) and Verspagen (1997b).

[16] We assume 14 OECD countries from which trade occurs. Besides Finland, France, Germany, Japan, the United Kingdom and the United States, these countries are Australia, Canada, Denmark, Italy, the Netherlands, Norway, Spain and Sweden. We are aware that some trade is neglected by taking only 14 countries, but on average over 90% of all trade is covered.

lag. To overcome this problem *IRD* and *IRF* are lagged one period.

B. Estimation Results

To get a grasp of the data, we first start with an analysis of the changes in upgrading of high-skilled labor on the impact of R&D. Hence, Table I reports the results of estimating these basic regressions of changes in R&D intensity[17] on changes in skill upgrading of high-skilled labor. We have divided the total high-skilled labor force into three categories (total high-skilled, white-collar high-skilled and S&Es) and four time periods (1975-1980, 1980-1985, 1985-1990 and 1990-1995). In addition, the same regressions are performed on industries categorized as “high technology” and “low technology”.

The first column reports the results of R&D intensity on changes in employment shares of high-skilled labor. In almost all cases, the estimated coefficients on R&D intensity are positive (with the exception of the low-technology sample in the United States) and significant at a five percent level. Only some of the results found for Finland (total sample), Japan (total and low-technology sample), the United Kingdom (low-technology sample) and the United States (low-technology sample) are not significant.

When we estimate the changes in employment shares of white-collar high-skilled workers (column 2) instead of total high-skilled employment, all coefficients are positive and all but one case (France low-technology sample) are significant at a five percent level. A remarkable result is that particularly the coefficients for the high-technology samples are significantly higher, whereas the coefficients for the low-technology sample are notably lower. This observation underlines the fact that the phenomenon of skill-upgrading is much

[17] Since we take R&D stocks (*RD*) instead of R&D flows, it is necessary to also take the time difference of the subsequent R&D intensity (*RD*/*Y*). The same argument holds true of the computation of spillovers *IRD*/*Y* and *IRF*/*Y*.

more present in high-technology industries than in low-technology industries. The coefficients are higher for two of the three countries (United Kingdom and United States), which can be contrasted with the results of Machin and Van Reenen, and lower for Japan. This shows that their analysis, at least for the United Kingdom and the United States, underestimated the change in employment shares due to changes in R&D intensity.

Finally, the third column of Table I shows the employment share changes for a particular kind of white-collar high-skilled labor: S&Es. Intuitively, we expect a positive relationship between changes in R&D intensity and changes in employment shares of S&Es. Indeed the results indicate that for all but one case (United States low-technology sample) the coefficients are positive and mostly significant at a five percent level (except for the Total, France, Germany and United Kingdom low-technology sample and the entire United States sample). Again, the changes in high-technology industries are remarkably higher than in the industry as a whole. However, S&Es do not seem to have profited as much from the change in R&D intensity as the other white-collar high-skilled workers, since the coefficients in the third column of Table I are mostly lower than the coefficients in the second column.

This indicates that other white-collar high-skilled workers such as legislators, senior officials, managers and other professionals have profited – in terms of employment shares – much more from increased effort put in R&D, which stresses the increasing importance of judicial, managing, “networking” and “communicating” skills in firms. Particularly, the new cluster of ICTs requires other skills and schooling. In this regard, Reich (1993) identifies “knowledge” and “information” workers or “symbolic analysts”. Bresnahan (1999) states that the mechanism does not work through managers and professionals literally using a computer. Instead, ICTs change the organization of bureaucratic production at the firm, industry and even multi-industry level.[18]

INSERT TABLE I OVER HERE

The results of implementing the more detailed approach of equation (6) are shown in Table II. First, we have regressed the change in the white-collar high-skilled employment share on the change in the growth of the capital stock and output, on the change in R&D intensity for three samples (total, high-technology and low-technology) and unreported country-specific time dummies. In addition, we have tested whether or not a constant returns to scale (crs) specification can be used to estimate this change. The results of the F-test are that crs can only be accepted for the low-technology sectors. In all other cases we have to reject the hypothesis of crs.[19]

In all six regressions R&D intensity is a significant variable explaining the change in white-collar high-skilled employment shares. This result is stronger in the crs estimates than in the non-crs estimates. In the non-crs estimates, the effect of the change in capital stock growth is a significant contributor in explaining the change in employment shares. The coefficient is strongly significant in all regressions pointing toward the embodiment of new technology in capital-intensive production methods. The change in growth of output does not seem to be important and the capital-output ratio is not significant either.

[18] This leads to an organizational complementarity between ICTs and highly skilled white-collar workers – see also Aghion, Caroli and García Peñalosa (1999). DiNardo and Pischke (1997) – in a critical assessment of Krueger's (1993) findings regarding the wage premium of computer users – reinforce Bresnahan's theory by providing evidence that not computers and ICTs as such are complementary to human capital, but that the complementarity between ICTs and high-skilled workers is to be found at the level of the firm and industry rather than at the level of the individual worker. In addition to the introduction of ICTs, communication and judicial skills complementary to computer skills are essential to observe possible niches and threats in an increasingly global market.

[19] The level of significance for which the hypothesis of crs is rejected, is 1% for the white-collar total, S&E total and S&E high-technology sample and 5% for the white collar high-technology sample.

If we include the change in domestic (*IRD*) and foreign (*IRF*) knowledge spillover intensities, we are able to explain an additional part of the change in the white-collar high-skilled employment share. It turns out that for the sample as a whole and in the high-technology sample, domestic knowledge spillovers significantly contribute to the change in employment shares. In the low-technology industries this observation cannot be made. In these industries R&D intensity is the major variable besides capital that explains the change in employment shares. Soete and Ter Weel (1999) argue in this regard that the significance of domestic knowledge spillovers confirms the growing economic and policy consensus on the importance of knowledge for industrial competitiveness which is closely related to the emergence of ICTs. This has resulted in a dramatic decline in the price of information processing – in a technologically driven digital convergence between communication and computer technology – and a rapid growth of international electronic networking. Indeed the coefficients regarding the indirect foreign knowledge spillovers are all significant, which confirms this observation. In addition, taking into account the construction of *IRF*, these results also refer to the debate on the impact of international trade. Acemoglu (1999) refers in this regard directly to the impact of international trade on skill upgrading and wage inequality, while Wood (1998) and Francois and Nelson (1998) refer to the increasing effects of globalization and the subsequent new opportunities for trade as a major cause of changes in employment shares and the subsequent wage inequality.

If once again we investigate S&Es as a separate group of white-collar high-skilled workers, we find that for the sample as a whole changes in R&D intensity and the growth of the capital stock explain the changes in employment shares.[20] Spillovers do not seem to contribute. This is of course a straightforward observation, since S&Es are the knowledge-creating workers using R&D and capital resources to develop and engage themselves in

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[20] Again, the crs estimates outperform the non-crs estimates, except for the low-technology sample.

innovative activities, whereas other white-collar workers absorb their knowledge either directly by using the codifiable part of this knowledge or indirectly by profiting from spillovers and technical change in general. The results for the high-technology sample are comparable, but in the low-technology sample none of the variables are able to explain the change in the employment share of S&Es.

INSERT TABLE II OVER HERE

4. Conclusions

These observations have a number of important implications for the notion of SBTC both in an empirical and in a theoretical sense. Empirically, we have established that both domestic and international spillovers are important contributors to the change in the employment share of white-collar high-skilled workers. For the total sample the coefficients of the spillover variables are comparable in size to the coefficients of R&D; it is what has been characterized as the codification of information and knowledge – see, e.g., Cowan, David and Foray (1999). Bresnahan (1999) argues in this regard that ICTs have not been substitutable for high levels of human cognitive skills nor for "people skills" in organizations and industries, but that the strategic use of ICTs has raised the demand for high-skilled workers. In addition, low-skilled workers are facing substitution from machine decision making to human decision making, for which their skills are not adequate or simply too low.

Theoretically, our results extend the approaches by Acemoglu (1999) and Dinopoulos and Segerstrom (1999) by stressing the international dimension of R&D merely by its ability to speed up technical change not only directly, but also indirectly at an increasing rate. Particularly, the introduction of new ICTs contributes to the increased potential for international codification and transferability. The possibility of ICTs to codify information and knowledge over both distance and time brings about more global access. Knowledge, including economic knowledge, becomes to some extent globally available. While the local capacities to use or have the competence to access such knowledge vary widely, the access potential is present. In other words, ICTs bring to the forefront the enormous potential for catching up, based upon cost advantages and economic transparency of (dis-)advantages, while stressing at the same time the crucial skills required in the capacity to access (international) codified knowledge. Managers, professionals and legislators are particularly important in this regard, and we have found that they profit most from recent technical change.

Data Appendix

A. Skills

In the cases where data were available in ISCO-88 format, occupations were aggregated by the OECD secretariat at different levels as follows:

White-collar high-skilled: legislators, senior officials and managers (group 1), professionals (group 2), technicians and associate professionals (including S&Es) (group 3). White-collar low-skilled: clerks, service workers (group 4), shop and market sales workers (group 5). Blue-collar high-skilled: skilled agricultural and fishery workers (group 6), craft and related trade workers (group 7). Blue-collar low-skilled: plant and machine operators and assemblers (group 8), elementary occupations (group 9).

B. Technology

The following 22 sectors are included in our analysis (ISIC code in parentheses): food, beverages, tobacco (31), textiles, leather, footwear (32), wood and wooden products (33), printing and publishing (34), chemicals with the exception of pharmaceuticals (351+352-3522), pharmaceuticals (3522), refined oil and related products (353+354), rubber and plastic products (355+356), glass, stone and clay (36), ferrous basic metals (371), non-ferrous basic metals (372), simple metal products (381), machinery (382-3825), computers and office machines (3825), electrical goods (383-3832), radio, TV, telecommunication equipment and electronic components (3832), ships and boats (3841), automobiles (3843), aerospace (3845), other transport equipment (384-3841-3843-3845), instruments (385) and other manufacturing (39).

The high-technology industries are: aerospace (3845), computers and office machines (3825), electrical goods (383-3832), pharmaceuticals (3522), and instruments

(385). The low-technology industries: food, beverages, tobacco (31), textiles, leather, footwear (32), wood and wooden products (33), printing and publishing (34), refined oil and related products (353+354), glass, stone and clay (36), ferrous basic metals (371), simple metal products (381) and ships and boats (3841).

C. EPO Matrix

INSERT EPO MATRIX OVER HERE

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TABLE I

BASIC REGRESSIONS OF CHANGES IN UPGRADING ON R&D INTENSITY – FIVE YEAR CHANGES: 1975-1980, 1980-1985, 1985-1990 AND 1990-1995

		Five-year changes in high-skilled employment share		
		Total high-skilled	White-collar high-skilled	Scientists & engineers
Total	Total	.008 (.003)	.020 (.004)	.007 (.001)
	Sample size	313	313	402
	High-tech	.023 (.005)	.039 (.009)	.040 (.007)
	Sample size	69	69	91
	Low-tech	.015 (.004)	.016 (.003)	.001 (.001)
	Sample size	130	130	167
Finland	Total	.003 (.004)	.015 (.003)	
	Sample size	66	66	
	High-tech	.019 (.012)	.033 (.012)	
	Sample size	15	15	
	Low-tech	.011 (.007)	.020 (.003)	
	Sample size	27	27	
France	Total	.031 (.020)	.046 (.018)	.004 (.001)
	Sample size	44	44	84
	High-tech	.137 (.065)	.150 (.058)	.030 (.011)
	Sample size	10	10	17
	Low-tech	.029 (.025)	.029 (.025)	.001 (.000)
	Sample size	18	18	36
Germany	Total	.027 (.006)	.017 (.004)	.003 (.001)
	Sample size	36	36	87
	High-tech			.030 (.013)
	Sample size			19
	Low-tech	.024 (.006)	.018 (.004)	.000 (.001)
	Sample size	16	16	36
Japan	Total	.012 (.019)	.022 (.007)	.021 (.003)
	Sample size	38	38	64
	High-tech			.059 (.008)
	Sample size			15
	Low-tech	.009 (.225)	.020 (.007)	.005 (.001)
	Sample size	18	18	27

		Five-year changes in high-skilled employment share		
		Total high-skilled	White-collar high-skilled	Scientists & engineers
U.K.	Total	.015 (.008)	.030 (.011)	.013 (.004)
	Sample size	66	66	87
	High-tech	.051 (.023)	.093 (.033)	.044 (.013)
	Sample size	15	15	20
	Low-tech	.020 (.027)	.026 (.012)	.001 (.001)
	Sample size	227	227	36
U.S.	Total	.037 (.025)	.052 (.020)	.008 (.009)
	Sample size	63	63	80
	High-tech	.024 (.009)	.025 (.001)	.026 (.021)
	Sample size	15	15	20
	Low-tech	-.013 (.019)	.008 (.003)	-.003 (.002)
	Sample size	24	24	32

Standard errors in parentheses. The time periods for Finland concerning the shares of high-skilled white-collar employment are 1975-1980, 1980-1985 and 1985-1990; for France 1982-1985 and 1985-1990; for Germany and Japan 1980-1985 and 1985-1990; for the United Kingdom 1981-1984, 1986-1988 and 1988-1992; and for the United States 1983-1985, 1985-1990 and 1990-1994. The column Scientists and Engineers shows for all countries the period 1975-1995 divided in five year periods, i.e. 1975-1980, 1980-1985, 1985-1990 and 1990-1995. For Germany, the figures in the first three periods apply to West Germany. For the final period data are taken from after the unification: 1991-1995.

TABLE II

CHANGE IN HIGH-SKILLED EMPLOYMENT SHARE EQUATIONS IN MANUFACTURING

			log (*K*/*Y*)	log (*K*)	log (*Y*)	(*RD*/*Y*)	(*IRD*/*Y*)	(*IRF*/*Y*)	Sample size	F-value
White-collar	Total	CRS	.000 (1.092)			.003 (2.027)			310	22.601
high-skilled			.000 (1.045)			.003 (2.020)	.003 (3.814)		310	15.205
			.000 (1.092)			.002 (1.320)		.001 (4.873)	310	16.206
			.000 (1.070)			.004 (2.168)	.002 (2.324)	.001 (1.999)	310	11.473
		Relax CRS		.066 (6.530)	.005 (1.001)	.003 (1.637)			310	
				.064 (6.412)	.003 (1.002)	.003 (1.489)	.002 (3.431)		310	
				.067 (6.713)	.004 (1.003)	.003 (1.753)		.003 (3.667)	310	
				.065 (6.563)	.004 (1.057)	.003 (1.992)	.001 (1.680)	.002 (2.108)	310	
	High-tech	CRS	.000 (1.419)			.014 (2.359)			67	6.915
			.000 (1.457)			.013 (2.360)	.003 (3.203)		67	6.199
			.000 (1.538)			.017 (3.014)		.002 (1.955)	67	6.774
			.000 (1.511)			.015 (2.711)	.002 (1.755)	.002 (1.938)	67	6.368
		Relax CRS		.063 (3.539)	.013 (1.004)	.009 (1.874)			67	
				.060 (3.530)	.009 (1.014)	.008 (1.892)	.001 (1.895)		67	
				.059 (3.482)	.015 (1.016)	.013 (2.115)		.003 (3.249)	67	
				.058 (3.467)	.012 (1.021)	.011 (1.823)	.001 (1.825)	.002 (1.974)	67	

			log (*K*/*Y*)	log (*K*)	log (*Y*)	(*RD*/*Y*)	(*IRD*/*Y*)	(*IRF*/*Y*)	Sample size	F-value
	Low-tech	CRS	.000 (.525)			.036 (3.302)			133	2.012
			.000 (.521)			.036 (3.289)	.000 (.070)		133	1.194
			.000 (.523)			.036 (3.312)		.005 (2.008)	133	1.598
			.000 (.526)			.036 (3.301)	.000 (.165)	.005 (2.016)	133	1.185
		Relax CRS		.063 (2.123)	-.006 (-.486)	.027 (1.981)			133	
				.063 (2.132)	-.006 (-.510)	.027 (1.945)	.001 (.272)		133	
				.064 (2.157)	-.006 (-.507)	.027 (1.970)		.005 (1.985)	133	
				.064 (2.141)	-.006 (-.505)	.027 (1.956)	.000 (.027)	.005 (1.946)	133	
Scientists and	Total	CRS	.000 (1.092)			.008 (3.806)			383	15.079
Engineers			.000 (1.066)			.007 (3.302)	.001 (.145)		383	15.040
			.000 (1.013)			.007 (3.401)		.062 (1.208)	383	15.040
			.000 (1.025)			.007 (3.163)	.001 (.181)	.065 (1.212)	383	15.000
		Relax CRS		.082 (5.781)	-.000 (-1.369)	.006 (3.254)			383	
				.082 (5.771)	-.000 (-1.364)	.006 (2.913)	.000 (.051)		383	
				.081 (5.669)	-.000 (-1.323)	.006 (3.024)		.030 (.606)	383	
				.081 (5.663)	-.000 (-1.337)	.006 (2.838)	.001 (.218)	.033 (.641)	383	
	High-tech	CRS	.001 (.937)			.042 (4.587)			78	8.291
			.001 (1.049)			.049 (4.597)	-.025 (-1.226)		78	8.222
			.001 (.933)			.041 (4.378)		.091 (.609)	78	8.140
			.001 (1.085)			.049 (4.611)	-.033 (-1.523)	.171 (1.090)	78	7.704

		log (*K*/*Y*)	log (*K*)	log (*Y*)	(*RD*/*Y*)	(*IRD*/*Y*)	(*IRF*/*Y*)	Sample size	F-value
	Relax CRS		.193 (4.336)	-.000 (-.967)	.032 (3.749)			78	
			.192 (4.344)	-.001 (-1.079)	.039 (3.929)	-.024 (-1.316)		78	
			.202 (4.313)	-.000 (-.949)	.033 (3.781)		-.091 (-.643)	78	
			.195 (4.148)	-.001 (-1.063)	.038 (3.871)	-.023 (-1.154)	-.029 (-.192)	78	
Low-tech	CRS	.000 (.006)			.001 (1.398)			167	.000
		-.000 (-.104)			.001 (.861)	.003 (.692)		167	.000
		-.000 (-.058)			.001 (1.076)		.036 (.550)	167	.000
		-.000 (-.104)			.001 (.859)	.003 (.420)	.003 (.030)	167	.000
	Relax CRS		.012 (1.528)	-.000 (-.059)	.001 (1.056)			167	
			.011 (1.416)	.000 (.011)	.001 (.736)	.002 (.407)		167	
			.011 (1.452)	-.000 (-.021)	.001 (.878)		.020 (.301)	167	
			.011 (1.411)	.000 (.011)	.001 (.733)	.002 (.273)	-.001 (-.012)	167	

T-values in parentheses. The time periods for Finland concerning the shares of high-skilled white-collar employment are 1975-1980, 1980-1985 and 1985-1990; for France 1982-1985 and 1985-1990; for Germany and Japan 1980-1985 and 1985-1990; for the United Kingdom 1981-1984, 1986-1988 and 1988-1992; and for the United States 1983-1985, 1985-1990 and 1990-1994. The column concerning Scientists and Engineers shows for all countries the period 1975-1995 divided in five year periods, i.e. 1975-1980, 1980-1985, 1985-1990 and 1990-1995. For Germany, the figures in the first three periods concern West Germany. For the final period data are taken from after the unification: 1991-1995.

The *F*-value is defined as $F \quad \frac{(\; e_R^2 \quad e_{UR}^2)/m}{e_{UR}^2/(N \quad k)}$, where e_R^2 resp. e_{UR}^2 is the residual sum of squares of the restricted resp. unrestricted regression, *m* is the number of linear restrictions, *k* is the number of parameters in the unrestricted regression and *N* is the number of observations. The test statistic follows the *F* distribution with *m*, (*N*-*k*) degrees of freedom. The decision rule to test the null hypothesis of constant returns to scale is: if the computed *F* exceeds $F\,(m, N \quad k)$, where $F\,(m, N \quad k)$ is the critical *F* at the level of significance, we may reject the null hypothesis of constant returns to scale, otherwise we may accept it.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1e+34	.000	.007	.000	.004	.284	.263	.001	.000	.002	.000	.000	.019	.091	.000	.002	.003	.000	.001	.000	.000	.039	.010
	.006	.000	.002	.026	.085	.005	.001	.016	.018	.002	.091	.042	.249	.003	.012	.013	.000	.006	.002	.004	.050	.083
	.003	.017	.000	.204	.074	.008	.000	.020	.017	.001	.000	.247	.096	.004	.004	.018	.001	.006	.002	.016	.092	.061
	.003	.088	.003	.000	.105	.022	.003	.006	.011	.008	.003	.034	.163	.041	.006	.024	.001	.004	.001	.001	.105	.087
	.013	.018	.000	.011	.000	.167	.025	.002	.039	.004	.002	.018	.085	.004	.007	.013	.000	.001	.000	.001	.043	.014
	.025	.002	.000	.003	.261	.000	.006	.000	.001	.000	.000	.003	.031	.000	.000	.001	.000	.000	.000	.000	.023	.002
	.005	.003	.000	.007	.371	.070	.000	.000	.029	.005	.000	.042	.111	.004	.005	.046	.000	.001	.000	.000	.106	.004
	.006	.126	.025	.016	.046	.005	.005	.000	.012	.002	.001	.119	.142	.007	.007	.156	.000	.093	.001	.023	.144	.029
	.003	.004	.007	.042	.135	.008	.001	.001	.000	.005	.001	.107	.212	.002	.008	.020	.001	.005	.001	.001	.049	.020
	.000	.003	.000	.002	.035	.002	.001	.000	.024	.000	.187	.095	.123	.001	.001	.030	.000	.007	.000	.000	.021	.004
	.000	.002	.000	.016	.069	.007	.003	.001	.020	.298	.000	.085	.092	.002	.008	.043	.000	.007	.000	.001	.015	.010
	.004	.003	.016	.034	.027	.004	.002	.004	.038	.012	.009	.000	.187	.004	.016	.052	.002	.026	.002	.004	.051	.024
	.029	.020	.002	.016	.069	.014	.003	.002	.020	.007	.006	.110	.000	.005	.007	.024	.002	.039	.003	.004	.060	.030
	.000	.001	.001	.006	.006	.001	.000	.000	.001	.000	.000	.008	.012	.000	.075	.027	.000	.004	.000	.002	.075	.019
	.000	.002	.000	.001	.017	.001	.000	.000	.004	.001	.001	.011	.010	.056	.000	.187	.000	.001	.001	.005	.065	.008
	.001	.002	.001	.005	.008	.000	.000	.001	.009	.002	.007	.038	.029	.020	.355	.000	.000	.012	.001	.006	.059	.005
	.000	.004	.001	.002	.004	.000	.000	.001	.004	.000	.000	.038	.088	.002	.001	.012	.000	.444	.010	.049	.035	.015
	.001	.005	.005	.057	.019	.001	.000	.044	.039	.002	.001	.085	.194	.003	.007	.027	.003	.000	.004	.080	.033	.023
	.000	.000	.003	.004	.008	.000	.000	.005	.005	.001	.000	.062	.153	.006	.014	.028	.029	.133	.000	.015	.077	.024
	.000	.001	.002	.003	.002	.000	.000	.001	.003	.001	.000	.044	.061	.003	.005	.065	.004	.479	.003	.000	.041	.007
	.011	.003	.001	.022	.071	.111	.005	.001	.005	.002	.001	.026	.085	.044	.038	.035	.000	.005	.002	.002	.000	.019
	.009	.076	.003	.034	.026	.002	.001	.004	.009	.001	.001	.041	.121	.189	.042	.031	.003	.008	.001	.006	.110	.000

1. Food, beverages and tobacco, 2. Textiles, apparel and leather, 3. Wood products and furniture, 4. Paper, paper products and printing, 5. Pharmaceuticals, 6. Other chemicals, 7. Refined oil and related products, 8. Rubber and plastic products, 9. Glass, stone and clay, 10. Ferrous metals, 11. Non-ferrous metals, 12. Metal products, 13. Office and computing equipment, 14. Non-electrical machinery, 15. Radio, TV and communication equipment, 16. Electrical machinery, 17. Shipbuilding, 18. Automobiles, 19. Aerospace, 20. Other transport, 21. Instruments, 22. Other manufacturing

Columns are concerned with absorbing or receiving knowledge spillovers, and rows with generating knowledge

Source: Verspagen (1997b).