CROSS-COUNTRY ANALYSIS OF PRODUCTIVITY AND SKILLS AT SECTOR LEVEL

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Cross-country analysis of productivity and skills at sector level

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Sector Skills Development Agency: Research Series
Foreword

In October 2002 the Department for Education and Skills formally launched Skills for Business (SfB), a new UK-wide network of employer-led Sector Skills Councils (SSCs), supported and directed by the Sector Skills Development Agency (SSDA). The purpose of SfB is to bring employers more centre stage in articulating their skill needs and delivering skills-based productivity improvements that can enhance UK competitiveness and the effectiveness of public services. The remit of the SSDA includes establishing and progressing the network of SSCs, supporting the SSCs in the development of their own capacity and providing a range of core services. Additionally the SSDA has responsibility for representing sectors not covered by an SSC and co-ordinating action on generic issues.

Research, and developing a sound evidence base, are central to the SSDA and to Skills for Business as a whole. It is crucial in: analysing productivity and skill needs; identifying priorities for action; and improving the evolving policy and skills agenda. It is vital that the SSDA research team works closely with partners already involved in skills and related research to generally drive up the quality of sectoral labour market analysis in the UK and to develop a more shared understanding of UK-wide sector priorities.

The SSDA is undertaking a variety of activities to develop the analytical capacity of the Network and enhance its evidence base. This involves: developing a substantial programme of new research and evaluation, including international research; synthesizing existing research; developing a common skills and labour market intelligence framework; taking part in partnership research projects across the UK; and setting up an expert panel drawing on the knowledge of leading academics, consultants and researchers in the field of labour market studies. Members of this panel will feed into specific research projects and peer review the outputs; be invited to participate in seminars and consultation events on specific research and policy issues; and will be asked to contribute to an annual research conference.

The SSDA takes the dissemination of research findings seriously. As such it has developed this dedicated research series to publish all research sponsored by the SSDA and results are being made available in both hard copy and electronically on the SSDA website.

Lesley Giles
Director of Strategy & Research at the SSDA

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EXECUTIVE SUMMARY

The SSDA commissions research to develop understanding of key areas around its strategic goals, one of which is to work with partners to deliver improvements in productivity and business performance through skills development. This research project, undertaken for the SSDA by NIESR, seeks to explore the contribution of skills to productivity and in particular to understand sectoral differences in international productivity variations and the impact of skills.

Background

In the light of research evidence that workforce skills and training are positively related to productivity performance at sector and firm level, it is perhaps surprising that some international comparisons of relative productivity performance at sector and national level only attribute relatively small proportions of the identified productivity gaps to cross-country differences in workforce skill levels.

In this study we identify a number of reasons why the impact of skills on relative performance at sector and national level may not be captured through standard growth accounting and regression techniques used in earlier international comparisons, for example:

- Difficulties in measuring skills
- Misspecification of production functions in econometric analysis
- Failure to take account of potential complementarities between skills and other production inputs
- Failure to take account of mechanisms by which skills may have an *indirect* impact on productivity at sector and national level, for example, by contributing positively to the generation and distribution of economically valuable knowledge.

Our approach

Using new measures of skills derived from data on educational attainments and average hourly wages by qualification groups, we present a number of new analyses on sector-level datasets for the UK, US, France, Germany and the Netherlands in order to explore the links between workforce skills and productivity.

We begin by estimating a production function with and without human capital as an independent variable in order to observe the effects of skills on average labour productivity (i.e. on output controlling for labour inputs). The model is then gradually developed to allow for differences in the effects of human capital across countries and industries. We use panel estimation methods to exploit the combined time series and cross-sectional dimensions of our data, which enables us to control for industry-specific factors that might otherwise go undetected, and thus enhance understanding of international productivity differences of industry. We estimate 'catch-up' models of productivity growth which emphasise the scope for sectors in different countries with lower initial levels of productivity to grow faster than productivity leaders by using skilled labour to adopt and make use of technologies and work practices developed elsewhere. We also investigate the complementarity between different types of physical capital and skills and the role of skill-related externalities, or spillover effects, in which skilled labour may facilitate the identification and implementation of new knowledge and ideas and thus contribute to innovation and productivity. Thus, this study seeks to address many of the reasons why skills may not be captured through standard growth accounting and regression techniques.

Results

Our main findings are as follows:

1. Human capital *levels* are strongly related to average labour productivity levels across a wide range of sectors. *Growth* in human capital also contributes positively to productivity growth rates over fairly long periods of time in 'follower countries' which are seeking to bridge gaps in productivity between themselves and the 'leader country' at sector level. However, this catching-up effect tends to unfold over a relatively long timeframe. There is little evidence of growth in human capital having a short-term impact on productivity growth.

2. When we relax assumptions of full use of resources and allow for varying degrees of inefficiency in the use of production inputs, we find evidence that inefficiency is negatively related to human capital. Thus skills contribute indirectly as well as directly to labour productivity performance by helping to improve the way that all

resources are utilised. The UK performs well on technical efficiency in many sectors where it compares less favourably on average labour productivity. This suggests that the UK productivity disadvantage in those sectors is more due to shortcomings in terms of resource levels (for example, relatively low physical capital per hour worked) than to inefficiency in the use of resources.

3. At different times in different sectors and countries, workforce skills have contributed positively to productivity performance by facilitating the adoption and efficient use of new technologies such as Information and Communication Technologies (ICTs). However, the extent and nature of such complementarities appears to vary strongly between countries. As new technologies become established, the skill requirements associated with them may decline.

4. Human capital also contributes to productivity performance through positive contributions to Research and Development (R&D) and innovation. A key mechanism by which it may do so is through the development of 'absorptive capacity' at sector level, i.e. the capacity to make effective use of knowledge, ideas and technologies that become available through spillovers between firms, sectors and countries.

In the specific case of the UK it is notable in international comparisons that relative skill levels and relative productivity levels are frequently correlated at sector level. The evidence in this report suggests that many UK sectors which compare badly on workforce skill measures stand little chance of catching up with productivity leaders unless efforts are made to identify and fill key gaps in skills. Some of the sectors with the largest gaps in skills compared to other countries employ large numbers of people, for example, inland transport, retail and branches of engineering and vehicles.

Implications

The main findings of this report add to the urgency surrounding key recommendations made by the Leitch Review of Skills, for example:

- A stronger employer voice in vocational education and training provision to help meet skills needs and bridge the productivity gap

- Vocational qualifications to be made more relevant to the skills development needs of both employers and individuals to ensure that the skills acquired are those which will contribute most to improved productivity performance
- Improved incentives for individual workers to invest in their own skills development
- Greater data availability at sector level to help persuade employers of the benefits of increased investment in skills and training.

The pay-off to such improvements is unlikely to become evident in the short-term. However, our evidence suggests that skill improvements will contribute positively to productivity performance over the long term if they are combined with new investments in other production inputs with which skills are complementary, for example, new technologies and research and innovation.

1. Introduction

Over the long term, by operating with key partners, the Skills for Business network aims to address four strategic goals:

- Improvement in productivity, business and public services performance through specific strategic and targeted skills and productivity action;
- Reduction of skills gaps and shortages and anticipation of future needs;
- Increased opportunities to develop and improve the productivity of everyone in the sector’s workforce, including action to address equal opportunities;
- Improvement in the quality and relevance of public learning supply, including the development of apprenticeships, higher education and national occupational standards.

The SSDA commissions research to develop understanding in key areas around these specific goals, fill gaps in the existing knowledge and thus strengthen the evidence base on which policy and practice are developed. This study reports the findings of the research project “Understanding International Productivity Variations” to progress our understanding of variations in productivity between the UK and its international competitors and what underlies this by sector, to target more effective policy intervention. The research progresses existing econometric analysis to explore how skills can influence productivity directly and indirectly through externalities and complementarities.

There is now a great deal of research evidence to suggest that workforce skills and training are positively related to productivity performance at sector and firm level. Much of this literature was summarised by the National Skills Task Force (NSTF, 2000, Chapter 2). More recent contributions include Dearden et al. (2005) who find a strong association between workforce training and productivity at sector level in the UK and Haskel et al. (2003) who find that productivity performance at firm level is positively related to various measures of skill derived from the Employers Skill Survey.

In this context it may seem surprising that some international comparisons of relative productivity performance at national level, using growth accounting techniques, only attribute relatively small proportions of the identified productivity gaps to cross-country differences in workforce skill levels (O'Mahony and de Boer, 2002). Furthermore, a recent survey of econometric investigations of the impact of human capital on economic performance at national level concludes that, while the evidence of a positive effect for human capital is 'compelling', the empirical evidence is nonetheless 'still weak at various crucial points' (Sianesi and van Reenen, 2003: 192).

In spite of these findings, however, there are several reasons for believing that workforce skill differences may contribute to variations in international productivity performance in ways that are not easily captured through standard growth accounting and regression techniques. First, it is very difficult to derive adequate measures of workforce skill levels. Secondly, it is a feature of methodologies such as growth accounting that the respective contributions of different production inputs such as physical capital and workforce skills are evaluated separately and do not take account of potential complementarities between inputs – such as the contribution of workforce skills to the effective selection and utilisation of capital equipment. Thirdly, many studies of the relationship between skills and productivity have not sought to take account of mechanisms by which skills may have an *indirect* impact on productivity at sector and national level, for example, externalities – external effects of skills formation which raise the productivity of other workers besides those in receipt of training – and the potential contribution which workforce skills can make to the 'absorptive capacity' of firms, that is, their ability to identify and make use of knowledge which has been generated elsewhere.

In this report we present the results of new research which sheds light on all these issues, based on econometric analysis of two cross-country sector-level datasets. The first of these datasets – EPKE (Employment Prospects in the Knowledge Economy) – contains annual series for output, capital and labour inputs and workforce skills for 26 sectors in five countries (UK, US, France, Germany and the Netherlands) over the period 1979-2000. The second dataset – ISP (International Sector-level Productivity) – contains similar but more disaggregated data for 68 different sectors in the UK, US, France and Germany over a shorter time period (1995-2004). Both datasets cover a mix of manufacturing and service sectors.[1]

The report is ordered as follows: Section 2 discusses the issues surrounding measurement of labour quality and assesses recent growth accounting and econometric analyses of cross-country productivity performance at sector level. Section 3 provides descriptive statistics for both the EPKE and ISP datasets, including cross-country productivity and skills rankings at sector level. Sections 4-5 present estimates of the impact on average productivity levels and growth rates at sector level of cross-country differences in labour quality and various proxy measures designed to capture other channels by which skill differences might be expected to have indirect effects on relative productivity performance. Section 6 reports on the estimated relationship between skills and technical efficiency, making use of stochastic frontier analysis. Section 7 presents new evidence on the extent and nature of capital-skill complementarities. Section 8 investigates the links between workforce skills and measures of innovative performance and absorptive capacity at sector/country level. Section 9 summarises our main findings.

[1] EPKE is derived from a dataset which was initially prepared for a project funded through the Fifth Framework Programme of the European Union. ISP is derived from a dataset prepared for an international productivity comparisons study supported by the Department of Trade and Industry (DTI). We are grateful to the European Commission and the DTI for their support for these projects; these organisations are not responsible for views expressed in this report.

2. Cross-country comparisons of productivity and human capital: key research issues

This section describes the research foundations on which we have based our work. We discuss the difficulties of measuring human capital and then compare the standard growth accounting and econometric techniques used to assess the links between productivity and human capital in cross-country comparisons. Although human capital plays an important role in the theoretical analysis of economic growth, many researchers find that growth in measured human capital has only a small or non-existent impact on performance. We consider the possible reasons for such findings.

2.1 Definitions and measurement

Average Labour Productivity (ALP) is defined as the growth in average output per unit of labour input (for example, per worker or per worker-hour) over a specified period of time. By contrast, growth in another widely cited productivity measure – *Total Factor Productivity* (TFP), sometimes also referred to as Multi-Factor Productivity (MFP) – is defined as the increase in output that cannot be attributed to increases in the quantity and quality of physical capital, labour, materials and other inputs, for example, growth in output deriving from more efficient deployment of existing resources.

Thus TFP is evaluated as a residual after taking account of measured growth in other production inputs. As well as capturing improved efficiency in resource utilisation, it will also include the effects of 'disembodied' technical change, that is, technical improvements and innovations which are not embodied in measured capital inputs. Other variables which may be picked up by a TFP measure include economies of scale, capacity utilisation and measurement errors of different kinds.

'Human capital' is broadly defined by the OECD as 'the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being' (OECD, 2001:18). A narrower definition would focus on the skills and knowledge possessed by individuals which contribute to their productivity and for which they are paid by employers. The use of the term 'capital' in this context invokes the investments in education and training which are often necessary in order to acquire skills and knowledge. However, skills and knowledge can also be acquired through work experience, informal on-the-job learning and a variety of other means.

As an intangible asset, human capital is notoriously difficult to measure. In this paper we focus on education-based approaches to developing proxy measures of human capital since, for reasons of data availability, these are the most common measures used in cross-country analyses of the determinants of productivity and growth.[2] Education-based measures of human capital may generally be divided between:

- Education inputs – e.g. enrolments, years of schooling, indicators of education input quality (eg, class sizes)

- Education outputs – e.g. formal qualifications, indicators of education output quality (e.g. test scores, literacy standards)

Discussions in this area are sometimes hampered by the use of terms like 'attainments' (an output concept) to refer to input measures such as years of schooling. One example of this usage is in Barro and Lee (1993), the first of a series of papers describing a widely used multi-country dataset on years of completed schooling – a measure of attendance rather than attainment. One drawback of this is that the input measure will be overstated in countries where students are obliged to repeat certain years of schooling if they do not reach a minimum standard. In general, we suggest that education output measures such as formal qualifications – capturing something of what has actually been learned while undergoing education – are in principle to be preferred to education input measures such as attendance. However, since many skills are acquired in the workplace without formal certification, it is desirable to combine use of data on formal qualifications

[2] For a discussion of two other broad approaches to human capital measurement – cost-based and income-based approaches – see Le, Gibson and Oxley (2005).

with wage data which, under certain assumptions, may be regarded as indicative of worker productivity. We now go on to discuss recent growth accounting estimates which make use of this approach to comparing labour quality across countries at sector level.

2.2 Growth accounting

In order to assess the contribution of different production inputs such as physical capital and human capital to relative labour productivity performance at sector and/or national level, a common starting point is the productivity levels equivalent of growth accounting. This method was first rigorously set out in Solow (1957) and has been widely used in productivity studies ever since, in particular by Jorgenson and his collaborators (see, for example, Jorgenson, Gollop and Fraumeni, 1987). The theoretical underpinning for this approach is the neoclassical growth model, with underlying assumptions that all markets are competitive and that all factors in the production process are paid their marginal products, the sum of which exhausts all returns from pursuing those activities. In addition the use of value added to measure output involves the assumption that material input is separable from other inputs in the production function.

Under these assumptions TFP levels in country J relative to country K for industry *i* can be calculated using the Törnqvist discrete approximation to the Divisia index, given by:

(2.1) $$\ln(RTFP_{iJ,K}) = \ln(RY_{iJ,K}) - \alpha_{iJ,K}\ln(RL_{iJ,K}) - (1-\alpha_{iJ,K})\ln(RK_{iJ,K})$$

where $RY_{J,K}$ denotes value added in country J relative to country K (with nominal output converted to a common currency), RL is relative labour input, RK is relative capital stocks, and $\alpha_{J,K}$ is the share of labour in value added averaged over the two countries. Assuming constant returns to scale, the weight on capital is one minus labour's share of value added.

Analogously, comparing periods *t* and *t-1*, again letting *Y* denote real value added, L labour and K capital, and dropping the country subscript, the Törnqvist TFP index is given by:

(2.2) $\ln TFP_{i,t} - \ln TFP_{i,t-1} = (\ln Y_{i,t} - \ln Y_{i,t-1}) - \varpi_{il}(\ln L_{i,t} - \ln L_{i,t-1}) - (1-\varpi_{il})(\ln K_{i,t} - \ln K_{i,t-1})$

where ϖ_{il} is the share of labour in the value of output, averaged across periods *t* and *t-1*.

By estimating a variant of Equation (2.1), O'Mahony and de Boer (2002) decompose the gaps in ALP in 1999 between the UK and three comparator nations – the US, France and Germany – into three components: physical capital, skills and TFP. As shown in Table 2.1, inter-country differences in physical capital stocks per hour worked account for the single largest shares of the UK-US, UK-France and UK-German gaps in ALP, with the residual TFP accounting for another large proportion of the UK-US gap. By contrast, inter-country differences in measured skills account for relatively small proportions of the gaps in ALP, ranging from 1% in the UK/US case to 19% in the UK-German case.

Table 2.1: Decomposition of relative labour productivity levels, UK, US, France and Germany, 1999

	US	France	Germany
Relative ALP levels (value added per hour worked) – Index numbers: UK=100	130	129	117
Percentage contributions to ALP gaps:			
Physical capital	51	80	81
Workforce skills	1	12	19
TFP	48	8	0
Total	100	100	100

Source: O'Mahony and de Boer (2002)

Similar methods applied to a comparison of ALP growth in the same four countries between 1980-2001 find that the measured contributions of labour quality growth to total economy ALP growth are considerably smaller than the combined contributions of growth in ICT (information and communications technology) and non-ICT capital deepening on both sides of the Atlantic (Jorgenson, Ho and Stiroh, 2005; see Table 2.2).

Table 2.2: Contributions to ALP growth, US, UK, France and Germany, 1980-2001

	US	UK	France	Germany
Average Labour Productivity Growth (% per annum)				
1980-1989	1.58	1.87	3.04	1.88
1989-1995	1.40	2.79	1.71	3.05
1995-2001	2.23	1.71	1.43	1.29
Percentage contributions:				
ICT Capital Deepening				
1980-1989	25	12	6	10
1989-1995	31	10	12	9
1995-2001	41	42	27	36
Non-ICT Capital Deepening				
1980-1989	23	64	75	64
1989-1995	24	76	67	44
1995-2001	25	-12	17	54
Labour Quality				
1980-1989	19	6	8	14
1989-1995	26	18	36	11
1995-2001	10	18	13	18
Total Factor Productivity				
1980-1989	33	18	11	12
1989-1995	19	-4	-15	37
1995-2001	24	53	42	-8

Source: Jorgenson, Ho and Stiroh (2005)

In both these studies labour quality is measured by making use of education output data (formal qualifications) combined with relative earnings data which are intended to capture differences in relative productivity between different qualification groups. The use of relative earnings data for this purpose rests on the assumption of perfectly competitive markets in which a firm will hire an additional hour of labour up to the point where that person’s marginal productivity equals his/her marginal cost. Under this assumption, a measure of quality-adjusted total labour input can be obtained by weighting each different type of labour input (as signified by qualification levels) by its relative wage rate, or more specifically, with the share that each type of labour occupies in total labour compensation. A Törnqvist index of hours worked distinguished by skill type can then be computed, with each qualification group's share of the total wage bill as weights.

More formally, a *quality-adjusted labour index* (QL) is defined as:

(2.3) $$QL = \sum_h \bar{v}_h^L \Delta \ln L_h$$

where Δ is the first difference operator, L is hours worked for each of *h* labour types, v_h is the share of type h labour in the total wage bill, with the shares averaged across period t and t-1.

Labour quality (LQ) then equates to the difference between the quality-adjusted labour index and a standard measure of labour input, based on average annual hours per employee multiplied by the total number of workers:

(2.4) $$\Delta \ln LQ = \sum_h \bar{v}_h^L \Delta \ln L_h - \Delta \ln \sum_h L_h$$

There are a number of ways in which this labour quality measure may be flawed. In particular, the qualification categories found in one country may not be strictly comparable with qualification categories in another (due to different national-institutional arrangements for certification of education and training in each country). And employee wages may of course deviate from their marginal products due to imperfect labour market conditions and the operations of country-specific labour market institutions such as collective bargaining procedures and minimum wage legislation. However, this approach to labour quality measurement represents, in principle, a considerable improvement on the use of unweighted education input data as proxy indicators of skills.

The difficulties encountered in measuring human capital inputs may help to explain the relatively small estimated contributions of human capital to relative productivity levels and growth rates in many growth accounting studies. But another reason why growth accounting in particular may lead to underestimates of the relative contribution of human capital inputs to performance is that, in the growth accounting framework, the respective contributions of each production input must be evaluated separately without regard to potential complementarities between physical and human capital (such as those emphasized in the literature on skill-biased technological change; see Section 7 below).

By contrast, multivariate regression analysis provides far more scope than growth accounting methods for taking account of complementarities between production inputs and other ways in which human capital might have indirect effects on productivity (for example, through externalities to skills formation or knowledge spillovers). However, as we now go on to discuss, much econometric analysis of the determinants of productivity performance has been hampered by measurement problems and the limitations of many of the theoretical specifications that have been employed.

2.3 Multivariate regression analysis

A large number of studies have analysed the impact of human capital on productivity at the national economy level. The backbone of the majority of these studies is provided by the theory of growth, under the assumption of either exogenous (Mankiw et al., 1992) or endogenous growth (Benhabib and Siegel, 1994). The assumption of exogenous growth, which characterizes the neoclassical growth theory, implies that technological changes happen randomly and cannot be influenced by economic decision-makers. The main theoretical contribution within this framework is Solow's (1956) growth model, in which output at time (t), Y(t), is produced with a combination of physical capital, K(t) and labour, L(t):

(2.5) $$Y(t) = A(t)L(t)^{\alpha} K(t)^{1-\alpha} .$$

A(t) is an indicator of technological change. The production function underlying the Solow model is governed by the same simplifying assumptions discussed in the previous section, i.e. perfectly competitive markets, diminishing marginal returns and constant returns to scale.

In addition to the production function, the Solow growth model also specifies a relationship for the evolution over time of the capital stock. The change of capital over time, $\frac{dK}{dt}$, is determined by new investments, I(t), minus the depreciation of the existing capital stock, $\delta K(t)$, where δ is the depreciation rate:

(2.6) $$\frac{dK}{dt} = I(t) - \delta K(t) .$$

Investments are assumed to depend on the amount of output that is saved over time, therefore Equation (2.6) can be written as:

(2.7) $$\frac{dK}{dt} = sY(t) - \delta K(t)\,,$$

where s is the saving rate. Employment and technology are assumed to grow exogenously at the rates *n* and *g* respectively:

(2.8) $$L(t) = L(0)e^{nt}$$
$$A(t) = A(0)e^{gt}\,.$$

L(0) and A(0) are the levels of employment and technology at the beginning of the analysis. From Equations (2.5), (2.7) and (2.8) we can derive the steady state (equilibrium) level of output per capita, which is given by Equation (2.9) (in logarithms):

(2.9) $$\ln\left[\frac{Y}{L}\right] = \ln A(0) + gt + \gamma \ln(s) - \lambda \ln(n + g + \delta)\,.$$

This modelling framework can be modified to account for the presence of human capital. In the neoclassical growth model, human capital is treated simply as an additional factor of production, without assuming any interaction between human capital and technology. Therefore, following Mankiw et al. (1992), human capital (*h*) can be included in the theoretical specification and Equation (2.9) is then rewritten as follows:

(2.10) $$\frac{Y}{L} = \ln A(0) + gt + \gamma \ln(s) - \lambda \ln(n + g + \delta) + \phi \ln(h)\,.$$

In the neoclassical tradition economic, growth depends on the exogenous rate of technological change. Linked to the exogenous growth theory is the hypothesis of convergence, i.e. growth rates and income levels per person will tend to converge in all countries as follower countries gradually catch up with the productivity leader.

The assumption of exogenous technical change has met severe criticisms and there is now considerable interest in exploring mechanisms through which the decisions of firms and other economic agents can impact on the adoption and development of new technologies, i.e. technological change becomes endogenous to the model (Romer, 1986; Rebelo, 1991). The assumption of endogenous growth is at the heart of New Growth Theories. In these models the decision to invest in human capital is one of the possible ways through which agents can influence technological change and the interactions between human capital and technology play an important part in the theoretical and empirical analysis (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994). For example, Nelson and Phelps (1966) assume that the rate of growth of technology, *g*, depends on the gap between the actual level of technology, A(t), and what is defined as *theoretical knowledge*, T(t). Human capital contributes to the narrowing of this gap, according to the following relationship:

(2.11) $$g = c(h)\left[\frac{T(t) - A(t)}{A(t)}\right],$$

In the endogenous growth models there is no steady state level of income and differences among countries can persist over time, i.e. countries do not necessarily converge to the same level of per capita income.[3]

The two different approaches also imply a very different relationship between human capital and growth. As emphasized in Sianesi and Van Reenen (2003): "In the neoclassical tradition a one-off permanent increase in the human capital stock is associated with a one-off increase in the economy's growth rate, until productivity per worker hour has reached its new steady-state level. In New Growth theories the same one-off increase in human capital is associated with a permanent increase in the growth rate, implying higher benefits of education compared to the neoclassical models".

2.4 Empirical analysis of the impact of human capital on economic growth

Economic theory predicts that human capital will have a positive effect on output growth, both directly, as skilled workers are more productive, and indirectly as a highly qualified work force facilitates the absorption of knowledge and new technologies. Using data for a large number of developed and developing countries, Mankiw et al. (1992) estimate a relationship similar to Equation (2.10) above, by assuming that the economies are in steady state in 1985. Output is the log of GDP per working age population in 1985 and human capital is measured as the log of the average percentage of the working age population in secondary education over the period 1960-1985. The results show a positive and significant human capital coefficient for the whole sample (98 non-oil producing countries), for a sub-sample of 22 OECD countries and for an intermediate sample of 75 countries which excludes observations where measurement errors are

[3] 'Steady-state growth' is said to exist if an economy reaches a stage in which all variables such as population, national income and capital stock grow at (different) constant rates each year. By contrast, under 'balanced growth' all variables grow at the same constant rate each year.

likely to be particularly important. The introduction of a human capital variable also improves the fit of the empirical predictions of Solow's (1957) model as it produces more reliable estimates for the capital and labour coefficients. The inclusion of human capital also improves the fit on a convergence model, estimated in the second part of the paper.[4]

However, the analysis in Mankiw et al. (1992) presents several problems that cast doubt on the final results. Islam (1995) challenges the methodology used by observing that a cross-section analysis does not account for the heterogeneity across countries, because it implies the same production function throughout the sample. Islam advocates the use of panel data techniques, which allow for differences across countries by introducing country dummies into the empirical specification or by estimating a relationship expressed in rates of growth. Islam (1995) also criticizes the human capital variable used in Mankiw et al. (1992) and introduces a measure of human capital based on the average years of schooling in the total population over age 25. This measure, originally developed by Barro and Lee (1993), is considered superior to the variable used in Mankiw et al. (1992) because it is based on information on schooling at all levels, primary, secondary and higher, complete and incomplete. However, in Islam's panel data estimates the human capital variable appears with the 'wrong' sign and is statistically insignificant. Similar results can be found in De Gregorio (1992), Knight, Loayza and Villanueva (1993), Caselli, Esquivel and Lefort (1996), Hamilton and Monteagudo (1998).

Therefore, despite the importance that human capital plays in the theoretical analysis of economic growth, the empirical evidence has not always confirmed the theoretical predictions. In recent years some researchers have attributed these and similar findings of a small or non-existent impact of human capital on performance to inadequacies in the most commonly-used datasets. For example, Hanushek and Kimko (2000) discuss the inadequacy of schooling variables to reflect human capital because of the differences in the education systems in different countries. They then construct a new measure of

[4] In order to test the convergence hypothesis, Mankiw et al. (1992), regress the change in GDP between 1960 and 1985 on a constant, the level of output in 1960, the average investment rate and the average population growth rate for the period 1960-1985, the rate of technological growth and the human capital variable, defined as above. All variables are in logarithms.

labour force quality based on student performance in international tests of academic achievement in mathematics and science. These are the subjects that are more likely to affect the stock of knowledge within a country and hence growth. Their analysis includes both quantity of schooling, measured using the Barro-Lee (1993) estimates, and labour force quality. The latter variable plays a strong and significant role in determining growth in per capita GDP in several countries, observed over the period 1960-1990.

De la Fuente and Domenech (2006) also emphasize the importance of data quality in the analysis of human capital and growth. Their approach differs from Hanushek and Kimko (2000) as it goes back to the original approach of measuring human capital using more general information on schooling. However they also present a detailed discussion of the problematic issues related to some of the most commonly used measures for human capital, for example, the three versions of the Barro and Lee (1993, 1996, 2000) data.

For example, one of the problems related to the latter is the presence of sharp breaks and implausible changes in attainment levels over very short periods of time. This characteristic can seriously affect estimates based on panel data analysis, and can explain the poor performance of human capital proxies. De la Fuente and Domenech (2006) try to improve on the available human capital measures by constructing attainment series for the adult population for 21 OECD countries. They collect information from both national and international publications as well as unpublished sources in order to obtain a country-specific attainment profile. The information on attainment levels is then used to estimate the proportion of the population aged 25 and over that has started but not necessarily completed each of the different levels of education (illiterates, primary, lower and upper secondary, two levels of higher education).

Their empirical analysis is based on a Cobb-Douglas production function where human capital is introduced as an additional input. This can be written, in intensive form and taking logarithms, as follows:

(2.12) $$y_{it} = \alpha_0 + \beta k_{it} + \gamma h_{it} - \eta e_{it} + country + time + \mu_{it}\,,$$

where y_{it} is the log of output per employed worker, k_{it} is the log of the stock of physical capital, h_{it} is the average number of years of schooling, and e_{it} is the ratio of employment to adult population. The latter variable aims at correcting for the fact that data on educational attainment refer to adult population and not only to those in employment. *country* and *time* denote country and time dummies, respectively. Estimates for the period 1960-1995 are presented for Equation (2.12) and two alternative versions (without country dummies and in first differences) and using alternative human capital measures in order to compare their relative performance. The results show that their improved human capital measure leads to a strong and positive human capital impact on productivity across different specifications of the production function. These findings support earlier work by Krueger and Lindahl (2001) and Cohen and Soto (2001) which pointed to measurement error as a key reason why earlier studies had found that increases in educational attainment had little or no impact on growth.

Another reason for the poor performance of the human capital proxies in earlier studies can be found in the misspecification of the production function and the way the impact of human capital is modelled. Nelson and Phelps suggested in 1966 that simply including an index of education or human capital as an additional input would represent a gross misspecification of the productive process because it does not account for complementarities between human capital and technology diffusion. Specifically, in Nelson and Phelps' theoretical model, human capital is not simply another factor of production but one that enhances the ability of a country to adopt and develop innovations.[5] Their model implies that the Solow residual, or total factor productivity growth, is influenced by the level of human capital in the short run and by the exogenous rate of technology development in the long run. Empirical analysis needs to model this effect in order to correctly evaluate the impact of human capital on productivity.

Benhabib and Spiegel (1994) follow Nelson and Phelp's suggestion and propose a different model that allows human capital to affect the speed of technological catch up and diffusion. Specifically, human capital affects growth through two channels: by increasing a country's ability to innovate and by facilitating the adoption and diffusion of foreign technology. At any point in time the model assumes the presence of a country which is the leader in technology. The speed with which other nations catch up with this leader is a function of their human capital stock. Countries that are technologically

[5] Nelson and Phelps (2006) also mention the importance of innovation, and human capital, in generating positive externalities.

further away from the leader are characterized by a lower level of human capital and by a higher rate of growth compared to other countries because of the catch-up effect. On the other hand, countries that are closer to the leader in terms of human capital and technology will experience lower rates of productivity growth. This explains why human capital is often not significantly different from zero or has a negative impact in growth regressions. In section 5 below we report new analyses based on a ‘catch-up’ model of growth of this kind.

Many previous cross-country studies of productivity and growth have assumed homogeneous parameter estimates across a wide range of countries that are characterised by differences in, for example, income levels, standard of living, education systems and institutional frameworks. This raises some concerns about the reliability of such estimates and their usefulness for policy interventions. In our analysis, to which we now turn, we avoid some of the problems caused by country heterogeneity by making use of sector-level data in a relatively small number of advanced industrial countries at similar stages of development. In addition, the new indices of human capital that we have developed allow for heterogeneity not only across countries but also across industries within each country.

Summary:

Economic theory predicts that human capital will have a positive effect on economic growth. This has not been uniformly supported by empirical analysis. In this section, we have explored the growth accounting and regression techniques used to measure the relationship between productivity and human capital and identified problems relating to measurement of labour quality and to misspecification of production functions (for example, not taking account of possible complementarities between skills and the adoption of new technologies). In the rest of this report, we address these issues in detail and seek to provide more insights into the relationship between skills and productivity.

3. Performance comparisons

This section describes the datasets used in the analysis which include new measures of labour quality at sector level using data on educational qualifications and wages. We then present comparisons of average productivity levels and growth rates and average skill levels at sector level in each country.

3.1 Variable definitions

In both the EPKE and ISP datasets output is measured as gross value added. Values at constant prices in national currencies are converted to US$ using industry-specific purchasing power parity exchange rates. Labour input is measured as hours worked defined as the total number of persons engaged (employed plus self-employed) times the average number of hours worked per year.

In the EPKE dataset, capital input is measured by capital service flows and is constructed using information on investment in current and constant prices from six asset types: computers, communication equipment and software (ICT capital); transport equipment, other non-ICT machinery and equipment and non-residential structures (non-ICT capital). Total capital is derived by aggregating ICT and non-ICT capital using the average over two consecutive years of the share of each asset in total capital compensation. In the ISP dataset, capital stocks have been estimated using a perpetual inventory method that cumulates constant price investments and deducts the value of depreciated assets. This has been done applying sector-specific US (geometric) depreciation rates, with assets divided into plant and machinery, structures and vehicles.

In both datasets a measure of human capital (labour quality) is constructed using data on the total number of hours worked and average hourly wages by skill group. The classification of skill groups is based on educational attainment and the number of skill groups is allowed to vary in each country, according to the qualifications system within each country (see Appendix Table A1 for details of this classification). From these data we derive a measure of quality adjusted labour (QAL_U) by aggregating employment by skill levels multiplied by the wage relative to the unskilled category. For each country we compute the following:

(3.1) $$QAL\_U = \sum_{1}^{J} l_j * \frac{w_j}{w_{unsk}},$$

where l_j is the total number of hours worked by skill group j, J is the total number of skill groups, w_j is the wage relative to a specific skill group and w_{unsk} is the average wage of unskilled workers. Time and industry indices have been dropped to simplify the notation. The measure for human capital (*hc_u*) is then computed by subtracting the total number of hours worked (*th*) from QAL_U:

(3.2) $$hc\_u = QAL\_U - th.$$

A drawback of taking unskilled workers as the reference category for cross-country comparisons of labour quality is that the term 'unskilled' often refers to different categories of worker across countries. For example, in the UK it is defined as 'no qualifications or qualified below NVQ1 level' while in the US it refers to those who 'did not graduate from high school' (see Appendix Table A1). Therefore, in order to assess the value of our skills measure, we compute an alternative measure of labour quality which benchmarks on the highest qualifications category (First/Bachelor degree and above) where comparability across countries is arguably at its strongest. This second measure of quality adjusted labour (QAL_G) is defined as follows:

(3.3) $$QAL\_G = \sum_{1}^{J} l_j * \frac{w_j}{w_{grad}},$$

where w_{grad} is the average wage of graduates in employment. Since by design QAL_G < th, a second measure of human capital (*hc_g*) is defined by taking the ratio of QAL_G to the total number of hours worked:

(3.4) $$hc\_g = QAL\_G / th.$$

As will be shown below, in analysis of EPKE data, the two measures *hc_u* and *hc_g* are found to be highly correlated, and the estimated impacts of human capital on sector performance results does not differ greatly whichever measure of human capital is used.

Summary statistics for key variables analysed by country are presented in Appendix Tables A2-A10.

3.2 Relative productivity performance

Tables 3.1 and 3.2 provide information on how the UK compares against the other countries by sector in terms of average labour productivity (ALP) levels and growth rates in ALP and total factor productivity (TFP).

When we compare ALP levels in the year 2000 on the basis of EPKE data (Table 3.1A), there is not one of the 26 sectors where the UK enjoys a leadership position. The UK ranks second or second equal in mining and quarrying; paper, printing and publishing; rubber and plastics; and electrical and electronic equipment and instruments. It ranks last out of the five countries in textiles, leather and clothing; wood products; oil refining, coke and nuclear fuel; mechanical engineering; transport equipment; miscellaneous manufacturing; retailing; hotels and catering; communications; financial services; real estate and other business services; and non-market services.

However, in terms of ALP growth over the entire 1979-2000 period, the UK ranks first out of five in mining, chemicals, metal products, electricity, gas and water, construction, transport and real estate/business services (Table 3.1B). This better relative performance in productivity growth rates as compared to levels in some sectors is indicative of a ‘catching-up’ phenomenon in countries which lag in terms of productivity levels but may benefit in terms of productivity growth rates from the scope for acquiring new technologies and ideas from leader countries.[6] The sectors in which the UK has recorded relatively slow growth in ALP comprise a mix of manufacturing activities (e.g. textiles, clothing and leather, wood products, pulp and paper, and oil refining) and the retail and financial services sectors.

[6] See Section 5 below for discussion of catch-up models of productivity growth.

Table 3.1A: Average labour productivity levels in 2000: country rankings

Industry	USA	UK	Nether-lands	Germany	France
Agric./Forestry/ Fishing	2	3	1	5	4
Mining/Quarrying	3	2	1	5	4
Food/ Drink/ Tob.	3	4	1	5	2
Text./Leather/Footwear/Clothing	3	5	1	4	2
Wood/Wood Prod.	4	5	3	2	1
Pulp/Paper/ Paper Prod./ Printing/Publish.	4	2	5	3	1
Oil Refining/Coke/Nuclear Fuel	2	5	1	3	4
Chemicals	2	3	5	4	1
Rubber/Plastics	5	2	4	3	1
Non-Metallic Miner.Prod.	5	4	1	3	2
Basic Metals/Fabric. Metal Prod.	1	4	5	3	2
Mechanical Engineering	4	5	2	3	1
Electrical & Electronic Equip./Instruments	1	2	5	4	3
Transport Equipment	1	5	4	3	2
Furniture/Miscell. Manufact./Recycling	3	5	2	4	1
Electricity/Gas/Water	2	3	1	5	4
Construction	2	4	1	3	5
Repairs/Wholesale trade	1	3	5	2	4
Retail trade	1	5	4	3	2
Hotels/Catering	3	5	1	4	2
Transport	1	3	5	4	2
Communications	4	5	2	1	3
Financial Intermediation	2	5	1	3	4
Real Estate Activities/Business Services	4	5	1	2	3
Other Services	3	4	2	1	5
Non-Market Services	3	5	1	2	4

Source: EPKE
Notes: 1 = Best Performing Industry.

In respect of TFP growth rates, the UK ranks first in mining, chemicals, metal products and construction and last in the wood products, non-metallic mineral products, miscellaneous manufacturing, retail and wholesale sectors (Table 3.2). It should be noted that, although TFP growth is generally positively associated with ALP growth, there is no reason in principle why relatively good TFP performance should not coexist with relatively low ALP at sector and national level. For example, Crawford and Vogl (2006) note that the UK construction industry uses only about half the amount of capital per worker as in the German industry, which tends to reduce ALP in the UK. However, the UK appears to make more efficient use of its capital and labour inputs, as captured in the TFP growth measure in Table 3.2.

Table 3.1B: Average annual growth rates in average labour productivity (ALP), 1979-2000: country rankings

Industry	USA	UK	Netherlands	Germany	France
Agric./Forestry/ Fishing	1	5	4	3	2
Mining/Quarrying	3	1	5	4	2
Food/ Drink/ Tob.	5	2	1	3	4
Text./Leather/Footwear/Clothing	2	4	1	3	5
Wood/Wood Prod.	4	5	1	3	2
Pulp/Paper/ Paper Prod./ Printing/Publish.	5	4	1	2	3
Oil Refining/Coke/Nuclear Fuel	1	4	3	2	5
Chemicals	5	1	3	4	2
Rubber/Plastics	1	3	2	5	4
Non-Metallic Miner.Prod.	5	3	2	4	1
Basic Metals/Fabric. Metal Prod.	4	1	2	3	5
Mechanical Engineering	5	3	2	4	1
Electrical & Electronic Equip./Instruments	1	2	4	5	3
Transport Equipment	4	3	1	5	2
Furniture/Miscell. Manufact./Recycling	3	5	1	4	2
Electricity/Gas/Water	5	1	4	3	2
Construction	5	1	2	4	3
Repairs/Wholesale trade	1	2	4	5	3
Retail trade	1	4	3	5	2
Hotels/Catering	2	3	1	5	4
Transport	5	1	4	2	3
Communications	5	3	4	1	2
Financial Intermediation	4	5	3	1	2
Real Estate Activities/Business Services	5	1	4	2	3
Other Services	4	1	2	3	5
Non-Market Services	5	4	2	3	1

Source: EPKE
Note: 1 = Best Performing Industry

Table 3.2: Average annual growth rates in total factor productivity (TFP), 1979-2000: country rankings

Industry	USA	UK	Netherlands	Germany	France
Agric./Forestry/ Fishing	1	4	3	2	5
Mining/Quarrying	3	1	5	4	2
Food/ Drink/ Tob.	5	2	1	3	4
Text./Leather/Footwear/Clothing	2	4	1	3	5
Wood/Wood Prod.	4	5	1	2	3
Pulp/Paper/ Paper Prod./ Printing/Publish.	5	3	1	4	2
Oil Refining/Coke/Nuclear Fuel	1	3	4	2	5
Chemicals	5	1	3	4	2
Rubber/Plastics	2	4	1	5	3
Non-Metallic Miner.Prod.	4	5	1	3	2
Basic Metals/Fabric. Metal Prod.	4	1	3	2	5
Mechanical Engineering	5	3	1	4	2
Electrical & Electronic Equip./Instruments	1	2	4	5	3
Transport Equipment	4	2	1	5	3
Furniture/Miscell. Manufact./Recycling	2	5	1	4	3
Electricity/Gas/Water	5	2	4	3	1
Construction	5	1	2	3	4
Repairs/Wholesale trade	3	5	2	4	1
Retail trade	2	5	3	4	1
Hotels/Catering	3	4	2	5	1
Transport	5	3	4	1	2
Communications	5	3	4	2	1
Financial Intermediation	5	3	4	2	1
Real Estate Activities/Business Services	3	4	2	5	1
Other Services	5	2	3	4	1
Non-Market Services	5	4	2	3	1

Source: EPKE
Note: 1 = Best Performing Industry

3.3 Comparison of average skill levels

Table 3.3 shows cross-country comparisons of labour quality at the detailed sector level which is available in the ISP dataset. It is based on the ratio of quality-adjusted labour to total labour input defined in Equation (3.4) above, (QAL_G/th), which is benchmarked on the graduate qualifications category. The labour quality scores are thus effectively measured on a 0-1 scale where a value of 1 would indicate that all employees were qualified to graduate level. Not surprisingly, some of the highest scores in all four countries are in graduate-intensive sectors such as pharmaceuticals, computer services and R&D services.

On this measure the UK ranks first in only two of the 68 sectors: publishing and reproduction of recorded media. However, there are many sectors of manufacturing where the UK ranks second only to Germany among the four countries. The sectors where the UK ranks last on this measure of labour quality are heavily concentrated in service industries – in particular, retail, wholesale, transport and financial services – which account for a large proportion of total employment.

Summary:

Descriptive statistics on relative productivity performance at sector level suggest that the UK often compares badly against other advanced industrial countries in terms of average labour productivity levels. However, it compares more favourably in some sectors in terms of growth rates in labour productivity and total factor productivity. The latter measure captures, among other things, inter-country differences in the efficiency of use of existing capital and labour inputs.

For this report skill measures at sector level are based on educational output data (formal qualifications) and on mean wages by qualifications group. To the extent that wage differentials are reflective of differences in productivity, these measures should take some account of uncertified skills and knowledge which are acquired in the workplace following completion of initial education and training. Using a measure which is benchmarked on graduate labour quality in each country, the UK is found to rank first among four countries in only two out of 68 sectors while it ranks fourth out of four in 20 sectors.

Table 3.3: Average labour quality in the UK, US, France and Germany, analysed by sector
(measured on 0-1 scale where 1 = all employees are qualified to graduate level)

		Average labour quality					Rankings			
SIC code	Sector	UK	US	France	Germany		UK	US	France	Germany
01-05	Agriculture, forestry and fishing	0.62	0.60	0.54	0.72		2	3	4	1
10-14	Mining and quarrying	0.73	0.68	0.68	0.75		2	4	3	1
151	Production, processing and preserving of meat and meat products	0.61	0.51	0.60	0.69		2	4	3	1
155	Manufacture of dairy products	0.65	0.63	0.60	0.69		2	3	4	1
159	Manufacture of beverages	0.70	0.68	0.64	0.71		2	3	4	1
152-154; 156-158, 160	Other food manufacturing; tobacco manufacturing	0.63	0.59	0.59	0.69		2	4	3	1
171, 172, 173	Preparation and spinning of textile fibres, Textile weaving, Finishing of textiles	0.62	0.56	0.61	0.68		2	4	3	1
174, 175	Manufacture of made-up textile articles, except apparel, Manufacture of other textiles	0.61	0.56	0.61	0.68		3	4	2	1
176, 177	Manufacture of knitted and crocheted fabrics and articles	0.60	0.56	0.61	0.68		3	4	2	1
18	Manufacture of wearing apparel; dressing and dyeing of fur	0.61	0.56	0.59	0.69		2	4	3	1
19	Leather and footwear	0.60	0.58	0.60	0.69		2	4	3	1
20	Wood and wood products	0.63	0.56	0.59	0.69		2	4	3	1
211	Manufacture of pulp, paper and paperboard	0.63	0.64	0.63	0.69		3	2	4	1
212	Manufacture of articles of paper and paperboard	0.65	0.64	0.63	0.69		2	3	4	1
221	Publishing	0.78	0.71	0.68	0.75		1	3	4	2
222	Printing and service activities related to printing	0.65	0.71	0.68	0.70		4	1	3	2
223	Reproduction of recorded media	0.75	0.71	0.68	0.73		1	3	4	2
23	Mineral oil refining, coke and nuclear fuel	0.75	0.77	0.74	0.75		3	1	4	2
244	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	0.81	0.89	0.70	0.80		2	1	4	3
245	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	0.68	0.71	0.70	0.75		4	2	3	1
241-243, 246-247	Basic chemicals, agrochemicals, paints, coatings and other chemical products	0.75	0.77	0.70	0.75		3	1	4	2
251	Manufacture of rubber products	0.65	0.63	0.62	0.69		2	3	4	1
252	Manufacture of plastic products	0.62	0.61	0.61	0.69		2	4	3	1

		Average labour quality					Rankings			
SIC code	**Sector**	**UK**	**US**	**France**	**Germany**		**UK**	**US**	**France**	**Germany**
261	Manufacture of glass and glass products	0.66	0.62	0.61	0.70		2	3	4	1
262-268	Manufacture of ceramic products, bricks, tiles and construction products	0.64	0.61	0.61	0.71		2	4	3	1
274	Manufacture of basic precious and other non-ferrous metals	0.65	0.66	0.62	0.70		3	2	4	1
275	Casting of metals	0.65	0.57	0.62	0.70		2	4	3	1
271, 272, 273	Manufacture of basic iron and steel and of ferro-alloys, Manufacture of tubes, O	0.67	0.63	0.62	0.69		2	3	4	1
281	Manufacture of structural metal products	0.64	0.60	0.61	0.70		2	4	3	1
282, 283	Manufacture of tanks, reservoirs and containers of metal, manufacture of central	0.66	0.60	0.61	0.70		2	4	3	1
284-287	Other fabricated metal products	0.66	0.60	0.60	0.69		2	4	3	1
294	Manufacture of machine-tools	0.68	0.64	0.65	0.71		2	4	3	1
296	Manufacture of weapons and ammunition	0.79	0.71	0.81	0.73		2	4	1	3
297	Manufacture of domestic appliances n.e.c.	0.65	0.64	0.60	0.72		2	3	4	1
291-293, 295	General and special purpose machinery and other mechanical engineering products	0.68	0.64	0.65	0.73		2	4	3	1
30	Computers and office machinery	0.76	0.84	0.86	0.79		4	2	1	3
31	Electrical machinery	0.68	0.74	0.64	0.74		3	2	4	1
321	Manufacture of electronic valves and tubes and other electronic components	0.69	0.78	0.72	0.76		4	1	3	2
322, 323	Manufacture of radio, TV and telecommunications equipment	0.70	0.78	0.74	0.76		4	1	3	2
331	Manufacture of medical and surgical equipment and orthopaedic appliances	0.69	0.73	0.70	0.73		4	1	3	2
332-335	Other instrument engineering	0.71	0.83	0.69	0.75		3	1	4	2
341, 342	Manufacture of Motor Vehicles; bodies for motor vehicles; trailers	0.66	0.66	0.63	0.73		2	3	4	1
343	Manufacture of parts and accessories for motor vehicles and their engines	0.64	0.66	0.63	0.73		3	2	4	1
351	Building and repairing of ships and boats	0.68	0.63	0.71	0.74		3	4	2	1
352	Manufacture of railway and tramway locomotives and rolling stock	0.72	0.67	0.71	0.76		2	4	3	1
353	Manufacture of aircraft and spacecraft	0.74	0.78	0.71	0.78		3	2	4	1
354, 355	Manufacture of motorcycles and bicycles; Manufacture of other transport equipmen	0.66	0.64	0.63	0.75		2	3	4	1
361	Manufacture of furniture	0.63	0.57	0.60	0.69		2	4	3	1
362-366, 37	Other manufacturing nec, Recycling	0.64	0.61	0.60	0.70		2	3	4	1
40, 41	Electricity, gas and water supply	0.71	0.71	0.71	0.78		3	2	4	1

		Average labour quality					Rankings			
SIC code	Sector	UK	US	France	Germany		UK	US	France	Germany
45	Construction	0.65	0.60	0.62	0.73		2	4	3	1
50	Motor vehicle trade and repairs	0.61	0.62	0.62	0.73		4	3	2	1
51	Wholesale trade and commission trade	0.63	0.72	0.69	0.76		4	2	3	1
52	Retail trade and repair of household goods	0.61	0.64	0.65	0.74		4	3	2	1
55	Hotels and catering	0.61	0.57	0.62	0.69		3	4	2	1
60	Inland transport	0.61	0.61	0.64	0.75		4	3	2	1
61	Water transport	0.66	0.68	0.77	0.80		4	3	2	1
62	Air transport	0.71	0.73	0.76	0.78		4	3	2	1
63	Supporting and auxiliary transport activities; travel agents	0.64	0.70	0.67	0.74		4	2	3	1
64	Post and telecommunications	0.65	0.73	0.69	0.77		4	2	3	1
65	Financial services, except insurance and pension funding	0.72	0.79	0.76	0.81		4	2	3	1
66	Insurance and pension funding, except compulsory social security	0.71	0.79	0.75	0.81		4	2	3	1
67	Activities auxiliary to financial services	0.70	0.79	0.76	0.81		4	2	3	1
71	Renting of machinery and equipment	0.65	0.64	0.67	0.79		3	4	2	1
72	Computer services and related activities	0.81	0.90	0.90	0.89		4	1	2	3
73	Research and development	0.89	0.92	0.91	0.99		4	2	3	1
74	Other business services	0.74	0.81	0.77	0.81		4	2	3	1
90, 91, 92, 93	Other community, social and personal services	0.69	0.68	0.70	0.79		3	4	2	1

Source: ISP (Labour quality calculated on basis of QAL_G/th ratio as described in Section 3.1 of main text)

4. Productivity and skills at sector level: econometric analysis

Econometric analysis enables us to avoid some of the restrictive assumptions of growth accounting. We begin by estimating a production function with and without human capital as an independent variable in order to observe the effects of skills on average labour productivity (i.e. on output controlling for labour inputs). The model is then gradually developed to allow for differences in the effects of human capital across countries and industries. Finally, we use panel estimation methods to exploit the combined time series and cross-sectional dimensions of our data, which enables us to control for industry- specific factors that might otherwise go undetected.

4.1 Theoretical specification

Our theoretical framework is initially provided by an augmented Cobb-Douglas production function that includes human capital alongside the more traditional inputs, labour and capital:

(4.1) $$y_{it} = \alpha_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 h_{it} + country + time + \mu_{it}$$

where y_{it} is the log of value added, l_{it} is the log of the total number of hours worked, k_{it} is the log of total capital, h_{it} is the log of our human capital measure. *Country* and *time* denote country and time dummies respectively. Country dummies are intended to account for country-specific effects (for example, different institutional frameworks that influence the way firms operate in the market). Time dummies aim to capture the effects of periodic common shocks that might have affected industry productivity. Since our equation is expressed in logarithms, we can interpret the coefficients on labour, physical and human capital as showing the ‘elasticity’ of output to each factor of production (defined as the percentage change in output associated with a 1% change in each factor of production, all else being equal).

In every section of this chapter we also estimate a simplified version of Equation (4.1) that does not include human capital before going on to include human capital as an independent variable in subsequent specifications. This enables an immediate assessment of the impact of skills on average labour productivity (i.e. on output controlling for labour inputs). In every estimated equation we also test for the presence of constant returns to scale in order to better understand the properties of the production function. Returns to scale tell us how much the level of output increases when all factors of production increase by the same proportional amount. When there are constant returns to scale, the amount of total output increases exactly in proportion to the increase in all of the factors. If the firm doubles its use of all factors then total output doubles. When there are decreasing (increasing) returns to scale, the amount of total output increases less (more) than the increase in all of the factors. In terms of Equation (4.1), testing for constant returns to scales implies testing whether the sum of the coefficients on labour, physical capital and human capital equals 1.

At each stage our analysis addresses endogeneity issues by comparing estimates based on Ordinary Least Squares (OLS), panel data methods, and Instrumental Variable (IV) methods. As discussed in Sianesi and Van Reenen (2003), earlier studies on human capital and productivity assumed independence between the explanatory variables and the error term, i.e. all variables were treated as exogenous. However, if this assumption is not met, the OLS estimator produces biased coefficient estimates. An explanatory variable is endogenous when it is correlated with the residual of the equation, u_{it}. There might be several causes for the presence of endogeneity, such as omitted variable or measurement error. In production function estimation, the main cause of endogeneity is usually that one or more explanatory variables are determined simultaneously with the dependent variable. For example, in our case it is possible that industries characterized by high human capital are more productive, but it is also likely that high-performance industries invest more in human resources. A similar reasoning could be applied to the total number of hours worked. For total capital the simultaneity problem is likely to be less important.[7] However, problems in the measurement of capital stocks are usually a cause of concern. Omitted variable bias can occur when there is a correlation between an explanatory variable and the error term, for example, capital stocks and unobserved initial technological endowments and natural resources.

4.2 Benchmark model

Equation (4.1) is first estimated using the Pooled Ordinary Least Squares (POLS) estimator, which imposes the same coefficients on all industries and countries. This corresponds to running OLS on all observations pooled across time and cross sections.[8] The only source of cross-sectional heterogeneity is captured by the inclusion of country dummies. This is our benchmark model. In the remainder of our analysis we will gradually relax the assumption of homogeneous coefficients in order to capture differences across countries and industries.

Results 1: The Pooled model

Results based on POLS are presented in columns (1)-(4) of Table 4.1A. In the first column we estimate a standard Cobb-Douglas function with no human capital effect. The coefficients on total hours and total capital are positive and significant (i.e. hours and physical capital investment positively impact on productivity) and their size is consistent with prior expectations of each factor's share of value added. Overall, the estimates suggest the presence of decreasing returns to scale of approximately 0.7. The test for the presence of constant returns to scale rejects the null hypothesis of constant returns at the 5% level of significance.

[7] A different view is expressed, for example, in Benhabib and Joanovic (1991), Blomstrom, Lipsey and Zejan (1993) and discussed in Krueger and Lindahl (2001). These authors claim that physical capital is endogenous in a growth equation because investment is a choice variable and shocks to output are likely to influence the optimal level of investments. Moreover, because of capital-skill complementarity, countries may attract more investment if they raise their level of education. Parts of the returns to capital might then be attributable to education.

[8] In the estimation of Equation (4.1) we also allow for observations to be independent across industries but not within industries by clustering on sector/country observations. This means that the standard errors reported in table 4.1A are corrected for the presence of within industry serial correlation (intragroup correlation). Where clustering is used in subsequent estimations, it is indicated in notes to tables.

Columns (2)-(4) of table 4.1A show results of the estimation of the production function including human capital. We compare the performance of the two measures of human capital described in Section 3.1 in order to check the robustness of our results to different definition of human capital. These measures of labour quality are based, respectively, on benchmarking unskilled labour in each country (log QAL_U/th) and graduate-level labour in each country (log QAL_G/th).[9] In each case the coefficients are positively signed and strongly significant (i.e. human capital as measured here positively impacts on productivity). Also the implied effect of human capital on output is similar in all cases. The estimated unit change in log output resulting from a one standard deviation increase in log QAL_U/th is 0.14 compared to a 0.19 unit change resulting from a one standard deviation increase in log QAL_G/th.[10] This effect is very similar to the coefficient on the QAL_U-th measure of human capital.

We conclude therefore that the two different measures of labour quality are fairly similar in their ability to capture any relationship between skill and performance. In subsequent analysis we make greatest use of the levels measure of human capital $hc\_u = QAL\_U - th$, which can be entered alongside levels of physical capital and total (unskilled) labour input in the production function. This definition of human capital has the advantage of providing a more straightforward interpretation of the results. For example, in column (4) of table 4.1A, a 1% increase in human capital (hc_u) generates a 0.14% increase in output. Our results also show that the inclusion of hc_u decreases the coefficient on the total number of hours compared to column (1). This was expected since, if human capital is not separately identified, then part of the human capital impact is captured by total hours.

In the fifth column of Table 4.1A we correct for the presence of endogeneity in our explanatory variables by using a Two-Stage Least Squares (2SLS) estimator. Each of the right hand side variables is instrumented using its own value at time (t-1) and (t-2). The instrumental variable results show a slightly lower impact of total hours and a

[9] In Column 2 of Table 4.1A, log QAL_U/th is entered as a ratio instead of as a level (QAL_U-th) in order to provide a direct comparison with the QAL_G/th ratio.

[10] A variable is standardized by subtracting the mean and dividing by the standard deviation. This procedure enables an evaluation of the relative importance of independent variables which are measured in different units.

stronger human capital effect on value added. A 1% increase in human capital is associated with a 0.19% increase in output. These results are also robust to the use of slightly different instrument sets. The coefficient on total capital is not different from the POLS results, suggesting that for this variable the endogeneity problems are not too strong. The test statistics at the bottom of Table 4.1 show that the equation is correctly identified and the instruments used are valid.

In table 4.1B we compare results based on the EPKE and the ISP datasets. The ISP analysis shows a similarly positive impact of human capital on productivity (Table 4.1B). Due to the unavailability of French capital stocks data at the level of sectoral disaggregation which it is possible to obtain for the UK, US and Germany, this ISP analysis can only be carried out for the three latter countries and therefore the ISP results are compared against EPKE results for the UK, US and Germany alone.[11] Although the coefficient on log QAL_G/th using ISP data is twice as large as that in EPKE, the implied impact on output levels is fairly similar in both datasets, pointing to a 0.213 unit change in predicted log output in ISP and a 0.245 unit change in predicted log output in EPKE.

In the remainder of this section we focus on analysis of EPKE since it covers five countries and has a longer time series than ISP. We return to analysis of ISP in Section 6 in our investigation of the determinants of technical inefficiency, when we are able to make good use of the greater level of sectoral disaggregation in ISP in spite of the shorter ten-year period which it covers.

[11] The French national statistics agency INSEE has yet to make more detailed sectoral capital stocks estimates available to any researchers outside that organisation.

Table 4.1A: The impact of human capital on productivity: pooled model

Dependent variable: log value added (EPKE dataset)

	(1)	(2)	(3)	(4)	(5)
	POLS	POLS	POLS	POLS	IV (2SLS)
Log total hours (th)	0.530***	0.530***	0.557***	0.398***	0.337***
	(0.076)	(0.075)	(0.078)	(0.113)	(0.131)
Log physical capital	0.245***	0.244***	0.227***	0.247***	0.252***
	(0.058)	(0.058)	(0.059)	(0.057)	(0.057)
Log QAL_U/th		0.758***			
		(0.213)			
Log QAL_G/th			0.723***		
			(0.138)		
Log human capital (hc_u = QAL_U-th)				0.138**	0.194**
				(0.062)	(0.085)
Constant	6.483***	6.169***	6.675***	6.441***	6.180***
	(0.803)	(0.768)	(0.749)	(0.810)	(0.833)
Observations	2730	2567	2586	2567	2313
R-squared	0.838	0.859	0.859	0.857	0.861
Constant returns to scale	19.14 (0.000)	19.87 (0.000)	19.47 (0.000)	18.22 (0.000)	19.22 (0.00)
Anderson LR statistic (χ^2)					2272 (.000)
Hansen J statistic (χ^2)					7.934 (0.050)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. In column (5) all variables have been instrumented with their own value at time t-1 and t-2. The Anderson LR statistic is the Anderson (1984) canonical correlations likelihood-ratio test of whether the equation is identified. The null hypothesis is that the equation is underidentified. The Hansen J statistic is the appropriate test of overidentifying restrictions in the presence of heteroscedasticity. The null hypothesis is that all instruments are valid.

Table 4.1B: The impact of human capital on productivity: pooled model

Dependent variable: log value added
(ISP compared with EPKE – sectors in 3 countries: UK, US and Germany)

	(1)	(2)	(3)
	POLS	POLS	POLS
	ISP	ISP	EPKE
			3 countries
Log total hours (th)	0.714***	0.732***	0.668***
	(0.037)	(0.033)	(0.048)
Log physical capital	0.244***	0.202***	0.183***
	(0.036)	(0.032)	(0.060)
Log QAL_G/th		1.927***	0.911***
		(0.242)	(0.087)
Constant	-2.050***	-1.081***	5.847***
	(0.307)	(0.314)	(0.787)
Constant returns to scale			10.42 (0.002)
Observations	2040	2040	1586
R-squared	0.925	0.940	0.903

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Within the pooled model framework it is possible to allow for some parameter heterogeneity by interacting each explanatory variable with a set of dummies. To start with, we want to investigate how the returns to human capital vary across countries. To do so we interact each variable with the country dummies and we re-write Equation (4.1) as follows:

$$\begin{aligned} y_{it} = {} & \alpha_0 + \alpha_1 l_{it} * US + \beta_1 k_{it} * US + \gamma_1 h_{it} * US + \\ & \alpha_2 l_{it} * UK + \beta_2 k_{it} * UK + \gamma_2 h_{it} * UK + \\ & \alpha_3 l_{it} * FR + \beta_3 k_{it} * FR + \gamma_3 h_{it} * FR + \\ & \alpha_4 l_{it} * GE + \beta_4 k_{it} * GE + \gamma_4 h_{it} * GE + country + time + \upsilon_{it} \end{aligned} \tag{4.2}$$

Equation (4.2) also allows for a different intercept in each country and for common shocks by including intercept time dummies. Results are presented in Table 4.2 for the POLS and 2SLS IV estimation. As above, we start with the specification including only capital and labour. The results, presented in column (1), show similar output-labour elasticities in the US, UK and France. Germany and the Netherlands, on the other hand, appear to be characterized by a different production function compared to the other three countries. Specifically, we find a higher output-labour elasticity and a lower output-capital elasticity in Germany, while in the Netherlands we observe the reverse situation, i.e. lower output-labour elasticity and a higher output-capital elasticity.

Cross country differences can also be observed in the results presented in columns (2) and (4) where we account for the role of human capital. We carry out both POLS and 2SLS IV estimation. In all countries human capital has a positive and significant impact on output levels, with the degree of intensity varying between countries. The strongest impact is observed in the US where a 1% increase in human capital is associated with a 0.17% increase in output, followed in descending order by Germany and the Netherlands, France and the UK. In the UK a 1% increase in human capital leads to an estimated 0.09% increase in output, not much more than half the US effect.

These differences between countries in the impact of human capital on output are statistically significant. In fact, when we ran a Wald test of the null hypothesis of equal coefficients across countries, the null hypothesis was always rejected. This suggests that the relationship between human capital and productivity is statistically different even in countries that can be considered homogeneous in terms of standard of living and economic development.[12]

[12] For all specifications the hypothesis of constant returns to scale was rejected by our data.

Table 4.2: Heterogeneous coefficients across countries (EPKE)
Dependent variable: log value added

	(1)	(2)	(3)	(4)
	POLS	POLS	IV 2SLS	IV 2SLS
Log total hours – US	0.548***	0.374***	0.537***	0.330***
	(0.018)	(0.037)	(0.018)	(0.038)
Log physical capital – US	0.259***	0.274***	0.274***	0.288***
	(0.018)	(0.018)	(0.017)	(0.017)
Log total hours –UK	0.590***	0.508***	0.587***	0.509***
	(0.020)	(0.026)	(0.021)	(0.027)
Log physical capital – UK	0.183***	0.184***	0.192***	0.190***
	(0.019)	(0.019)	(0.020)	(0.020)
Log total hours – France	0.529***	0.474***	0.532***	0.474***
	(0.023)	(0.027)	(0.022)	(0.027)
Log physical capital – France	0.245***	0.227***	0.249***	0.228***
	(0.017)	(0.015)	(0.017)	(0.015)
Log total hours – Germany	0.762***	0.590***	0.758***	0.580***
	(0.027)	(0.042)	(0.028)	(0.044)
Log physical capital – Germany	0.043*	0.083***	0.053**	0.089***
	(0.024)	(0.024)	(0.025)	(0.025)
Log total hours – Netherlands	0.316***	0.206***	0.320***	0.199***
	(0.051)	(0.072)	(0.052)	(0.076)
Log physical capital – Netherlands	0.412***	0.411***	0.415***	0.409***
	(0.043)	(0.042)	(0.044)	(0.044)
Log human capital – US		0.169***		0.199***
		(0.031)		(0.033)
Log human capital – UK		0.090***		0.084***
		(0.021)		(0.022)
Log human capital – France		0.093***		0.093***
		(0.019)		(0.019)
Log human capital – Germany		0.141***		0.145***
		(0.031)		(0.032)
Log human capital – Netherlands		0.134**		0.146**
		(0.060)		(0.064)
Constant	5.984***	5.920***	5.883***	5.897***
	(0.172)	(0.177)	(0.174)	(0.178)
Time dummies	Yes	Yes	Yes	Yes
Observations	2730	2567	2470	2363
R-squared	0.846	0.863	0.852	0.868
Wald test (human capital)		16.20 (0.000)		16.39 (0.000)
Anderson LR statistic (χ^2)			15085	12502 (0.000)
Hansen J statistic (χ^2)			148.3	107.1 (0.000)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets. The human capital measure is log hc_u (=QAL_U-th). In columns (3) and (4) all variables have been instrumented with their own value at time t-1 and t-2. The Wald test is a test of the hypothesis of equal human capital coefficients across countries. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Human capital can also have a different impact on output depending on the industry under consideration. To investigate this issue further, we examine the relationship between skills and productivity in different groups of industries which are characterized by some common features. First we look at possible differences between the manufacturing and the non-manufacturing sectors by interacting all explanatory variables with dummies for manufacturing (M) and non-manufacturing (NM) as follows:

(4.3) $$y_{it} = \alpha_0 + \alpha_1 l_{it} * M + \beta_1 k_{it} * M + \gamma_1 h_{it} * M + \alpha_2 l_{it} * NM + \beta_2 k_{it} * NM + \gamma_2 h_{it} * NM + \\ + country + time + \upsilon_{it}$$

The results from estimating Equation (4.3) are presented in Table 4.3.

Our results reproduce a pattern usually found in growth accounting studies with non-manufacturing being characterized by higher labour elasticity and lower capital elasticity (O'Mahony and Vecchi, 2005). Similar to the results presented in Table 4.1, the inclusion of human capital slightly lowers the coefficient on total hours. The impact of human capital on output is positive and significant and our coefficient estimates suggest a stronger impact in manufacturing compared to non-manufacturing. However, the Wald test shows that the difference is not statistically significant.

Table 4.3: Heterogeneous coefficients across industries: Manufacturing versus Non-Manufacturing (EPKE)
Dependent variable: log value added

	(1)	(2)	(3)	(4)
	POLS	POLS	IV 2SLS	IV 2SLS
Log total hours – Manufacturing	0.391***	0.309***	0.396***	0.242***
	(0.025)	(0.032)	(0.026)	(0.039)
Log physical capital – Manufacturing	0.224***	0.222***	0.231***	0.222***
	(0.018)	(0.018)	(0.019)	(0.019)
Log total hours – Non-manufacturing	0.497***	0.381***	0.491***	0.335***
	(0.019)	(0.028)	(0.020)	(0.032)
Log physical capital – Non-manufacturing	0.160***	0.188***	0.175***	0.202***
	(0.019)	(0.020)	(0.020)	(0.021)
Log human capital – Manufacturing		0.121***		0.202***
		(0.022)		(0.032)
Log human capital – Non-manufacturing		0.112***		0.151***
		(0.018)		(0.022)
Constant	8.728***	8.315***	8.551***	7.886***
	(0.243)	(0.252)	(0.249)	(0.269)
Time dummies	Yes	Yes	Yes	Yes
Observations	2730	2567	2470	2313
R-squared	0.855	0.866	0.859	0.869
Wald test (total hours)	12.310 (0.000)	4.290 (0.039)	9.420 (0.000)	5.240 (0.000)
Wald test (physical capital)	6.070 (0.014)	1.710 (0.191)	4.350 (0.037)	0.570 (0.448)
Wald test (human capital)		0.140 (0.710)		2.820 (0.093)
Anderson LR statistic (χ^2)			15013 (0.000)	1684 (0.000)
Hansen J statistic (χ^2)			54.51 (0.000)	39.60 (0.000)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets. The human capital measure is log hc_u (=QAL_U-th). In columns (3) and (4) all variables have been instrumented with their own value at time t-1 and t-2. The Wald test is a test of the hypothesis of equal human capital coefficients across manufacturing and non manufacturing. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Finally, we investigate whether different groups of industries across the five countries are characterised by similar relationships between human capital and output according to their use of ICT capital. We start by dividing the industries into two groups, ICT and Non ICT intensive industries. An ICT intensive industry includes industries which are intensive either in production or use of ICT capital. The construction of the ICT-intensity dummies follows a taxonomy developed by Van Ark et al. (2002) which was based on the shares of US industries' ICT capital in total capital. The list of industries included in each group can be found in Appendix Table A11. After constructing two dummy variables for the two groups of sectors, we interact them with each explanatory variable, obtaining the following specification:

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1 l_{it} * ICT + \beta_1 k_{it} * ICT + \gamma_1 h_{it} * ICT + \\ &\alpha_2 l_{it} * NonICT + \beta_2 k_{it} * NonICT + \gamma_2 h_{it} * NonICT + \\ &country + time + \upsilon_{it} \end{aligned} \tag{4.4}$$

In this equation, *ICT* is the dummy for ICT-intensive industries (both using and producing), *NonICT* is the dummy for non-intensive use of ICT. The results from the estimation of Equation (4.4) are presented in Table 4.4. Comparing the coefficients on labour and physical capital we can see that there is a higher labour coefficient and a lower capital coefficient in the ICT intensive sectors compared to the non-ICT intensive. The estimated impact of human capital is greater in the ICT intensive industries. In all specifications coefficient estimates are significantly different across the two groups of industries suggesting higher labour and human capital elasticities in ICT intensive industries and higher capital elasticity in the non-ICT intensive sectors.

Overall, the pooled analysis predicts significantly positive returns to human capital, consistent with many previous analyses of the relationship between *levels* of productivity and skills. At the same time, we find significant inter-country and inter-industry differences in returns to human capital, suggesting a high degree of heterogeneity in the relationship between human capital and productivity. In the next section we investigate the heterogeneity issue further by using panel estimation methods.

Table 4.4: Heterogeneous coefficients across industries: ICT versus Non-ICT intensive sectors (EPKE)

Dependent variable: log value added

	(1)	(2)	(3)	(4)
	POLS	POLS	IV 2SLS	IV 2SLS
Log total hours – ICT sectors	0.758***	0.599***	0.756***	0.531***
	(0.019)	(0.031)	(0.020)	(0.037)
Log physical capital – ICT sectors	0.080***	0.089***	0.088***	0.102***
	(0.014)	(0.013)	(0.014)	(0.014)
Log total hours – Non - ICT sectors	0.398***	0.349***	0.393***	0.306***
	(0.020)	(0.027)	(0.020)	(0.032)
Log physical capital – Non-ICT sectors	0.382***	0.374***	0.392***	0.376***
	(0.017)	(0.017)	(0.017)	(0.017)
Log human capital – ICT sectors		0.162***		0.216***
		(0.023)		(0.029)
Log human capital – Non-ICT sectors		0.066***		0.106***
		(0.018)		(0.024)
Constant	5.566***	5.870***	5.866***	5.887***
	(0.192)	(0.191)	(0.191)	(0.197)
Time dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2730	2567	2470	2313
R-squared	0.853	0.870	0.860	0.875
Wald test (total hours)	193.620 (0.000)	55.490 (0.000)	185.190 (0.000)	35.470 (0.000)
Wald test (physical capital)	174.100 (0.000)	160.450 (0.000)	165.560 (0.000)	140.590 (0.000)
Wald test(human capital)		15.780 (0.000)		14.340 (0.000)
Anderson LR statistic (χ^2)			15563 (0.000)	2224 (0.000)
Hansen J statistic (χ^2)			88.92 (0.000)	54.33 (0.000)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets. The human capital measure is log hc_u (=QAL_U-th). In columns (3) and (4) all variables have been instrumented with their own value at time t-1 and t-2. The Wald test is a test of the hypothesis of equal human capital coefficients across ICT and Non-ICT industries. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

4.3 Panel data analysis

The POLS estimator provides an easy way to analyse data but it does not fully exploit the panel structure of the data. In this section we carry out our analysis using panel data techniques. In doing so we are able to control for some types of omitted variable, for example, industry-specific factors that we cannot measure (unobserved heterogeneity).

Panel data analysis assumes that the error term μ_{it} can be decomposed into two components:

(4.5) $$\mu_{it} = e_i + w_{it},$$

where e_i is the industry-specific effect. This is constant over time but varies over the cross-sectional dimension. The second term, w_{it}, is a transitory component (or idiosyncratic disturbance) that changes over time and cross-sections. The latter is assumed to be uncorrelated with the explanatory variables. The assumptions regarding the first term, e_i vary according to the panel data method used.

In this section we test the robustness of our results to using four different panel data methods: the fixed effect, the first difference estimator, the random effect and the between effect. As noted in Section 2.4, previous panel data analysis of the impact of human capital on productivity at national level has often proved unsuccessful. For example, Islam (2003) reports a negative and insignificant human capital coefficient when using the fixed effect estimator. His main conclusion is that the fixed effects model, by relying on the time series variation of the data and discarding cross-sectional variation (for example, in countries' technology levels and institutional characteristics), is not suitable for capturing the impact of human capital on output. Our analysis, by comparing the performance of different panel data estimators, will offer further insights on this issue.

Results 2: the Fixed Effects and First Difference models.

In the Fixed Effects ('Within') Model, we control for omitted variables that differ between country/industry combinations but are constant over time. This is done by running a regression on the deviations of the observations from their means:

(4.6) $$y_{it} - \overline{y_i} = \alpha(l_{it} - \overline{l_i}) + \beta(k_{it} - \overline{k_i}) + \gamma(h_{it} - \overline{h_i}) + time + (\mu_{it} - \overline{\mu_i})$$

In Equation (4.6) y_{it} is the log of value added, l_{it} is the log of the total number of hours worked, k_{it} is the log of the stock of physical capital and h_{it} is log human capital. The bar over a variable indicates its mean over time. Applying the OLS estimator to Equation (4.6) produces the Fixed Effects Estimator (FE).[13] The de-meaning procedure removes the industry-specific effect, discussed in the previous section – see Equation (4.5) – as this does not change over time. The FE model does assume that there is some arbitrary correlation between the explanatory variables and the unobserved heterogeneity between country/industry combinations.

In Table 4.5, column (1) we present the results from estimation of a simplified version of Equation (4.6) that excludes human capital. The results imply an elasticity of output to total hours worked of approximately 0.44 and an output-capital elasticity of 0.2. In general the FE estimates imply decreasing returns to scale of around 0.6-0.7 and the test for the presence of constant returns to scale always rejects the constant returns to scale assumption. In the absence of large pure profits, decreasing returns to scale at the firm level implies that firms consistently price output below marginal cost, which is not economically viable (Basu and Fernald, 1997; Vecchi, 2000). In column (2) we find a positive and significant human capital coefficient but its impact is smaller than the results presented in the previous section (0.024 compared to 0.138). However, the results improve when we correct for the presence of endogeneity by instrumenting the right hand side variables with their own lagged values and using the Two Stage Least Squares estimator (FE 2SLS). In column (4) the human capital effect is approximately

[13] Note that the deviation from the mean transformation is equivalent to running a regression on a specification that includes intercept dummies for each cross section.

three times larger than in column (2), although it is still smaller than in the POLS analysis discussed in the previous section.

Hence, contrary to previous studies such as Islam (2003), our fixed effects model does produce a positive and significant effect of human capital on average labour productivity (i.e. value added controlling for labour inputs). However, we need to understand the large difference in the coefficient estimates produced by the POLS and FE methods. It is possible that the fixed effects estimator, by eliminating the variations across groups in the de-meaning procedure, underestimates the human capital effect which is likely to be characterized by cross-sectional variation.

Table 4.5: Fixed effect results (EPKE)

Dependent variable: log value added in deviation from its mean

	(1)	(2)	(3)	(4)
	FE	FE	FE- IV	FE - IV
Log total hours	0.443***	0.402***	0.435***	0.354***
	(0.090)	(0.086)	(0.090)	(0.081)
Log physical capital	0.201***	0.203***	0.216***	0.211***
	(0.077)	(0.075)	(0.073)	(0.067)
Log human capital		0.024**		0.071**
		(0.012)		(0.029)
Constant	7.913***	7.762***		
	(1.319)	(1.234)		
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2730	2567	2470	2313
Number of industry/country combinations	130	127	130	127
R-squared	0.531	0.559	0.549	0.563
Constant returns to scale	15.730 (0.000)	19.520 (0.000)	15.150 (0.000)	20.910 (0.000)
Anderson LR statistic (χ^2)			7018	461.6
Hansen J statistic (χ^2)			6.200 (0.045)	5.841 (0.120)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, corrected for clustering, are in brackets. The human capital measure is log hc_u (=QAL_U-th). In columns (3) and (4) all variables have been instrumented with their own value at time t-1 and t-2. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

The first difference estimator

Another way of removing unobserved heterogeneity is to apply the Pooled OLS estimator to a model expressed in first differences (FD) and logs as follows:

(4.7) $$\Delta y_{it} = \beta_1 \Delta th_{it} + \beta_2 \Delta k_{it} + \beta_3 \Delta h_{it} + \Delta u_{it} ,$$

where, for example, $\Delta y_{it} = y_{it} - y_{it-1}$. The first difference transformation eliminates the unobserved effect as well as any time-invariant variable (for example country dummies). The results from estimating Equation (4.7) are presented in Table 4.6.

Table 4.6: First difference results (EPKE)

Dependent variable: rate of growth of value added

	(1)	(2)	(3)	(4)
	FD	FD	FD 2SLS	FD 2SLS
Change in log total hours	0.466***	0.499***	0.436***	0.395***
	(0.066)	(0.068)	(0.127)	(0.093)
Change in log physical capital	0.122*	0.118*	0.148**	0.178***
	(0.071)	(0.070)	(0.058)	(0.060)
Change in log human capital		-0.001		-0.007
		(0.002)		(0.005)
Constant	0.039***	0.030***	0.023***	0.024***
	(0.005)	(0.006)	(0.002)	(0.002)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2600	2440	2340	2186
R-squared	0.148	0.182	0.127	0.155
Constant returns to scale	32.230 (0.000)	26.420 (0.000)	13.060 (0.003)	21.660 (0.000)
Anderson LR statistic (χ^2)			748.5	525.2
Hansen J statistic (χ^2)			2.309 (0.315)	2.495 (0.476)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, corrected for clustering, are in brackets. The human capital measure is log hc_u (=QAL_U-th). In columns (3) and (4) all explanatory variables have been instrumented with their own value at time t-1 and t-2. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

The first difference model produces coefficient estimates for labour and capital inputs that are lower compared to prior expectations regarding factor shares in value added. The coefficient on human capital is negatively signed and not significantly different from zero. This negative result for the human capital variable in a growth regression is not surprising as several other studies fail to find a positive impact of human capital growth on output growth (Islam, 1995; Barro and Sala-i-Martin, 1995; Benhabib and Spiegel, 1994). As discussed in Section 2.4 this could be due in part to measurement errors that particularly affect the time series dimension of human capital (Islam, 2003; De la Fuente and Domenech, 2006).

As noted by Islam (1995), both the FE and the FD estimators produce estimates based on the time dimension of the data because they remove the source of cross-sectional variation. However, the cross-sectional variation seems to matter more in determining the effect of human capital on productivity because of, for example, institutional differences between countries. It may also be the case that growth in human capital has more of an impact on long-term growth in productivity than short-term growth. Year-to-year variation in education attainments may simply be less likely to contribute to contemporaneous productivity changes. These considerations help to explain why we get weaker estimates of the links between human capital and productivity with the FE and FD methods. Accordingly, we now extend our analysis to two other panel data techniques that put more emphasis on cross-sectional variation in the data: the between and the random effects models.

Results 3: Between effects and random effects panel data estimation

In the between effect model, the production function Equation (4.1) is expressed by taking the average over time of each variable, as follows:

(4.8) $$\overline{y_i} = \alpha \overline{l_i} + \beta \overline{k_i} + \gamma \overline{h_i} + country + \overline{\eta_i} \ .$$

The bar over a variable indicates its mean and *i* subscript denotes industry. The time subscript is missing because by taking the average of each variable we end up carrying out cross-section estimation. For the same reason, time dummies do not appear in Equation (4.8). Country dummies, on the other hand, can be included. The between effects (BE) estimator is the application of the OLS method to Equation (4.8). As in the previous section, we will also estimate Equation (4.8) allowing for endogeneity of the regressors using the Two Stage Least Squares estimator (BE 2SLS).

The BE estimator reflects purely cross-sectional variation in the data and removes all time series information. If Islam's (1995) conclusions about the relationship between human capital and growth are correct, we expect this estimator to produce positive and significant estimates of the human capital elasticity. However, the loss of the time series dimension makes the BE estimator less efficient compared to other panel data techniques. For this reason we also look at the random effects (RE) estimator, which combines the information contained in the FE and BE models. For example, the RE estimator of the human capital coefficient, $\hat{\gamma}_{RE}$, can be described as:

(4.9) $$\hat{\gamma}_{RE} = \Psi\hat{\gamma}_{BE} + (1-\Psi)\hat{\gamma}_{FE},$$

where a 'hat' over a variable denotes the estimated coefficient. Equation (4.9) represents the RE model as a weighted average of the BE and the FE models, the weight represented by Ψ which is determined by the variance of the BE estimator. The estimation of the RE model cannot be carried out using OLS because that will generate standard errors that are too low. Instead, we use the more complex Generalised Least Squares (GLS). As for the previous estimations, we also use instrumental variables in order to correct for endogeneity.

An important feature that distinguishes the RE from the FE model is the assumption made on the correlation between the covariates and the heterogeneous component of the error term. While the FE model assumes the presence of some correlation, the RE model assumes no correlation between the explanatory variables and the unobserved heterogeneity. This assumption can be tested by means of a Hausman test. The Hausman test compares the coefficient estimates of the FE (consistent) estimator and the RE (efficient) estimators. Rejection of the null implies that RE is inconsistent and therefore estimates based on FE are generally preferred.

Table 4.7 presents the results from the estimation of the BE and RE models. The bottom panel shows the 2SLS estimates. The between estimator produces high and significant estimates of the human capital coefficient, as well as more reasonable predictions about the returns to scale (approximately 0.9), compared to, for example, the FE method. Consistent with previous estimates, the hypothesis of constant returns to scale is rejected. The 2SLS results assign a higher coefficient value to human capital and to physical capital, although the difference is not statistically significant. The coefficient estimates for human capital are higher but in line with the predictions for the pooled model presented in Table 4.1 (0.138 for the POLS and 0.194 for the 2SLS estimator). As discussed in Griliches (1998), when most of the variability of the data is between rather than within cross sections, the BE and the POLS estimates are very close. This also supports the discussion in Islam (1995) in relation to the poor performance of human capital when cross-sectional variation is removed from the data.

The GLS RE model produces human capital estimates of 0.027 and 0.076, which are very close to the FE results presented earlier. It is important to note that when constructing the weighted average of the BE and the FE estimates, the GLS RE will give more weight to the FE when the time series dimension of the data is quite large (Nerlove, 1996). This seems to be the case in our analysis[14].

[14] Also note that the Hausman test rejects the null hypothesis when using instrumental variable, implying that the FE estimates are, in this case, preferred to those produced by the RE model.

Table 4.7: Between effects (BE) and random effects (RE) results

Dependent variable: log value added

Part A:	**(1)**	**(2)**	**(3)**	**(4)**
	BE	**BE**	**RE**	**RE**
Log total hours	0.574***	0.341***	0.481***	0.448***
	(0.058)	(0.103)	(0.078)	(0.076)
Log physical capital	0.312***	0.293***	0.235***	0.240***
	(0.062)	(0.060)	(0.071)	(0.069)
Log human capital		0.214***		0.027**
		(0.081)		(0.012)
Constant	4.129***	5.021***	6.853***	6.908***
	(0.573)	(0.667)	(0.945)	(0.867)
Observations	2730	2567	2730	2567
Number of industry/country combinations	130	127	130	127
R-squared	0.826	0.851	0.818	0.838
Constant returns to scale	9.650 (0.002)	15.070 (0.000)	29.490 (0.000)	19.890 (0.000)
Hausman test (χ^2 and p values)			0.640 (0.726)	0.490 (0.921)
Part B: 2SLS	**(1)**	**(2)**	**(3)**	**(4)**
	BE	**BE**	**RE**	**RE**
Log total hours	0.571***	0.334***	0.475***	0.399***
	(0.057)	(0.102)	(0.019)	(0.022)
Log physical capital	0.317***	0.299***	0.250***	0.248***
	(0.061)	(0.059)	(0.019)	(0.020)
Log human capital		0.216***		0.076***
		(0.081)		(0.013)
Constant	4.101***	4.999***	6.682***	0.000
	(0.567)	(0.660)	(0.311)	(0.000)
Observations	2470	2313	2470	2313
Number of industry/country combinations	130	127	130	127
R-squared	0.820	0.844	0.825	0.847
Constant returns to scale	9.470 (0.000)	15.130 (0.000)	181.150 (0.000)	179.430 (0.000)
Hausman test (χ^2 and p values)			30.620 (0.000)	14.900 (0.000)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, corrected for clustering, are in brackets. In the instrumental variable estimation all explanatory variables have been instrumented with their own values at time t-1 and t-2. The Anderson LR statistic and the Hansen J statistic are not available for the between and random effect models. The Hausman test is a test of the hypothesis of consistency and efficiency of the random effect estimator. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Summary:

The analysis presented in this section has shown that human capital plays an important and significant role in determining productivity levels (i.e. output levels at a given level of labour input). This result is robust to the use of different estimation methods, with the exception of an equation in first differences. We present a summary of the results in Table 4.8. Our preferred results are those that control for endogeneity so only 2SLS estimates are presented. The estimated human capital coefficient ranges in size between 0.071 (FE model) and 0.216 (BE). These differences in the coefficient estimates are consistent with the view that the cross-sectional variation in human capital (e.g. between sectors and countries) is more relevant to productivity performance than variation over time in human capital. This explains why the fixed effect and the random effect estimators result in smaller human capital coefficients compared to the pooled OLS model and the BE model.

Table 4.8: Human capital coefficient estimates across different estimation methods

(2SLS results)

	POLS	FE	FD	BE	RE
Human capital	0.194***	0.071**	-0.007	0.216***	0.076***

Furthermore, when we investigate the determinants of growth rates in output (using the FD estimator), the simple inclusion of human capital as another factor of production points to a negative and insignificant human capital impact. In the next section we explore this issue further using an alternative specification for the relationship between human capital and output growth.

5. 'Catch-up' models of productivity growth

In this section we specify the production function in ways that allow for the possibility of human capital effects having stronger effects over time in sectors and countries that have a lot of catching-up to do in order to match productivity levels in leader countries.

5.1 Human capital and output growth: an alternative specification

As discussed in Section 2.4, the poor performance of human capital in productivity growth regressions may be explained in part by the misspecification of the production function and the way the impact of human capital is modeled. Following Nelson and Phelps (1966), Benhabib and Spiegel (1994) propose a different model that allows human capital to assist less productive countries to 'catch up' with productivity leaders by increasing their ability to innovate and by facilitating the adoption and diffusion of foreign technology. Their econometric specification captures the catching-up effect by including the level of human capital[15] and the initial level of output in a growth accounting regression:

(5.1) $$(y_T - y_0) = (a_T - a_0) + \alpha(k_T - k_0) + \beta(l_T - l_0) + \gamma h + \theta y_0 + (\varepsilon_T - \varepsilon_0).$$

In Equation (5.1) the log difference of output is regressed on the log growth of total factor productivity (a_T-a_0), the log difference of the capital stock and employment (*k* and *l*), the log level of human capital (*h*) and the log of the initial level of output (y_0). The last term is an error term that is assumed to be independent of changes in the factors of production and the level of human capital. Their estimates of Equation (5.1) produced significant and positive coefficients for human capital.

In this section we estimate Equation (5.1) with the EPKE dataset so that all differences are defined as the difference between the level of a variable in the year 2000 and its value in the year 1982. All coefficients are expected to have a positive sign, with the exception of the level of output at the beginning of the sample period in 1982 (y_0). According to Benhabib and Spiegel (1994) this model should outperform more standard

[15] Human capital stock is measured following estimates developed by Kyriacou (1991).

growth models, where all variables are expressed in differences and no allowance is made for the catching-up process, that is:

(5.2) $$(y_T - y_0) = (a_T - a_0) + \alpha(k_T - k_0) + \beta(l_T - l_0) + \gamma(h_T - h_0) + (\varepsilon_T - \varepsilon_0)$$

Table 5.1 presents a comparison of the performance of this standard growth regression model and the specification in Equation (5.1). The estimation is carried out using Ordinary Least Squares (OLS) with heteroscedasticity-robust standard errors (White 1980).

In column (1) we present the specification in log differences of all variables. Similar to our first difference results presented in the previous section, we do not find a significant human capital impact on productivity (note, however, that the change in human capital is now positively signed). Results in columns (2) to (4) are based on the alternative approach proposed by Benhabib and Spiegel. In column (2) human capital stock is included in the regression but without the inclusion of the level of output, its impact is still not significantly different from zero. In column (3), on the other hand, we include the level of output in 1982, which is significant and characterised by the expected negative sign, indicating that countries with a higher level of output (closer to the frontier) experience a slower growth compared to countries that are farther away from the frontier. In this model the impact of human capital is positive and significant and the size of the effect (0.139) is close to the value reported in Benhabib and Spiegel's paper (0.128)[16]. A slightly stronger human capital effect is found when including country dummies in the analysis, as in column (4). Also note that the coefficients on human capital are approximately the same as those estimated using the BE model. This shows the robustness of our results to different estimation methods and different specifications of the production function.

[16] See Benhabib and Spiegel (1994), Table 4, Model (2), p. 159.

Table 5.1: Catch-up models of productivity growth (EPKE)
Dependent variable: growth of value added between 1982-1998 - (18 year gap)

	(1)	(2)	(3)	(4)	(5)	(6)
Growth in physical capital, 1982-98	0.188*	0.213**	0.225**	0.373***	0.271***	0.224**
	(0.104)	(0.101)	(0.111)	(0.118)	(0.103)	(0.099)
Growth in total hours, 1982-98	0.456***	0.443***	0.433***	0.232**	0.401***	0.379***
	(0.094)	(0.108)	(0.110)	(0.115)	(0.113)	(0.116)
Growth in labour quality, 1982-98	0.028					
	(0.029)					
Average human capital, 1982-98		0.011	0.139***	0.146***	0.018	0.029
		(0.021)	(0.047)	(0.049)	(0.028)	(0.029)
Log value added, 1982			-0.205***	-0.220***		
			(0.056)	(0.061)		
Log TFP, 1982					-0.202***	
					(0.062)	
Log TFP gap, 1982						0.051
						(0.050)
Country dummies	No	No	No	Yes	Yes	Yes
Constant	0.339***	0.209	2.063***	2.347***	0.146	-0.023
	(0.037)	(0.261)	(0.444)	(0.617)	(0.356)	(0.374)
Observations	127	127	127	127	127	127
R-squared	0.277	0.275	0.390	0.426	0.352	0.317

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets.

We also explore variations in this initial model by replacing the initial level of output as a control variable with the initial level of TFP (column (5)) and with a measure of the gaps in TFP levels between the leader country and follower countries in each industry (column (6)). The latter follows the 'TFP gap' measure developed by Griffith et al. (2004) which is assumed to capture the scope for technology transfer between countries (see Appendix Table A12 for country rankings on this measure). The results in Table 5.1, column (5) show that, as expected, output growth is negatively and significantly related to the starting level of TFP in 1982 since less productive countries in terms of levels in each sector have more scope for catching up with the leader country. However, the human capital variable is not significantly different from zero in this specification. In the case of the TFP gap measure in 1982, column (6) shows that neither this measure nor the human capital measure are statistically significant.

The results presented so far are based on a cross-section regression because we consider changes in output between the first and last observations in the sample. The question arises however whether this type of 'catch-up' model will capture human capital effects on year-on-year productivity growth rates. In order to make better use of the information in our data set we estimate a first-difference version of the Benhabib and Spiegel model (1 year gap model), as well as taking long differences of the data in what we define as a 3-year and a 5-year gap model. The results are presented in Table 5.2.[17]

Table 5.2: Catch-up models of productivity growth: 1, 3 and 5 year gap
Dependent Variable: Growth in Value Added

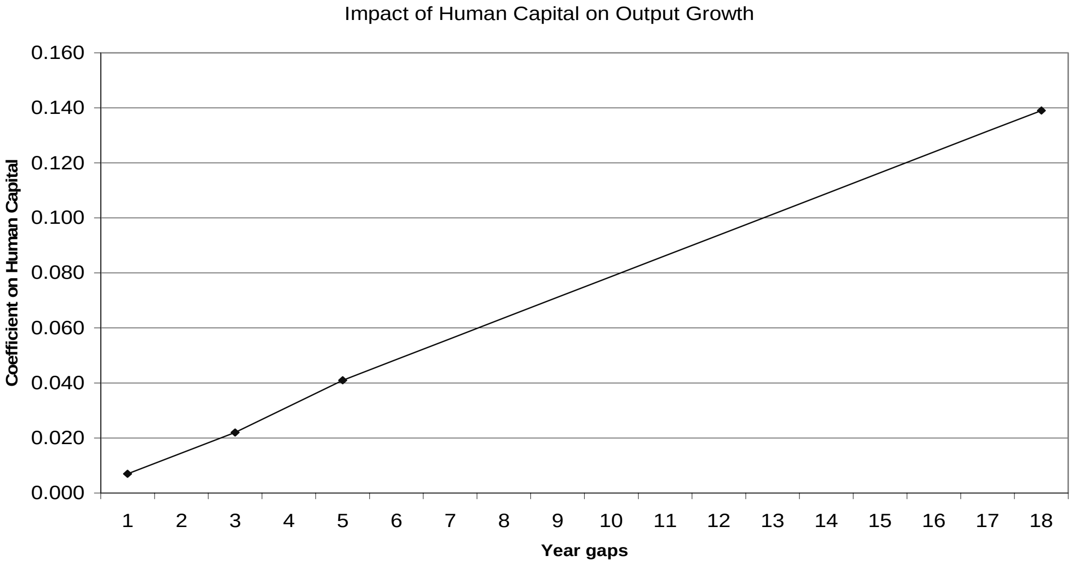
	1 year gap	3 year gap	5 year gap
Growth in physical capital	0.119*	0.159***	0.128**
	(0.070)	(0.060)	(0.061)
Growth in total hours	0.459***	0.476***	0.488***
	(0.075)	(0.103)	(0.083)
Labour Quality (unskilled base)	0.007***	0.022***	0.041***
	(0.002)	(0.008)	(0.014)
Log Value Added (t-n)	-0.008***	-0.033***	-0.062***
	(0.003)	(0.010)	(0.018)
Constant	0.068	0.412***	0.724***
	(0.044)	(0.113)	(0.186)
Observations	2465	635	381
R-squared	0.180	0.272	0.311

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets.

[17] We also estimate the 1, 3, and 5 year gap model using TFP levels and TFP gaps instead of value added. The full set of results can be found in Appendix Tables A13-A15.

In general it seems that the catch-up model generates more explanatory power over longer periods than in the short run. Thus the coefficient on the log starting value of output grows larger as the gap in time is extended first to three and then to five years (columns (2) and (3) in Table 5.2). In the same specification the coefficient on the human capital variable is statistically significant in all models and grows over time from 0.007 (1 year gap) to 0.022 (3 year gap) and 0.041 (5 year gap). The estimates of the human capital coefficient in the different models are also presented in Figure 5.1 to give a visual representation of the stronger impact of human capital on output growth as the time lag is increased.

Figure 5.1: Estimated coefficients on human capital variable in catch-up models of productivity growth



Summary:

'Catch-up' models emphasise the scope for sectors in different countries with lower initial levels of productivity to grow faster than productivity leaders by using skilled labour to adopt and make use of technologies and work practices developed elsewhere. In this type of model we expect to see a negative coefficient on initial levels of output and a positive coefficient on average labour quality. Both of these hypotheses are supported by our empirical analysis. However, our results also suggest that the catching-up effect unfolds over a relatively long time frame. Year on year growth in human capital is unlikely to have an immediate effect on productivity.

6. Workforce skills and technical efficiency

In the econometric analysis undertaken in Sections 4-5, it has been implicitly assumed that all industries are using their resources at maximum efficiency and that differences in productivity are therefore due to different resource endowments (e.g. physical capital or skilled labour). In this section we relax the assumption of optimal use of resources by estimating a frontier production function. This represents the maximum output that can be produced given available resources. When resources are not fully utilised an industry/country will lie below the frontier and the distance from the frontier provides a measure of technical inefficiency. Following this method, we can calculate efficiency scores to assess the relative performance of each industry. In general, high levels of technical efficiency contribute positively to labour productivity. However, in some sectors low-productivity countries may do well on efficiency measures because they make effective use of their relatively limited resources.

6.1 Frontier analysis

Recall from Section 2.2 that in growth accounting studies it is possible to decompose cross-country gaps in average labour productivity (ALP) into three components:

- differences in physical capital per hour worked
- differences in labour quality
- the Total Factor Productivity (TFP) residual which, among other things, captures cross-country differences in the efficiency of use of resources

In this section we use the ISP dataset to explore cross-country differences in efficiency of resource use by making use of Stochastic Frontier Analysis (SFA) which relaxes the assumption of full use of resources and allows for varying degrees of inefficiency in use of production inputs.

Frontier analysis was developed in Farrell (1957) and has since found a large number of applications in analysis of both private and public sector performance (see, for example, Kneller and Stevens, 2003). This type of analysis starts by identifying the production frontier at which producers are either achieving maximum output with a given set of resources (including technologies) or are achieving a given output at minimum cost. Once the frontier has been identified, it is possible to obtain estimates of efficiency levels for each economic unit (in our case, sector/country combination) by measuring the distance between the unit and the frontier. The further away from the frontier, the higher is the level of implied technical inefficiency. For our purposes we are then interested in whether and to what extent cross-country differences in technical inefficiency at sector level are attributable to skill differences.

The two most commonly used frontier methods are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA identifies the frontier with the best performing industry in the sample and assumes that all deviations from the frontier are caused by technical inefficiencies. No allowances are made for measurement errors or other random components (Kumbhakar and Lovell, 2000). The stochastic frontier method makes such allowances and produces efficiency scores based on econometric estimation, therefore making this approach more consistent with the panel data estimation undertaken in previous chapters.

The most intuitive way of understanding SFA and frontier analysis in general is to think that the actual output produced can be lower than the maximum output that can be feasibly produced using the available resources. Let us define Y_A as actual output for industry *i* at time *t*, and $Y_{MAX\,it}$ as maximum (frontier) output. Technical efficiency (TE_{it}) for industry *i* at time *t* can then be derived as:

(6.1) $$TE_{it} = \frac{Y_{A_{it}}}{Y_{MAX_{it}}}$$

Rearranging, we can write:

(6. 2) $$Y_{A_{it}} = Y_{MAX_{it}} * TE_{it} = f(x_{it}, \beta) * TE_{it}$$

The level of efficiency in each industry must be in the interval [0,1]. If TE_{it}=1, the industry lies on the frontier and it is achieving the optimal output with the technology embodied in the production function. When TE<1, the industry lies within the frontier and it is not making the most of production inputs. Since output is assumed to be strictly positive, the degree of technical efficiency is also assumed to be positive (TE>0). By defining $TE_{it} = \exp(-u_{it})$ [18], we can rewrite Equation (6.2) as follows:

$$Y_{A_{it}} = f(x_{it}, \beta)\exp(-u_{it}) \quad (6.3)$$
$$u_{it} \geq 0$$

Equation (6.3) defines a deterministic frontier where all the deviations from maximum output are caused by inefficiencies. However, maximum output and actual output could differ because of exogenous shocks. This implies that:

$$Y_{A_{it}} = f(x_{it}, \beta)\exp(v_{it})\exp(-u_{it})$$
$$v_{it} \leq 0 \quad (6.4)$$
$$u_{it} \geq 0$$

where v_{it} captures the effect of exogenous shocks on output.
Taking the natural log of both sides of the equation yields:

$$\ln(y_{Ait}) = \ln\{f(x_{it}, \beta)\ \} + v_{it} - u_{it} \quad (6.5)$$

Assuming a Cobb-Douglas production function[19] for the deterministic kernel, and expressing the function in logs we can derive the following specification:

$$Y_{it} = \beta_{0i} + \beta_1 \ln(th_{it}) + \beta_2 \ln(ktot_{it}) + v_{it} - u_{it}\,. \quad (6.6)$$

In Equation (6.6) th_{it} is total hours worked and $ktot_{it}$ is total capital.

The inefficiency term, u_{it}, can be interpreted as the percentage deviation of observed performance from the industry's own frontier performance. Estimation of Equation (6.6) requires assumptions about the distribution of the composite error term $(v_{it} - u_{it})$. v_i is a

[18] This specification bounds technical efficiency between 0 and 1, as long as u_{it} is positive.
[19] Different functions can be used to specify the frontier, such as the Translog or the CES (Constant Elasticity of Substitution) function. These different specifications can affect the efficiency scores. However, Kneller and Stevens (2003) using a sample of 82 countries over a 28 year period, show that the differences disappear when labour is adjusted for human capital and that the effect of different specifications on the ranking of the scores is minor.

normal random variable, distributed independently of u_{it}. Different assumptions can be made for the distribution of the inefficiency term u_{it}. This can be specified, for example, as a half-normal or a truncated normal distribution.

With panel data it is possible to choose how to model the behaviour of the inefficiency term (u_{it}) as it varies over time. Specifically we can either estimate a time invariant or a time varying technical efficiency model. The latter is usually preferred when several years of data are available. Several time-varying models have been proposed in the existing literature. Here we follow Battese and Coelli (1992) and we model the inefficiency effects as:

(6.7) $$u_{it} = \exp\{-\eta(t - T_i)\}u_i$$

where T_i is the last time period in the i_{th} panel, η is a decay parameter that captures the rate of change in technical efficiency over time, and u_i is a truncated normal variable. When $\eta > 0$ the degree of inefficiency decreases over time; when $\eta < 0$ the degree of inefficiency increases over time, when $\eta = 0$ technical inefficiency remains constant. Equations (6.6) and (6.7) are estimated using maximum likelihood estimation.

The longer the panel, the less likely it becomes that technology remains constant. This makes it desirable to include time among the regressors as a proxy for technical change. Although this practice is commonplace in the estimation of production functions based on panel data, it is relatively uncommon in the estimation of production frontiers using panel data. One possible reason is that production frontier models based on panel data are making increasing use of time-varying technical efficiency specifications, and it may be difficult to disentangle the separate effects of technical change and technical efficiency change when both effects are proxied by the passage of time.

As discussed in Section 4.2, for this analysis we make use of the ISP dataset in order to take advantage of its relatively high level of sectoral disaggregation (68 sectors in the UK, US and Germany). We begin by estimating a frontier production function where total output is a function of the log of the total number of hours worked, total capital and human capital (*QAL_G/th*):

(6.8) $Y_{it} = \beta_{0i} + \beta_1 \ln(th) + \beta_2 \ln(ktot_{it}) + \beta_3 \ln(QAL\_G / th) + country + v_{it} - u_{it}$

where *country* identifies country dummies. We follow Battese and Coelli (1992) in assuming that the error term is distributed as truncated normal and it changes over time according to the specification (6.7) discussed above. Therefore, and differently from previous specifications, we do not include time dummies in the frontier equation. The results are presented in Table 6.1. For comparison purposes, we present the OLS (pooled model) result, the time-invariant and the time-varying frontier estimates:

Table 6.1: OLS and frontier analysis of the determinants of productivity

	OLS estimates	**Time-invariant frontier estimates**	**Time-varying frontier estimates**
Log Total Hours	0.732*** (0.033)	0.531*** (0.020)	*0.610*** (0.022)*
Log Physical capital	0.202*** (0.032)	0.350*** (0.015)	*0.293*** (0.022)*
Log QAL_G/th	1.927*** (0.242)	0.926*** (0.130)	0.620*** (0.139)
UK dummy	-0.207*** (0.069)	-0.220*** (0.064)	-0.179*** (0.055)
GE dummy	-0.401*** (0.076)	-0.369*** (0.062)	-0.123*** (0.070)
Constant	-1.081*** (0.314)	0.763***(0.243)	0.129 (0.295)
γ		0.910*** (0.006)	0.905*** (0.004)
η		Restricted to be 0	0.013*** (0.001)
Log likelihood		486.956	546.769
Number of obs.	2040	2040	2040

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Standard errors in brackets. Results are based on the ISP data set.

The coefficient estimates do not differ significantly between the time-invariant and the time-varying model. This is not surprising given that the value of η is very small in the second model, indicating a slight increase in technical efficiency over time. Nevertheless the coefficient is significantly different from zero. Hence, the time-varying technical efficiency model will be preferred in the remainder of the analysis. The country dummies for the UK and Germany indicate that across all observations, all else being equal, frontier output is lower in the UK and Germany than it is in the reference country, in this case the US. The frontier estimation results differ significantly from OLS, indicating that inefficiency is playing an important part in relative productivity performance. This is confirmed by the size of the parameter γ. This is defined as:

(6.9) $$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$$

where σ_u^2 is the variance of the inefficiency term and $(\sigma_u^2 + \sigma_v^2)$ is the variance of the composite error term. The parameter γ must lie between 0 and 1 and it gives an indication of the importance of inefficiencies in our model. When γ=1 all the deviations from the frontier output are caused by inefficiencies and the SFA is not different from the deterministic frontier (DEA). When γ=0 the model collapses into the OLS model, as all deviations from the frontier are caused by random disturbances. In our case the value of γ is very high, suggesting the presence of large inefficiencies.

6.2 Determinants of inefficiency

The estimation of a stochastic production frontier provides a benchmark against which to estimate technical efficiency. However, in order to have a better understanding of why industries vary in the extent to which they use resources effectively, we need to extend frontier analysis and introduce some factors that might affect efficiency. These are usually called environmental or exogenous factors and are assumed to be beyond the control of the firms/industry (Kumbhakar and Lovell, 2000). However, there have been cases where variables that appear in the production frontier also enter the specification of inefficiency in order to capture their dual role, i.e. their impact on production and their impact on inefficiency (Kneller and Stevens, 2006).

In this section we follow the latter approach and we treat human capital as an input in the production process and as a determinant of inefficiency. The specification of the production function is given by:

(6.10) $$Y_{it} = \beta_{0i} + \beta_1 \ln(ktot_{it}) + \beta_2 \ln(QAL\_G\ ) + country + v_{it} - u_{it}$$

where *QAL_G* stands for total quality adjusted labour input, taking graduate-quality labour as the benchmark (see Section 3.1 for details).

Inefficiency is modelled as dependent on the level of human capital, country dummies and a time trend. Country dummies capture the effect of country institutions on inefficiency (Prescott, 1998; Parente and Prescott, 2000). The introduction of the time trend intends to capture the impact of technological changes on inefficiency, i.e. we expect inefficiency to decline following technological developments. The level of inefficiency is therefore defined as:

(6.11)
$$u_{it} = \alpha_0 + \alpha_1 \ln(hc) * US + \alpha_2 \ln(hc) * UK + \alpha_3 \ln(hc) * GE + \\ + \alpha_4 trend + countries + \varepsilon_{it}$$

Human capital, *hc*, measured as *QAL_G/th*, is interacted with the country dummies in order to account for different impacts of human capital on inefficiency across different institutional settings. The random variable ε_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-z_{it}\alpha$, where z_{it} is the vector of explanatory variables associated with the technical inefficiency of industries over time.

Equations (6.10) and (6.11) are jointly estimated using Maximum Likelihood estimation. The results are presented in Table 6.2.

Table 6.2: Estimation of production frontier and the determinants of inefficiency

	(1) Frontier production function	**(2) Inefficiency**
Log total quality adjusted labour (QAL_G)	0.743*** (0.009)	
Log Physical capital	0.207***(0.009)	
US*Human capital		-1.160*** (0.255)
UK*Human capital		-1.391***(0.514)
GE*Human capital		-0.427***(0.171)
Time trend		-0.015***(0.004)
γ	0.584*** (0.059)	
Log likelihood	-906.574	
Number of obs.	2040	

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Standard errors in brackets. Results are based on the ISP data set.

The measure of labour used in the estimation of the production frontier is adjusted for human capital, hence the output-labour elasticity is larger in Table 6.2 than in Table 6.1 where human capital and total hours were treated separately. The different specification of the production function adopted here has an impact on the capital coefficient whose size is now closer to expectations based on prior knowledge of factor shares.

Turning to the determinants of inefficiency, we see that human capital is highly significant and has the expected negative sign in all countries, indicating that increases in human capital reduce inefficiency and therefore reduce the distance from the frontier. This has also been interpreted as evidence of the role of human capital in technology absorption (Kneller and Stevens, 2006). The impact is stronger in the UK, where a one percent increase in human capital leads to an estimated 1.4% decrease in inefficiency, compared to a 1.2% decrease in the USA and a 0.4% reduction in Germany. The time trend is also negatively signed, showing that technological developments have an impact (albeit small) in reducing inefficiencies.

6.3 Efficiency estimates

From the estimation of a frontier production function we can obtain estimates of technical efficiency (*TE*) for each industry and time period. These are derived as follows:

(6.12) $$TE_{it} = \exp(-\hat{u}_{it})$$

As discussed above, *TE* ranges between 0 and 1. The closer *TE* is to 1 the higher the efficiency level. In Table 6.3 we present the average efficiency estimates derived from our preferred specification, i.e. the model that allows for human capital to affect both productivity and inefficiency. Next to the efficiency scores we also present country rankings which provide an easy way to assess the relative performance of each industry.

The results (Table 6.3) show that differences in efficiency are large, both across industries and within the same industry in different countries. For example, mean efficiency in the textile industry is 0.45 in the US, 0.47 in the UK and 0.84 in Germany. The UK is ahead of the US and Germany in some 24 of the 68 sectors, covering a wide range of manufacturing and service activities. This may seem surprising given the UK's relatively poor productivity performance in many of these same sectors. However, it needs to be remembered that efficient use of resources is only one element in productivity performance and that in many sectors cross-country differences in productivity are driven primarily by resource input levels (e.g. physical capital per hour worked). For example, it is possible for a country to perform badly on ALP in some sectors because of relatively low levels of physical capital-intensity but to perform well on technical efficiency because it makes effective use of the limited capital resources at its disposal.

Table 6.3: Average efficiency score by country and industry, 1995-2004, with country rankings
(Sectors highlighted in bold where UK is ahead on technical efficiency)

Industry	US	UK	GE	Rank US	Rank UK	Rank GE
Agriculture	0.46	0.36	0.52	2	3	1
Mining	0.76	0.82	0.72	2	1	3
Meat	0.50	0.52	0.87	3	2	1
Dairy	0.67	0.57	0.14	1	2	3
Beverages	0.56	0.72	0.67	3	1	2
Other food	0.80	0.68	0.20	1	2	3
Textiles	0.45	0.47	0.84	3	2	1
Textile articles	0.61	0.49	0.91	2	3	1
Knitted fabrics	0.48	0.40	0.81	2	3	1
Wearing apparel	0.59	0.39	0.78	2	3	1
Leather	0.43	0.52	0.86	3	2	1
Wood	0.56	0.44	0.69	2	3	1
Paper	0.77	0.67	0.15	1	2	3
Paper articles	0.64	0.63	0.13	1	2	3
Publishing	0.81	0.89	0.12	2	1	3
Printing	0.56	0.73	0.45	2	1	3
Printing serv.	0.84	0.85	0.20	2	1	3
Record. Media	0.78	0.88	0.21	2	1	3
Oil ref.	0.89	0.91	0.14	2	1	3
Pharmaceutical	0.88	0.77	0.13	1	2	3
Soap, perfume	0.81	0.84	0.15	2	1	3
Basic chemic.	0.62	0.65	0.12	2	1	3
Rubber	0.69	0.59	0.12	1	2	3
Plastic	0.68	0.70	0.14	2	1	3
Glass	0.70	0.75	0.14	2	1	3
Ceramic	0.66	0.55	0.11	1	2	3
Precious metal	0.54	0.61	0.12	2	1	3
Casting of met.	0.56	0.49	0.36	1	2	3
Basic iron & steel	0.66	0.69	0.11	2	1	3
Struct. Metal prod.	0.64	0.69	0.12	2	1	3
Tanks	0.71	0.64	0.12	1	2	3
Fabric. Metal prod.	0.68	0.62	0.13	1	2	3
Machine tools	0.74	0.71	0.12	1	2	3
Weapons	0.69	0.58	0.12	1	2	3
Domestic appliances	0.70	0.72	0.13	2	1	3
Computers	0.55	0.75	0.39	2	1	3
Electrical machinery	0.75	0.64	0.13	1	2	3
Electronic components	0.71	0.49	0.62	1	3	2
Radio, TV	0.75	0.56	0.66	1	3	2
Medical equip.	0.78	0.70	0.37	1	2	3
Other instrum.	0.77	0.74	0.12	1	2	3
Motor vehicles	0.78	0.50	0.12	1	2	3

Parts & engine.	0.69	0.46	0.11	1	2	3
Buildings, boats rep.	0.60	0.66	0.74	3	2	1
Railway	0.66	0.70	0.35	2	1	3
Aircraft	0.78	0.82	0.23	2	1	3
Motorcycles	0.68	0.50	0.35	1	2	3
Transport equip.	0.61	0.52	0.69	2	3	1
Furniture	0.65	0.59	0.93	2	3	1
Recycling	0.88	0.85	0.44	1	2	3
Electricity, gas	0.75	0.73	0.11	1	2	3
Construction	0.69	0.61	0.11	1	2	3
Motor trade	0.75	0.67	0.12	1	2	3
Wholesale	0.56	0.44	0.84	2	3	1
Retail	0.51	0.36	0.76	2	3	1
Hotels	0.62	0.41	0.61	1	3	2
Inland transport	0.60	0.67	0.50	2	1	3
Water transp.	0.63	0.65	0.11	2	1	3
Air transp.	0.62	0.58	0.76	2	3	1
Travel agents	0.77	0.71	0.37	1	2	3
Post & telec.	0.87	0.90	0.15	2	1	3
Financial serv.	0.84	0.77	0.23	1	2	3
Insurance & pension	0.91	0.84	0.15	1	2	3
Aux. fin. Serv.	0.60	0.77	0.26	2	1	3
Renting machin.	0.89	0.89	0.15	1	2	3
Computer serv.	0.80	0.89	0.28	2	1	3
R&D	0.72	0.81	0.13	2	1	3
Other bus. Serv.	0.65	0.53	0.12	1	2	3
ALL INDUSTRIES	**0.68**	**0.65**	**0.35**	**1**	**2**	**3**

Table 6.4 presents summary statistics on technical efficiency performance. The USA has the highest average efficiency, followed by the UK and Germany, and the lowest variability in efficiency scores (0.124). The UK and Germany are characterized by the highest maximum scores while the UK has the highest minimum score. Figure 6.1 shows changes over time in average efficiency scores in the three countries. The UK and the US are characterised by very similar average scores in manufacturing, construction and service sectors, moving closely together over time. In manufacturing and services both the UK and the US display an upward trend for most of the time between 1995-2004. In Germany, on the other hand, technical efficiency is well below US and UK levels throughout the period in manufacturing, construction and services (with a downward trend apparent in manufacturing over most of the period). This is consistent with other

evidence of weak performance on total factor productivity in Germany compared to the US and UK (O'Mahony and de Boer, 2002).

Table 6.4: Summary statistics of technical efficiency performance, 1995-2004

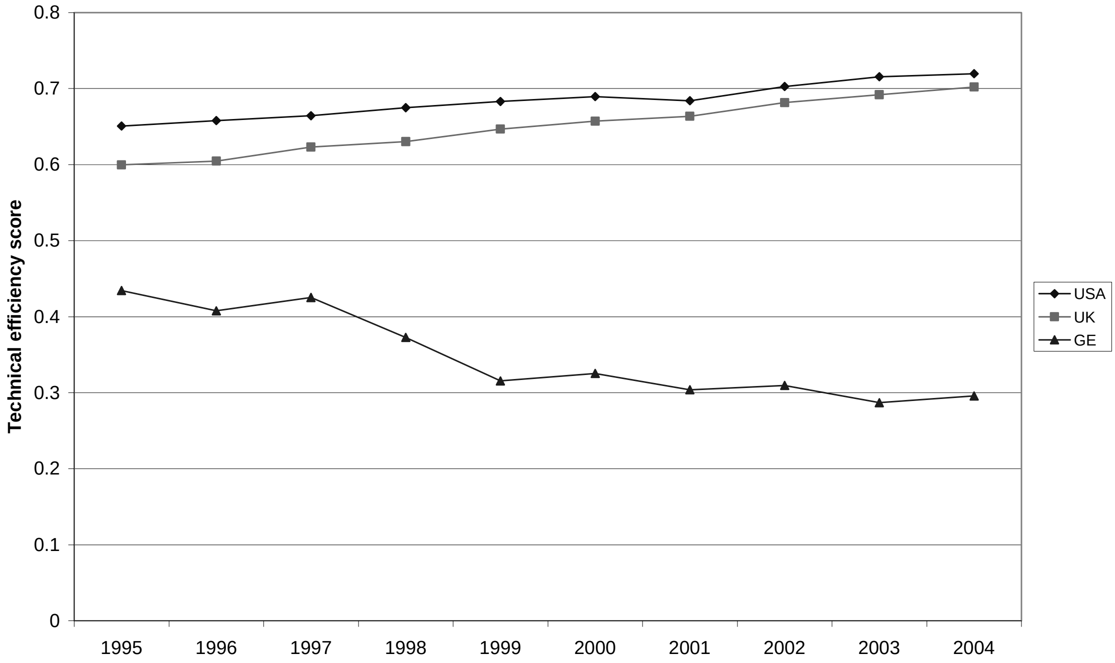
Country	Average	Standard deviation	Minimum	Maximum
USA	0.684	0.123	0.163 (Other business services)	0.918 (Activities auxiliary of financial services)
UK	0.650	0.154	0.319 (Agriculture, forestry and fishing)	0.934 (Financial services, except insurance and pension funding)
GE	0.348	0.333	0.100 (Manufacture of medical and surgical equipment and orthopaedic appliances)	0.999 (Casting of metals)

Summary:

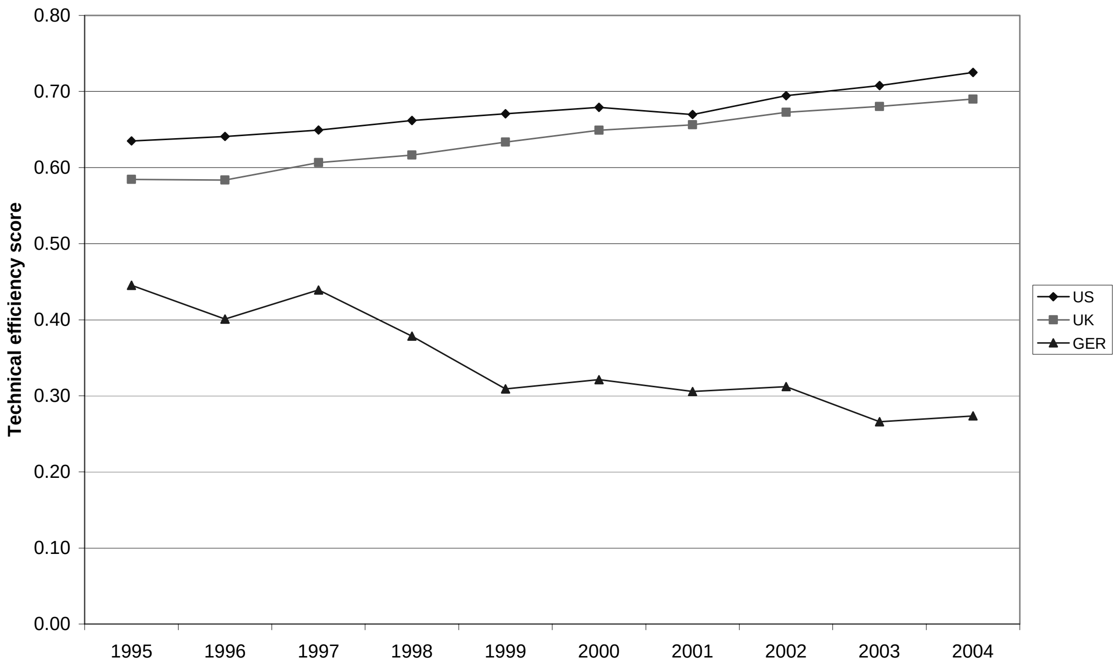
When we relax the assumption of full use of resources and allow for varying degrees of inefficiency in the use of production inputs, we find evidence that technical inefficiency is negatively related to human capital. Thus skills contribute indirectly as well as directly to labour productivity performance by helping to improve the way that all resources are utilised. The UK performs well on technical efficiency in many sectors where it compares less favourably on average labour productivity. This suggests that the UK productivity disadvantage in those sectors is more due to shortcomings in terms of resource levels (for example, relatively low physical capital per hour worked) than to inefficiency in the use of resources.

Figure 6.1: The time pattern of technical efficiency, overall country averages, 1995-2004

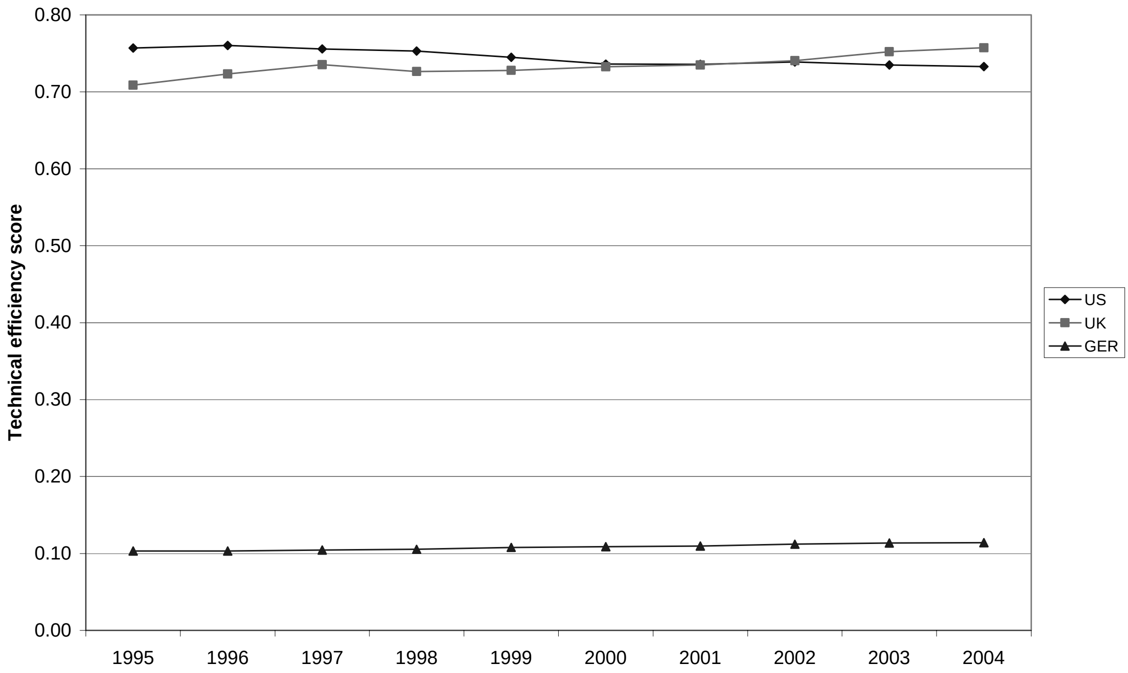
A: All sector



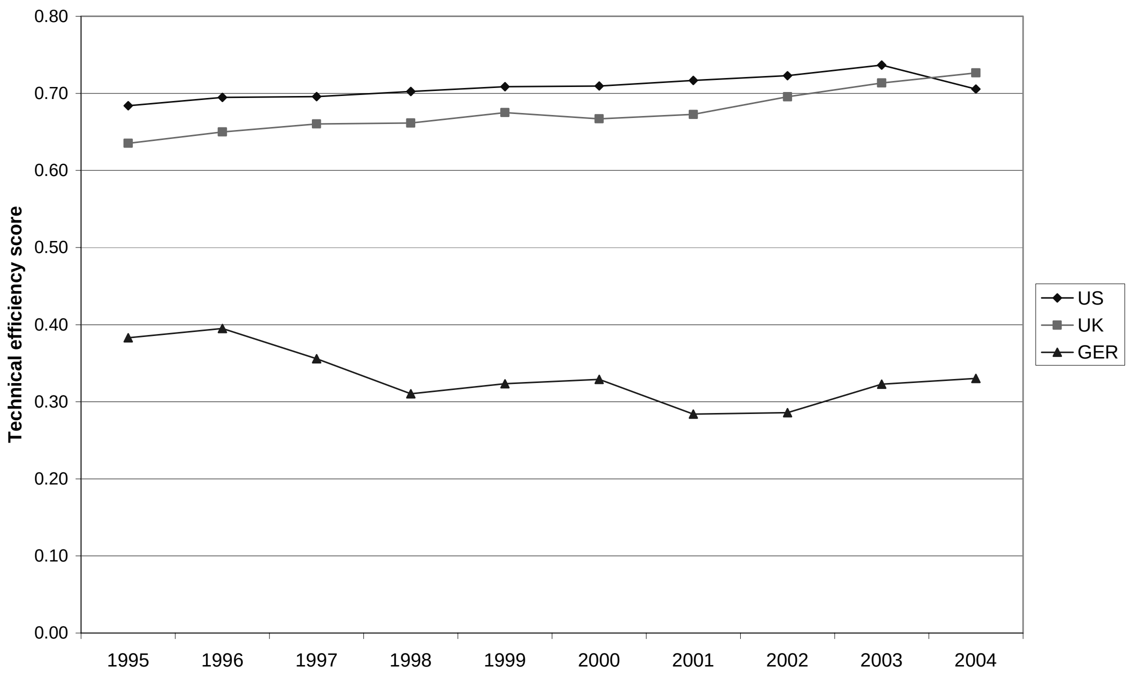
B: Manufacturing



C: Construction



D: Services



7. Capital-skill complementarities and skill-biased technical change

Human capital can affect productivity not only directly as a factor of production but also indirectly through its impact on physical capital accumulation. In fact, new capital may require specific skills in order to become operative. At the same time, the availability of skilled workers can facilitate the adoption of new technologies. The objective of this section is to investigate the complementarity between different types of physical capital and skills and hence add to our understanding of the indirect relationship between human capital and growth. In particular, we are interested in the role of Information and Communication Technologies (ICTs) so we extend our analysis to differentiate between types of capital. In the UK, we find support for the idea that highly-skilled workers have been complementary to the adoption and diffusion of ICT equipment

7.1 Background

In addition to the analysis presented in Sections 4-6, understanding the relationship between skills and productivity requires analysis of how skills interact with other production inputs, in particular, the extent to which skills may be either complements to or substitutes for different kinds of capital and technology. For example, if skilled labour is a prerequisite for the selection, installation, operation and improvement of physical capital equipment, then it is important for analyses of the contribution of skills to relative productivity performance to try and find ways of taking the complementarities between skills and physical capital into account.

Following Griliches (1969), several studies – many of them making use of US manufacturing data – have examined quantitative evidence relating to a hypothesis of ‘capital-skill complementarity’ (CSC). Under this hypothesis physical capital and skilled labour are predicted to be more complementary to each other as production inputs than are physical capital and unskilled labour. An example of evidence supporting CSC would be if changes in physical capital-intensity (measured, for example, as average physical capital per hour worked) are found to be positively related to changes in the ratio of skilled to unskilled labour or to the skilled/unskilled wage premium. As a proposition CSC is related to, but separate from, the notion of skill-biased technical change (SBTC), i.e. the argument that skilled labour is more complementary to the introduction and/or effective utilisation of new technologies than is unskilled labour.

Both the CSC and SBTC literatures are dominated by the experience of recent decades and thus benefit from some historical perspective. For example, Goldin and Katz (1998) report evidence that both CSC and SBTC were at work in US manufacturing between 1909 and 1940 as producers moved to continuous-process and batch methods of production and made greater use of electricity. Caselli (1999) points out that while some technological revolutions such as electrification and ICTs have been skill-biased in nature, others such as the development of assembly-line technology were more complementary to unskilled labour. Indeed, technologies of a ‘de-skilling’ kind tend to be introduced more quickly than do skill-biased technologies precisely because in the latter case the new required skills are likely to be costly and time-consuming to develop.

In terms of production theory, the CSC hypothesis essentially states that the elasticity of substitution between physical capital and unskilled labour is greater than that between physical capital and skilled labour. In order to test this hypothesis it is necessary to define a form of the production function that is sufficiently general to allow for different elasticities of substitution.

Much recent research on capital-skill complementarities has been carried out as part of efforts to account for increasing wage differentials. For example, Krusell et al. (2000) present a detailed theoretical and empirical analysis of the impact of capital-skill complementarity on the skill premium, i.e. the wages of skilled labour relative to those of unskilled labour. Their approach is to modify a standard two-factor CES aggregate production function by developing a four-factor aggregate production function that distinguishes among capital equipment, capital structures, skilled labour, and unskilled labour and allows for different elasticities of substitution among the factors. They define skilled labour as ‘requiring college completion or better (at least 16 years of school)’. Using aggregate US data for the period 1963-1992, they find that capital-skill complementarities have put strong upward pressure on the skill premium throughout the period.[20]

Duffy et al. (2004) examine the evidence for capital-skill complementarity using a panel data set of 73 countries over the period 1965-1990. The theoretical analysis is based on a non-linear two-level CES production function, following previous contributions by Krusell et al. (2000) and Fallon and Layard (1975). For all countries they use five alternative proxies for skilled labour, all of them education input measures derived from the Barro-Lee (2001) data set:
(1) workers who have attended some postsecondary education
(2) workers who have completed secondary education
(3) workers who have attended some secondary education
(4) workers who have completed primary education
(5) workers who have attended some primary education.

Their findings provide some support for the CSC hypothesis but only when the threshold for defining a skilled worker is relatively low – for example, workers who have attended some primary education or who have completed primary and attended some secondary education. These thresholds are lower than those used as proxy indicators of skilled labour by other researchers in the CSC literature. In addition, as Duffy et al. point out, their evidence on CSCs is quite weak as their central results are not robust to different estimation techniques. They speculate that the weak CSC effect in their findings may reflect the varying stages of industrial development of the 73 countries in the study.

A more common specification used in the analysis of the relationship between wages, skills and physical capital starts from a Translog cost function[21], where total costs (*TC*) are a function of different types of labour, their relative wages, the capital stock and the output produced. In the simplest case, we can assume two types of labour, skilled (*Ls*)

[20] However, for a critique of the CES specification used by Krusell et al. (2000), see Ruiz-Arranz (2004) who strongly advocates the use of translog specifications for tests of capital-skill complementarity.
[21] This type of cost function was introduced by Christensen et al. (1973). For recent examples, see Berman et al. (1994), Machin and Van Reenen (1998), O'Mahony et al. (2006).

and unskilled (*Lu*), with relative wages defined as *Ws* and *Wu*. Defining *K* as the capital stock and Y as output, we can then write the following relationship[22]:

$$TC = f(Lu, Ls, Wu, Ws, K, Y, \varepsilon) \quad (7.1)$$

which includes an error term that captures all those factors that are not specifically modelled.

From Equation (7.1) it is possible to derive wage share equations for skilled and unskilled workers. The wage shares sum to unity so, in the simple case of only two skill groups, the equation for skilled workers is the only one that needs to be estimated:

$$\frac{Ws}{WT} = \beta_0 + \beta_1 \frac{Ws}{Wu} + \beta_2 \frac{K}{Y} + \varepsilon \quad (7.2)$$

In Equation (7.2) *WT* is the total wage bill, Ws/Wu is the ratio of skilled to unskilled wages and *K/Y* is the capital-output ratio. β_1 can be positive or negative according to whether the elasticity of substitution between skilled and unskilled labour is below or above one. K/Y captures the degree of capital-skill complementarity. If β_2>0 we have capital skill complementarity, while if β_2<0 we have capital-skill substitution.

Using this approach, Berman et al. (1994) present estimates based on US manufacturing industries that support the presence of capital-skill complementarity but also show that capital accumulation does not explain much of the observed skill upgrading. A more important role is played by the impact of new technology. This work relies on a relatively simple definition of skilled and unskilled labour defined, respectively, as non-production and production workers. [23]

[22] In same cases equation (7.1) also includes intermediate materials (Chennels and Van Reenen, 1999), and energy inputs (Betts, 1997).

[23] In the US production workers are 'workers engaged in fabricating, processing, assembling, inspecting and other manufacturing'. Non-production workers are 'personnel, including those engaged in supervision, installation and servicing of own product, sales, delivery, professional, technological, administrative, etc.'

The relative importance of new technology in explaining increased relative demand for skilled labour is also highlighted by Ruiz-Arranz (2004) who makes use of aggregate US data for 1965-99. She finds, firstly, that capital-skill complementarity is largely attributable to growth in IT capital and, secondly, that the effects of this complementarity on the skilled wage premium are exceeded by the effects of innovations which are biased towards the use of skilled labour and economies in the use of unskilled labour. In this study skilled and unskilled labour are again defined as a relatively simple dichotomy, with skilled labour equating to workers who hold at least a college degree (minimum 16 years of education).

7.2 New evidence on capital-skill complementarity

In our investigation of these issues we use the EPKE dataset which (unlike ISP) enables us to distinguish between non-ICT capital (structures, non-ICT equipment and vehicles) and ICT capital (computers, software and communication equipment). Thus, we estimate two different versions of Equation (7.2) taking wage shares by qualification group in each country as dependent variables:

(7.3) $$\left(\frac{Ws_{ji}}{WT_i}\right) = \beta_i + \beta_K \ln\left(\frac{K_i}{Y_i}\right) + time + \varepsilon_i \,,$$

(7.4) $$\left(\frac{Ws_{ji}}{WT_i}\right) = \beta_i + \beta_{Knict} \ln\left(\frac{Knict_i}{Y_i}\right) + \beta_{Kict} \ln\left(\frac{Kict_i}{Y_i}\right) + time + \varepsilon_i \,,$$

Here the time subscript has been dropped for simplicity, Ws_{ji} is the wage bill of skill group *j* in industry *i*, WT_i is the total wage bill for a particular industry, K_i is total capital in that industry, $Knict_i$ is total non-ICT capital and $Kict_i$ is total ICT capital, Y_i is value added and *time* denotes year dummies. We follow Berman et al. (1994) in replacing the relative wage term in Equation (7.2) with year dummies since it is not plausible to treat relative wages as exogenous and it is difficult to find suitable instruments. The country-specific skill classification is the same used for the construction of labour quality variables as discussed in Section 3.1.

Tables 7.1-7.5 present the results from estimating Equations (7.3) and (7.4) for each skill group and for each country. All estimates have been carried out using a Fixed Effect estimator (FE), corrected for the presence of within-group serial correlation. In each case Instrumental Variables (IV) estimates are shown due to likely endogeneity in the relationship between capital and skills (Machin and van Reenen, 1998). Ten equations have been estimated for the US and the UK, twelve for France, six for Germany and twelve for the Netherlands reflecting the number of different skill groups which are identified for each country.

In the US the results in Table 7.1A show a strong capital-skill complementarity for the highest skill group (University graduates) and capital-skill substitution for two of the intermediate skill groups (Associate degree holders and High school graduates). When we divide total capital into its two main components (Table 7.1B), we observe that ICT capital is complementary to the two intermediate groups but is associated with substitution for the unskilled group of workers. Non-ICT capital is a substitute for Associate degree holders but is found to be complementary to unskilled workers. This suggests that some forms of non-ICT capital contribute to a de-skilling process, with low skilled workers replacing workers with intermediate or high skills. This result may also reflect the impact of service industries where much investment takes the form of buildings and vehicles that may be positively associated with employment of low-skilled labour, in contrast to investments in automation in manufacturing.

For the UK there is more evidence than in the US of ICT capital-skill complementarity at graduate level. It is interesting that the same kind of complementarity between non-ICT capital and unskilled workers arises in the UK as in the US. At intermediate levels ICT capital is complementary with NVQ4-level workers and a substitute for the lowest-skilled in the UK. Non-ICT capital is negatively related to the wage shares for all groups in between graduates and the unskilled (Table 7.2).

Table 7.3 presents the results for France. In this country we find evidence of capital skill complementarity for the highest and the top intermediate skill groups. Similar to the results for the US and the UK, the complementarity relationship affects ICT capital rather than non-ICT capital. ICT capital is complementary to university graduate- and technician-level (Bac+2) skills and a substitute for workers in the two lowest-skilled groups.

In Germany and in the Netherlands (Tables 7.4 and 7.5) we do not find any evidence of capital-skill complementarity, whether we consider capital as a whole or the ICT/non-ICT components. In both countries ICT capital is a substitute for all types of workers, with the exception of graduate workers in the Netherlands where the impact of ICT capital is not significantly different from zero. This result might reflect the presence of rigidities in the labour market that prevents wages from fully capturing changes in labour productivity. This in turn may be the consequence of specific institutions in those countries (e.g. collective bargaining arrangements) and/or more general macroeconomic factors, such as the German reunification in 1989.

Table 7.1: Estimated relationship between physical capital-output ratios and wage shares, analysed by qualification group – United States (IV estimates)

A: Total capital

	(1)	(2)	(3)	(4)	(5)
Wage shares	Graduate	Associate degree	Some college but no degree	High school graduates	Not qualified to high school level
Total capital/ Output	0.109*** (0.027)	-0.009** (0.004)	0.002 (0.009)	-0.116*** (0.016)	0.021 (0.014)
Observations	589	620	620	620	620
R-squared	0.579	0.543	0.338	0.565	0.635
Anderson LR statistic (χ^2)	955.7 (0.000)	1556 (0.000)	1556 (0.000)	1556 (0.000)	1556 (0.000)
Hansen J statistic (χ^2)	4.960 (0.0259)	0.109 (0.741)	0.0976 (0.755)	7.948 (0.00481)	0.371 (0.543)

B: ICT and non-ICT capital

	(1)	(2)	(3)	(4)	(5)
Wage shares	Graduate	Associate degree	Some college but no degree	High school graduates	Not qualified to high school level
Non-ICT capital/ output	0.052 (0.033)	-0.020*** (0.004)	-0.010 (0.011)	-0.082* (0.043)	0.062*** (0.012)
ICT capital/ Output	0.016 (0.013)	0.004*** (0.001)	0.007** (0.003)	-0.013 (0.013)	-0.015*** (0.001)
Observations	682	682	682	682	682
R-squared	0.513	0.684	0.385	0.428	0.813
Anderson LR statistic (χ^2)	707.0 (0.000)	1265 (0.000)	1252 (0.000)	707.0 (0.000)	1252 (0.000)
Hansen J statistic (χ^2)	4.815 (0.0901)	4.837 (0.0891)	2.332 (0.312)	5.690 (0.0581)	3.805 (0.149)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Table 7.2: Estimated relationship between physical capital-output ratios and wage shares, analysed by qualification group – United Kingdom (IV estimates)

A: Total capital

	(1)	(2)	(3)	(4)	(5)
Wage shares	Graduate	NVQ4	NVQ 3	NVQ 1-2	Not qualified to NVQ 1 level
Total capital/ Output	0.081*** (0.030)	0.007 (0.006)	-0.047* (0.026)	-0.056** (0.022)	0.015 (0.047)
Observations	594	594	594	594	594
R-squared	0.451	0.563	0.455	0.384	0.698
Anderson LR statistic (χ^2)	1610 (0.000)	1610 (0.000)	1610 (0.000)	1610 (0.000)	1610 (0.000)
Hansen J statistic (χ^2)	2.083 (0.149)	1.577 (0.209)	2.573 (0.109)	2.272 (0.132)	1.250 (0.263)

B: ICT and non-ICT capital

	(1)	(2)	(3)	(4)	(5)
Wage shares	Graduate	NVQ4	NVQ 3	NVQ 1-2	Not qualified to NVQ 1 level
Non-ICT capital/ output	0.025 (0.020)	-0.018*** (0.007)	-0.096** (0.042)	-0.048* (0.025)	0.137*** (0.049)
ICT capital/ Output	0.024*** (0.008)	0.008*** (0.002)	0.018 (0.013)	-0.002 (0.010)	-0.047*** (0.016)
Observations	593	593	593	593	593
R-squared	0.501	0.621	0.488	0.354	0.783
Anderson LR statistic (χ^2)	1364 (0.000)	1364 (0.000)	1364 (0.000)	1364 (0.000)	1364 (0.000)
Hansen J statistic (χ^2)	3.496 (0.174)	2.176 (0.337)	2.994 (0.224)	3.453 (0.178)	2.552 (0.279)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Table 7.3: Estimated relationship between physical capital-output ratios and wage shares, analysed by qualification group – France (IV estimates)

A: Total capital

	(1)	(2)	(3)	(4)	(5)	(6)
Wage shares	Graduate (Bac + 3 or higher)	Bac+2 (Technician-level)	Bacca-laureate	Vocational skills (e.g. CAP)	Other formal qualifications	No formal qualifications
Total capital/ Output	0.047*** (0.008)	0.073*** (0.016)	-0.025 (0.016)	-0.035** (0.015)	-0.016*** (0.006)	-0.044*** (0.015)
Observations	510	510	510	510	510	510
R-squared	0.358	0.613	0.134	0.206	0.141	0.557
Anderson LR statistic (χ^2)	1405 (0.000)	1405 (0.000)	1405 (0.000)	1405 (0.000)	1405 (0.000)	1405 (0.000)
Hansen J statistic (χ^2)	2.255 (0.133)	0.122 (0.727)	1.288 (0.256)	0.0332 (0.855)	3.702 (0.054)	0.0585 (0.809)

B: ICT and non-ICT capital

	(1)	(2)	(3)	(4)	(5)	(6)
Wage shares	Graduate (Bac + 3 or higher)	Bac+2 (Technician-level)	Bacca-laureate	Vocational skills (e.g. CAP)	Other formal qualifications	No formal qualifications
Non-ICT capital/output	-0.007 (0.022)	-0.051** (0.021)	-0.004 (0.018)	0.014 (0.030)	0.016* (0.010)	0.028 (0.040)
ICT capital/ Output	0.023** (0.010)	0.059*** (0.013)	-0.011 (0.009)	-0.007 (0.018)	-0.011 (0.008)	-0.048*** (0.018)
Observations	510	480	510	510	510	510
R-squared	0.256	0.584	0.126	0.095	0.128	0.581
Anderson LR statistic (χ^2)	136.1 (0.000)	99.25 (0.000)	136.1 (0.000)	136.1 (0.000)	136.1 (0.000)	136.1 (0.000)
Hansen J statistic (χ^2)	2.553 (0.279)	6.605 (0.037)	1.318 (0.517)	2.010 (0.366)	2.375 (0.305)	1.593 (0.451)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Table 7.4: Estimated relationship between physical capital-output ratios and wage shares, analysed by qualification group – Germany (IV estimates)

A: Total capital

	(1)	(2)	(3)
Wage shares	Graduate	Intermediate qualifications	Not qualified to craft level
Total capital/Output	-0.032** (0.013)	-0.174*** (0.038)	-0.077*** (0.022)
Observations	425	425	425
R-squared	0.376	0.266	0.356
Anderson LR statistic (χ^2)	771.0 (0.000)	771.0 (0.000)	771.0 (0.000)
Hansen J statistic (χ^2)	0.928 (0.335)	0.061 (0.805)	0.823 (0.364)

B: ICT and non-ICT capital

	(1)	(2)	(3)
Wage shares	Graduate	Intermediate qualifications	Not qualified to craft level
Non-ICT capital/output	0.005 (0.022)	-0.059* (0.035)	-0.032 (0.035)
ICT capital /Output	-0.018* (0.010)	-0.072*** (0.013)	-0.037*** (0.010)
Observations	450	425	450
R-squared	0.514	0.685	0.601
Anderson LR statistic (χ^2)	327.3 (0.000)	221.9 (0.000)	327.3 (0.000)
Hansen J statistic (χ^2)	0.874 (0.646)	5.681 (0.058)	0.0929 (0.955)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

Table 7.5: Estimated relationship between physical capital-output ratios and wage shares, analysed by qualification group – Netherlands (IV estimates)

A: Total capital

	(1)	(2)	(3)	(4)	(5)	(6)
Wage shares	Graduate (HBO or higher)	HAVO/ VWO	MAVO	MBO	LBO/ VBO	Primary education or below
Total capital/ Output	-0.154** (0.060)	-0.013 (0.011)	-0.014 (0.016)	-0.055*** (0.013)	-0.036 (0.025)	-0.034 (0.022)
Observations	494	494	494	494	494	494
R-squared	0.437	0.120	0.100	0.333	0.165	0.118
Anderson LR statistic (χ^2)	1791 (0.000)	1791 (0.000)	1791 (0.000)	1791 (0.000)	1791 (0.000)	1791 (0.000)
Hansen J statistic (χ^2)	0.291 (0.590)	0.553 (0.457)	1.951 (0.162)	4.335 (0.037)	1.456 (0.228)	3.354 (0.067)

B: ICT and non-ICT capital

	(1)	(2)	(3)	(4)	(5)	(6)
Wage shares	Graduate (HBO or higher)	HAVO/ VWO	MAVO	MBO	LBO/ VBO	Primary education or below
Non-ICT capital/output	-0.018 (0.124)	0.009 (0.009)	-0.008 (0.013)	-0.041 (0.036)	-0.024 (0.022)	-0.033 (0.029)
ICT capital/ Output	0.002 (0.012)	-0.009*** (0.002)	-0.008*** (0.003)	-0.008* (0.005)	-0.013*** (0.003)	-0.010*** (0.004)
Observations	520	494	520	520	520	520
R-squared	0.135	0.431	0.420	0.396	0.374	0.258
Anderson LR statistic (χ^2)	79.24 (0.000)	74.78 (0.000)	79.24 (0.000)	79.24 (0.000)	79.24 (0.000)	79.24 (0.000)
Hansen J statistic (χ^2)	6.465 (0.039)	1.107 (0.575)	0.143 (0.931)	4.977 (0.083)	3.707 (0.157)	4.358 (0.113)

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. For details of the Anderson LR statistic and the Hansen J statistic, see notes to Table 4.1A.

HBO is tertiary education, of a vocational type. HAVO/VWO/MAVO is general education which normally leads to entry into a higher level, taking up to 4 to 6 years of study after primary school. LBO/VBO and MBO are vocational schooling, taking up to a maximum of 4 to 6 years after primary school (O'Mahony and Van Ark, *EU productivity and competitiveness: an industry perspective*, European Communities 2003).

In the US, the UK and France our results are consistent with a long-running literature which has highlighted the role of highly-educated or skilled workers in facilitating early adoption of new technologies in general (Nelson and Phelps, 1966; Welch, 1970; Schultz, 1975; Bartel and Lichtenberg, 1987). More recent studies have focused on the role of skills in facilitating the effective utilisation of ICTs (for example, Brynjolfsson, Hitt and Yang, 2002). However, while in the UK and France high-skilled workers may have a favourable impact on productivity and growth via their complementarity with ICT capital, in the US it is the complementarity between ICT capital and higher intermediate skills that is important.

These findings may reflect the relatively early adoption of ICTs in the US. For example, in a study of the relationship between information technology and the demand for educated workers at industry level in the US, Chun (2003) distinguishes carefully between the adoption and use effects of information technology and finds that both have contributed substantially to the increased relative demand for college graduates. Interestingly, however, he also suggests that while adoption is positively related to highly skilled workers, as the new technology becomes fully implemented, firms may be able to replace highly skilled workers with lower-paid less-skilled workers. According to this view skill-biased technical change may therefore be a temporary phenomenon. This perspective finds support in Ruiz-Arranz (2004) who suggests that, as ICT equipment becomes more user-friendly over time, so it becomes more accessible to lower-skilled workers.

Summary:
This section has investigated a possible indirect relationship between skills and productivity by exploring the extent and nature of complementarities between physical capital and skills. We conclude that highly-skilled workers have been complementary to the adoption and diffusion of ICT equipment (and to related changes in products and work organisation) in three of the five countries in recent decades, including the UK. However, there is no such evidence for Germany and the Netherlands. More generally, it is important to note that, if the US is anything to go by, the degree of complementarity between high-level skills and ICT capital in the UK may well diminish over time due to a decline in demand for the skills specifically associated with ICT adoption.

8. Innovation, knowledge spillovers and skills

The extent to which knowledge production and diffusion contributes to improvements in productivity through either process or product innovations is a developing research area. In this section we investigate the role of skill-related externalities, or spillover effects, in which skilled labour may facilitate the identification and implementation of new knowledge and ideas which have been generated elsewhere. We consider the relationship between R&D investment and human capital, the production of knowledge and finally the combined effects of R&D, knowledge, innovation and skills on output productivity. We hypothesise that skilled labour contributes positively to both the development of knowledge and to the absorption and use of knowledge generated elsewhere. This is a relatively under-explored area at sector level. Our findings suggest that skills make a positive and significant contribution to both innovation and productivity.

8.1 Background

Externalities arise when the costs or benefits of an economic activity 'spill over' onto a third party. Pollution is a classic example of a negative externality. By contrast, a positive externality may occur if, for example, private sector decisions to invest in skills development yield benefits to individuals or employers other than those who have made the decisions to invest in skills formation.

The potential for skills-related externalities emerges in O'Mahony (1998) who uses multivariate research methods to investigate the role of physical capital, workforce skills and R&D expenditure in explaining Anglo-German labour productivity differences in manufacturing. All three production inputs are found to have a significant impact on relative productivity but only workforce skills has a coefficient greater than that implied by standard growth accounting methods. This finding indicates that external effects from human capital formation may help to raise the productivity of all workers in a sector. Redding (1996) suggests that skills may be a strategic complement to R&D, with externalities arising from combined investments in skills by workers and in R&D by employers.

In the wake of the development of New Growth Theory where technological change is endogenous to the model (see Section 2.3 above), many attempts have been made to assess the impact of positive externalities on productivity and growth performance. It has become common in the literature to refer to positive externalities as *spillovers* and we therefore adopt this usage (although in principle spillovers may take a negative as well as positive form, in the same way as externalities). In the context of New Growth Theory spillovers offer a plausible explanation of increasing returns to scale at macroeconomic level without any necessity to abandon the assumptions of perfect competition and constant returns to scale at the firm level (Lucas, 1988).

Much of this research has focussed on knowledge spillovers associated with R&D spending. R&D produces new ideas and knowledge conducive to new product development (product innovation) or to new ways of producing existing products (process innovation). It is hard for firms to prevent other firms from gaining access to, at least, some of their research results and indeed much new knowledge transfers easily along supply chains, as well as to the final consumer, thus increasing the benefits or *social returns* from initial investments in R&D (Griliches, 1992).

Jaffe (1996) identifies three kinds of spillovers (positive externalities) according to the channels by which they make their presence felt:

1. *Market spillovers* – benefits for consumers and non-innovating firms which arise through the normal workings of markets (e.g. cost reductions arising from process innovations)
2. *Knowledge spillovers* – whereby knowledge created within one firm becomes available to other firms (e.g. through 'reverse engineering' or through inter-firm mobility of engineers and scientists)
3. *Network spillovers* – whereby individual firms making use of related and interdependent technologies help to achieve a critical mass of users which raises the value of these technologies for all firms concerned (for example, increased connections to the Internet which allow most firms to organise their activities more efficiently).

A related typology derived from Harris and Robinson (2004) distinguishes between the following (positive) spillovers:

1. *Intra-industry spillovers*: e.g. demonstration effects such as imitation of new products and processes; labour market effects such as improved access to a supply of trained staff with industry-specific skills
2. *Inter-industry spillovers*: e.g. transfer of new technologies, management practices, ideas and 'solutions to problems' up and down supply-chains
3. *Agglomeration spillovers*: e.g. improved access to pools of skilled labour in local labour markets; access to wider range of business services in local areas.

There are therefore a number of different mechanisms – many of them skills-related – which may in principle contribute to productivity growth through spillovers. Recent research on the external effects of R&D and other investments has emphasised that it is not a cost-free process for organisations to benefit from spillovers. In order to identify and make effective use of knowledge, ideas and technologies that become available through spillovers, what is required is 'absorptive capacity' which may be developed through organisations' own investments in R&D (Cohen and Levinthal, 1989) and more generally through the development or acquisition of high levels of workforce skills.

The idea of absorptive capacity goes back at least to Arrow (1969) and it captures the idea that the implementation of new technologies, ideas and knowledge depends on the knowledge, skills and efforts which firms are able to apply to this task. Thus, for example, Benhabib and Spiegel (1994) find that human capital stocks are positively associated with individual countries' ability to narrow the gap between themselves and the world-leading nation in terms of productivity. Eaton and Kortum (1996) find that inward technology diffusion increases with a country's human capital. Xu (2000) provides evidence suggesting that the reason why relatively rich countries benefit more than poorer countries from hosting US multinational subsidiaries may be due to higher threshold levels of human capital in rich host countries. Caselli and Coleman (2001) find that computer imports are positively correlated with measures of human capital. Hanushek and Kimko (2000) argue that the quality, and not only the quantity of human capital, matters for technology diffusion.

The absorptive capacity literature initiated by Cohen and Levinthal (1989, 1990) puts particular emphasis on 'the two faces of R&D', that is, the role of R&D in both generating innovations and in enabling the assimilation of innovations generated elsewhere. In a recent cross-country analysis at sector level between 1974-1990, Griffith et al. (2004) explore the impact of absorptive capacity on TFP growth, expressed as a function of: (i) R&D intensity (ii) a 'TFP gap' measure defined in terms of the gap in TFP levels between each country and the leader country, assumed to capture the scope for technology transfer (iii) human capital defined in terms of the percentage of the population that has participated in higher education, and (iv) the interactions between the TFP gap measure and, respectively, R&D intensity and human capital. The results show that TFP growth is positively related to the size of the TFP gap, consistent with the convergence literature. More importantly, the coefficient on the TFP gap/R&D intensity interaction term is positive, thus providing support for a key hypothesis relating to absorptive capacity, namely, that the further a country is behind the TFP leader in a particular industry, the greater is the contribution that R&D makes to improving TFP growth performance. The coefficients on the human capital and R&D intensity/human capital interaction terms are also positive and significant although not so high in absolute terms as those attached to absorptive capacity. Griffith et al. conclude therefore that both R&D and workforce skills help to stimulate productivity growth via their effects on innovation and absorptive capacity.

Kneller and Stevens (2006) investigate the role of human capital and absorptive capacity in explaining cross-country differences in productivity levels through stochastic frontier analysis, using data for nine industries in 12 OECD countries. Their results show that human capital (measured as average years of schooling) contributes positively and significantly to reducing technical inefficiency (that is, the distance of a country's average productivity level from the lead-country frontier level). However, in their analysis an R&D stock measure, which the authors interpret as measuring the effect of R&D on absorptive capacity, does not have a statistically significant effect on reducing technical inefficiency.

8.2 Estimation procedures

R&D expenditure and patent counts are widely accepted (though imperfect) measures of innovation inputs and outputs respectively. For this project we have integrated data on R&D spending, patents and citations with the EPKE dataset in order to explore the links between R&D, knowledge production and productivity at sector level, and to assess the role of human capital at each stage in the innovation process. In so doing we follow the influential approach suggested by Griliches (1979) which focuses on the flow path through which investment in research generates knowledge which subsequently may contribute to output productivity growth. Previous research simply considered an augmented Cobb-Douglas production function with an R&D variable added to the right hand side. Laying down the foundation for further research in the area, Griliches and Pakes (1984) proposed a series of equations to distinguish a 'knowledge production function' from the standard output production function to which knowledge may contribute:

(8.1) $k = \beta_0^1 + \beta_m^1 X_m^1 + \varepsilon^1$

(8.2) $p = \beta_0^2 + \beta_k k + \beta_l^2 X_l^2 + \varepsilon^2$

(8.3) $q = \beta_0^3 + \beta_p p + \beta_j^3 X_j^3 + \varepsilon^3$

In this approach (8.1) represents an R&D investment equation where *k* is R&D intensity and (8.2) models innovation output, *p*, as a function of R&D among other factors. The dependent variable, *p*, is a measure of knowledge production (such as patents). Equation (8.3) is a standard production function making use of knowledge where *q* is a selected output indicator. X_m^1, X_l^2 and X_j^3 are vectors of explanatory variables in the respective equations (see Loof and Heshmati, 2002, for further details).

In empirical applications care must be taken to address econometric problems of simultaneity or selectivity bias. Simultaneity in this case can be a problem because the variables which affect innovation or R&D investment may also affect the final output production function. Consequently, correlation between explanatory variables and disturbances may interfere with model estimation. In the simple specification above, where the dependent variable in one equation is used as an independent variable in a following one, OLS regressions will be biased and inconsistent. To address this, several different approaches have been adopted by researchers, for example, estimating a series of simultaneous equations (Crepon, Duguet and Mairesse, 1998), using predicted values of dependent variables in sequential regressions (Griffith et al., 2006) and estimating Instrumental Variable equations (Loof and Heshmati, 2000). Firm-level studies of this kind are also faced with problems of sample selection (since not all firms will perform observable R&D) and hence a four-stage estimation model is often set up with a preliminary equation to estimate the probability that firms will actually undertake R&D.

In general, the relationship between firm-level innovation and productivity has been well analysed, typically exploiting Community Innovation Surveys and other rich data sources. However, much of this research has been confined to cross-sectional analysis. In general, sector-level studies of R&D and productivity have tended to be neglected, even though the macroeconomic importance of the role of R&D in economic growth has received significant attention (Cameron, 2000). Englander et al. (1988) suggest that industry aggregation actually presents a positive way of using patent data, aggregated up from firm level. Because of volatility in time-series of patent data (for reasons which may be independent of innovation level), noise is less of a problem when aggregated up and considered in cross-country analysis at industry level over a number of years (Englander et al. 1988).

8.3 Data description

For this study we have combined the 20 year time series of output, physical capital and skills data in EPKE with similarly long time series of patent, citation and R&D data at sector level in the five countries. The patent and citation data are available for 13 manufacturing sectors in the EPKE database (derived from the European Patent Office database and matched to sector level by researchers at CESPRI, Bocconi University, Milan).[24] R&D investment data for the same industries and countries come from the OECD Analytical Business Enterprise Research and Development Database (ANBERD). To avoid the complications of estimating R&D stocks, we follow Loof and Heshmati's (2002) advice that current levels of R&D investment in year *t* can be used as an acceptable proxy for permanent R&D because industries do not experience major fluctuations in investment behaviour.

In addition to the patent data, we also have access to data on the citations attached to those patents which distinguish between 'same-country' citations and foreign citations. Citations acknowledge information or knowledge sources which typically have resulted

[24] We are grateful to Gianluca Tarasconi and Francesco Lissoni for providing these data.

from past research in the same or in a related technology field, so far as citing firms are concerned (Mancusi, 2004). Arguably, the more that firms cite knowledge sources in their own country, the greater is the accumulated research and knowledge base of the industry of which they are part, and hence the greater is the collective ability of that industry to make successful use of knowledge generated in foreign countries. Hence we make use of same-country citation measures to proxy absorptive capacity at sector/country level in our productivity analysis.

Table 8.1 shows how R&D expenditure as a proportion of gross output varied between sectors and countries in 1980, 1990 and 2000. Three industries (chemicals, electronics and transport equipment, including aerospace) clearly have the highest R&D intensity in each country, although the ordering of these three varies by country. In 2000 the UK was an R&D leader among the five countries in just two industries: chemicals (including pharmaceuticals) and petroleum and coal products (including North Sea oil). The US was ahead in wood products, paper, printing and publishing, metal products and electrical/electronic engineering. France led in rubber and plastics and non-metallic mineral products; Germany in textiles, clothing and leather goods, transport equipment and furniture and miscellaneous manufacturing. The Netherlands led in food, drink and tobacco and mechanical engineering in 2000.

Table 8.1: R&D intensity (R&D expenditure as a percentage of Gross Output) for 1980, 1990, 2000, analysed by sector and country

Industry	YEAR	UK	US	France	Germany	Netherlands
Food/Drink/Tobacco	1980	0.37	0.23	0.14	0.15	**0.39**
	1990	**0.40**	0.34	0.26	0.15	**0.40**
	2000	0.44	0.28	0.34	0.19	**0.59**
Textiles/Leather/Footwear/ Clothing	1980	0.17	0.11	0.12	**0.30**	0.10
	1990	0.11	0.22	0.14	**0.33**	0.25
	2000	0.19	0.18	0.32	**0.75**	0.30
Wood/Wood Products	1980	0.12	0.42	0.12	**0.53**	0.02
	1990	0.11	0.44	0.11	**0.71**	0.06
	2000	0.08	**0.19**	0.08	0.12	0.07

Industry	YEAR	UK	US	France	Germany	Netherlands
Paper, Printing and publishing	1980	0.15	**0.34**	0.07	0.13	0.06
	1990	0.14	**0.34**	0.10	0.09	0.09
	2000	0.07	**0.61**	0.10	0.12	0.10
Petroleum and Coal Products	1980	**1.42**	0.80	0.43	0.20	0.42
	1990	**2.96**	1.37	1.14	0.41	0.68
	2000	**1.14**	0.51	0.54	0.14	0.17
Chemicals	1980	3.38	2.73	2.43	**4.52**	3.16
	1990	**6.51**	4.42	4.14	5.60	3.86
	2000	**8.46**	4.86	4.14	4.95	2.58
Rubber/Plastics	1980	0.36	**1.35**	1.25	0.94	0.47
	1990	0.37	1.08	**1.58**	0.92	0.52
	2000	0.29	0.97	**1.73**	1.20	0.53
Non-metallic mineral products	1980	0.65	**0.89**	0.49	0.59	0.15
	1990	0.56	**0.98**	0.62	0.83	0.17
	2000	0.44	0.92	**0.98**	0.87	0.40
Metal Products	1980	0.37	**0.53**	0.39	0.48	0.37
	1990	0.36	0.55	0.55	**0.64**	0.51
	2000	0.33	**0.61**	0.51	0.56	0.51
Mechanical Engineering	1980	2.06	1.43	0.79	**2.26**	0.90
	1990	1.99	1.54	1.55	**2.12**	0.81
	2000	2.27	2.40	1.82	2.28	**2.92**
Electrical and Electronic Equipment	1980	8.00	**8.88**	2.56	5.69	6.77
	1990	5.48	**9.70**	7.22	6.69	7.80
	2000	3.37	**9.50**	5.26	4.16	7.39
Transport equipment	1980	4.93	**6.92**	4.20	3.94	1.53
	1990	4.60	**7.78**	5.60	4.96	1.68
	2000	4.13	4.84	3.31	**5.61**	0.85
Furniture, miscellaneous manufacturing; recycling	1980	**0.73**	0.55	0.24	0.08	N/A
	1990	0.23	**0.53**	0.16	0.10	N/A
	2000	0.17	0.26	0.29	**0.52**	N/A

Source: OECD ANBERD

Examining the data at 10 year intervals indicates how R&D investment has changed over time in specific industries and where the lead country has changed. In chemicals, we can see that R&D investment in the UK increased between 1980 and 2000, with the UK taking the lead by 1990. Conversely, in Electrical and Electronic Equipment, the UK dropped from the second highest in 1980 and 1990 to the lowest proportion of gross output invested in R&D by 2000. There are only three industries where one country has maintained a lead in R&D throughout the 1980-2000 period: Germany in textiles and clothing, the US in paper, printing and publishing and the UK in petroleum and coal products.

In terms of patent applications per hour worked, we focus solely on the four European countries since US patenting activity is under-represented at the European Patent Office.[25] On this measure, as shown in Table 8.2, the Netherlands leads in ten of the 13 manufacturing sectors, followed by Germany (ahead in three sectors). The UK ranks second in food, drink and tobacco patenting but is either third or fourth in all the other sectors. When we turn to our intended proxy measure for sector-level absorptive capacity (same-country citations per hour worked), Germany is the clear leader among the four European countries in 11 sectors (Table 8.3). The only sector where the UK fares comparatively well on this measure is food, drink and tobacco where it shares leadership with the Netherlands.

[25] The same would be true in reverse if we were looking at US Patent Office data: there European countries are under-represented. Further research is needed to be able to make appropriate adjustments for 'home-country advantage' in use of patenting data.

Table 8.2: Patent applications per hour worked, 1979-1998, analysed by sector and country (Index numbers: UK = 100)

	UK	France	Germany	Netherlands
Food/Drink/Tobacco	100	23	23	434
Textiles/Leather/Footwear/Clothing	100	247	447	595
Wood/Wood Products	100	109	214	265
Paper, Printing and publishing	100	103	167	88
Petroleum and Coal Products	100	293	165	873
Chemicals	100	97	111	242
Rubber/Plastics	100	165	170	456
Non-metallic mineral products	100	226	199	359
Metal Products	100	232	270	290
Mechanical Engineering	100	215	154	438
Electrical and Electronic Equipment	100	198	146	549
Transport equipment	100	191	235	121
Furniture, miscellaneous manufacturing; recycling	100	183	201	81

Source: EPO, CESPRI

Table 8.3: Same-country citations per hour worked, 1979-1998, analysed by sector and country (Index numbers: UK = 100)

	UK	France	Germany	Netherlands
Food/Drink/Tobacco	100	65	75	101
Textiles/Leather/Footwear/Clothing	100	91	127	84
Wood/Wood Products	100	64	219	167
Paper, Printing and publishing	100	74	115	38
Petroleum and Coal Products	100	127	144	112
Chemicals	100	83	120	85
Rubber/Plastics	100	88	112	74
Non-metallic mineral products	100	133	158	100
Metal Products	100	114	162	93
Mechanical Engineering	100	106	137	126
Electrical and Electronic Equipment	100	104	134	107
Transport equipment	100	112	151	76
Furniture, miscellaneous manufacturing; recycling	100	190	162	60

Source: EPO, CESPRI

8.4 Innovation, skills and productivity

In order to explore the links between R&D investment, innovation outputs, skills and productivity we estimate a series of equations, using predicted values of dependent variables in sequential regressions in a similar way to Griffith et al. (2006) in order to take account of likely endogeneity at each stage of the estimation. The analysis is carried out for 13 manufacturing sectors in the UK, France, Germany and the Netherlands.[26] Since we are dealing with sector-level data, with R&D activity recorded in all sectors under consideration, we do not face selectivity issues as is the case for researchers undertaking firm-level analysis. Therefore, we proceed immediately to estimating the determinants of R&D intensity, which is then followed by a knowledge production function and subsequently by an output production function:

$$\ln R\&D_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln LabQual_{it} + \beta_3 \ln Open_{it} + country + time + \varepsilon_{1,it} \quad (8.4)$$

$$\begin{aligned} \ln Patent_{it} &= \beta_0 + \beta_1 \ln R\&D_{it} + \beta_2 \ln C_{it}(t-1) + \beta_3 \ln Foreign_{it}(t-1) \\ &+ country + industry + \varepsilon_{2,it} \end{aligned} \quad (8.5)$$

$$\begin{aligned} \ln VA_{it} &= \beta_0 + \beta_1 \ln Patent_{it} + \beta_2 \ln K_{it} + \beta_3 Hours_{it} + \beta_4 \ln LabQual_{it} \\ &+ country + time + \varepsilon_{3,it} \end{aligned} \quad (8.6)$$

Our choice of determining variables is guided by firm-level research in this area (e.g. Crepon et al., 1998 and Griffith et al., 2006) but we also take advantage of available sector-level data to pay more attention to the role of human capital and absorptive capacity than is generally feasible in firm-level studies. In Equation (8.4) we use physical capital (K), human capital (*LabQual*) and a measure of market 'openness' (*Open* - export share of production) to explain R&D intensity (R&D spending as a percentage of gross output). This equation is estimated as a Pooled OLS regression with time and country dummies. In Equation (8.5) with patents per hour worked as the dependent variable we use the predicted value of R&D intensity as an explanatory variable in knowledge production. In addition, lagged same country citations per hour worked (C_{it}) are used as a measure of absorptive capacity (for the reasons outlined above) and lagged foreign

[26] As noted above the US cannot be included in this analysis because we only have access to European Patent Office data which tend to understate US patenting activity.

patents *(Foreign)* are used as an indicator of potential knowledge spillovers between countries which might contribute to knowledge production. To account for differing propensities to patent across industries, industry dummies are included in this equation. However, time dummies are excluded as patenting behaviour is not expected to be cyclical. In the productivity Equation (8.6) we follow a similar specification to the output production functions described in Section 4. However, for this analysis we also include the predicted patents per hour worked measure as a proxy for knowledge inputs into production.

The results are particularly interesting. Firstly, R&D intensity is positively and significantly related to market openness and to human capital (Table 8.4, column (1)). Secondly, patents per hour worked is positively and significantly related to predicted R&D intensity and to our measures of absorptive capacity (i.e. same country citations) and foreign spillover potential (the latter measured by lagged foreign-produced patents) (Table 8.4, column (2)). Thirdly, productivity is positively and significantly related to the predicted knowledge measure (patents per hour worked) and to two different measures of human capital, one benchmarked on graduate-quality labour (column (3)) and the other benchmarked on unskilled labour (column (4)).

These findings therefore provide evidence of the positive contribution that human capital makes at different stages of the production process to relative innovation and productivity performance at sector level.

Summary:
This section has investigated the relationship between innovation and skills and their combined effects on productivity. Analysis of manufacturing sectors in four European countries shows a strong role for human capital in contributing to R&D intensity. Knowledge production, proxied by patent output, is positively and significantly related to proxy measures of absorptive capacity (same-country citations) and external knowledge spillover potential (foreign patents). In the output production function, the coefficients on patents and human capital are both positive and significant, consistent with other research in this area. Thus human capital has a significant and positive impact on productivity, both directly (in output production) and indirectly through its positive links with R&D intensity and knowledge production.

Table 8.4: Estimated determinants of R&D intensity, knowledge production and labour productivity (EPKE)

	(1)	(2)	(3)	(4)
Dependent variable:	**Log R&D intensity (R&D as % of gross output)**	**Log patents per hour worked**	**Log output (value added)**	**Log output (value added)**
Log Openness (Exports as % of sales)	1.660*** (0.232)			
Log physical capital	0.205** (0.099)		0.146*** (0.019)	0.144*** (0.018)
Log predicted R&D intensity		0.119** (0.055)		
Log same country citations per hour worked (t-1)		0.480*** (0.032)		
Log foreign patents (t-1)		0.148*** (0.051)		
Log total hours (th)			0.445*** (0.037)	0.449*** (0.036)
Log predicted patents per hour worked			0.075*** (0.010)	0.073*** (0.010)
Log Human capital (QAL_G/th)	0.871* (0.453)		0.182*** (0.053)	
Log Human capital (QAL_U/th)				0.303** (0.134)
Constant	-6.762*** (2.440)	-0.972 (0.592)	7.207*** (0.449)	7.864*** (0.373)
Time dummies	Yes	No	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	No	Yes	No	No
Observations	979	905	905	905
R-squared	0.552	0.943	0.788	0.788

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level in columns (1) and (2).

9. Summary and assessment

In the light of research evidence that workforce skills and training are positively related to productivity performance at sector and firm level, it is perhaps surprising that some international comparisons of relative productivity performance at sector and national level only attribute relatively small proportions of the identified productivity gaps to cross-country differences in workforce skill levels.

In this study we have identified a number of reasons why the impact of skills on relative performance at sector and national level may not be captured through standard growth accounting and regression techniques, for example:

- Difficulties in measuring skills
- Misspecification of production functions in econometric analysis
- Failure to take account of potential complementarities between skills and other production inputs
- Failure to take account of mechanisms by which skills may have an *indirect* impact on productivity at sector and national level, for example, by contributing positively to the generation and distribution of economically valuable knowledge.

Using new measures of skills derived from data on educational attainments and average hourly wages by qualification groups, we have carried out a number of new analyses on sector-level datasets for the UK, US, France, Germany and the Netherlands in order to explore the links between workforce skills and productivity.

Our main findings are as follows:

1. Human capital *levels* are strongly related to average labour productivity levels across a wide range of sectors. *Growth* in human capital also contributes positively over fairly long periods of time to productivity growth rates in 'follower countries' which are seeking to bridge gaps in productivity between themselves and the 'leader country' at sector level. However, there is little evidence of growth in human capital having a short-term impact on productivity growth (Sections 4-5).

2. When we relax assumptions of full use of resources and allow for varying degrees of inefficiency in the use of production inputs, we find evidence that human capital is negatively related to inefficiency. Thus skills contribute indirectly as well as directly to labour productivity performance by helping to improve the way that all resources are utilised (Section 6).

3. At different times in different sectors and countries, workforce skills have contributed positively to productivity performance by facilitating the adoption and efficient use of new technologies such as Information and Communication Technologies (ICTs). However, the extent and nature of such complementarities appear to vary strongly between countries. As new technologies become established, the skill requirements associated with them may decline (Section 7).

4. Human capital also contributes to productivity performance through positive contributions to R&D and innovation. A key mechanism by which it may do so is through the development of 'absorptive capacity' at sector level, i.e. the capacity to make effective use of knowledge, ideas and technologies that become available through spillovers between firms, sectors and countries (Section 8).

In the specific case of the UK it is notable in international comparisons that relative skill levels and relative productivity levels are frequently correlated at sector level. The evidence in this report suggests that many UK sectors which compare badly on workforce skill measures stand little chance of catching up with productivity leaders unless efforts are made to identify and fill key gaps in skills. Table 9.1 suggests that some of the sectors with the largest gaps in skills compared to other countries employ large numbers of people, for example, inland transport, retail and branches of engineering and vehicles.

The countries chosen for comparison in this report present well-known contrasts with the UK in terms of human capital formation. On the one hand, for example, the US benefits from a long-established mass higher education system; on the other hand, German productivity is enhanced in many ways by the skills developed through its apprenticeship system. In recent years the UK has gone a long way towards catching up with the US in terms of mass higher education but has made less obvious progress in terms of apprenticeships and other intermediate-level training. The effects of this uneven skill development will vary between sectors depending on the mix of higher and intermediate skills which is required by the majority of employers in each sector. What is important is not to seek to follow any particular foreign skills model but rather to develop better means for UK employers' skill requirements to be identified and to inform the design and delivery of vocational training provision.

In this context the main findings of this report add to the urgency surrounding key recommendations made by the Leitch Review of Skills, for example:

- A stronger employer voice in vocational education and training provision to help meet skills needs and bridge the productivity gap
- Vocational qualifications to be made more relevant to the skills development needs of both employers and individuals to ensure that the skills acquired are those which will contribute most to improved productivity performance
- Improved incentives for individual workers to invest in their own skills development
- Greater data availability at sector level to help persuade employers of the benefits of increased investment in skills and training.

The pay-off to such improvements is unlikely to become evident in the short-term. However, our evidence suggests that skill improvements will contribute positively to productivity performance over the long term if they are combined with new investments in other production inputs with which skills are complementary, for example, new technologies and research and innovation.

Clearly, analysis of inter-country productivity gaps based on growth accounting alone is likely to under-estimate the impact of skills on relative performance precisely because the technique is unable to take account of complementarities between skills and other assets. At the same time, because many of the benefits of skills are indirect in nature, it is difficult to obtain a more accurate measure of the *specific* contribution of skills to inter-country productivity gaps at sector or national level by any other means. However, the econometric analyses presented in this report provide empirical confirmation that cross-country productivity gaps at sector level are significantly related to gaps in skills, and that bridging those gaps in skills is a necessary (though not sufficient) condition for the productivity differences to be eliminated.

Future research in this area could usefully proceed in a number of directions, including:

(1) developing new qualifications- and wage-based skill measures that might enable the separate effects of higher and intermediate-level skills on productivity, innovation and growth to be identified through econometric analysis

(2) submitting our findings on the contribution of human capital to the research and innovation process to further empirical scrutiny by augmenting relevant datasets with US patent and citation data to supplement the European Patent Office data

(3) extending the relevant datasets to include other countries (e.g. in Scandinavia) which develop skills in different ways from the US, Germany and France with which the UK is most often compared

(4) complementing cross-country econometric analysis at sector level with sector-specific studies which would investigate the practical effects at workplace level of different national systems of employer engagement in skills development (using a mix of quantitative and qualitative research techniques).

Table 9.1: Gaps in labour quality between UK and leader countries among the US, France and Germany (derived from Table 3.3) – percentage point differences on 0-100 scale where 100 = all employees qualified to graduate level

SIC code	Sector	Gap between UK and leader country (pp)
71	Renting of machinery and equipment	14
61	Water transport	14
60	Inland transport	14
52	Retail trade and repair of household goods	13
51	Wholesale trade and commission trade	12
332-335	Other instrument engineering	12
50	Motor vehicle trade and repairs	12
64	Post and telecommunications	12
67	Activities auxiliary to financial services	11
01-05	Agriculture, forestry and fishing	11
90, 91, 92, 93	Other community, social and personal services	10
73	Research and development	10
63	Supporting and auxiliary transport activities; travel agents	10
66	Insurance and pension funding, except compulsory social security	10
30	Computers and office machinery	9
321	Manufacture of electronic valves and tubes and other electronic components	9
65	Financial services, except insurance and pension funding	9
72	Computer services and related activities	9
354, 355	Manufacture of motorcycles and bicycles; Manufacture of other transport equipment	9
19	Leather and footwear	9
244	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	9
45	Construction	8
176, 177	Manufacture of knitted and crocheted fabrics and articles	8
18	Manufacture of wearing apparel; dressing and dyeing of fur	8
343	Manufacture of parts and accessories for motor vehicles and their engines	8
322, 323	Manufacture of radio, TV and telecommunications equipment	8
55	Hotels and catering	8
151	Production, processing and preserving of meat and meat products	8
174, 175	Manufacture of made-up textile articles, except apparel, Manufacture of other textiles	8
245	Manufacture of soap and detergents, cleaning and polishing preparations, perfume	8
62	Air transport	7
40, 41	Electricity, gas and water supply	7
74	Other business services	7
297	Manufacture of domestic appliances n.e.c.	7
252	Manufacture of plastic products	7
31	Electrical machinery	7

SIC code	Sector	Gap between UK and leader country (pp)
262-268	Manufacture of ceramic products, bricks, tiles and construction products	7
341, 342	Manufacture of Motor Vehicles; bodies for motor vehicles; trailers	6
171, 172, 173	Preparation and spinning of textile fibres, Textile weaving, Finishing of textiles	6
361	Manufacture of furniture	6
211	Manufacture of pulp, paper and paperboard	6
351	Building and repairing of ships and boats	6
362-366, 37	Other manufacturing nec, Recycling	6
281	Manufacture of structural metal products	6
222	Printing and service activities related to printing	6
20	Wood and wood products	5
291-293, 295	General and special purpose machinery and other mechanical engineering products	5
152-154; 156-158, 160	Other food manufacturing; tobacco manufacturing	5
275	Casting of metals	5
261	Manufacture of glass and glass products	5
274	Manufacture of basic precious and other non-ferrous metals	5
251	Manufacture of rubber products	4
212	Manufacture of articles of paper and paperboard	4
352	Manufacture of railway and tramway locomotives and rolling stock	4
353	Manufacture of aircraft and spacecraft	4
282, 283	Manufacture of tanks, reservoirs and containers of metal, manufacture of central	4
331	Manufacture of medical and surgical equipment and orthopaedic appliances	4
155	Manufacture of dairy products	4
284-287	Other fabricated metal products	4
294	Manufacture of machine-tools	3
271, 272, 273	Manufacture of basic iron and steel and of ferro-alloys, Manufacture of tubes, Other first processing of iron and steel	2
241-243, 246-247	Basic chemicals, agrochemicals, paints, coatings and other chemical products	2
296	Manufacture of weapons and ammunition	2
23	Mineral oil refining, coke and nuclear fuel	2
10-14	Mining and quarrying	2
159	Manufacture of beverages	2
221	Publishing	0
223	Reproduction of recorded media	0

Source: ISP

APPENDIX TABLES

Table A1: Qualification categories employed in the measurement of human capital quality

Country	Qualification group Number	Description
USA	1	Bachelor degrees and above
	2	Associate degree
	3	Some college, no degree
	4	High school graduate
	5	Did not complete high school
UK	1	First degree and above
	2	Other NVQ4
	3	NVQ3
	4	NVQ2 & NVQ1
	5	No formal qualification
France	1	Bachelor degree and above
	2	Baccalaureate plus 2 years college
	3	Baccalaureate
	4	Vocational (CAP, BEP or similar)
	5	General Education (BEPC)
	6	No formal qualification
Germany	1	Higher education (16+ years of education)
	2	Vocational degree
	3	No degree
Netherlands	1	Master degree and above
	2	HBO*
	3	HAVO/VWO**
	4	MAVO**
	5	MBO***
	6	LBO/VBO***
	7	Primary education or below

*HBO is tertiary education, of a vocational type. **HAVO/VWO/MAVO is general education which normally leads to entry into a higher level, taking up to 4 to 6 years of study after primary school. *** LBO/VBO and MBO are vocational schooling, taking up to a maximum of 4 to 6 years after primary school (O'Mahony and Van Ark, *EU productivity and competitiveness: an industry perspective*, European Communities 2003).

Table A2: Summary statistics USA (EPKE)
(Average levels 1979-2000, 26 industries)
(Values in $000)

	N	Mean	SD	Max	Min
Value Added	572	211540.60	276952.00	1562837.00	10643.91
Total Hours	572	8219.48	10683.63	62463.43	255.00
Total Capital	546	51626.16	43668.87	245030.20	2373.54
Human Capital	567	5088.93	10501.37	79297.54	96.69
ICT Capital	572	6032.01	12705.12	134190.60	34.20
Non-ICT Capital	572	56699.47	48130.84	265064.30	3242.00

Table A3: Summary statistics USA (EPKE)
(Average rate of growth, 1979-2000, 26 industries)

	N	Mean	SD	Max	Min
Value Added	546	2.80	7.99	58.41	-36.42
Total Hours	546	0.46	4.03	12.66	-19.10
Total Capital	546	3.40	3.50	15.10	-6.45
Human Capital	546	0.39	0.80	4.09	-3.71
ICT Capital	546	14.79	9.99	65.26	-21.74
Non-ICT Capital	546	2.04	2.63	11.33	-6.42

Table A4: Summary statistics UK (EPKE)
(Average levels 1979-2000, 26 industries)
(Values in $000)

	N	Mean	SD	Max	Min
Value Added	572	28589.21	30616.55	173364.20	2233.60
Total Hours	572	1774.56	1919.70	9577.08	62.43
Total Capital	546	8494.75	8088.97	53529.29	702.16
Human Capital	551	894.78	1923.20	11064.86	2.18
ICT Capital	572	481.79	955.94	7281.79	1.53
Non-ICT Capital	572	8982.85	8372.60	55083.56	811.92

Table A5: Summary statistics UK (EPKE)
(Average rate of growth, 1979-2000, 26 industries)

	N	Mean	SD	Max	Min
Value Added	546	1.82	5.76	22.87	-17.59
Total Hours	546	-1.36	5.31	15.74	-43.01
Total Capital	546	2.81	4.08	20.08	-8.36
Human Capital	545	0.62	1.62	12.34	-6.45
ICT Capital	546	17.08	10.64	55.90	-8.27
Non-ICT Capital	546	1.76	3.76	19.03	-10.86

Table A6: Summary statistics France (EPKE)
(Average levels 1979-2000, 26 industries)
(Values in $000)

	N	Mean	SD	Max	Min
Value Added	572	30857.60	36669.31	224767.00	1736.76
Total Hours	572	1446.04	1750.27	9262.47	39.96
Total Capital	546	14260.47	18447.17	97808.09	62.97
Human Capital	458	482.64	1324.97	11429.34	0.14
ICT Capital	572	414.84	702.96	5423.37	0.10
Non-ICT Capital	572	14814.56	19159.94	103384.30	64.19

Table A7: Summary statistics France (EPKE)
(Average rate of growth, 1979-2000, 26 industries)

	N	Mean	SD	Max	Min
Value Added	546	1.51	5.99	22.71	-35.47
Total Hours	546	-1.14	2.92	6.77	-12.88
Total Capital	546	2.42	3.79	48.65	-6.43
Human Capital	450	0.38	2.21	14.37	-27.31
ICT Capital	546	13.62	8.40	84.24	-7.63
Non-ICT Capital	546	1.92	3.76	47.94	-6.94

Table A8: Summary statistics Germany (EPKE)
(Average levels 1979-2000, 26 industries)
(Values in $000)

	N	Mean	SD	Max	Min
Value Added	572	46988.87	51230.88	289863.60	2015.55
Total Hours	572	2097.93	2152.58	11559.93	35.15
Total Capital	546	18095.50	14244.82	58762.64	1323.91
Human Capital	497	1002.56	1506.01	13627.91	12.41
ICT Capital	572	974.42	1419.13	13939.05	10.87
Non-ICT Capital	572	19445.01	14825.25	61083.59	1785.89

Table A9: Summary statistics Germany (EPKE)
(Average rate of growth, 1979-2000, 26 industries)

	N	Mean	SD	Max	Min
Value Added	546	1.26	6.97	74.12	-55.57
Total Hours	494	-1.01	4.00	18.13	-20.49
Total Capital	546	2.01	3.11	17.52	-5.73
Human Capital	475	0.37	0.37	3.42	-1.67
ICT Capital	546	11.23	7.21	39.74	-17.70
Non-ICT Capital	546	1.08	2.79	13.47	-6.10

Table A10: Summary statistics Netherlands (EPKE)
(Average rate of growth, 1979-2000, 26 industries)

	N	Mean	SD	Max	Min
Value Added	546	2.48	5.94	36.60	-41.90
Total Hours	494	-0.27	3.96	12.25	-17.13
Total Capital	546	2.84	3.34	18.34	-7.36
Human Capital	251	0.31	0.82	3.1	-4.1
ICT Capital	546	21.43	16.22	250.23*	-13.88
Non-ICT Capital	546	1.89	3.07	17.75	-7.26

*This value refers to Electricity, Gas and Water Industry.

Table A11: Taxonomy of EPKE sectors between 'ICT sectors' (ICT producers and intensive users) and 'Non-ICT sectors'

EPKE Industry	Industry Name	SIC Codes	ICT/Non ICT
1	Agric./Forestry/ Fishing	01-05	Non-ICT
2	Mining/Quarrying	10-14	Non-ICT
3	Food/ Drink/ Tob.	15-16	Non-ICT
4	Text./Leather/Footwear/Clothing	17-19	Non-ICT
5	Wood/Wood Prod.	20	Non-ICT
6	Pulp/Paper/ Paper Prod./ Printing/Publish.	21-22	ICT
7	Oil Refining/Coke/Nuclear Fuel	23	Non-ICT
8	Chemicals	24	Non-ICT
9	Rubber/Plastics	25	Non-ICT
10	Non-Metallic Miner.Prod.	26	Non-ICT
11	Basic Metals/Fabric. Metal Prod.	27-28	Non-ICT
12	Mechanical Engineering	29	ICT
13	Electrical & Electronic Equip./Instruments	30-33	ICT
14	Transport Equipment	34-35	ICT
15	Furniture/Miscell. Manufact./Recycling	36-37	ICT
16	Electricity/Gas/Water	40-41	Non-ICT
17	Construction	45	Non-ICT
18	Repairs/Wholesale trade	50-51	ICT
19	Retail trade	52	ICT
20	Hotels/Catering	55	Non-ICT
21	Transport	60-63	Non-ICT
22	Communications	64	ICT
23	Financial Intermediation	65-67	ICT
24	Real Estate Activities/Business Services	71-74	ICT
25	Other Services	90-99	Non-ICT
26	Non-Market Services	75-85	Non-ICT

Source: Derived from Van Ark et al. (2002)

Table A12: Relative TFP and country ranking

Industry	year	USA	UK	FR	GE	ND	Rank USA	Rank UK	Rank FR	Rank GE	Rank ND
Agric./Forestry/ Fishing	**1979**	**0.52**	**1.00**	**0.38**	**0.24**	**0.85**	**3**	**1**	**4**	**5**	**2**
Agric./Forestry/ Fishing	**1990**	**0.95**	**0.95**	**0.44**	**0.33**	**1.00**	**3**	**2**	**4**	**5**	**1**
Agric./Forestry/ Fishing	**2000**	**1.00**	**0.75**	**0.48**	**0.31**	**0.88**	**1**	**3**	**4**	**5**	**2**
Mining/Quarrying	1979	0.20	0.16	0.60	0.21	1.00	4	5	2	3	1
Mining/Quarrying	1990	0.30	0.25	0.63	0.22	1.00	3	4	2	5	1
Mining/Quarrying	2000	0.29	0.48	0.38	0.19	1.00	4	2	3	5	1
Food/ Drink/ Tob.	**1979**	**1.00**	**0.61**	**0.91**	**0.57**	**0.65**	**1**	**4**	**2**	**5**	**3**
Food/ Drink/ Tob.	**1990**	**1.00**	**0.74**	**0.87**	**0.63**	**0.77**	**1**	**4**	**2**	**5**	**3**
Food/ Drink/ Tob.	**2000**	**0.78**	**0.72**	**0.80**	**0.66**	**1.00**	**3**	**4**	**2**	**5**	**1**
Text./Leather/Footwear/Clothing	1979	0.60	0.50	1.00	0.50	0.69	3	4	1	5	2
Text./Leather/Footwear/Clothing	1990	0.80	0.63	0.90	0.69	1.00	3	5	2	4	1
Text./Leather/Footwear/Clothing	2000	0.64	0.49	0.77	0.51	1.00	3	5	2	4	1
Wood/Wood Prod.	**1979**	**1.00**	**0.72**	**0.94**	**0.74**	**0.50**	**1**	**4**	**2**	**3**	**5**
Wood/Wood Prod.	**1990**	**1.00**	**0.54**	**0.96**	**0.55**	**0.60**	**1**	**5**	**2**	**4**	**3**
Wood/Wood Prod.	**2000**	**0.79**	**0.48**	**1.00**	**0.76**	**0.78**	**2**	**5**	**1**	**4**	**3**
Pulp/Paper/ Paper Prod./ Printing/Publish.	1979	1.00	0.99	0.99	0.55	0.39	1	3	2	4	5
Pulp/Paper/ Paper Prod./ Printing/Publish.	1990	0.94	1.00	0.96	0.73	0.47	3	1	2	4	5
Pulp/Paper/ Paper Prod./ Printing/Publish.	2000	0.65	1.00	0.74	0.57	0.43	3	1	2	4	5
Oil Refining/Coke/Nuclear Fuel	**1979**	**0.09**	**0.16**	**0.86**	**0.22**	**1.00**	**5**	**4**	**2**	**3**	**1**
Oil Refining/Coke/Nuclear Fuel	**1990**	**0.15**	**0.10**	**0.14**	**0.18**	**1.00**	**3**	**5**	**4**	**2**	**1**
Oil Refining/Coke/Nuclear Fuel	**2000**	**0.33**	**0.22**	**0.30**	**0.29**	**1.00**	**2**	**5**	**3**	**4**	**1**
Chemicals	1979	1.00	0.50	1.00	0.59	0.13	1	4	2	3	5
Chemicals	1990	1.00	0.62	0.92	0.57	0.15	1	3	2	4	5
Chemicals	2000	0.84	0.71	1.00	0.59	0.15	2	3	1	4	5
Rubber/Plastics	**1979**	**0.41**	**0.74**	**1.00**	**0.69**	**0.37**	**4**	**2**	**1**	**3**	**5**
Rubber/Plastics	**1990**	**0.61**	**0.92**	**1.00**	**0.79**	**0.57**	**4**	**2**	**1**	**3**	**5**

Rubber/Plastics	**2000**	**0.67**	**0.84**	**1.00**	**0.68**	**0.54**	**4**	**2**	**1**	**3**	**5**
Non-Metallic Miner.Prod.	1979	0.52	0.88	0.66	0.69	1.00	5	2	4	3	1
Non-Metallic Miner.Prod.	1990	0.43	0.92	0.73	0.56	1.00	5	2	3	4	1
Non-Metallic Miner.Prod.	2000	0.39	0.62	0.73	0.58	1.00	5	3	2	4	1
Basic Metals/Fabric. Metal Prod.	**1979**	**0.94**	**0.66**	**1.00**	**0.75**	**0.39**	**2**	**4**	**1**	**3**	**5**
Basic Metals/Fabric. Metal Prod.	**1990**	**1.00**	**0.94**	**0.97**	**0.90**	**0.44**	**1**	**3**	**2**	**4**	**5**
Basic Metals/Fabric. Metal Prod.	**2000**	**1.00**	**0.84**	**0.91**	**0.85**	**0.42**	**1**	**4**	**2**	**3**	**5**
Mechanical Engineering	1979	1.00	0.56	0.79	0.69	0.51	1	4	2	3	5
Mechanical Engineering	1990	1.00	0.74	0.97	0.91	0.79	1	5	2	3	4
Mechanical Engineering	2000	0.83	0.68	1.00	0.82	0.88	3	5	1	4	2
Electrical & Electronic Equip./Instruments	**1979**	**0.51**	**0.36**	**0.83**	**1.00**	**0.40**	**3**	**5**	**2**	**1**	**4**
Electrical & Electronic Equip./Instruments	**1990**	**0.98**	**0.83**	**0.92**	**1.00**	**0.63**	**2**	**4**	**3**	**1**	**5**
Electrical & Electronic Equip./Instruments	**2000**	**1.00**	**0.49**	**0.44**	**0.35**	**0.15**	**1**	**2**	**3**	**4**	**5**
Transport Equipment	1979	1.00	0.29	0.48	0.65	0.30	1	5	3	2	4
Transport Equipment	1990	1.00	0.44	0.63	0.73	0.46	1	5	3	2	4
Transport Equipment	2000	1.00	0.45	0.86	0.55	0.61	1	5	2	4	3
Furniture/Miscell. Manufact./Recycling	**1979**	**0.64**	**1.00**	**0.68**	**0.74**	**0.70**	**5**	**1**	**4**	**2**	**3**
Furniture/Miscell. Manufact./Recycling	**1990**	**0.88**	**1.00**	**0.84**	**0.76**	**0.97**	**3**	**1**	**4**	**5**	**2**
Furniture/Miscell. Manufact./Recycling	**2000**	**0.97**	**0.76**	**0.94**	**0.67**	**1.00**	**2**	**4**	**3**	**5**	**1**
Electricity/Gas/Water	1979	0.66	0.24	0.23	0.26	1.00	2	4	5	3	1
Electricity/Gas/Water	1990	0.60	0.33	0.33	0.23	1.00	2	4	3	5	1
Electricity/Gas/Water	2000	0.61	0.48	0.39	0.28	1.00	2	3	4	5	1
Construction	**1979**	**0.88**	**0.46**	**0.46**	**0.62**	**1.00**	**2**	**4**	**5**	**3**	**1**
Construction	**1990**	**0.66**	**0.39**	**0.42**	**0.56**	**1.00**	**2**	**5**	**4**	**3**	**1**
Construction	**2000**	**0.73**	**0.59**	**0.44**	**0.54**	**1.00**	**2**	**3**	**5**	**4**	**1**
Repairs/Wholesale trade	1979	1.00	0.89	0.76	0.96	0.37	1	3	4	2	5
Repairs/Wholesale trade	1990	0.82	0.94	1.00	0.91	0.39	4	2	1	3	5

Repairs/Wholesale trade	2000	0.99	1.00	0.72	0.80	0.36	2	1	4	3	5
Retail trade	**1979**	**1.00**	**0.58**	**0.60**	**0.67**	**0.35**	**1**	**4**	**3**	**2**	**5**
Retail trade	**1990**	**1.00**	**0.46**	**0.77**	**0.67**	**0.39**	**1**	**4**	**2**	**3**	**5**
Retail trade	**2000**	**1.00**	**0.41**	**0.58**	**0.54**	**0.28**	**1**	**4**	**2**	**3**	**5**
Hotels/Catering	1979	0.27	0.20	0.48	0.23	1.00	3	5	2	4	1
Hotels/Catering	1990	0.25	0.17	0.38	0.24	1.00	3	5	2	4	1
Hotels/Catering	2000	0.23	0.14	0.32	0.18	1.00	3	5	2	4	1
Transport	**1979**	**1.00**	**0.64**	**0.80**	**0.37**	**0.50**	**1**	**3**	**2**	**5**	**4**
Transport	**1990**	**1.00**	**0.78**	**0.88**	**0.39**	**0.48**	**1**	**3**	**2**	**5**	**4**
Transport	**2000**	**1.00**	**0.91**	**0.81**	**0.56**	**0.49**	**1**	**2**	**3**	**4**	**5**
Communications	1979	0.64	0.37	0.45	0.54	1.00	2	5	4	3	1
Communications	1990	0.54	0.40	0.78	0.68	1.00	4	5	2	3	1
Communications	2000	0.43	0.54	0.76	1.00	0.86	5	4	3	1	2
Financial Intermediation	**1979**	**0.59**	**0.39**	**0.22**	**0.35**	**1.00**	**2**	**3**	**5**	**4**	**1**
Financial Intermediation	**1990**	**0.40**	**0.34**	**0.40**	**0.42**	**1.00**	**4**	**5**	**3**	**2**	**1**
Financial Intermediation	**2000**	**0.58**	**0.43**	**0.41**	**0.58**	**1.00**	**3**	**4**	**5**	**2**	**1**
Real Estate Activities/Business Services	1979	0.43	0.40	0.26	0.58	1.00	3	4	5	2	1
Real Estate Activities/Business Services	1990	0.43	0.33	0.31	0.55	1.00	3	4	5	2	1
Real Estate Activities/Business Services	2000	0.41	0.35	0.28	0.49	1.00	3	4	5	2	1
Other Services	**1979**	**1.00**	**0.38**	**0.76**	**1.00**	**0.98**	**2**	**5**	**4**	**1**	**3**
Other Services	**1990**	**1.00**	**0.34**	**0.57**	**0.98**	**0.82**	**1**	**5**	**4**	**2**	**3**
Other Services	**2000**	**0.98**	**0.53**	**0.59**	**1.00**	**0.94**	**2**	**5**	**4**	**1**	**3**
Non-Market Services	1979	1.00	0.75	0.51	0.76	0.89	1	4	5	3	2
Non-Market Services	1990	1.00	0.89	0.59	0.75	0.96	1	3	5	4	2
Non-Market Services	2000	0.80	0.62	0.72	0.78	1.00	2	5	4	3	1

Source: EPKE. Derived following the methodology outlined in Griffith, Redding and Van Reenen, 2004. Relative TFP is each country's TFP as a proportion of that in the frontier and is equal to 1 for the frontier and less than 1 for non-frontier countries. The further away from 1 the greater a country's distance from the technology frontier.

Table A13: Catch-up models of productivity growth: 1 year gap (EPKE)

Dependent Variable: Annual Growth in Value Added

	(1)	(2)	(3)	(4)
Growth in physical capital	0.110 (0.071)	0.119* (0.070)	0.102* (0.061)	0.090 (0.064)
Growth in total hours	0.442*** (0.071)	0.459*** (0.075)	0.528*** (0.072)	0.521*** (0.072)
Labour Quality (unskilled base)	0.002 (0.002)	0.007*** (0.002)	0.001 (0.001)	0.001 (0.001)
Log Value Added (t-1)		-0.008*** (0.003)		
Log TFP (t-1)			-0.011** (0.005)	
Log TFP gap (t-1)				0.002 (0.005)
Constant	-0.029 (0.026)	0.068 (0.044)	0.015 (0.015)	0.011 (0.015)
Observations	2465	2465	2465	2465
R-squared	0.173	0.180	0.140	0.135

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets.

Table A14: Catch-up models of productivity growth: 3 year gap (EPKE)

Dependent Variable: Change in Value Added

	(1)	(2)	(3)	(4)	(5)
Growth in physical capital	0.187*** (0.055)	0.153** (0.060)	0.159*** (0.060)	0.176*** (0.058)	0.154** (0.060)
Growth in total hours	0.490*** (0.102)	0.462*** (0.097)	0.476*** (0.103)	0.483*** (0.095)	0.466*** (0.096)
Growth in average labour quality	0.016 (0.026)				
Average labour quality		0.004 (0.005)	0.022*** (0.008)	0.003 (0.004)	0.004 (0.005)
Log Value added (t-3)			-0.033*** (0.010)		
Log TFP (t-3)				-0.045*** (0.012)	
Log TFP gap (t-3)					0.008 (0.012)
Constant	0.055*** (0.015)	0.009 (0.062)	0.412*** (0.113)	0.030 (0.061)	0.043 (0.058)
Observations	508	635	635	635	635
R-squared	0.256	0.244	0.272	0.263	0.245

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets.

Table A15: Catch-up models of productivity growth: 5 year gap (EPKE)

Dependent variable: Change in Value Added

	(1)	(2)	(3)	(4)	(5)
Growth in physical capital	0.157*** (0.058)	0.121** (0.060)	0.128** (0.061)	0.145** (0.058)	0.122** (0.060)
Growth in total hours	0.488*** (0.075)	0.472*** (0.079)	0.488*** (0.083)	0.497*** (0.078)	0.478*** (0.078)
Growth in average labour quality	0.057* (0.032)				
Average labour quality		0.008 (0.008)	0.041*** (0.014)	0.006 (0.008)	0.008 (0.008)
Log Value Added (t -5)			-0.062*** (0.018)		
Log TFP (t-5)				-0.073*** (0.021)	
Log TFP gap (t-5)					0.015 (0.019)
Constant	0.084*** (0.031)	0.054 (0.103)	0.724*** (0.186)	0.087 (0.099)	0.042 (0.100)
Observations	254	381	381	381	381
R-squared	0.309	0.263	0.311	0.289	0.265

Notes: ***=significant at 1%, **=significant at 5%, *=significant at 10%. Heteroscedasticity-robust standard errors are in brackets.

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