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Macroeconomic benefits of vocational education and training

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The **European Centre for the Development of Vocational Training** (Cedefop) is the European Union's reference centre for vocational education and training. We provide information on and analyses of vocational education and training systems, policies, research and practice. Cedefop was established in 1975 by Council Regulation (EEC) No 337/75.

Europe 123, 570 01 Thessaloniki (Pylea), GREECE
PO Box 22427, 551 02 Thessaloniki, GREECE
Tel. +30 2310490111, Fax +30 2310490020
E-mail: info@cedefop.europa.eu
www.cedefop.europa.eu

Foreword

The contribution of VET to economic competitiveness is often underestimated. This is partly because it has not been systematically measured and evidenced. The study undertaken by Cedefop aims to fill this gap by investigating the macroeconomic benefits of VET.

Skills development begins in the education system and continues over the life course as workers engage in adult education, continuing vocational education and training (VET), and on-the-job learning. The skills developed in compulsory education are usually recognised and certified through qualifications. However, not all the skills acquired after initial education, when workers are engaged in lifelong learning, will lead to qualifications. Consequently, considerable efforts were made in the study to consider both the outcomes of initial VET and the skills acquired through participation in continuing training. The study focuses on Denmark, Germany, France, the Netherlands, Sweden and the UK, which have very different VET systems and so permit comparative analysis of macroeconomic benefits according to the type of VET system in place in a country.

The results show that economic success depends on the availability of skills developed at different levels (low, lower- and upper-intermediate and high) both in general and vocational education. In countries where the effect of VET on productivity is stronger – i.e. those with a tradition of apprenticeship in VET (Denmark, Germany, and the Netherlands) – various types of qualification, general and vocational, obtained at various levels, appear to complement each other. Upper-intermediate vocational skills also have a positive impact on labour productivity when vocational skills are broadly defined to include those acquired through employer-provided continuing training. Again, the effect on productivity is stronger in countries where the apprenticeship system is common. In the remaining countries higher academic skills tend to be more important for increasing productivity than VET, but the effect of academic education is reinforced by skills acquired through continuing training at work. This study underlines that learning in the workplace, both in initial and continuing VET, makes a fundamental contribution to productivity and comes to support policy efforts to develop apprenticeship and adult learning.

We trust that this report will contribute to better understanding of the potential of vocational skills, including those acquired through workplace learning, to foster economic growth. We hope that it will provide a basis for policies that aim to improve education and training at all levels, with a combined focus on general and vocational education, at European level and in individual Member States.

Joachim James Calleja
Director

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Table of contents

List of tables, figures and boxes

Tables

Figures

Boxes

Executive summary

Report aims and methods

Improvements in workforce skills are essential for European countries to achieve higher economic growth rates and compete effectively against other advanced industrial nations. However, policy prescriptions rarely differentiate types of education and skill acquisition. For example, with the exception of recent work done by Cedefop, little effort has been made to assess the relative importance of skills acquired through vocational education and training (VET) compared to skills acquired through other types of education. In this report we set out to fill some of this gap in knowledge by investigating the macroeconomic benefits of VET in selected EU Member States. VET is defined here as organised or structured activities that aim to provide people with the knowledge, skills and competences necessary to perform a job or a set of jobs or for particular occupations.

Many of the economic effects of different kinds of skill are hard to identify because they are indirect. Skills are not deployed in isolation but have to be combined with other production inputs, such as machinery and equipment, before they can make a contribution to economic performance. There is also a key methodological issue that needs to be resolved to identify the indirect effects of skills on performance: the measurement of skills.

We tackle the issue of measurement head-on by developing two different skill measures. First, we use education output data to derive a measure (admittedly imperfect) of the stock of certified skills; this is combined with relative earnings data by skill level to capture the importance of uncertified skills (on the assumption that these would be rewarded in wages). Second, we make use of estimates of training capital stocks derived from survey data on employer-provided training in each country. These training capital measures capture some (though not all) uncertified skills and lend themselves to being combined in our analyses with measures of the certified skills recognised through formal qualifications.

International qualification and training level comparisons

We identify five different qualification groups: higher (bachelor degree and above), upper-intermediate vocational, lower-intermediate vocational, lower-intermediate general, and low-skilled.

The division between the higher and upper-intermediate groups corresponds to the boundary between long-cycle and short-cycle higher education. In terms of traditional vocational qualifications, technician-level qualifications in the upper-intermediate vocational group are separated from craft-level qualifications in the lower-intermediate vocational group.

The data are compiled for six EU Member States – Denmark, Germany, France, the Netherlands, Sweden and the UK – chosen for diversity in terms of their predominant modes of VET: either based on apprenticeship training (Denmark, Germany and the Netherlands) or on school-based VET (France, Sweden and the UK). The six countries also vary sharply in terms of job-related training provided by employers.

Vocational skills and productivity

The empirical analysis shows a stable long-run relationship and a weaker short-run relationship between skills and average labour productivity (ALP), the measure of productivity adopted throughout the analysis. It also shows differences in the ways the various types of skills affect productivity.

The analysis provides considerable evidence of a positive relationship between upper-intermediate vocational skills and relative ALP performance, especially in the production sectors. This positive relationship is found to occur primarily in countries where apprenticeship is common and is stronger when vocational skills are broadly defined to include uncertified skills acquired through employer-provided training.

Lower-intermediate vocational skills appear to reinforce the impact of information and communication technologies (ICTs) on productivity, especially in countries where VET is predominantly based on apprenticeship training. High-level academic skills reinforce the impact of ICT capital on productivity in countries where the VET system is mainly school-based.

Vocational and other certified skills

Complementarity between types of skills can be explained as follows. First, skilled employees in workplaces help to raise the productivity of low-skilled colleagues (Kirby and Riley, 2008). Second, better skilled employees at intermediate and lower levels of organisations allow senior managers and professional staff to think strategically and do their own jobs well rather than engage in day-to-day ‘fire-fighting’ activities (dealing with problems that could have been avoided if the workforce as a whole had higher levels of skill and competence). The productivity of high-skilled workers may be augmented by the presence of intermediate-skilled workers.

Although the positive effects of vocational skills on economic performance are sometimes overshadowed by the effects of high-level and intermediate general skills, this study shows intermediate vocational skills as complementary.

In production sectors in countries where VET systems are largely apprenticeship-based, intermediate vocational skills are complementary to the use of high-level skills. In market services in countries with strong apprentice training systems, high-skilled labour is complemented by upper-intermediate vocational-skilled labour but not by other types.

The study also indicates that, in all countries, upper-intermediate and lower-intermediate vocational skills both complement – that is, increase the productivity of – low-skilled labour. In countries where VET systems are heavily based on apprenticeship training, we also find that both upper- and lower-intermediate vocational-skilled labour complement lower-intermediate general-skilled labour. However, upper-intermediate vocational-skilled labour and lower-intermediate vocational-skilled labour do not complement each other; in some cases they are substitutes for each other.

These patterns of complementarity are not observed in countries where VET systems are largely classroom-based. In the production sectors in these countries, upper-intermediate vocational skills tend to be substitutes (rather than complements) for higher skills. In market services sectors, complementarity mainly involves low skills and lower-intermediate skills (both general and vocational).

Concluding remarks

The impact of skills on productivity is more pronounced in countries where VET is based on apprenticeship training. This suggests that the context in which skills are developed is important in determining the ultimate effect of skills on productivity.

Vocational skills tend to play a more important role in production sectors in countries where VET is based on apprenticeship training. In market sectors in countries where VET is school-based, high (academic) skills are more prominent. This suggests that vocational skills have greater impact on productivity in sectors and countries that have a longer tradition in the use of vocational skills. Cultural, political and socioeconomic forces that affected the historical evolution of the vocational system will cast a long shadow on the ways skills affect productivity

Uncertified skills developed through job-related training provided by employers are important and reinforce the impact of certified vocational skills on labour productivity. Productivity performance is increased by developing a mix of skills, of various levels and orientation, and not by relying too heavily on the expansion of a single type of skill. Developing a mix of intermediate and high-level skills will also enable complementarities between skill groups to flourish. Complementarity between skills is more developed in countries in which VET is based on apprenticeship training and in production sectors.

CHAPTER 1.
Introduction

Improvements in workforce skills are widely held to be essential for European countries to achieve higher economic growth rates and compete effectively against other advanced industrial nations (European Commission, 2010a; 2010b). These policy prescriptions are supported by research findings which show a positive relationship between skills and economic performance. For example, Barrell et al. (2011) find that growth in measured skills contributed positively to growth in output and in labour productivity in 10 European countries and in Japan and the US in 1978-2007. Timmer et al. (2010), using data from the EU KLEMS project ([1]), also find that upskilling the workforce contributes positively to growth. Previous literature showing similar results includes Jorgenson et al. (2005) for the US and O'Mahony (2012) for comparisons across five countries.

Much of the policy emphasis on skills tends to focus on skills or educational attainments in general, or on particular levels of skills and attainment (high-level skills or basic literacy and numeracy). Few attempts have been made to differentiate between different types of education and skill acquisition, such as to assess the relative importance of skills acquired through vocational education and training (VET) compared to skills acquired through other types of education. Recent work from Cedefop aimed at the showing the positive impact of VET on various market (wages (Cedefop, 2011b), firms' performance indicators (Cedefop, 2011c), productivity in sectors (Cedefop, 2012)) and non-market outcomes (job satisfaction in companies (Cedefop, 2011a), measures of social capital for individuals (Cedefop, 2011e), and civic competences and health in countries (Cedefop, 2011d)) is the exception.

In this report we seek to fill some of this gap in knowledge by investigating the macroeconomic benefits of investing in VET in EU Member States. VET is defined here as 'all more or less organised or structured activities that aim to provide people with knowledge, skills and competences necessary to perform a job or a set of jobs…. [or to enter a] range of occupations' (Cedefop et al., 2004, p. 13).

([1]) The EU KLEMS project ran from 2003 until 2008. It was funded by the European Commission, Directorate General for Research as part of the sixth framework programme, priority 8: policy support and anticipating scientific and technological needs. KLEMS refers to capital, labour, energy, material and service inputs. See http://www.euklems.net/ [accessed 11.11.2013] for further details.

Analysing the impact of skills on productivity is made difficult by the complex interaction between the use of skills and other production inputs such as capital and ICT. The most basic forms of analysis – those based on growth accounting – capture the direct effects of growth in measured skills on economic performance and do not take account of positive effects arising from indirect effects of skills, such as complementarities with other production inputs such as ICT capital. Alternative approaches using multivariate regression methods are better in capturing indirect effects of this kind. However, as Sianesi and van Reenen (2003) point out, indirect links between skills and economic performance at national level are sometimes hard to identify because of the methodological issues that remain unresolved: the measurement of skills and appropriate ways of modelling the potential channels of influence of skills on economic performance.

In this report we tackle the first issue, that of measurement, by developing measures of skills, based on qualifications, wage and training data, which differentiate clearly between qualifications gained through general education and qualifications gained through VET.

We also address the second issue of modelling the potential channels of influence of skills on economic performance through multivariate analysis, using new measures of job-related training, diffusion of new and innovative technologies.

The empirical applications make use of data from six EU Member States – Denmark, Germany, France, the Netherlands, Sweden and the UK – selected to cover a wide range of different VET institutions.

The report is ordered as follows. In Chapter 2 we survey recent literature on different European VET systems and the potential impacts of vocational and other skills on economic performance. In Chapter 3 we describe how new skill measures have been estimated and present descriptive statistics for the six countries based on these new measures. Chapter 4 reports growth accounting estimates of the impact of vocational and other skills on labour productivity growth in the six countries. Chapter 5 employs multivariate regression methods to assess the impact of vocational skills on average labour productivity levels and on the effective utilisation of new technologies. Chapter 6 reports evidence relating to complementarities between vocational and general skills. Chapter 7 summarises main findings and offers concluding remarks.

CHAPTER 2.
Vocational education and training, skills and economic performance

There is great diversity in VET systems in Europe and there are reasons to believe that skills formation regimes have an influence on the way in which skills interact with capital (and ICT investment) and affect (labour) productivity.

We first review the incidence of VET across Europe, followed by salient characteristics of the VET systems of the six countries included in the study to explain the reasons that led to their selection. We then review the literature on the channels of influence by which skills appear to affect economic performance and go on to assess available evidence on the specific role of vocational skills in these processes.

2.1. VET systems in Europe

OECD-collated data on upper secondary education enrolments show marked differences between European countries in the extent to which their education systems are oriented towards VET. Table 1 covers 20 European countries and shows the proportion of upper secondary students enrolled on vocational courses ranging from 24% in Hungary to 77% in Austria (column 2). At the same time, the proportion of upper secondary enrolments on ‘apprenticeship-type’ vocational courses, i.e. those combining school attendance with work-based training, ranges from zero in Greece, Italy and Sweden to 47% in Denmark (column 3). This measure only provides a rough indicator of the incidence of apprenticeship training because countries differ greatly in the ways that combined school and work-based training are organised.

The six countries selected for investigation in this study are highlighted in bold in Table 1. They are a highly varied group in terms of their orientation towards VET and specifically to apprenticeship ([2]) or similar training. Among these countries, the highest share of vocational students at upper secondary level (67%) is found in the Netherlands which also has a middle-ranking share (20%) of students involved in apprenticeship training. Denmark and Germany are ranked at a medium level in terms of overall orientation towards VET but have relatively high shares of apprentices. Sweden has the same share of vocational

([2]) The way apprenticeships are organised varies across countries.

students as Germany (57%) but, according to the data, none of them are undergoing apprenticeship training. France has about 44% of upper secondary students undertaking vocational courses and 12% of apprentice training. Of the six countries, the UK has the lowest share (31%) of upper secondary students engaged in vocational education and has only a modest proportion involved in apprenticeship or similar training programmes (approximately 9%).

Table 1. **Enrolments in upper secondary programmes (% of total enrolments in upper secondary education) in public and private institutions by programme orientation, 2008, various European countries (ordered by proportion engaged in vocational education)**

	General	Vocational	TOTAL	Combined school and workplace-based vocational education
AT	23	77	100	35
CZ	26	74	100	33
BE	27	73	100	3
SK	28	72	100	29
FI	32	68	100	13
NL	33	67	100	20
LU	38	62	100	14
IT	41	59	100	0
DE	43	57	100	43
SE	43	57	100	0
NO	45	55	100	16
DK	52	48	100	47
PL	54	46	100	6
FR	56	44	100	12
ES	56	44	100	2
IE	66	34	100	2
UK	69 ([a])	31	100	9 ([b])
EL	69	31	100	0
PT	69	31	100	nk
HU	76	24	100	14

NB: nk = not known

([a]) Includes some pre-vocational education.

([b]) No estimate shown in the OECD publication. 9% is an NIESR estimate based on labour force survey (LFS) data which show the proportion of 16-18 year-olds in the UK in 2008 who were studying for educational qualifications of some kind and had also received job-related training in the previous 13 weeks or reported being engaged in apprentice training.

Source: OECD, 2010a, Indicator C1, Table C1.4.

These differences between countries in the level and form of VET participation reflect profound differences in national institutional structures relating to training.

In Germany, for example, influential employer associations and trade unions combine at sector level in many branches of manufacturing and services to organise apprentice training and periodically update and modernise the content of training programmes. Many individuals are willing to accept relatively low pay during apprentice training because of the assured career prospects associated with it (Ryan, 2001). Post-training wages are also relatively compressed by international standards and this helps to create incentives for companies to invest in apprentice training, as do the relatively thin external labour markets which enhance the matches between training companies and employees (Mohrenweiser and Zwick, 2008).

By contrast, UK apprentice training has long depended on individual employers being prepared to accept potential losses of trained workers to non-training firms. A long tradition of apprenticeship is only found in certain branches of manufacturing, transport and communications and in some service sectors (notably hairdressing and hospitality). But even in those sectors firms sharply reduced their apprentice numbers during the 1980s and, until recently, have failed to respond significantly to government efforts to rebuild apprentice training (Gospel, 1998; Ryan and Unwin, 2001; Steedman, 2010) ([3]).

Inter-country differences in legislation may also play a part in shaping employer attitudes to apprentice training. Legislation in Germany defines the responsibilities of government, employers and a wide range of partners in relationship to apprenticeships (Fuller and Unwin, 2008). By comparison, the UK has only a very recent (2009) record of passing apprentice-related legislation.

An interesting feature of Danish vocational training is that, although it seems to be strongly work-based (as shown in Table 1). Danish employers in many sectors tend to be more reluctant than their German counterparts to offer training places. There is pressure from many employers for training to be provided in vocational colleges instead of workplaces. However, the Danish funding system offers strong incentives for employers to participate in shaping training in colleges (Grollmann et al., 2003). Vocational skills development in Denmark also takes place largely through continuing, rather than initial, training, partly because of the resources devoted to upskilling unemployed workers (Bosch and Charest, 2008).

France has only a modest share of apprentice trainees at upper secondary level but is distinctive for the resources devoted to technician-level qualifications such as the BTS and DUT, ([4]) typically gained two years after completion of the main secondary school-leaving qualification, the *baccalauréat*. Students

([3]) In response to government financial incentives, apprenticeship enrolments have grown sharply in the UK over the past 10 years. However, the growth took place from a relatively low base and apprentice-trained workers remain a substantially smaller proportion of the workforce in the UK than in countries such as Germany (Steedman, 2010). Most UK apprentice trainees are aiming for a level of qualification below that attained by apprentices in Germany (ibid).

([4]) BTS (*brevet de technicien supérieur* [advanced technician certificate]);
DUT (*diplôme universitaire de technologie* [university degree in technology]).

completing these qualifications can then choose whether to seek to move into skilled employment or to progress to higher education courses. This is partly aided by work placements for many French students on full-time courses and the development of 'higher apprenticeships' for growing minorities of students at technician level (Mehaut, 2008).

The relatively high proportion of vocational students at upper secondary level in the Netherlands reflects the comparatively early age at which secondary school pupils are divided between vocational and general (academic) education. 'Tracking' of vocational students starts at age 14 and the system offers the possibility of continued transfers through medium and higher levels of vocational education from that point onwards (van den Dool, 1989; Cedefop ReferNet Netherlands, 2009). In a study of student transitions from school to employment, Iannelli and Raffe (2007) identify the Netherlands as a country with relatively strong links between vocational education and employment, by European standards, with an apprentice track running parallel to the school-based vocational education route. The Netherlands has the third highest apprentice share of upper secondary enrolments among the six countries considered here but this is less than half that in Germany and Denmark.

By contrast, Sweden relies almost wholly on school-based VET and is sometimes criticised for relatively weak links between VET and employment. Kuczera et al. (2008) argue that full-time vocational schools in Sweden find it hard to keep up with employers' skill needs. Although Sweden largely relies on school-based VET, it has substantially larger shares of upper secondary students undertaking VET of some kind than is found in the UK.

These six countries also vary greatly in the extent to which their education systems are geared towards higher education, and in their different mixes of long-cycle and short-cycle higher education. Here we follow OECD definitions of different higher education categories:

(a) long-cycle higher education: 'tertiary-type A programmes (ISCED 5A) [which] are largely theory-based and are designed to provide sufficient qualifications for entry to advanced research programmes and professions with high-skill requirements, such as medicine, dentistry or architecture. Tertiary-type A programmes have a minimum cumulative theoretical duration (at tertiary level) of three years' full-time equivalent, although they typically last four or more years' (OECD, 2002, p. 375);

(b) short-cycle higher education: 'tertiary-type B programmes (ISCED 5B) [which] are typically shorter than those of tertiary-type A and focus on practical, technical or occupational skills for direct entry into the labour market, although some theoretical foundations may be covered in the respective programmes. They have a minimum duration of two years full-time equivalent at the tertiary level' (OECD, 2002, p. 376).

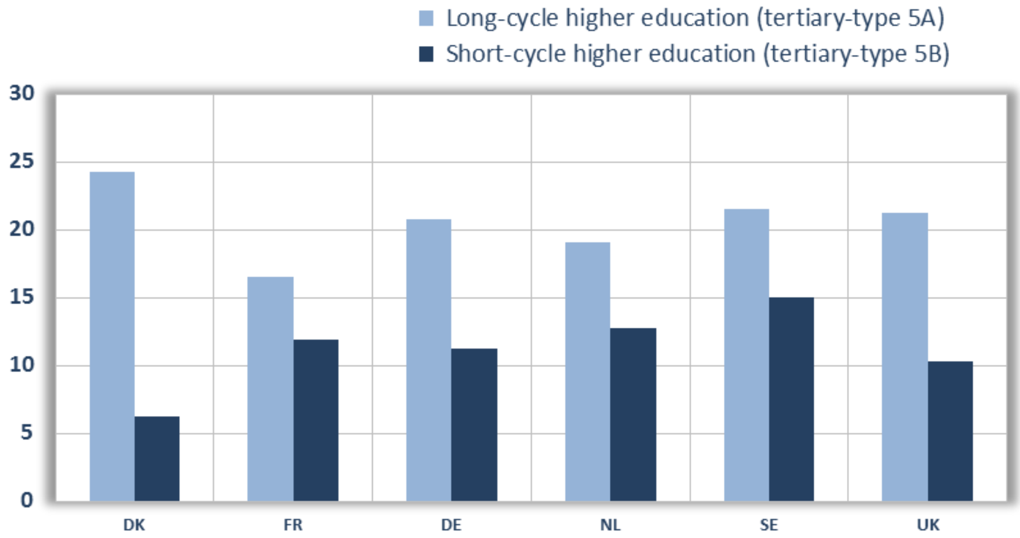
In France, the latter type of education often corresponds to a technician training route which – just as at upper secondary level – comprises a mix of full-time courses and apprentice-type training programmes. Short-cycle higher education generally differs from long-cycle higher education, not just by offering shorter courses leading to qualifications below bachelor degree level, but also by being less theoretical and more occupation-focused (more often combined with practical experience) than most long-cycle higher education courses.

Other variations on this distinction between academic higher education courses and more practical or occupation-specific higher education courses are found in Germany and Denmark. In Germany graduates from *Fachhochschulen* (universities of applied sciences) represent 40-50% of all higher education graduates, while in Denmark holders of professional bachelor degrees from colleges offering medium-cycle higher education represent more than 60% of all higher education graduates ([5]). Although the length of these higher education courses (typically four years) is similar to that in long-cycle higher education, graduates from German *Fachhochschulen* and Danish professional bachelor degree courses have a much more practical and work-related education than counterparts in traditional universities.

Figure 1 shows the proportions of the workforce in each of the six countries in 2007 whose highest qualifications were obtained in either long-cycle or short-cycle higher education. The highest shares of long-cycle higher education qualifications are found in Denmark and the UK; the lowest are in France. The highest shares of short-cycle higher education qualifications are found in Sweden, while the lowest is found in Denmark. Short-cycle higher education qualifications represent only 21% of all higher education qualifications among the Danish workforce compared to 40-42% in France, the Netherlands and Sweden. Such differences in the mix of higher education qualifications, with some countries focusing more than others on the development of vocational or occupation-specific skills, may well have implications for relative economic performance; this is one of the issues examined in this report.

([5]) Estimates of the mix of graduates in Germany derived from Mikrozensus, 2004; Danish estimates derived from Statbank Denmark database for 2008.

Figure 1. **Higher education qualifications held by workforce, 2007**



NB: For definitions of long-cycle and short-cycle higher education, see main text. For details of classification of qualifications in each country, see Table 2 where 'higher' corresponds to long-cycle higher education and 'upper-intermediate' corresponds to short-cycle higher education.

Sources: Derived from UK labour force survey; France – *enquête-emploi*; German socioeconomic panel; Denmark labour force survey; estimates provided by Central Bureau of Statistics, Netherlands, and Statistics Sweden.

2.2. Channels of skills influence on economic performance

Many of the key mechanisms by which we might expect skills to exert an influence on economic performance are connected with new technologies and knowledge transfer and innovation processes. Much of the literature on these topics emphasises the role of high-level skills (university graduates) rather than intermediate vocational skills (technicians, craft workers and other employees with qualifications below university graduate level). However, it is possible to identify channels of influence by which intermediate vocational skills also contribute to economic performance.

2.2.1. Skill base and the adoption and utilisation of ICT

Following the growth in use of information and communications technologies (ICTs) in recent decades, extensive literature has developed around the concept of skill-biased technical change, i.e. the argument that skilled labour is more complementary to the introduction and/or effective use of new technologies (ICT) than unskilled (Autor et al., 1998; Machin and van Reenen, 1998). US evidence suggests that skills play a key role in the effective use of ICTs (Bresnahan et al., 2002), and that there has been a complementarity over several decades between

ICTs and the educated labour required to perform non-routine tasks (Autor et al., 2003).

However, not all new technologies require high levels of skill for their implementation. As Caselli (1999) points out, while some technological revolutions such as electrification and ICT have been skill-biased in nature, others, such as the development of assembly-line technology, were more complementary to unskilled labour. However, his central point is that technologies of a ‘de-skilling’ kind tend to be introduced more quickly than skill-biased variants precisely because the latter require new skills that are likely to be costly and time-consuming to develop.

Several studies in European countries have supported US evidence of a positive relationship between workforce education or skills and the adoption of new technologies. Examples include firms in Spain (Bayo-Moriones and Lera-López, 2007), Switzerland (Hollenstein, 2004), Portugal (Barbosa and Faria, 2008) and Ireland (Haller and Siedschlag, 2008). The observation is that high-skilled workers can contribute more than the low-skilled to the selection, installation, operation and maintenance of ICTs and also to their adaptation to firm-specific requirements. This positive relationship between education or skill levels and ICT adoption also holds in cross-country studies involving European and other industrial nations (Hargittai, 1999; Gust and Marquez, 2004).

However, not all types of education or skill are necessarily of equal value in ICT adoption. Krueger and Kumar (2004) develop a model of technology adoption and economic growth which suggests that specialised vocational education in some European countries may be less well suited to developing the skills needed to adapt to fast-changing technologies than the general or academic education more common in the US. This may help explain why the US has tended to outperform European countries in terms of both productive applications of ICT and in the estimated contribution of ICTs to growth in labour productivity (O’Mahony and van Ark, 2003; Van Ark et al., 2008). However, the cross-country comparisons (Section 2.1) suggest it is unwise to generalise too much about European education systems since, even within Europe, there are marked differences between countries in the mix of general and vocational education.

Assessment of the types of skill best suited to ICTs is complicated by the fact that the level of skills required for rapid adoption of ICTs may differ from the skills required for their subsequent use. O’Mahony et al. (2008) report that ICT-related demand for university graduates in the US was particularly strong in the 1980s, suggesting that early adoption of ICT in the US was aided by the greater availability of university-educated workers in the US at that time compared to European countries such as Britain, France and Germany. However, during the following decade, ICT-related demand for workers with subgraduate (intermediate) qualifications increased in the US.

This is consistent with evidence reported by Chun (2003). In a study of the relationship between ICTs and the demand for educated workers in US industry level, in which he distinguished between the adoption and use effects of information technology and found that both had contributed substantially to the increased relative demand for university graduates. However, his evidence also suggested that, while adoption is positively related to high-skilled workers, as the new technology becomes fully implemented, firms may be able to replace these with lower-paid less-skilled workers. This does not preclude an interim phase in which high-level skills assist firms to experiment with new methods of work organisation that make best use of ICTs. However, as the new technologies become more established and ICT equipment becomes more user-friendly, fewer graduates are likely to be needed as ICTs become more complementary to workers with skills below graduate level (Ruiz-Arranz, 2004).

2.2.2. Knowledge transfer and innovation

Some of the most important channels of influence by which cross-country differences in skills may affect relative performance are skills-related externalities, or spillover effects, relate to innovation ([6]). Examples include the transfer of knowledge between firms, sectors and countries through collaboration on R&D and technical problem-solving among skilled workers involved in supply-chains (Lundvall, 1992) and the mobility of highly-qualified engineers and scientists between firms (Saxenian, 1994; Mason et al., 2004).

Knowledge transfer processes of this kind exemplify the contributions that workforce skills make to innovation and are reinforced by the complementarities between skills and other production inputs. Brandenburg et al. (2007), focusing on European firms, find that innovation performance at firm level is enhanced by a combination of skills and R&D investments. In a cross-country analysis at sector level between 1974 and 1990, Griffith et al. (2004) show that R&D spending and high-level skills help to stimulate productivity growth via their combined effects on innovation. At national economy level, Benhabib and Spiegel (1994) find that human capital stocks are positively associated with a country's ability to narrow the gap between itself and the world-leading nation in terms of productivity. Eaton and Kortum (1996) report that technology inflows increase with a country's human capital.

([6]) Skill-related externalities may occur if 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.

One of the most well-known mechanisms for such diffusion is foreign direct investment (FDI), which research evidence suggests is attracted to economies with a high-skills base while simultaneously bringing new technologies and knowledge which augment the skills base of host countries (Barrell and Pain, 1997; Blomstrom and Kokko, 2003). Some of the specific channels by which FDI can contribute to innovation in host countries include technology transfer, interactions with domestic suppliers, skill upgrading in local labour markets, and additions to the level of competition at regional and national levels (Harris and Robinson, 2004). However, the impact of spillovers through investment by multinational enterprises may be reduced if home-country firms lack the 'absorptive capacity' to take full advantage of new knowledge and technologies or are unable to withstand the increase in competition.

'Absorptive capacity' here refers to the ability to identify and make effective use of knowledge, ideas and technologies that become available through spillovers (Cohen and Levinthal, 1989). Some of the implications of this literature are that absorptive capacity will be higher as more firms and countries themselves engage in R&D and innovation. For example, Cassiman and Veugelers (2006) identify a complementarity at firm level between internal R&D activities and external knowledge acquisition.

At each stage of this process – recognising useful external knowledge, seeing how it might be applied and then successfully making use of it within firms – high levels of skill are a precondition for success. As shown by Keller (2006), increased openness of national economies to foreign trade only contributes to long-term growth if firms in those countries have sufficient skills to make effective use of new goods and technologies, and if skills are accumulated at a faster rate than before the change in trade regime.

Interactions between skilled workers in different firms also play an important role in knowledge transfer along supply-chains; this is another mechanism by which workforce skills may contribute to spillovers affecting firm-level performance. In particular, supply-chains involving innovative skill-intensive firms have greater prospects of becoming 'developmental' in nature (with close collaborative relationships between supply-chain partners) rather than 'dependent' (with suppliers being used primarily to cut costs) ([7]).

In industries such as auto and aerospace manufacturing, the lead customers in supply-chains now seek to speed up new product development times and reduce costs by requiring first-tier and second-tier suppliers to produce goods to meet performance specifications rather than to conform to blueprints (Brown,

([7]) For more discussion of this distinction between developmental and dependent supply-chains, see Turok (1993) and Brown (2000).

1998; Petersen et al., 2003). This obliges suppliers to develop their own design capabilities; for those firms with the skills base to succeed in doing so, future growth prospects may be improved by increased knowledge spillovers within those supply-chains. Brown (2000) shows how supplier linkages of this kind have contributed to rapid employment growth in high-tech firms supplying specialised services to aerospace customers in Sweden.

Breschi and Lissoni (2001) point out that it is important not to describe all types of knowledge flow as 'pure' spillovers, since knowledge exchange may derive from contractual relationships (between firms and their suppliers, or between firms and university-based researchers) in which the originators of the knowledge are able to appropriate at least some returns on their knowledge-generating activities. However, in the case of supply-chain interactions and university-firm interactions, much knowledge exchange and transfer tends to occur through the relationships developed by skilled and knowledgeable individuals on all sides and is not marketised. Collaboration between individual engineers and scientists in different organisations is often based on informal information trading and reciprocal favours (Von Hippel, 1987).

2.3. Intermediate vocational skills and economic performance

Much of the evidence on the complementarities between skills, ICTs and innovation emphasises the role of high-level skills (such as university graduates) rather than intermediate vocational skills (technicians, craft workers and other employees with qualifications below university graduate level). However, as ICTs have become more established, intermediate vocational skills have become more important for the effective use of these technologies (Mason et al., 2008). In France, many of the technician-level courses described in Section 2.1 are designed to produce specialists in information technology areas (Ministère de l'éducation nationale, 2010). Similarly, in Germany apprentice training programmes are regularly updated and modernised to take account of advances in ICTs and associated software (Steedman, 2010). Training of this kind equips intermediate-skilled workers to make incremental improvements to ICTs as well as carry out operation and maintenance tasks.

Intermediate vocational skills also make key contributions to the absorptive capacity which firms require if they are to make effective use of knowledge, ideas and technologies generated outside their organisations. Using the distinction suggested by Zahra and George (2002), high-skilled employees such as professional engineers and scientists may contribute disproportionately to potential absorptive capacity (the identification and acquisition of useful external knowledge) but firms' ability to apply this knowledge will depend on intermediate-skilled, as well as on high-skilled, employees. For example, there are many key support roles for technicians in product design and development areas and for craft-skilled workers in improving production processes.

High levels of workforce skills across the board also support organisational changes such as shorter chains of command and flatter hierarchical structures, designed to improve productivity and efficiency. Examples of such improvements are reduced costs of information transfer, faster reactions to market changes, and lower costs of monitoring and supervision (Caroli et al., 2001; Caroli and van Reenen, 2001).

In this context it is important to understand the complementarities between high-skilled and intermediate vocational skill groups, and to recognise the mutual interdependence between them. On the one hand, there is evidence that the presence of skilled employees in workplaces helps to raise the productivity of low-skilled colleagues (Kirby and Riley, 2008). There is also evidence that the higher the skills at intermediate and lower levels of organisations, the better able are senior managers and professional staff to think strategically and do their own jobs well rather than engage in day-to-day 'fire-fighting' activities (dealing with problems that could have been avoided if the workforce as a whole had higher levels of skill and competence). The productivity of high-skilled workers may be augmented by the presence of intermediate-skilled workers. This latter point emerged from comparisons of matched samples of establishments in Germany and the UK during the 1980s and 1990s in which German firms were found to benefit from senior managers not being required to provide detailed supervision for craft-trained workers in sectors as diverse as mechanical engineering and hotels (Prais, 1995).

These are examples of the mechanisms by which skills may affect economic performance. They need to be properly specified in empirical models if macroeconomic analysis is to succeed in identifying any effects of skills on performance. Before turning to empirical analysis, we first detail the various problems in measuring skills and how these have been tackled to develop a measure of different skills stock as required by the purpose of this study.

CHAPTER 3.
Measures of skills: old and new

Research on the impact of human capital on national economic performance invariably comes up against the problem that, as an intangible asset, workforce skills are very difficult to measure. In this section we first discuss some of the different approaches to skill measurement taken by researchers in the past. We then go on to present two skill measures developed to permit this project to distinguish adequately between vocational and other types of skill.

3.1. Key issues in skill measurement

Early studies of the role of human capital (skills) in explaining economic performance relied for its measurement on input measures such as years of schooling; these tended to capture attendance rather than attainment, a concept more closely related to skills. Some of the shortcomings of years-of-schooling measures of skill are highlighted by Hanushek and Kimko (2000) who construct a new measure of labour force quality (skills) based on student performance in international tests of academic achievement in mathematics and science. This measure is found to play a strong and significant role in determining growth in per capita GDP in several countries, observed over the period 1960-90. Years-of-schooling measures, based on Barro and Lee (1993) estimates, prove in contrast to be statistically insignificant when the test-based indicator of labour force quality is included.

No test scores are available to enable us to develop internationally comparable measures of different types of skill, such as general and vocational skills. However, data on formal (certified) qualifications are widely available. In contrast to years of schooling measures, data on formal qualifications have the obvious advantage of being output-based and capturing something of what has actually been learned while in education and training, rather than just signifying attendance. But they have the equally clear disadvantage of ignoring skills acquired in the workplace without formal certification, and they are also often subject to significant measurement error (Mason et al., 2012).

De la Fuente and Domenech (2006) constructed a data set on educational attainments for the adult population in 21 OECD countries. They took care to avoid sharp breaks and implausible changes in measured attainment levels over short periods of time that tend to reflect changes in data collection methods rather than changes in skills or attainment levels. Their results point to a strong and positive impact of attainment on productivity and support earlier work by Krueger and Lindahl (2001) which identified measurement error as a key reason why many earlier studies had found that increases in educational attainment had little or no impact on growth.

Other researchers, such as Jorgenson et al. (2005), make use of data on formal qualifications combined with relative earnings data. A key reason for incorporating earnings data is to try and capture the effects of uncertified skills (gained through informal training and/or experience) which it is expected will contribute to workers' productivity levels in combination with skills acquired during certified education and training. This approach 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 wage rate relative to low-skilled labour or the share that each type of labour occupies in total labour compensation.

Since relative wages are largely determined by employer demand, it can be argued that wage-based measures of relative labour quality go some way to capturing differences in relative productivity between different qualification groups which reflect group members' possession of uncertified skills as well as certified educational attainments. However, employee wages may deviate from their marginal products due to imperfect labour market conditions. Further, the extent of divergence between wages and marginal products may vary systematically between countries due to country-specific labour market institutions such as collective bargaining procedures and minimum wage legislation. This problem is discussed in Section 3.3.

The importance of uncertified skills has been noted by Ingram and Neumann (2006) who attribute increasing variation in wage income within formal qualification groups in the US to unobserved skill heterogeneity within those categories. They report evidence that other measures of skill such as mathematical ability or hand-eye coordination (derived from analysis of job characteristics) contribute substantially to the increase in wage dispersion among workers in different formal qualification groups.

There are also good reasons to believe that uncertified skills, developed through employment-based training and experience, may be complementary to certified skills. One of the great regularities in empirical research on employer-provided training is that highly-educated employees typically receive more training than employees with few or no formal qualifications. Economic theory points to three main reasons why this outcome should be expected. First, high levels of ability (as signified by education qualifications) are likely to contribute to higher (and quicker) returns on training provision by employers (Booth, 1991;

Green, 1993; Lynch and Black, 1998; Acemoglu and Pischke, 1998). Second, highly-qualified workers are more able to share investment in their education and training as they tend to be better paid (and thus less credit-constrained) than low-qualified workers (Greenhalgh and Mavrotas, 1994). Third, in some institutional and labour market settings, ‘compressed’ wage structures may develop such that wages increase more slowly than productivity as skills increase, thus providing further incentives to employers to support further training for workers who are already well-qualified (Acemoglu and Pischke, 1999; Booth and Zoega, 2004).

As well as reflecting a mix of certified and uncertified skills, qualification-based skill measures, weighted by relative wages, will also partly reflect differing wage returns on vocational and academic education. The verdict is still uncertain on the issue of whether vocational and general education attracts different wage returns. Using comparable EU data, Cedefop (2011b) found that returns on training, on general and on vocational education are roughly of equal magnitude. However, most UK and US studies on this suggest that the skills most likely to attract high wage returns are those developed in full-time academic education. Murnane et al. (1995) find that much of the increase in the college (university) wage premium in the US during the 1980s reflected increasing returns on cognitive skills. In the UK, McIntosh (2006) finds substantially higher wage returns on academic than vocational qualifications during the 1990s. However, some of these findings may reflect the predominance of full-time academic education routes in both countries, which leads employers to screen for high levels of ability via assessment of job candidates’ academic qualifications.

By contrast, in countries such as Germany and Austria where apprenticeship training routes are well-established, returns on apprentice qualifications compare favourably with those from college-based education (Winkelmann, 1996; Fersterer and Winter-Ebmer, 2003). This conclusion is basically true even when account is taken of a different selection problem to that found in the UK and the US: that employers providing apprentice training in countries like Germany and Austria seek to select the best school leavers (Fersterer et al., 2008). Other studies of European countries suggest that participation in combined school- and work-based training supports labour market entry. Both Hannan et al. (1999) and Gangl (2000) show that the provision of such training is correlated at country level with lower unemployment risks for trainees compared to leavers from general (academic) secondary education courses.

In this context, our objective in this study is to develop measures of skill at country level which take as much account as possible of both certified and uncertified skills and any complementarities between them. We now go on to develop two different skill measures which are comparable across the six countries under consideration. First, we make use of education output data (formal qualifications) combined with relative earnings data to try to capture differences in relative productivity between different qualification groups. Second, we present estimates of training capital stocks derived from survey data on employer-provided training in each country. These training capital measures capture some (though not all) uncertified skills and lend themselves to being combined in our later analyses with measures of the certified skills recognised through formal qualifications. As a preliminary step towards developing these two skill measures, we now go on to discuss how formal qualifications in each of the six countries should be allocated between high-level, intermediate and low-level qualification groups.

3.2. Classification of qualifications used in this study

In recent years, time series of stocks of workforce qualifications in European countries have been made available in the EU KLEMS data set which identifies three main qualification groups as follows:

(a) university graduates;

(b) holders of intermediate-level qualifications;

(c) those without formal qualifications (O'Mahony and Timmer, 2009).

In EU KLEMS the intermediate category is a large residual category consisting of people who do not hold bachelor degrees or equivalent qualifications but who have formal qualifications (diplomas or certificates) of some kind. The lower boundary of the EU KLEMS intermediate category varies between countries as it reflects the specific nature of the qualifications system in each country.

To carry out an assessment of the comparative benefits of VET and general education in the six countries of interest, we needed to define the boundary between intermediate and low-level qualifications in a way that is more directly comparable between countries. We also needed to be able to disaggregate the intermediate category between vocational and general qualifications in an internationally comparable way.

To carry out classification of qualifications in as objective a way as possible, we defined five different qualification groups in terms of different levels on the 1997 international standard classification of education (ISCED) scale ([8]):

- higher (bachelor degree and above), ISCED level 5A, 6;

([8]) While this project was in progress, Unesco announced the 2011 revision of ISCED (see http://www.uis.unesco.org/Education/Documents/UNESCO_GC_36C-19_ISCED_EN.pdf). We continued to work with the ISCED 1997 scale for classification of qualifications in each country since the publications on which we rely for allocation of qualifications to ISCED levels all refer to ISCED 1997.

- upper-intermediate vocational, ISCED level 4, 5B;
- lower-intermediate vocational, ISCED level 3B – vocational orientation;
- lower-intermediate general, ISCED level 3A – general orientation;
- low-skilled, ISCED level 3C, 2 or lower.

The division between the higher and upper-intermediate groups corresponds to the boundary between long-cycle and short-cycle higher education discussed in Section 2.1. In all six countries most upper-intermediate education is vocational or occupation-specific: this is not true at lower-intermediate level where there is a clear split between general and vocational education.

Information to support the classification of qualifications in this way was derived from Cedefop country reports ([9]) showing how qualifications in each of the six countries are allocated to different levels on the ISCED scale. We have also drawn on summary files prepared by Unesco for additional information on programme orientation (whether they are general or vocational in nature) ([10]).

Apart from defining the boundary between the intermediate and low-skilled categories in an internationally comparable way, the key differences here from the EU KLEMS classification of qualifications are:

(a) separation of technician-level and short-cycle higher education qualifications at ISCED 5B from other tertiary qualifications at 5A and above (which comprise bachelor degrees and postgraduate qualifications);

(b) differentiation between upper- and lower-intermediate qualifications in the way shown, so that, for example, craft-level qualifications (in the lower-intermediate vocational group) are separated from technician-level qualifications (in the upper-intermediate vocational group);

(c) differentiation between qualifications gained from completing courses at upper secondary level which denote levels of attainment sufficient to permit entry to tertiary education (3A, 3B) and those gained from completing lower-level courses (3C) ([11]).

([9]) Cedefop ReferNet Denmark, 2009; Cedefop ReferNet France, 2009; Cedefop ReferNet Germany, 2009; Cedefop ReferNet Netherlands, 2009; Cedefop ReferNet Spain, 2009; Cedefop ReferNet United Kingdom, 2009; Cedefop, 2009).

([10]) The web link for the Unesco draft report is: http://www.uis.unesco.org/Education/Documents/ISCED_RM_2-3_proposal_EN.pdf.

([11]) In Sweden and the UK, qualifications classified as ISCED 3A typically require at least one year, and often two, more study than qualifications classified to ISCED 3C (Schneider, 2008a; Halldén, 2008).

We used national data sources to carry out this classification of qualifications ([12]) and derive the proportions of the workforce holding different types of qualification.

The resulting time series were then extrapolated back to 1980 for each country with the aid of country-specific labour input files available on the EU KLEMS database (www.euklems.net, November 2008 release). We can have confidence in this extrapolation since qualification stocks change slowly from one year to the next, as relatively small numbers of retirements and withdrawals from the workforce are replaced by small numbers of new entrants.

Table 2 shows how qualifications listed in these national data sources have been allocated to each of the five qualification groups ([13]).

Table 3 shows that our estimates of the share of each country's workforce qualified at higher level (at least to bachelor degree or equivalent level) are broadly in line with EU KLEMS estimates for all countries except Denmark and Germany ([14]). These differences reflect our decision that professional bachelor degrees in Denmark and *Fachhochschule* diplomas in Germany (which typically require four years of tertiary education to complete) are nearer to bachelor degrees and equivalent qualifications than they are to any upper-intermediate qualifications gained in short-cycle higher education.

([12]) The data used are the UK labour force survey 1993-2007, the French *enquête-emploi* 1990-2007, the German socioeconomic panel 1984-2007, the Dutch labour force survey 1996-2007 (Central Bureau of Statistics), the Danish labour force survey 1993-2007 (Statbank), and the Swedish labour force survey 1995-2007 (Statistics Sweden).

([13]) Only the German and the UK national labour force survey data enabled us to estimate the stocks of workers whose vocational qualifications were gained through apprenticeship training or combined school and work-based training rather than through school- or college-based education. This is not a significant problem for Sweden where apprenticeship training has never become established (see Section 2.1). However, it is a serious gap in information for Denmark, France and the Netherlands. As a result, it has not been possible to disaggregate estimates of stocks of vocational qualifications between apprentice and non-apprentice categories in a comparable way across countries. In the empirical analysis we take account of cross-country differences in apprentice training provision by roughly distinguishing between 'high-apprenticeship' countries and 'low-apprenticeship' countries on the basis of the apprenticeship flows data shown in Table 1.

([14]) We compare our new estimates against EU KLEMS-based estimates in 2005 because this is the latest year for which EU KLEMS qualifications estimates are available.

By contrast, our estimates of the proportions of the workforce in the low-skilled category are only close to EU KLEMS estimates for Denmark. For France, the Netherlands, Sweden and the UK our estimates are well above EU KLEMS while for Germany our estimate is well below. These differences reflect the more detailed attention that we have paid to defining the boundary between intermediate and low-skilled qualifications, as described above.

Focusing on the structure of workforce qualifications in 2005 (Table 3A), we observe the following patterns of difference:

(a) five of the six countries now have a fifth or more of the workforce qualified to university graduate (bachelor degree) level or above. France is the only exception (16%);

(b) in the upper-intermediate vocational category (equating to short-cycle higher education or, in some countries, technician-level education and training), Sweden is highest at 15%. Elsewhere, the upper-intermediate vocational share ranges from 6% in Denmark to 13% in the Netherlands;

(c) at lower-intermediate vocational level, Germany is well ahead at 56%, reflecting its well-established craft apprentice training system. The next highest are Denmark (43%) and France (35%). Sweden has a very low proportion of the workforce in this category (11%);

(d) the highest share of lower-intermediate general qualifications is found in the UK (28%). The lowest shares of employees in this category are in Denmark (4%), Germany (6%) and France (8%);

(e) Sweden has the highest share of low-skilled workers (41%); the smallest share of low-skilled workers is found in Germany (6%).

Table 2. **Classification of qualifications as listed in labour force surveys and other national data sources**

	Higher	Upper-intermediate	Lower-intermediate vocational	Lower-intermediate general	Low-skilled
DK	• Medium-cycle higher education; bachelor; • long-cycle higher education; • PhD degree	• Short-cycle higher education	• Vocational upper secondary school; • vocational education	• General upper secondary school	• Basic school 8-10 grade
DE	• Abschluss einer Universität (wissenschaftlichen Hochschule, auch Kunsthochschule), Promotion; • Abschluß an einer Verwaltungsfachhochschule Fachhochschulabschluß (auch Ingenieurschulabschluß)	• Meister-/Techniker oder gleichwertiger Fachschulabschluss; • Abschluss einer 2- oder 3-jährigen Schule des Gesundheitswesens; • Abschluss an einer Fach- oder einer Berufsakademie Abschluss der Fachschule in der ehemaligen DDR; • Beamtenausbildung	• Anlernausbildung oder berufliches Praktikum; • Berufsvorbereitungsjahr; • Abschluss einer Lehrausbildung; • Vorbereitungsdienst für den mittleren Dienst in der öffentlichen Verwaltung; • Berufsqualifizierender • Abschluss an einer Berufsfachschule/Kollegschule; • Abschluss einer 1-jährigen Schule des Gesundheitswesens	• Realschulabschluss, Abitur	• Haupt-(Volks-) schulabschluss; • No formal qualifications
FR	• Grande école, diplôme d'ingénieur; • 2ème ou 3ème cycle universitaire; • 1er cycle universitaire	• BTS, DUT; • paramédical ou social avec baccalauréat général; • paramédical ou social sans baccalauréat général	• Baccalauréat technologique, BAC pro. et brevet professionnel; • BEI, BEC, BEA; • CAP, BEP, et BEPC;CAP, BEP seul	• baccalauréat général et diplôme technique secondaire; • baccalauréat général seul	• BEPC seul; • CEP; • aucun diplôme
NL	• HBO; • WO bachelor; • Master; • Doctor;	• MBO4	• MBO 2+3	• HAVO, VWO	• Primary; • VMBO, MBO1, AVO onderbouw; • AVO onderbouw
SE	• Postgraduate education; • post-secondary education 3 years or more	• Vocational post-secondary education, less than 3 years; • general post-secondary education, less than 3 years	• Vocational upper secondary education 3 years	• General upper secondary education 3 years	• Upper secondary education, 2 years or less; • primary and secondary education 9-10 years; • primary and secondary education less than 9 years

	Higher	Upper-intermediate	Lower-intermediate vocational	Lower-intermediate general	Low-skilled
UK	• Higher degree; • NVQ level 5; • first (bachelor) degree; • other degree	• NVQ level 4; • diploma in higher education; • foundation degree; HNC/HND/BTEC higher, etc.; • teaching – further education; • teaching – secondary education; • teaching – primary education; • teaching – foundation stage; • teaching – level not stated; • nursing, etc.; • RSA higher diploma; • other higher education below bachelor degree level	• NVQ level 3; • trade apprenticeship; • NVQ level 2 or equivalent; • GNVQ/GSVQ intermediate; • RSA diploma; • City & Guilds craft/part 2; • BTEC/SCOTVEC first or general diploma, etc.	• A-level or equivalent; • advanced Welsh baccalaureate; • international baccalaureate; • Scottish 6-year certificate/CSYS; • SCE higher or equivalent; • access qualifications; • AS-level or equivalent; • intermediate Welsh baccalaureate; • O-level, • GCSE grade A*-C or equivalent	• NVQ level 1 or equivalent; • Foundation Welsh baccalaureate; • GNVQ/GSVQ foundation level; • CSE below grade 1, • GCSE below grade C; • BTEC/SCOTVEC first or general certificate; • SCOTVEC modules; • RSA other; • City & Guilds foundation/part 1; • YT/YTP certificate; • key skills qualification; • basic skills qualification; • entry level qualification; • no qualifications

Source: Author calculation.

Sweden's high share of low-skilled workers may seem surprising but it could reflect our decision to draw the boundary between lower-intermediate and low-skilled at three years of upper secondary education or equivalent. In a recent review of Swedish upper secondary education, Lundahl et al. (2010) note that reforms to increase the length of vocational upper secondary courses beyond two years were not implemented until 1994 ([15]);a relatively high proportion of older age groups in the workforce may still hold qualifications below our threshold for inclusion as lower-intermediate.

Table 3. **Workforce qualifications in six Member States, 2005, all industries, unweighted qualification group shares of total employment: comparison of new estimates and EU KLEMS-based estimates**

A: Stock of qualifications, 2005 *(% of total employment)*						
	Higher	**Upper-intermediate vocational**	**Lower-intermediate vocational**	**Lower-intermediate general**	**Low-skilled**	**Total**
DK	24	6	43	4	22	100
DE	21	11	56	6	6	100
FR	16	12	35	9	28	100
NL	19	13	26	19	23	100
SE	22	15	11	11	41	100
UK	21	10	21	28	20	100

B: EU KLEMS-based estimates *(% of total employment)*				
	Higher	**Intermediate**	**Low-skilled**	**Total**
DK	8	64	28	100
DE	9	62	28	100
FR	15	66	19	100
NL	12	82	6	100
SE	20	65	15	100
UK	19	69	12	100

Source: EU KLEMS.

The evolution of qualifications structures between 1980 and 2005 in each country is shown in Figure 2; all six countries have seen progressive reduction in the low-skilled share of employment and an increase in the high-skilled share. The UK is distinctive for rapid growth in the high-skilled share of employment and the fact that, at lower-intermediate level, growth in general qualifications has outpaced growth in vocational qualifications. In France, growth in upper-

([15]) Note that this reform followed years of pressure from both employers and unions in Sweden who argued that 'the existing two-year programmes did not provide enough qualified and flexible manpower to meet national economic goals and the modern worker needed more theoretical education and workplace training' (Lundahl et al., 2010, p. 49).

intermediate vocational qualifications has almost kept up with growth in higher qualifications while, at lower-intermediate level, the share of vocational qualifications continues to exceed that of general qualifications by a substantial margin. In Germany the majority share of lower-intermediate vocational qualifications existed at start of the period and has been maintained. In Denmark and Sweden, the bulk of growth in qualification shares has occurred in the lower-intermediate vocational and higher categories but the share of low-skilled workers in Sweden remains much higher than in Denmark. In the Netherlands, the reduction in the low-skilled share of employment since 1980 primarily reflects growth in the lower-intermediate general category as well as in the high-skilled share.

3.3. Accounting for uncertified skills: summary indices of quality-adjusted labour

In the previous section, the quality of the labour input was approximated by initial qualification level. This approximation does not reflect the accumulation of skills and experience that takes place at work, nor does it account for the accumulation of skills through participation in training and adult education in general. It is reasonable to assume that skilled labour is more productive than non-skilled labour input and this neglecting to account for uncertified skills results in underestimation of the contribution of labour to productivity growth.

Sections 3.3 and 3.4 describe two different approaches used to derive a stock of skills accounting for uncertified skills. The first approach combines the estimates of qualification group shares of employment with information on relative wage, producing an index of quality-adjusted labour (QAL). In common with the skill measures developed by Jorgenson et al. (2005), this approach uses the assumption that all labour markets are perfectly competitive, so that relative wages reflect the marginal products of different categories of labour and capture the productivity-enhancing effects of uncertified skills – such as those acquired through informal employer-provided training or government-financed active labour market programmes (ALMPs) – as well as those acquired through certified education and training.

Figure 2. **Highest qualifications held by those in employment, 1980-2005**

NB: See Table 2 for classification of qualifications.
Sources: Author calculation.

The adjustment for quality, further detailed in Box 1, is implemented in four steps:

(a) compute the stock of workers with a given qualification level;
(b) multiply the stock of workers by the average number of hours worked to obtain a measure of the labour input for each qualification level;
(c) weight the labour input (calculated as above) by a factor proportional to the ratio of the average wage earned by workers with a given qualification level to the average wage earned by workers with no qualifications;
(d) sum the weighted labour input across qualification levels and divide it by the total number of hours worked in the economy to obtain the country measure of quality adjusted labour, *S**.

It is possible that employee wages 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. Our response to these concerns is two-fold.

First, in calculating QAL we take advantage of the fact that all qualification groups in each of the six countries have been defined in terms of common ISCED-based categories so that we are not obliged to make use of country-specific wage data. Rather we are able to apply common wage ratios to qualification group share data for each country in the form of employment-weighted six-country averages of qualification-related wage differentials. Second, in our multivariate analysis (described in detail in the methodological annex), we seek to take some account of institutional differences between countries by entering controls for unobserved country-specific characteristics.

Figure 3 shows how the six countries vary in the absolute levels and growth rates of the quality adjusted skill indices S^* in the period 1980-2007. Germany remains in the lead throughout this period; partly reflecting the fact that large-scale apprentice training was well established there before 1980. However, the lead narrowed greatly between 1980 and 2007, reflecting more rapid growth in certified qualifications in the other countries (especially in the UK) in this period.

Box 1. **Derivation and decomposition of the index of quality-adjusted labour**

The number of workers in a given qualification group generate a certain amount of working hours, producing a measure of hours worked by skill group: l_{pj} is the total number of hours worked by qualification group *p* in country *J*, *n* is the total number of qualification groups. These are transformed into 'effective units of labour' relative to the unskilled category by weighting them with a measure of the relative wage this skill group commands relative to the wage commanded by the low-skilled: w_{pj} is the average hourly wage of workers in qualification group *p* and w_{oj} is the average hourly wage of unskilled workers. The index of quality-adjusted labour (QAL) reads:

(1) $$QAL_j = \sum_{p=1}^{n} l_{pj} * \frac{w_{pj}}{w_{oj}} ,$$

Having derived estimates of *QAL* for each country using common wage ratios, a measure of skills in country *j* is first derived for the starting year by taking the ratio of QAL inputs to the total number of hours worked (l_j):

(2) $$S*_j = \left(\frac{QAL_j}{l_j} \right)$$

Ideally, the quality adjusted skill measure *S** would be calculated using time-varying qualifications-wage ratios over the 1980-2007 period. However, pay data by qualification level are not available for the entire period in any country and we only have pay data by qualification level for significant lengths of time in three of the six countries. For the other three countries the required pay data are available for recent years such as 2002 and 2006. Therefore, *S** was based on the employment-weighted six-country average of a single set of country-specific benchmark qualifications-wage ratios averaged over the 2002-06 period. The wage weights are shown in the table below.

Average hourly pay ratios of qualification groups relative to low-skilled category, all countries, 2002-06

		Higher	Upper-intermediate	Lower-intermediate vocational	Lower-intermediate general	Low-skilled
DK	2002-06 average	1.73	1.47	1.15	1.18	1.00
DE	2002-06 average	1.82	1.39	1.17	1.05	1.00
FR	2002-06 average	1.83	1.33	1.08	1.21	1.00
NL	2002	1.84	1.39	1.20	1.20	1.00
SE	2002-06 average	1.43	1.21	0.96	1.10	1.00
UK	2002-06 average	2.34	1.71	1.28	1.30	1.00
Employment-weighted seven-country average, 2002-06		1.97	1.45	1.17	1.21	1.00

Growth rates of this skill measure over time are then estimated through a Tornqvist indexation procedure, with qualification groups weighted by their shares of the total wage bill in each country ([a]).

Following Hellerstein et al. (1999) and Jones (2001), our measure of *QAL* has the advantage that it can be easily decomposed between unskilled and skilled labour as follows:

(3) $$QAL_j = L_o + \sum_{p=1}^{n} (\sigma_{\mathrm{p}} + 1) L_p$$

where there are n different skilled worker groups and (σ_p+1) is the marginal product of worker group p relative to the unskilled worker group 0, which we assume equates to $(wage_p/wage_0)$

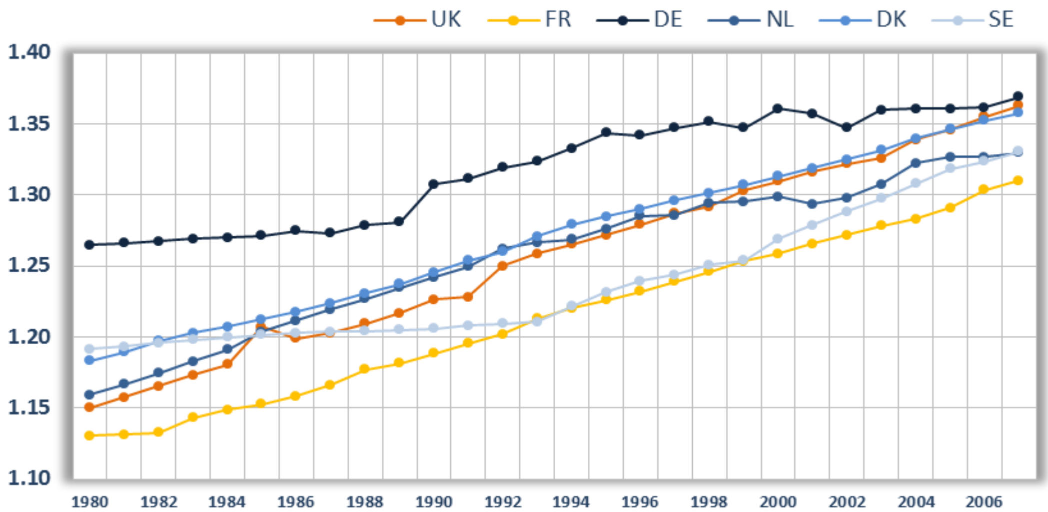
This approach is common enough in production function analysis when people wish to examine the relationship between productivity and skills or education. It is similar to the one used by Brown and Medoff (1978) in their analysis of productivity and unionisation. The skill measure is shown in equation 3. For example, Jones (2001) sets up the following Cobb-Douglas function, with a preliminary assumption of constant returns:

$$Y = AK^{1-\alpha}\left[L_o + \sum_{i=1}^{n}(\gamma_i + 1)L_i\right]^{\alpha} \tag{4}$$

where in her analysis L_o is workers without formal schooling and L_i is workers of educational level i.

([a]) A Tornqvist index is a discrete approximation to a continuous Divisia index which is a weighted sum of the growth rates of various components, where the weights are the component's shares in total value. Tornqvist indices are commonly used in growth accounting analyses (see Jorgenson et al., 1987; Timmer et al., 2010).

Figure 3. **Growth in Tornqvist skills indices using common wage ratios, 1980-2007**



Sources: Authors' calculation on EU KLEMS data.

3.4. Estimates of training capital stocks

In addition to accounting for uncertified skills by weighting qualification group shares by relative wage ratios, we also used a second approach relying on intangible training capital stocks. These training stocks are derived from survey data on employer-provided training, which is an important source of uncertified skills (even if we acknowledge that a small part of this training might have led to certification). In the empirical analysis we are able to combine the training capital stocks with unweighted measures of qualification group shares of employment to estimate the joint effects of uncertified and certified skills on economic performance. This measure can only be considered as an imperfect measure of skills, since it does not capture all forms of uncertified skills, such as those acquired through work experience or participation in active labour market programmes. However, unlike *S**, it does not require any assumption that relative wages equate to relative marginal products. Also, the use of unweighted qualification group share measures avoids the problem of double-counting that would occur if training capital stocks were to be combined with *S** (since wages respond to training). Thus our second skill measure provides a useful check on our analyses on results generated using *S**.

Training capital stocks measures are derived using a methodology borrowed from the intangible assets literature (O'Mahony, 2012), which is detailed in Box 2.

The estimates of intangible training capital per hour worked (in USD, 1997 prices) for the whole workforce and for each separate skill group in aggregate market sectors in each country in the period 1995-2007 are shown in Table 4. The highest level of training capital stocks per hour worked throughout this period is found in the UK, with Denmark ranking second. Since the higher-educated tend to receive more job-related training than the lower-educated in most countries, we expect to find that average training capital per hour worked is highest for high-skilled workers; this expectation is borne out in four of the six countries, with Denmark and Sweden as notable exceptions. In the former, average training capital per hour worked for intermediate-skilled workers in 2007 was about a third higher than for high-skilled workers.

Box 2. **The capital training stock**

The approach treats training as an activity largely undertaken by firms who pay the direct costs of training programmes and also incur indirect costs in terms of production output foregone (Corrado et al., 2009).

Estimating investments in continuing training by employers requires a monetary valuation of the number of hours of training received by workers. Data derived from the EU labour force survey and the Eurostat continuous vocational training surveys are used to estimate hours of training, calculated as numbers of workers trained times average duration of training, which are then multiplied by the average hourly cost of this training. Investments in continuous training in industry *i*, country *j* and time period *t* are calculated by:

(5) $$TI_{i,j,t} = HTR_{i,j,t} C_{i,j,t}$$

where *TI* = nominal expenditures on investments in training, *HTR* = total hours spent training per worker and *C* is the cost of an hour's training. Since average training durations are reported for the previous four weeks, this is converted to an annual basis, allowing for time lost due to holidays and other forms of absence. Hourly costs *C* have two elements: the direct costs of training (costs of running courses or external fees) and the opportunity costs of production or leisure time foregone due to time spent on training. Both time away from production and leisure are valued at the market wage, as in Jorgenson and Fraumeni, 1992.

To estimate the impact of these training investments on productivity, it is necessary to convert investment values to volumes and construct measures of intangible training capital stocks. As both the direct and indirect components of the hourly costs vary with wages through time, it seems natural to use an earnings index to deflate nominal investments to a constant price series. The perpetual inventory method that cumulates investments and deducts depreciation is then employed to convert real investments to capital stocks. The most common assumption employed on the form of the depreciation function is geometric decay. If we let *I* denote investment, *K* denote capital and *d* the depreciation rate, geometric decay allows capital at time *t* to be estimated as:

(6) $$K_t = K_{t-1}(1-d) + I_t$$

Geometric decay implies that proportionally more of the asset is depreciated early in its use. It is common in the intangibles literature to employ relatively high depreciation rates to take account of the idea that many of these investments are associated with new technologies that change rapidly: we employ a 25% depreciation rate for the estimates used here. For a discussion of the sensitivity of the intangible training capital stock estimates to the underlying assumptions, see O'Mahony, 2012.

Finally, we estimate measures of intangible investments in training by skill type for all countries, with workers disaggregated between those with higher qualifications (ISCED 5-6), intermediate-level qualifications (ISCED 3-4) and low-level qualifications (ISCED 1-2). These ISCED categories do not correspond exactly with the split between higher, intermediate and low-skilled outlined in Section 3.2 but they are the best approximations possible given the available data on employer-provided training. The small sample sizes in the available survey data demand focus on those elements that are robustly estimated by skill type in the underlying survey. For each skill group we estimate equation 5 using data on the proportions trained, hours trained and opportunity costs by skill group but allowing other elements such as the direct costs and training during working hours to be the same across skill groups.

Source: Authors' calculation.

Table 4. **Average training capital per hour worked, market sectors, 1995, 2000, 2005 and 2007, USD (1997 constant prices)**

		(1) 1995	(2) 2000	(3) 2005	(4) 2007
DK	All employees	1.32	1.27	1.42	1.55
	High-skilled	0.52	0.63	0.84	0.95
	Intermediate-skilled	1.39	1.21	1.22	1.26
	Low-skilled	0.78	0.81	0.99	1.29
DE	All employees	0.45	0.51	0.69	0.69
	High-skilled	0.97	1.03	1.52	1.57
	Intermediate-skilled	0.35	0.39	0.47	0.46
	Low-skilled	0.42	0.52	0.94	0.88
FR	All employees	0.67	0.71	1.00	1.07
	High-skilled	2.58	2.19	3.00	3.02
	Intermediate-skilled	0.53	0.51	0.70	0.74
	Low-skilled	0.43	0.56	0.67	0.70
NL	All employees	0.64	0.63	1.06	1.22
	High-skilled	1.77	1.43	2.42	2.87
	Intermediate-skilled	0.57	0.59	0.93	1.04
	Low-skilled	0.40	0.39	0.66	0.72
SE	All employees	1.35	1.21	1.40	1.08
	High-skilled	2.31	1.79	2.11	1.58
	Intermediate-skilled	3.06	2.21	2.23	1.63
	Low-skilled	0.43	0.43	0.47	0.38
UK	All employees	1.60	1.80	2.21	2.06
	High-skilled	3.55	3.55	3.95	3.46
	Intermediate-skilled	1.44	1.53	1.85	1.75
	Low-skilled	1.20	1.46	1.84	1.64

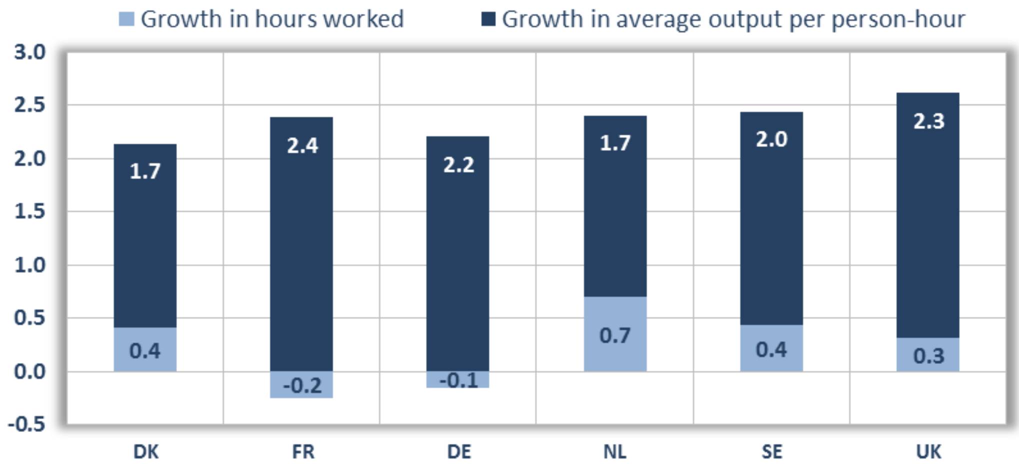
Source: Derived from EU labour force surveys and continuous vocational training surveys (see O'Mahony, 2012, for details of estimating procedure).

CHAPTER 4.
Productivity and skills: growth accounting estimates

4.1. Output growth and labour productivity

The fastest average annual rate of growth in output between 1981 and 2007 in the six countries under consideration was found in the UK (2.6%), Sweden and the Netherlands (both 2.4%). Figure 4 shows that average labour productivity (ALP) grew by an average 2.4% per year in France between 1981and 2007, closely followed by the UK (2.3%) and Germany (2.2%).

Figure 4. **Average annual growth rates in output, hours worked and labour productivity, 1981-2007**

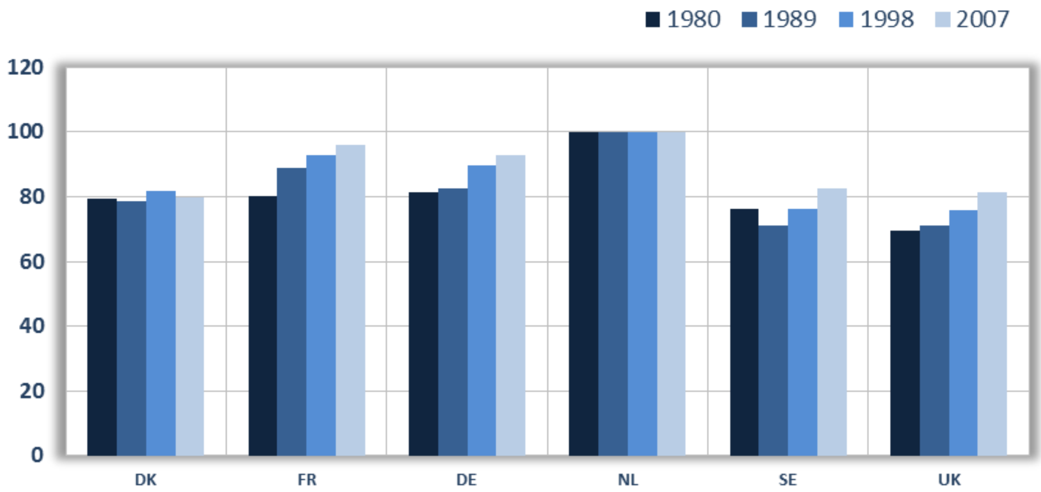


Source: NiGEM database (v2.10).

The productivity leader in comparisons of ALP levels at macroeconomic level throughout this period was the Netherlands. The figure for Denmark was 80%, the UK 81% and Sweden 83% (Figure 5). However, the ALP gaps between France and Germany and the Netherlands narrowed substantially over these three decades: by 2007, ALP in France was about 96% of the Dutch level while German ALP was 93% of the Dutch level ([16]).

([16]) These estimates of ALP levels across countries are based on conversion of output values from domestic currencies to a common currency (USD) using 2005 purchasing power parity exchange rates. The level of real (constant-price) gross domestic product (GDP) is calculated at basic prices, not market prices, to remove the distorting effects of cross-country differences in tax and subsidy regimes. In national accounting terms, GDP at basic prices equals GDP at market prices *less* taxes on products *plus* subsidies on products.

Figure 5. **Relative labour productivity levels, 1980, 1989, 1998 and 2007**
(Index numbers: productivity leader = 100)



Source: NiGEM database (v2.10).

These macro-level descriptions conceal areas of relative strength and weakness at sector level in each country. In 2007, the Netherlands was ahead in five of 16 market sectors: food and drink manufacturing, chemicals and related industries, basic metals and fabricated metal products, wholesale and retail, and transport and storage services (Table 5). Germany led in three sectors (transport equipment, business services and other community, social and personal services), Sweden in three sectors (electrical and electronic engineering, other production – agriculture, mining and utilities – and post and telecommunications services, France in two sectors (mechanical engineering and hotels and catering services); and the UK in other manufacturing.

4.2. Vocational skills and labour productivity growth

In this section we use growth accounting techniques to decompose the sources of ALP growth into those due to changes in capital per hour worked, skills and total factor productivity (TFP); the last of these is taken to measure the speed of technological progress, since it is strongly influenced by the efficiency with which existing resources are combined (Hulten, 2001), as set out in the annex (equation A.8). After identifying the contribution to ALP growth from the total rise in wage-weighted skills (S^*), we decompose the aggregate skill measure into the five skill groups described in Section 3.2 to estimate the respective contributions from each skill group to ALP growth.

Table 5. **Average labour productivity (gross output per worker-hour), analysed by sector, 2007**
(Index numbers: productivity leader = 100)

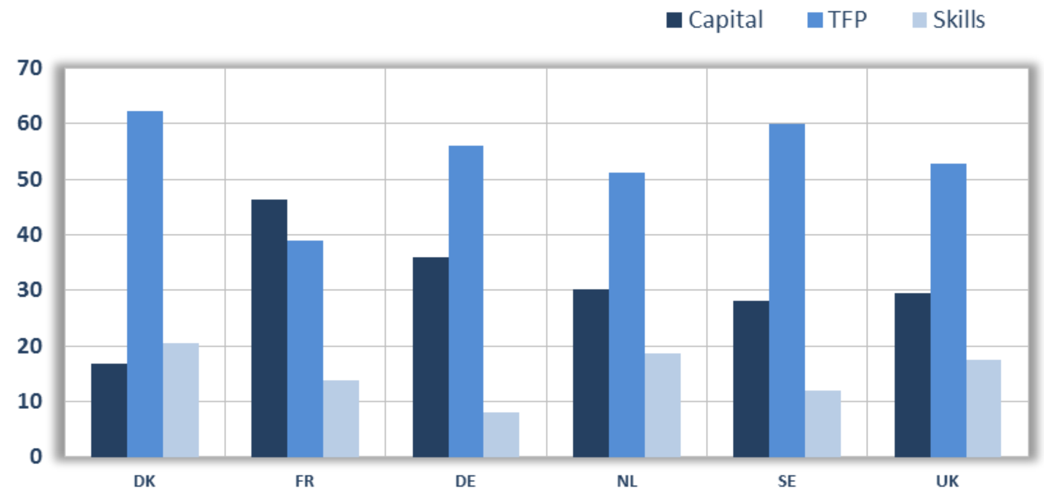
	DK	FR	DE	NL	SE	UK
Food products, beverages and tobacco	43	32	36	100	46	36
Chemicals, rubber, plastics, fuel	31	80	46	100	60	42
Basic metals and fabricated metal products	47	69	74	100	99	54
Mechanical engineering	47	100	73	36	63	98
Electrical and electronic engineering	11	25	25	13	100	22
Transport equipment	17	69	100	44	56	50
Other manufacturing	88	72	83	56	80	100
Other production	63	45	51	73	100	69
Construction	99	79	81	82	85	94
Wholesale and retail	90	72	80	100	69	44
Hotels and restaurants	63	100	80	82	22	51
Transport and storage	31	33	22	100	23	27
Post and telecommunications	18	30	29	23	100	44
Financial intermediation	82	70	45	86	78	62
Business services	76	62	100	63	90	80
Community, social and personal services	83	90	100	78	56	46

Source: EU KLEMS.

Figure 6 shows that, over the 1981-2007 period, the contribution of growth in aggregate skills to ALP growth was substantially smaller than the contributions made by growth in capital per hour worked (capital deepening) in five of the six countries. The exception was Denmark, where the skills contribution just exceeded the contribution made by capital deepening. The contribution made by skills was also substantially smaller than the contribution made by TFP growth in all countries.

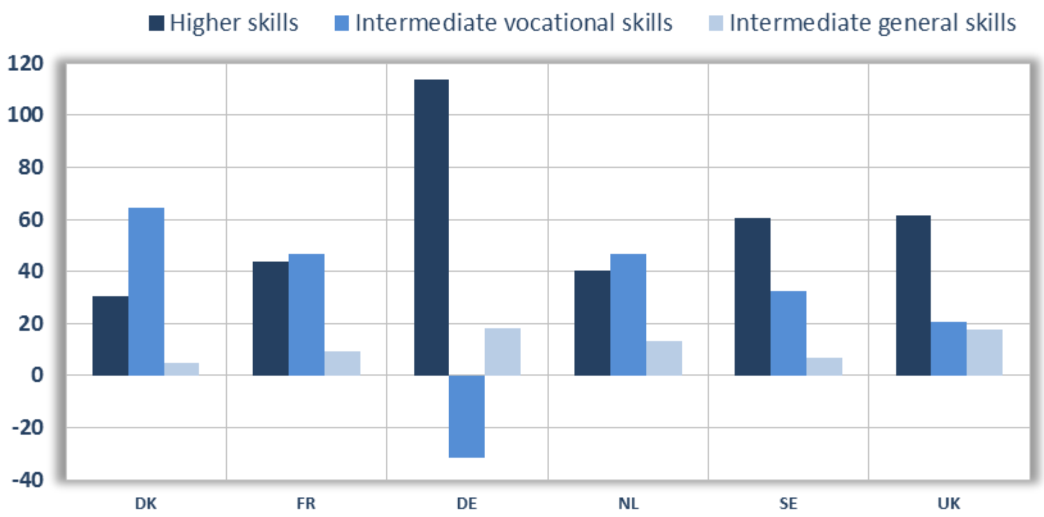
Table 6 shows details of these decompositions for three nine-year time periods between 1981 and 2007. Skills accumulation made small but positive contributions to ALP growth in all countries in each of these time periods but this contribution was markedly lower in Germany than in the other countries. This reflects the fact that, as shown in Figure 2, the proportion of low-skilled workers was already comparatively low in Germany at the start of the period, whereas the other five countries saw substantial declines in the low-skilled share of employment over this period. Overall, the combined contributions of growth in upper- and lower-intermediate vocational skills were positive across 1981-2007 in all countries except Germany (Figure 7). Again, the explanation lies in the lack of growth in the employment share of intermediate vocational skilled workers in Germany, where this skill group was already comparatively large at the start of the period (Figure 2). Sweden and the UK also experienced positive contribution made by growth in high-level skills during 1981-2007, exceeding the growth contributions of intermediate vocational skills (Figure 7). However, in Denmark, the Netherlands and France, the combined contributions of growth in upper- and lower-intermediate vocational skills exceeded the high-skills contribution over this period.

Figure 6. **Average contributions of growth in physical capital per hour worked, TFP and skills to growth in output per person-hour, 1981-2007**



Source: Authors' calculations, EU KLEMS.

Figure 7. **Skill group shares of total higher and intermediate skills contributions to growth in output per person-hour, 1981-2007**



Source: Authors' calculation.

The small contribution of skills to income growth is a general result (Timmer et al., 2010) that can be ascribed, at least partly, to the inability of growth accounting to represent correctly the contributions made by skills to productivity performance; this is because it cannot take account of complementarities between production inputs (such as the role of skills in supporting the effective use of new technologies). Consequently, the next section analyses the combined effects of skills and other production inputs and complementarities between different skill groups.

Table 6. **Decomposition of average annual growth rates in output, 1981-2007**

		DK	FR	DE	NL	ES	SE	UK
Average annual growth in output (%)								
(A) GDP at basic prices (% change per annum)	1981-89	2.3	2.4	2.0	1.9	2.4	2.4	2.9
	1990-98	2.3	1.8	2.3	2.9	2.2	1.7	2.1
	1999-2007	1.8	2.2	1.8	2.5	3.7	3.2	2.8
of which: percentage point contributions to average annual growth in output								
(B) hourly labour input (unadjusted)	1981-89	0.3	-0.8	-0.2	-0.2	-0.4	1.1	0.5
	1990-98	0.2	-0.4	-0.2	1.2	0.6	-0.7	-0.2
	1999-2007	0.7	0.4	0.0	1.1	3.6	0.9	0.6
(C) output per person-hour	1981-89	2.0	3.3	2.3	2.1	2.8	1.3	2.4
	1990-98	2.1	2.1	2.6	1.6	1.7	2.4	2.4
	1999-2007	1.1	1.7	1.8	1.4	0.1	2.3	2.2
of which: percentage point contributions to average annual growth in output per person-hour								
(D) physical capital per hour worked (capital deepening)	1981-89	0.5	1.4	0.8	0.8	1.2	0.5	0.5
	1990-98	0.2	1.1	1.0	0.4	1.3	0.9	0.8
	1999-2007	0.2	0.8	0.6	0.4	0.4	0.3	0.7
(E) TFP	1981-89	1.2	1.6	1.4	0.9	1.1	0.8	1.4
	1990-98	1.4	0.6	1.2	0.9	-0.1	1.3	1.1
	1999-2007	0.6	0.6	1.1	0.8	-0.7	1.6	1.1
(F) skills accumulation	1981-89	0.4	0.3	0.1	0.5	0.4	0.1	0.4
	1990-98	0.4	0.4	0.4	0.3	0.4	0.2	0.4
	1999-2007	0.3	0.3	0.1	0.2	0.3	0.4	0.4
of which: percentage point contributions to average annual growth in skills accumulation								
(G) higher-skilled	1981-89	0.2	0.4	0.2	0.3	0.5	0.1	0.5
	1990-98	0.3	0.4	0.8	0.4	0.5	0.3	0.7
	1999-2007	0.4	0.4	0.2	0.2	0.5	0.7	0.8
(H) upper-intermediate vocational	1981-89	0.3	0.1	-0.1	0.1	0.3	0.0	0.2
	1990-98	0.3	0.3	0.0	0.1	0.2	0.1	0.1
	1999-2007	0.3	0.1	-0.2	0.1	0.1	0.0	0.0
(I) lower-intermediate vocational	1981-89	0.5	0.5	-0.1	0.6	0.2	0.0	0.3
	1990-98	0.3	0.2	-0.1	0.1	0.1	0.1	0.1
	1999-2007	0.0	0.0	0.1	0.0	0.1	0.4	0.0
(J) lower-intermediate general	1981-89	0.0	0.1	0.2	0.3	0.3	0.0	0.3
	1990-98	0.1	0.1	0.0	0.1	0.3	0.1	0.3
	1999-2007	0.0	0.1	0.0	-0.1	0.2	0.0	-0.1
(K) low-skilled	1981-89	-0.6	-0.8	-0.1	-0.9	-0.8	-0.1	-0.9
	1990-98	-0.5	-0.7	-0.3	-0.3	-0.8	-0.5	-0.8
	1999-2007	-0.4	-0.3	-0.1	-0.1	-0.6	-0.7	-0.3

NB: Percentage point contributions to GDP, output per person-hour and skills accumulation may not sum to total amounts due to rounding.

CHAPTER 5.

Vocational skills and economic performance

The impact of different types of education and training on average labour productivity will be assessed with the help of production functions that relate a given measure of output (average labour productivity, GDP per hour worked) to the input needed to produce it: the factors of production, capital (per hour worked, the capital labour ratio) and labour (the measures of certified and uncertified skills developed in the previous chapter). In so doing, we seek to take account of some of the main channels of influence by which skills are expected to affect economic performance such as through contributions to innovation and supporting the introduction of new technologies.

5.1. Vocational skills and productivity

The precise estimation of the impact of skills on average labour productivity by country is a made difficult by the small number of observations per country (28 in most cases). Despite the relatively small sample sizes for each country, the results in Table 7 (columns 1 to 6) show that *S**, the wage-weighted measure of aggregate skills, tends to be positively related to productivity. In Germany and Denmark the relationship is positive and statistically significant. In the four other countries large standard errors associated to the coefficient on *S** result in lack of statistical significance. Data across countries were pooled together in one single data set to maximise the sample size ([17]). This relatively larger data set (consisting of 155 observations) can be considered as one single time series, and the analysis of this data set will be carried out accordingly.

([17]) To examine the potential to pool all observations together, the extent of heterogeneity in this group of countries was studied by means of the common correlated effects (Pesaran, 2006). Ordinary least squares (OLS) is applied to country-specific production functions, with cross-sectional averages of the independent variables as well as the dependent variable added to each country's specification. In addition to addressing parameter heterogeneity, the common correlated effects method enables some account to be taken of common unobserved factors omitted from the panel. Cross-section dependence appears naturally when studying economic data due to, for instance, market integration processes, globalisation of economic activity, offshoring processes, or because of the presence of common shocks like oil price shocks. The results suggest that the pooled data from the six countries can be considered as one larger data set.

Table 7. **Common correlated effects estimates of country-specific production functions, 1980-2007, macro-level data set, wage-weighted skill measure**

	(1) UK	(2) FR	(3) DE	(4) NL	(5) DK	(6) SE	(7) All
Capital-labour ratio	0.4575***	0.0993	0.1074	0.4602***	0.2317**	0.0283	0.2617***
	(0.106)	(0.186)	(0.072)	(0.083)	(0.108)	(0.288)	(0.077)
Skills (S*)	0.5216	-0.4330	0.9475**	-0.4148	6.3282***	0.9370	0.0897
	(0.573)	(1.027)	(0.388)	(0.428)	(1.767)	(1.886)	(0.393)
Trend	0.0244***	0.0104	0.0019	0.0036	-0.0386***	-0.0122	0.0013
	(0.007)	(0.009)	(0.008)	(0.006)	(0.010)	(0.022)	(0.008)
Observations	**28**	**28**	**28**	**28**	**28**	**15**	**1 155**

NB: Estimated using common correlated effects mean group estimator. Ancillary parameters, the coefficients on cross-section averages of skills, capital labour ratios and labour productivity, are not shown. The smaller number of observations for Sweden reflects the unavailability of data on capital services for the years 1980-92. Each model in columns 1-6 includes a country-specific linear trend term. Coefficient averages in column 7 have been computed as outlier-robust means. Standard errors are shown in brackets. The skill measure *S** is based on wage-weighted qualification group shares of total hours worked. Test statistics for column 7: Wald chi square = 11.46 (p=0.003); root mean squared error = 0.0074.

An error correction model (ECM) is used for the upwards trend in the skill measure *S** and average labour productivity, which can be modelled as a stable long-term relationship (Table 8) ([18]). The coefficient on the error correction term describes what happens when there are deviations from the long-run relationship between labour productivity and skills. It has the expected negative significant sign, which identifies a stable long-run relationship: when labour productivity overshoots the values implied by its long-run relationship it will have to decrease over time to converge to it again. The capital-labour ratio and skills (labour input) are found, as expected, to be significantly positively related to labour productivity in the long run. Table 8 also shows the presence of short-run relationships. When the level of skill (or the capital labour ratio) increases in a given year, an increase in average labour productivity can be expected one year on.

([18]) See methodological annex for a description of error-correction models and the rationale for using them.

Table 8. **ECM estimates of average labour productivity, 1980-2007, macro-level data set, quality adjusted labour input**

All countries	1980-2007
Long run Error correction term (t-1)	-0.2196*** [0.050]
Short run Capital-labour ratio (t-1)	0.0638** [0.018]
Skills (S*) (t-1)	0.0904** [0.037]
Observations	137
Log likelihood	489.10
Adj. R2	0.558
SEE	0.007

NB: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Ordinary least squares estimates of error correction models, weighted by average country share of total employee compensation. The dependent variable is the first difference of log output per hour worked. All independent variables are also in logarithms. Heteroscedasticity-robust standard errors shown in brackets have been corrected for clustering at country level. All models include country dummies, cross-sectional means of the dependent variable in lagged levels and first differences and up to two lagged differences of independent variables. The skill measure *S** is based on wage-weighted qualification group shares of total hours worked.

The aggregate measure of skills $S*$ can be further disaggregated in the five skill groups to investigate the differential impact of the various types of skills on average labour productivity. The results are presented in Table 9. The measure of vocational skilled labour input attracts a positive significant coefficient, whereas the impact of higher skills and lower-intermediate general skills is not significant (Table 9, column 1). The results suggest that, in the long term, a one percentage point rise in the vocational-skilled share of employment is associated with a 0.143 percentage point rise in ALP ([19]). Disaggregating vocational skills further between upper-intermediate and lower-intermediate suggests that it is the former that are driving the positive significant relationship with productivity performance (Table 9, column 2).

The lack of a positive significant relationship between high-level skills and relative productivity performance is surprising because previous studies have found such a relationship in country-level analysis (Vandenbussche et al., 2006) and country/sector-level analysis (Mason et al., 2012). These findings are sensitive not just to the composition of each sample of countries but also to the way that different skill levels are defined in each study. To assess the impact of definitional differences, we investigate the effects of combining our measures of high-level skills and upper-intermediate vocational skills. The coefficient on this

([19]) This long-run parameter is calculated as (0.0439/0.3073) = 0.143 where 0.0439 is the coefficient on vocational skills in the ECM regression and 0.3073 is the error correction term (see annex, equation A.10 and surrounding text in Section A.5 for details of ECM specifications).

combined high-level/upper-vocational skills variable turns out to be positive and significant and twice the size of the previous coefficient on upper-vocational skills alone (Table 9, column 3). For the study, upper-intermediate vocational skills are kept separate from high-level skills because the former typically refers to much more occupationally-specific forms of education and training than the latter, and VET is the main focus of this report. However, as shown in the next chapter, complementarities between high-level and vocational skills appear to contribute positively to productivity performance in several countries and sectors; the results shown in Table 9, column 3 may be picking up some of these effects.

As a check on the robustness of these initial macro-level results, we estimate similar models (ECM) using a different and larger data set based on cross-country sector-level data. The small number of years for which sectoral data are available renders analysis at sectoral level unfeasible. However, the number of observations are substantially increased by pulling all the sectoral data together, and this allows for some refinements in the analysis, such as enabling us to distinguish between 'apprenticeship' countries (Denmark, Germany and the Netherlands) where VET systems strongly feature employment-based training combined with part-time study in vocational colleges, and 'school-based VET ' countries (France, Sweden and the UK) where VET is more commonly delivered through classroom-based vocational schooling alone ([20]). We are also able to distinguish between clusters of sectors: production ([21]), market service ([22]) and ICT-intensive sectors in each country ([23]).

([20]) See Section 2.1 for information about the relative importance of apprenticeship training in each country. This distinction between 'apprenticeship' and 'school-based VET' countries cannot do full justice to inter-country variation in stocks of apprentice-trained workers for which the relevant data do not exist in most countries. However, it provides a rough basis for assessing differences between countries in which apprentice training has been widespread over the years and those where very little apprentice training has taken place.

([21]) Food products, beverages and tobacco; chemicals, rubber, plastics, fuel; basic metals and fabricated metal products; mechanical engineering; electrical and electronic engineering; transport equipment; other manufacturing; other production and construction.

([22]) Wholesale and retail; hotels and restaurants; transport and storage; post and telecommunications; financial intermediation; business services; and community, social and personal services.

([23]) ICT-intensive industries are defined following the taxonomy developed by van Ark et al. (2002) and comprise: mechanical engineering, electrical and electronic engineering, transport equipment, other manufacturing, wholesale and retail, post and telecommunications, financial intermediation and business services.

Table 9. **ECM estimates of average labour productivity, 1980-2007, macro-level data set, wage-weighted skill measure**

All countries	Model 1	Model 2	Model 3
(A) Long run skill parameters:			
Vocational skills	0.1428*** (0.025)		
Upper-intermediate vocational skills		0.0734** (0.017)	
Higher plus upper-intermediate vocational skills			0.1261** (0.037)
(B) ECM regression coefficients:			
Error correction term (t-1)	-0.3073*** [0.031]	-0.2881*** [0.059]	-0.3200*** [0.019]
Capital-labour ratio (t-1)	0.1343*** [0.019]	0.1367*** [0.021]	0.1171** [0.036]
Higher skills_wtd (t-1)	-0.0091 [0.014]	0.001 [0.009]	
Higher plus upper-intermediate vocational skills_wtd (t-1)			0.0403** [0.011]
Vocational skills_wtd (t-1)	0.0439*** [0.010]		
Upper-intermediate vocational skills_wtd (t-1)		0.0212** [0.008]	
Lower-intermediate vocational skills_wtd (t-1)		0.0051 [0.008]	0.0029 [0.008]
Lowerintermediate general skills_wtd (t-1)	0.0176 [0.015]	0.0066 [0.011]	0.0113 [0.009]
Low skills (t-1)	0.0178 [0.029]	0.0177 [0.024]	0.0165 [0.029]
Observations	137	137	137
Log likelihood	499.55	503.85	498.48
Adj. R2	0.578	0.592	0.575
SEE	0.0072	0.0071	0.0072

NB: ***= significant at 1%, **= significant at 5%, *= significant at 10%.

Part A shows estimated long-run parameters of those skill variables which are found to be statistically significant in error correction model (ECM) regressions.

Part B shows the ECM estimates, weighted by average country share of total employee compensation. The dependent variable is the first difference of log output per hour worked. All independent variables are also logged. Heteroscedasticity-robust standard errors shown in brackets have been corrected for clustering at country level. All models include country dummies, cross-sectional means of the dependent variable in lagged levels and first differences and up to two lagged differences of independent variables. The suffix _wtd denotes use of skill measures based on wage-weighted qualification group shares of total hours worked.

The results from this approach suggest a weak, i.e. statistically not significant, relationship between skills and labour productivity when countries are pooled together or when countries are divided into apprenticeship-based and non-apprenticeship based VET groups. Table 10 shows a positive relationship between upper-intermediate vocational skills and relative productivity in production sectors, while high-level skills attract a positive and statistically significant coefficient in service sectors. One possible explanation for the weak link between skills and productivity might be due to gaps in wage data for most countries, the wage-weighted skill measure (S*) being unable to take account of changing wage returns for different qualifications over time. Therefore, we turn to our second skill measure. This seeks to capture the mix of certified and uncertified skills in each country more directly by taking account of skills acquired through employer-provided training as well as (unweighted) qualification group shares of employment ([24]).

Given that training capital stocks data are available for the time period 1995-2007, the shorter time dimension of the panel can be effectively handled by a fixed effects model (see equation A.12 in the methodological annex) ([25]).

Table 11 shows the interaction between certified and uncertified skills. Certified skills could be reinforced and augmented by uncertified skills developed through employer-provided training. The effects of combining certified skills with training capital stocks are captured by interaction terms. A positive and significant coefficient on this interacted variable will enable us to test whether there is a positive relationship between productivity and different types of skill, even if we will not be able to distinguish between the following two interpretations:

(a) all else being equal, average labour productivity (ALP) is enhanced by certified skills reinforced by uncertified skills developed through employer investments in job-related training;

(b) all else being equal, ALP is enhanced by the greater effectiveness of employer-provided training in the presence of high certified levels of skills among the workforce.

([24]) See Table 3 panel A for descriptive statistics on unweighted qualification group shares of employment and Table 4 for the average training capital per hour worked.

([25]) Coefficients on unweighted skill group shares of employment in Table 11 are not directly comparable with weighted skill group coefficients in Table 10 for various reasons. First, the estimation methods and time periods are different. Second, in the ECM specifications the wage-weighted summary measure of skills *S** is fully disaggregated and the low-skilled group is included as a regressor; by contrast, in the fixed effects specifications using unweighted skill group measures, the low-skilled group serves as a reference category for the intermediate and high-level skill groups.

Table 11 ([26]), column 1 shows the results for all market sectors in six countries between 1995 and 2007, with certified skills disaggregated between the higher, upper-intermediate vocational, lower-intermediate vocational and lower-intermediate general groups while also controlling for average training capital per hour worked for high-skilled and intermediate-skilled workers ([27]). Only high-level skills are found to be positively and significantly related to ALP levels. Column 2 shows positive significant effects on the interacted skill/training capital measures at both high-skilled level and at upper-intermediate level.

These findings suggest that ALP performance is positively related to certified skills being reinforced by uncertified skills developed through employer investments in job-related training. ALP is also enhanced by the greater effectiveness of employer-provided training in the presence of high certified levels of skills among the workforce. While this finding in relation to upper-intermediate skills supports the macro-level results, our estimates at country/sector level point to a stronger role for high-level skills than was suggested by the macro-level analysis.

Table 12 investigates the relationship between the various types of skills (certified and uncertified) in apprenticeship- and school-based VET systems. The significantly positive interaction effect between high-level skills and training capital occurs primarily in school-based VET countries possibly because, in such countries – France and the UK – employer investments in training capital are heavily concentrated on the high-skilled (Table 4).

([26]) To address endogeneity issues concerning the skill and training capital variables, we first consider whether instrumental variable methods should be used instead of ordinary least squares methods. Instrumental variable methods produce consistent estimates so long as the chosen instruments are correlated with potentially endogenous variables while being uncorrelated with the error term in the main regression equation in each case. Instrumental variable models use a generalised method of moments (GMM) estimator, with lagged values of independent variables used as instruments (Hayashi, 2000; Baum et al., 2003). The instruments satisfy the required conditions; further tests of the exogeneity of the skill and training capital variables suggest that ordinary least squares estimates should be preferred to instrumental variable estimates. In the presence of heteroscedasticity (clearly indicated by Pagan-Hall statistics for these models), the C statistic is an appropriate test of a null hypothesis that potentially endogenous regressors are in fact exogenous (Baum et al., 2003). In this case we test for potential endogeneity of all skill and training capital variables and the interactions between them. The test suggests that the more efficient ordinary least squares estimates should be preferred to instrumental variable estimates (Hansen, 1982; Baum et al., 2003; Kleibergen and Paap, 2006).

([27]) As described in Section 3.4, further disaggregation of intermediate training capital estimates between different categories of intermediate skills is not feasible due to small cell sizes in the EU labour force survey data on which these estimates are based.

In apprenticeship-based VET countries there are positive and significant interactions between training capital and both upper–intermediate vocational skills and lower-intermediate general skills. The result for lower-intermediate general skills may be driven by the relatively high levels of employer-provided training for intermediate-skilled workers in countries such as Denmark and the Netherlands (Table 4). The positive coefficient on the interaction between training capital stocks and lower-intermediate vocational skills is five times larger in apprenticeship-based VET countries than in school-based VET countries but the standard errors attached to these coefficients are too large for them to achieve statistical significance.

The impact of the various skills on ALP differs across sectors. In production sectors, consistent with the result obtained with the wage-weighted skill measure (S*), upper–intermediate skills are found to have a positive influence on ALP. In contrast to the results in Table 10, Table 13 shows that higher skills also have a positive impact on ALP and their effect is reinforced by training capital with high-level skills. Lower-intermediate vocational skills have a positive impact on ALP in service sectors, as do upper-intermediate vocational skills reinforced by training capital (in upper-vocational skills).

Taken together with the macro-level estimates, these results provide considerable evidence of a positive relationship between upper-intermediate vocational skills and relative ALP performance, especially in the production sectors. This positive relationship is found to occur primarily in apprenticeship-based VET countries and the relationship is stronger when vocational skills are broadly defined to include uncertified skills acquired through employer-provided training as well as certified vocational skills. However, these estimates provide only limited evidence of positive effects of lower-intermediate vocational skills. In school-based VET countries (and in the service industries) high-level skills tend to contribute more to relative productivity than vocational skills, largely because of the disproportionate share of employer-provided training received by high-skilled workers in those countries. We now go on to explore some of the mechanisms by which different types of skill may contribute to economic performance.

Table 10. **ECM estimates of average labour productivity, 1980-2007, country/sector-level data set, wage-weighted skill measure**

	Production sectors	Service sectors
(A) Long-run skill parameters:		
Upper-intermediate vocational skills	0.3007** (0.160)	
Higher skills		0.4874*** (0.176)
(B) ECM regression coefficients:		
Error correction term (t-1)	-0.0540*** [0.013]	-0.0401*** [0.010]
Capital-labour ratio (t-1)	0.0452*** [0.017]	0.0257* [0.013]
Higher skills_wtd (t-1)	-0.0074 [0.010]	0.0195*** [0.007]
Upper-intermediate vocational skills_wtd (t-1)	0.0162** [0.008]	0.0011 [0.010]
Lower-intermediate vocational skills_wtd (t-1)	-0.023 [0.016]	0.0005 [0.013]
Lower-intermediate general skills_wtd (t-1)	-0.0145 [0.010]	-0.0117 [0.013]
Low skills (t-1)	0.0041 [0.008]	0.0211 [0.013]
Observations	1 251	973
Log likelihood	2 378.67	2 071.97
Adj. R2	0.274	0.365
SEE	0.0372	0.0297

NB: See Table 9.

Table 11. **Fixed effects estimates of average levels of labour productivity, 1995-2007, country/sector-level data set, unweighted skill measure**

All countries, all market sectors	Without interactions	With interactions
Capital-labour ratio	0.3673** [0.147]	0.2722* [0.155]
Higher skills	0.1055* [0.061]	0.2278*** [0.084]
Upper-intermediate vocational skills	0.0417 [0.050]	0.1317** [0.057]
Lower–intermediate vocational skills	0.0276 [0.085]	0.1364 [0.094]
Lower-intermediate general skills	0.0459 [0.059]	0.1222* [0.070]
Average high-skilled training capital per hour worked	0.0644 [0.080]	0.2395*** [0.086]
Average intermediate-skilled training capital per hour worked	-0.070 [0.111]	0.3703 [0.248]
Training capital (higher)*higher skills		0.0708** [0.029]
Training capital (intermediate)*upper-intermediate vocational		0.0774* [0.039]
Training capital (intermediate)*lower-intermediate vocational		0.0816 [0.098]
Training capital (intermediate)*lower- intermediate general		0.0552 [0.055]
Observations	1 248	1 248
Adj. R2	0.602	0.633
F statistic	16.82	18.83
SEE	0.084	0.080
R-squared	0.608	0.64

NB: ***= significant at 1%, **= significant at 5%, *= significant at 10%.

Columns 1-2 show fixed effects ordinary least squares estimates; columns 3-4 show instrumental variable generalised method of moments estimates. All estimates are weighted by average country share of total employee compensation. The dependent variable is log average labour productivity (average value added per hour worked). All independent variables are also logged. Heteroscedasticity-robust standard errors shown in brackets have been corrected for clustering at country/sector level. All models include year dummies. The skill measures are unweighted qualification group shares of total hours worked.

Table 12. **Fixed effects estimates of average levels of labour productivity, 1995-2007, country/sector-level data set, unweighted skill measure, all market sectors**

	Apprentice countries		School-based VET countries	
	Without interactions	With interactions	Without interactions	With interactions
Capital-labour ratio	0.4938*** [0.159]	0.3928*** [0.141]	0.3652* [0.184]	0.3275 [0.195]
Higher skills	0.1119 [0.103]	0.1246 [0.148]	0.3076** [0.127]	0.4761*** [0.117]
Upper-intermediate vocational skills	0.0843* [0.047]	0.1660** [0.073]	0.0502 [0.100]	0.0579 [0.074]
Lower-intermediate vocational skills	0.6522 [0.445]	0.7687* [0.430]	-0.1031 [0.094]	0.0512 [0.119]
Lower-intermediate general skills	0.0924* [0.051]	0.1822** [0.076]	-0.0028 [0.109]	0.1237 [0.095]
Average high-skilled training capital per hour worked	0.3040*** [0.072]	0.2851*** [0.101]	-0.0528 [0.092]	0.2717 [0.175]
Average intermediate-skilled training capital per hour worked	-0.0515 [0.107]	0.6769** [0.302]	-0.0626 [0.114]	0.0039 [0.325]
Training capital (higher)*higher skills		0.0200 [0.051]		0.1105** [0.046]
Training capital (intermediate)*upper-intermediate vocational		0.0954** [0.046]		-0.0186 [0.085]
Training capital (intermediate)*lower-intermediate vocational		0.2592 [0.203]		0.0554 [0.103]
Training capital (intermediate)*lower-intermediate general		0.1124** [0.044]		0.0133 [0.059]
Observations	624	624	624	624
Adj. R2	0.6169	0.6346	0.6589	0.6874
F statistic	18.67	54.3	18.37	22.54
SEE	0.0673	0.0658	0.0891	0.0853

NB: ***= significant at 1%, **= significant at 5%, *= significant at 10%.

Fixed effects ordinary least squares estimates, weighted by average country share of total employee compensation. The dependent variable is log average labour productivity (average value added per hour worked). All independent variables are also logged. Heteroscedasticity-robust standard errors shown in brackets have been corrected for clustering at country/sector level. All models include year dummies. The skill measures are unweighted qualification group shares of total hours worked.

Table 13. **Fixed effects estimates of average levels of labour productivity, 1995-2007, country/sector-level data set, unweighted skill measure, all countries, production, and service sectors**

	Production sectors		Service sectors	
	Without interactions	With interactions	Without interactions	With interactions
Capital-labour ratio	0.2204 [0.170]	0.2159 [0.144]	0.5211*** [0.177]	0.4416** [0.203]
Higher skills	0.1046 [0.080]	0.3234*** [0.077]	0.1345 [0.103]	0.1751 [0.146]
Upper-intermediate vocational skills	0.0078 [0.057]	0.2093** [0.083]	0.0256 [0.061]	0.1201** [0.058]
Lower-intermediate vocational skills	-0.1031 [0.108]	0.1372 [0.093]	0.0779 [0.104]	0.134 [0.118]
Lower-intermediate general skills	-0.0032 [0.052]	-0.041 [0.084]	0.1183 [0.082]	0.1721** [0.073]
Average high-skilled training capital per hour worked	-0.0575 [0.095]	0.4517*** [0.094]	0.0829 [0.111]	0.0479 [0.110]
Average intermediate-skilled training capital per hour worked	-0.0483 [0.100]	0.0983 [0.324]	-0.039 [0.183]	0.6953* [0.395]
Training capital (higher)*higher skills		0.1661*** [0.029]		0.0089 [0.045]
Training capital (intermediate)*upper-intermediate vocational		0.1003 [0.066]		0.1215*** [0.043]
Training capital (intermediate)*lower-intermediate vocational		0.1144 [0.131]		0.1362 [0.111]
Training capital (intermediate)*lower-intermediate general		-0.0847 [0.061]		0.0875 [0.065]
Observations	702	702	546	546
Adj. R2	0.6341	0.7114	0.6214	0.6401
F statistic	15.68	50.59	32.6	81.96
SEE	0.0839	0.0745	0.0787	0.0767

NB: See Table 12.

5.2. Vocational skills, ICT and innovation

Many of the key mechanisms by which skills exert an influence on national economic performance are connected with innovation, including cross-border knowledge transfer and the introduction of new technologies. Much of the literature on these topics emphasises the role of high-level skills rather than intermediate vocational ones. However, it is possible to identify at least two channels of influence by which (intermediate and upper) vocational skills may potentially also contribute to economic performance:

(a) vocational skills may contribute to more effective use of ICTs;

(b) vocational skills may play key support roles in absorptive capacity (being 'open' to ideas) and in research and development (expenditures on R&D) areas. The measure for openness to new ideas is derived from indicators of foreign trade, inflows of foreign direct investment (FDI), involvement in the European single market and membership of the EU ([28]).

To assess the empirical relevance of the first channel of influence, physical capital services are disaggregated between ICT capital and non-ICT capital, the latter is interacted with the measure of skills to explore whether the impact of ICT on average labour productivity is enhanced when ICT capital and skilled labour input are used together.

The relationships above are not borne out in macro-level data (over the period 1980-2007); the coefficients on the interaction of the various (wage-weighted) skill measures with ICT investments are all not statistically significant.

We check the robustness of this (non) result using the sector-level data set (data on ICT capital usage are available at sector level) and the unweighted skill measure while controlling for training capital per hour worked (using fixed effect models). This approach returns a more positive image of the interaction between ICT capital and skilled labour input. Across the six countries, in all market sectors, we find evidence of positive effects on productivity of ICT use combined with intermediate vocational skills (at both upper- and lower-intermediate levels) and lower-intermediate general skills (Table 14, column 2). The contributions to the impact of ICT capital on ALP made by intermediate vocational and general skills are greater in apprenticeship-based VET countries (column 4) than in school-based VET countries where, again, high-level skills predominate (column 6). Intermediate vocational and general skills also contribute positively to the impact of ICT capital on ALP in service sectors (Table 15, column 4) and in ICT-intensive sectors (column 6). In production sectors the productivity-enhancing effects of ICT use are greatest when combined with high-level and upper-intermediate vocational skills.

([28]) The openness measure is derived from factor analysis of the trade, foreign direct investment (FDI), European single market and EU indicators; this extracts a single factor with an eigenvalue in excess of one, which explains 59.3% of the total variation of these four variables (Kaiser-Meyer-Olkin measure of sampling adequacy = 0.674). This factor score is readily interpretable as a summary measure of openness. Foreign trade involvement is measured by the ratio of exports plus imports to total output. FDI is measured by the ratio of FDI to total output. The European single market variable mirrors the official timing of the programme and starts in 1986 at 0 and gradually rises to 1 in 1993. The EU membership variables apply to countries that joined the EU after 1980 and increase from 0 to 1 over a three-year period to capture the gradual process of integration of a country into membership of the EU.

The data lent little support to importance of the role of skill in increasing absorptive capacity (the second channel of influence): all the coefficients on R&D spending (as percentage of GDP) and on the interaction terms between the openness measures and the various types of skilled labour are statistically insignificant. Since we do not have data for the components of the openness measure at sector level, we cannot pursue this line of enquiry further ([29]).

([29]) The impact of the various skill measures on the growth of labour productivity was also investigated. No statistically significant association between wage-weighted skills was found in the macro-level data spanning the period 1980-2007. In the sector/country data set vocational skills were positively associated with ALP growth (when reinforced by training capital in upper-intermediate skills) in production sectors and in conjunction with training capital in lower-intermediate skills in service sectors. The role of (unweighted) skills in supporting the catch-up process with the productivity leader is limited. In apprentice countries and in service sectors, the impact of intermediate-level training on productivity growth is larger in countries that are further away from the productivity leader than in countries close to the leader. In this case, training is found to accelerate productivity growth in countries lagging behind, and so supports the catch-up process. However, these are the only instances in which this happens, so we conclude that there is very little evidence of vocational skills improving the ability of productivity-lagging countries to catch up with productivity leaders.

Table 14. **Fixed effects estimates of average levels of labour productivity, 1995-2007, country/sector-level data set, unweighted skill measure, all market sectors**

All market sectors	All countries		Apprentice-based VET countries		School-based VET countries	
	Without interactions	With interactions	Without interactions	With interactions	Without interactions	With interactions
ICT capital-labour ratio	0.0402 [0.068]	0.6660*** [0.129]	-0.0703 [0.089]	0.7737*** [0.278]	0.1056 [0.093]	0.6435*** [0.187]
Non-ICT capital-labour ratio	0.2112 [0.127]	0.1559 [0.110]	0.4911** [0.186]	0.4580*** [0.157]	0.0421 [0.149]	-0.0171 [0.138]
Higher skills	0.1509** [0.071]	0.1836*** [0.060]	0.1468 [0.103]	0.1870** [0.091]	0.3227** [0.137]	0.3473*** [0.090]
Upper-intermediate vocational skills	0.0432 [0.055]	0.0634 [0.041]	0.0984* [0.056]	0.1012** [0.048]	-0.0031 [0.105]	0.0386 [0.083]
Lower-intermediate vocational skills	0.0268 [0.079]	0.0359 [0.085]	0.5009 [0.418]	0.3833 [0.376]	-0.0669 [0.081]	0.0637 [0.090]
Lower-intermediate general skills	0.0343 [0.064]	0.0083 [0.038]	0.0796 [0.051]	0.0065 [0.041]	-0.0152 [0.121]	0.1906* [0.100]
Average high-skilled training capital per hour worked	0.0589 [0.084]	0.0883* [0.053]	0.2468*** [0.074]	0.1295* [0.073]	-0.0585 [0.105]	-0.0551 [0.062]
Average intermediate-skilled training capital per hour worked	-0.0914 [0.108]	-0.1173 [0.105]	-0.0259 [0.105]	-0.0977 [0.088]	-0.0558 [0.121]	0.0526 [0.101]
ICT capital*higher skills		0.0329 [0.030]		-0.0021 [0.037]		0.1064*** [0.033]
ICT capital*upper-intermediate vocational		0.0821** [0.036]		0.1563** [0.076]		0.0437 [0.045]
ICT capital*lower-intermediate vocational		0.1316*** [0.038]		0.2167*** [0.076]		0.0618* [0.037]
ICT capital*lower-intermediate general		0.1273*** [0.028]		0.1169*** [0.024]		0.0663 [0.044]
Observations	1 248	1 248	624	624	624	624
Adj. R2	0.567	0.6492	0.6243	0.696	0.6259	0.7028
F statistic	13.27	17.5	23.28	69.92	13.59	22.94
SEE	0.0873	0.0786	0.0667	0.06	0.0933	0.0832

NB: See Table12.

Table 15. **Fixed effects estimates of average levels of labour productivity, 1995-2007, country/sector-level data set, unweighted skill measure, production, service and ICT-intensive sectors**

All countries	Production sectors		Service sectors		ICT-intensive sectors	
	Without interactions	With interactions	Without interactions	With interactions	Without interactions	With interactions
ICT capital-labour ratio	-0.0396 [0.069]	0.3706* [0.204]	0.1299 [0.112]	1.0860*** [0.212]	0.0942 [0.132]	0.7934*** [0.263]
Non-ICT capital-labour ratio	0.3967 [0.297]	0.3911 [0.253]	0.1142 [0.121]	0.0586 [0.097]	0.1728 [0.142]	0.157 [0.117]
Higher skills	0.1101 [0.082]	0.0943 [0.070]	0.2226 [0.135]	0.2893*** [0.091]	0.1597 [0.133]	0.1473 [0.128]
Upper-intermediate vocational skills	-0.0074 [0.060]	0.058 [0.050]	0.0278 [0.083]	0.0345 [0.051]	0.0311 [0.108]	0.0527 [0.078]
Lower-intermediate vocational skills	-0.1582 [0.115]	-0.0962 [0.133]	0.0837 [0.102]	-0.0095 [0.103]	0.1404 [0.104]	0.0834 [0.119]
Lower-intermediate general skills	-0.0017 [0.055]	0.016 [0.039]	0.1039 [0.107]	-0.0886 [0.059]	0.1617* [0.082]	0.0028 [0.068]
Average high-skilled training capital per hour worked	-0.0254 [0.094]	0.0249 [0.060]	0.1374 [0.098]	0.0023 [0.097]	-0.0032 [0.150]	-0.0353 [0.132]
Average intermediate-skilled training capital per hour worked	-0.106 [0.112]	-0.0828 [0.093]	-0.1206 [0.180]	-0.0381 [0.167]	-0.1005 [0.214]	-0.0541 [0.209]
ICT capital*higher skills		0.0972** [0.044]		0.0234 [0.035]		0.0106 [0.048]
ICT capital*upper-intermediate vocational		0.1360** [0.060]		0.0942** [0.040]		0.1040** [0.048]
ICT capital*lower-intermediate vocational		-0.0689 [0.078]		0.2603*** [0.056]		0.1444** [0.063]
ICT capital*lower-intermediate general		-0.0066 [0.028]		0.2251*** [0.043]		0.1559*** [0.048]
Observations	702	702	546	546	624	624
Adj. R2	0.638	0.715	0.534	0.692	0.642	0.704
F statistic	16.10	15.46	23.29	86.17	39.47	104.2
SEE	0.0834	0.0741	0.0873	0.071	0.0909	0.0827

NB: See Table 12.

CHAPTER 6.
Certified skill group complementarities

In addition to the complementarity between certified and uncertified skills, and to that between ICT capital and some types of skilled labour input, a degree of complementarity between certified skill groups might be expected. Intermediate vocational skills may be complementary to the use of high-level skills, for example, in playing key support roles in product design and development and in improving production processes. If two skill groups are complements, productivity is improved when these groups of workers are used in combination (rather than separately). If they are quantity substitutes, there may be scope for the two groups of workers to be used interchangeably (see Box 3 for further details on how the degree of complementarity can be obtained from empirical estimates).

To investigate, we use ECM methods similar to those used in Chapter 4 for the period 1980-2007. Sweden is excluded from the sample because of missing data on capital services for 1980-92, which leaves too few data points to implement ECMs. The remaining countries are classified either as having largely apprenticeship-based (Denmark, Germany and the Netherlands) or classroom-based (France and the UK) VET systems. Industries are divided between production and market service sectors.

The long-run elasticities of complementarity between all skill group pairs are shown in Table 16, which also reports the error-correction coefficient for each share equation. This always appears negative and significant, indicating the existence of stable long-run relationships.

The results in the bottom part of Table 16 point to a significant difference in mean factor cost shares between countries with largely apprenticeship-based VET systems and those with largely classroom-based systems. In the former, the lower-intermediate vocational-skilled group accounts on average for a quarter of total production costs; the low-skilled group accounts on average for 7-8% of total production costs. In countries with classroom-based VET systems, the lower-intermediate vocational-skilled group accounts on average for a smaller share of total production costs (15-16%) while the low-skilled group makes up a quarter of production costs. We also see (summing across mean factor shares) that, in comparison to countries with largely classroom-based VET systems, labour costs account on average for a smaller share of total production costs in countries with largely apprenticeship-based VET systems. The corollary is that capital costs account for a larger share of total production costs in these countries.

The estimated (long-run) elasticities suggest a generalised pattern of complementarity between skills in production sectors in high apprenticeship countries. Complementarity between skills is also observed, in some instances, in the market services: intermediate vocational skills tend to be complementary to the use of high-level skills; higher skills are complemented by upper-intermediate vocational skills; lower-intermediate vocational skills are complemented by the use of both intermediate general skills and low skills; and low skills tend to be complementary to the use of upper-intermediate skills.

These generalised patterns of complementarity between certified skills are not observed in countries where VET systems are largely classroom-based. In production sectors in these countries, upper-intermediate vocational skills tend to be substitutes (rather than complements) for higher skills. Lower-intermediate vocational skills and low skills are complementary to the use of upper- and lower-intermediate vocational skills. In the market services sectors lower-intermediate vocational skills are complementary to the use of both intermediate general skills and low skills. Finally, low skills are complementary to the use of upper-intermediate vocational.

Generally, upper- and lower-intermediate vocational-skilled labour are complementary (augment productivity of) to the use of low-skilled labour across the board.

Table 16. **ECM estimates of elasticities of complementarity between five skill groups, 1980-2007, country/sector-level data set, all countries except for Sweden, unweighted skill measure. P-values in parentheses**

Industry sector	Apprenticeship-based VET countries		School-based VET countries	
	Production	Market services	Production	Market services
Skill group pairs				
Higher, upper-intermediate vocational	1.712*** (5.52)	1.771*** (2.70)	-1.773** (-2.45)	-0.686 (-1.46)
Higher, lower-intermediate vocational	1.273*** (5.57)	0.508 (1.04)	0.00547 (0.01)	0.550 (1.35)
Higher, lower-intermediate general	1.951*** (4.49)	0.321 (0.54)	0.868* (1.73)	0.493 (0.86)
Higher, low-skilled	2.502*** (3.83)	0.671 (0.63)	-0.993* (-1.89)	0.683* (1.93)
Upper-intermediate vocational, lower-intermediate vocational	-0.111 (-0.48)	-0.0885 (-0.27)	-2.289*** (-3.98)	-0.164 (-0.28)
Upper-intermediate vocational, lower-intermediate general	1.917*** (3.08)	1.281* (1.96)	-0.285 (-0.39)	-0.0407 (-0.05)
Upper-intermediate vocational, low-skilled	2.579*** (5.48)	3.417*** (4.52)	1.517*** (3.40)	1.598*** (4.39)
Lower-intermediate vocational, lower-intermediate general	0.711** (2.37)	0.821*** (2.80)	-0.374 (-1.09)	1.389** (2.38)
Lower intermediate vocational, low-skilled	2.183*** (6.23)	1.384** (2.52)	1.403*** (4.48)	0.609* (1.93)
Lower intermediate general, low-skilled	0.541 (0.79)	0.549 (0.88)	-0.130 (-0.43)	0.318 (0.74)
Error-correction terms				
Higher skilled	-0.248*** (-11.13)	-0.190*** (-8.40)	-0.257*** (-8.75)	-0.392*** (-14.26)
Upper-intermediate vocational skills	-0.347*** (-14.44)	-0.244*** (-13.07)	-0.337*** (-12.94)	-0.277*** (-14.40)
Lower-intermediate vocational skills	-0.362*** (-14.21)	-0.229*** (-7.93)	-0.315*** (-13.10)	-0.243*** (-11.63)
Lower-intermediate general skills	-0.346*** (-12.79)	-0.351*** (-14.98)	-0.555*** (-15.77)	-0.371*** (-14.89)
Low-skilled	-0.190*** (-13.06)	-0.159*** (-11.03)	-0.246*** (-12.34)	-0.283*** (-12.04)
Mean cost shares				
Higher skilled	0.085572	0.072185	0.084146	0.125262
Upper-intermediate vocational skills	0.056246	0.047464	0.052997	0.054468
Lower-intermediate vocational skills	0.259113	0.269543	0.154561	0.137048
Lower-intermediate general skills	0.030945	0.039317	0.071350	0.152650
Low-skilled	0.072064	0.076210	0.247490	0.243738

NB: Long-run elasticities estimated within a dynamic factor share system derived from a translog production function; elasticities evaluated at weighted mean factor shares; sample period 1980-2007; skill groups: high-skilled (HIGH), upper-intermediate vocational-skilled (UIV), lower-intermediate vocational-skilled (LIV), lower-intermediate general-skilled (LIG), and low-skilled (LOW); Apprenticeship-based VET countries comprise Denmark, Germany and the Netherlands; school-based VET countries comprise France and the UK; production (market services) sector includes eight industries; symmetry and homogeneity imposed in the long-run and short-run coefficients; each share equation includes country*industry-specific fixed effects and time trends (differential factor bias); lagged dependent variable terms allowed to vary across industry*country groups; up to three lags considered; cross-sectional means of the dependent and lagged dependent variables included to correct for cross-sectional correlation within share equations; dynamic term in log output included; estimated by iterated feasible generalised nonlinear least squares; weights imposed in estimation; the models pass basic tests for serial-correlation.

Box 3. **Assessing the degree of complementarity between production inputs**

Complementarity is assessed by means of the Hicks' elasticity of complementarity (HEC) (Hicks, 1970; Sato and Koizumi, 1973) derived from the production function which describes how inputs X_1 …. X_n combine to produce output Y. Production inputs X_i and X_j are then classified as complements if $HEC_{ij}>0$ and substitutes if $HEC_{ij}<0$. If an input pair are complements, an increase in the use of one input raises the marginal productivity of the other and vice versa (for given output prices and other input levels).

The production function is specified as a translog because of its flexibility, which allows the derivation of various elasticities from the estimates (see, e.g. Berndt and Christensen, 1973; Stern, 2010). The parameters of the production function are recovered from a system of factor share equations that includes input quantities as the exogenous variables. This approach was chosen because, in the data set, workers' wages in different industry/country/year/skill groups are less well measured than are hours worked.

There are six inputs: capital stock (X_0) and five different types of labour (the five skill groups: high-skilled, upper-intermediate vocational, lower-intermediate vocational, lower-intermediate general and low-skilled)

Equation 7 shows the translog production function (after imposing the standard symmetry and homogeneity constraints):

(7) $$lnY = \propto + \sum_{i=0}^{5} \propto_i lnX_i + \frac{1}{2}\sum_{i=0}^{5}\sum_{j=0}^{5}\gamma_{ij} lnX_i\, lnX_j + \propto_T T + (\tfrac{1}{2})\gamma_{TT}T + \sum_{i=0}^{5}\gamma_{iT}T lnX_i$$

where Y is real value added, and X_i is hours worked by labour type. T is a time trend to capture technical progress. The inclusion of interaction terms between the time trend and other inputs allows for factor-biased technical progress, remaining parameters are to be estimated. The production function yields the following factor share system for estimation:

(8) $$S_i^k = \propto_i^k + \sum_j \gamma_{ij}(lnX_j^k - lnX_0^k) + \gamma_{iT}^k T + \varepsilon_i \ , \ i = 1 \dots 5$$

where the superscript k denotes the industry, S_i^k denotes the share of labour type i in total costs for industry k, and the inputs retain their interpretation. ε_i is an error term with zero mean and variance σ_i^2; the remaining symbols denote parameters to be estimated. The constant term and the coefficient on the time trend are allowed to vary across industry/country to allow for heterogeneity in the production technology and in the factor bias of technical change ([a])

Within this set up the HEC can be derived as (Grant and Hamermesh, 1981):

(9) $$HEC_{ij} = \gamma_{ij}/[s_i s_j]+1$$

We evaluate the HEC at the sample weighted mean value of factor shares; all years receive equal weight, country/industry weights are equivalent to their average share of sample total labour costs.

([a]) Equation 8 specifies a set of long-run relationships. We estimate these using a ECM including up to three lags to avoid problems of spurious correlation. We allow the dynamic terms in the lagged dependent variable to vary across industry/country groups to facilitate short-run parameter heterogeneity in the spirit of the pooled mean group estimator (Pesaran et al., 1999). We include cross-sectional means of the dependent and lagged dependent variables to correct for cross-sectional correlation within the share equations. Observations are weighted by the industry/country group sample average share of total labour costs.

CHAPTER 7.
Conclusions

This report set out to investigate the macroeconomic benefits of VET by using various measures of skills for six countries – Denmark, Germany, France, the Netherlands, Sweden and the UK – chosen for diversity in their predominant modes of VET. Some focus primarily on apprenticeship training (Denmark, Germany and the Netherlands) while others typically provide VET through full-time vocational schooling (France, Sweden and the UK).

The skill measures are based on stock of qualifications: five different qualification groups were defined in terms of different levels and orientation (vocational or general). The division between the higher and upper-intermediate groups corresponds to the boundary between long-cycle and short-cycle higher education. In terms of traditional vocational qualifications, technician-level qualifications in the upper-intermediate vocational group are separated from craft-level qualifications in the lower-intermediate vocational group.

Considerable effort was devoted to deriving measures of the stock of uncertified skills. Two methods were used:

(a) weighting the various groups of certified skills by the ratio of the wage in the group to the wage of low-skilled workers (on the assumption that uncertified skills will be rewarded in wages);
(b) developing a measure of the training stock at the various educational levels.

Growth accounting analysis using the first measure of skills suggests that vocational skills made positive contributions to growth in average labour productivity (ALP) in five of the six countries between 1980 and 2007. The exception was Germany but only because the vocational-skilled group was already comparatively large in Germany at the start of this period. In three countries – Germany, Sweden and the UK – the growth contributions of intermediate vocational skills were exceeded by the positive contribution made by growth in high-level skills. However, in Denmark, France and the Netherlands the combined contributions of growth in upper- and lower-intermediate vocational skills exceeded the high-skills contribution to ALP growth.

Growth accounting tends to underestimate the contributions made by all types of skill to productivity performance because it cannot take account of complementarities between production inputs (e.g. the role of skills in aiding effective use of new technologies).

When we turn to regression techniques to account for these complementarities, the results show a stable long-run relationship and a weaker short-run relationship between skills and productivity.

There are differences in the ways the various types of skills affect productivity. The results provide considerable evidence of a positive relationship between upper-intermediate vocational skills and relative ALP performance, especially in production sectors. This positive relationship is found to occur primarily in apprenticeship-based VET countries and is stronger when vocational skills are broadly defined to include uncertified skills acquired through employer-provided training. However, these estimates provide only limited evidence of positive effects of lower-intermediate vocational skills. In countries where VET is more commonly provided through classroom-based vocational schooling (and in the service industries) high-level skills tend to contribute more to relative productivity than vocational skills, largely because of the disproportionate share of employer-provided training received by high-skilled workers in those countries.

A positive assessment of the impact of lower-intermediate vocational skills emerges from regression analysis of the role of skills in supporting the diffusion of information and communication technologies (ICTs). We find evidence that employment of both lower- and upper-intermediate vocational skills contributes to more effective use of ICTs (helping to improve relative ALP levels) alongside similarly positive effects of combining ICT use with high-level and lower-intermediate general skills. The contributions made by intermediate vocational and general skills are greater in countries where apprenticeship training is strong than in school-based VET countries where high-level skills predominate. Intermediate vocational and general skills also contribute positively to relative ALP when combined with ICT use in service sectors and in ICT-intensive sectors. In production sectors the productivity-enhancing effects of ICT usage are greatest when combined with high-level and upper-intermediate vocational skills.

The estimated (long-run) elasticities suggest a generalised pattern of complementarity between certified skills in production sectors in high apprenticeship countries. Complementarity between skills is also observed in some instances in market services where intermediate vocational skills tend to be complementary to the use of high-level skills.

These generalised patterns of complementarity between certified skills are not observed in countries where VET systems are largely classroom-based. In the production sectors in these countries, upper-intermediate vocational skills tend to be substitutes (rather than complements) for higher skills. In the market services sectors, complementarity involves mainly low skills and lower-intermediate skills (both general and vocational).

These findings have several implications for national and European policy-makers.

First, it is clear that the impact of skills on productivity is more pronounced in countries where VET is based on apprenticeship training. This suggests that the context in which skills are used is important in determining the ultimate effect of skills on productivity.

Second, vocational skills tend to play a more important role in production sectors in countries where VET is based on apprenticeship training. In contrast, in market sectors in countries where VET is based on schools, high (academic) skills are more prominent. This suggests that vocational skills have a stronger impact on productivity in sectors and countries that have a longer tradition in the use of vocational skills. Cultural and socioeconomic and political factors which affected the historical evolution of the use of skills will cast a long shadow on the ways skills would affect productivity (Iversen, 2005; Iversen and Stephens, 2008; Thelen, 2004).

Third, certified vocational skills typically contribute to higher productivity when reinforced by uncertified skills developed through job-related training provided by employers. This kind of training is especially important in countries which lack strong apprenticeship systems, since many valuable skills are best learned – or can only be learned – in workplaces, not in full-time study settings. However, even workers whose initial training takes the form of an apprenticeship are subsequently likely to need continuing training to help update and improve their skills. The more vocational skills are developed through continuing training for adult workers, the greater will be the contribution of vocational skills to macroeconomic performance.

Finally, productivity performance is augmented by developing a mix of intermediate-level and high-level skills, not by relying too heavily on the expansion of higher education to bachelor degree level at the expense of intermediate skills development. Developing a mix of intermediate and high-level skills will also enable complementarities between skill groups to flourish. For example, vocational-skilled workers may provide essential support services for high-skilled workers while the economic contributions of vocational-skilled workers may be enhanced by working together with high-skilled colleagues. The pattern or complementarity between skills is more developed in countries in which VET is based on apprenticeship training and in production sectors.

List of abbreviations

ALP	average labour productivity
CVET	continuous vocational education and training
ECM	error correction model
FDI	foreign direct investment
GDP	gross domestic product
ICT	information and communication technology
OLS	ordinary least squares
QAL	quality-adjusted labour
TFP	total factor productivity
VET	vocational education and training

Country codes

BE	Belgium
CZ	Czech Republic
DK	Denmark
DE	Germany
IE	Ireland
EL	Greece
ES	Spain
FR	France
IT	Italy
LU	Luxembourg
HU	Hungary

NL	Netherlands
AT	Austria
PL	Poland
PT	Portugal
SK	Slovakia
FI	Finland
SE	Sweden
UK	United Kingdom
NO	Norway

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Annex
Overview of research methods used in the study

A.1 Performance measures

Our investigations focus on the estimated impact of different kinds of skill on average labour productivity (ALP) which is defined as the average output per unit of labour input (e.g. output per worker or per worker-hour). ALP is important to any country because it is a long-run influence on real wages and living standards.

A.2 Data sets

In these analyses we make use of two data sets covering the six countries under investigation:

(a) a macro-level data set containing information on variables including constant-price output (gross value added), hours worked, capital services and measured skill levels at whole-economy level for the years 1980-2007;

(b) a sector-level data set containing information on similar variables for 16 different sector groups in each of the six countries. Most of these variables are available at country/sector level for the full 1980-2007 period. However, estimates of training capital stocks are only available for the period 1995-2007. Definitions of the 16 sector groups according to standard industrial classification (SIC) codes are shown in Table 17. Non-market services such as public administration, education, health and owner-occupied housing are excluded because of the difficulties in measuring output in these sectors and the frequent lack of comparability in the ways in which national statistical agencies seek to surmount such difficulties.

There are two main reasons for carrying out analyses at country/sector level as well as at macro level. First, statistical inference in macro-level analysis is hampered by the relatively small number of data observations available at whole economy level. By contrast, the number of observations at country/sector level is far greater. Without the sector-level data set we would not be able to make use of the training capital stocks estimates which are only available from 1995.

Second, there is a strong conceptual argument for disaggregating by sector to explore the economic effects of different types of skill. The persistence of very different patterns of wage returns to different kinds of education and training in European countries such as Germany and the UK serves as a reminder that employers in each country have tended to adopt very different patterns of sectoral specialisation in keeping with predominant modes of skill formation. This was illustrated by comparisons of matched samples of establishments in Germany and the UK during the 1980s and the 1990s which found that German firms tended to achieve higher levels of productivity than their British counterparts in sectors such as mechanical engineering and food processing where craft apprentice skills are highly valued (Prais, 1995). By contrast, UK firms compared more favourably in sectors such as chemicals and electronics where there is little demand for craft-level skills but a high demand for university graduates (Mason and Wagner, 1999).

Table 17. **Definitions of sector groups in country/sector data set**

	SIC code
Food products, beverages and tobacco	15-16
Chemicals, rubber, plastics, fuel	23-25
Basic metals and fabricated metal products	27-28
Mechanical engineering	29
Electrical and electronic engineering	30-33
Transport equipment	34-35
Other manufacturing	17-22, 26, 36-37
Other production	2-5, 10-14, 40-41
Construction	45
Wholesale and retail	50-52
Hotels and restaurants	55
Transport and storage	60-63
Post and telecommunications	64
Financial intermediation	65-67
Business services	71-74
Community, social and personal services	90-93

Source: Authors' calculation.

The economic returns on different mixes of skills, and different modes of skills acquisition, may vary sharply between sectors within countries as well as between countries. Further, cross-country differences in productivity performance at national level may be driven partly by different patterns of sectoral specialisation and skills utilisation. Such contrasts generally tend to be masked in macro-level analyses but may be distinguishable in cross-country comparisons at sector level.

A.3 Investigating the relationship between production inputs and outputs

The two main methods of quantitative analysis employed to investigate the relationship between production inputs, such as skilled labour, and final outputs are growth accounting and multivariate regression analysis. Both approaches stem from the same basic framework – neoclassical production theory – but differ in their assumptions and in the quantitative tools employed in the analysis.

Both methods begin with the specification of a production function that maps the production inputs to final output, representing the productive capacity of an economy. With two factors of production this can be expressed as:

(A.1) $$Y = f\left(K_t, L_t, T_t\right)$$

where Y is the final output good, K is the physical capital stock, L is labour input and T is an efficiency indicator which may be termed total factor productivity (TFP). Growth in TFP – sometimes also referred to as multi-factor productivity (MFP) – is defined residually as the increase in output that cannot be attributed to increases in the quantity and quality of K or L. TFP captures, among others, the extent to which growth in output derives from more efficient deployment of existing resources.

However, despite these similarities, the growth models underlying growth accounting and regression-based methods typically differ sharply. Growth accounting is wedded to neoclassical growth theory, which assumes that technical change is exogenous in nature (i.e. technical changes are assumed to happen randomly and not as the result of actions taken by economic decision-makers). In this framework there are diminishing returns on reproducible inputs. By contrast, in recent decades regression-based analyses of the kind presented in this report have increasingly been based on models derived from new growth theories; in these the decisions of firms and other economic agents can affect the adoption and development of new technologies, so that technical change becomes endogenous to the model (Romer, 1986; Lucas, 1988; Aghion and Howitt, 1998).

Building in particular on early insights by Nelson and Phelps (1966), this theoretical framework allows decisions to invest in human capital to be modelled as 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 analysis. Depending on the specifications of the models, diminishing returns no longer play a crucial role and growth can emerge in equilibrium through accumulation of human or innovation capital.

In addition to the ability of regression-based methods to take account of the insights of new growth theories, these methods are more flexible than growth accounting in their underlying assumptions and ability to take account of sources of growth other than inputs. For example, account can be taken of variables such as research and development (R&D) spending, foreign direct investment (FDI) and measures of openness to capture the economy’s ability to absorb technology from abroad.

By contrast with growth accounting, multivariate regression analysis provides more scope for taking account of interactions between production inputs and indirect effects of skills on productivity. It is notable that cross-country international comparisons of relative productivity performance using growth accounting techniques tend to attribute relatively small proportions of the identified productivity gaps to cross-country differences in workforce skill levels (O'Mahony and de Boer, 2002). This likely reflects the fact that, in growth accounting exercises, 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 selection and effective use of capital equipment and the contributions made by workforce skills to absorptive capacity).

However, growth accounting is a powerful descriptive tool that provides 'stylised facts' that anchor subsequent analysis. Used sensibly, growth accounting and regression-based methods can complement each other, so this report presents results derived using both methods.

A.4 Growth accounting

Following the theoretical framework for growth accounting set out in Solow (1957), if we start with a two-factor production model of the kind expressed in equation A.1, and totally differentiate this equation with respect to time and assume perfect competition in factor markets and a homothetic production function ([30]), the partial derivatives of the production function may be rearranged to obtain a decomposition of the growth rate of output into the sum of the growth rates of each input, weighted by their relative factor share, plus the growth in TFP:

(A.2) $$d\ln(Y_t) = \theta_{K_t} d\ln(K_t) + \theta_{L_t} d\ln(L_t) + dA_t$$

where θKt is the share of output accruing to capital, θLt is the labour share and dAt is the growth rate of TFP, defined as:

(A.3) $$dA_t = \frac{f_{T_t} T_t}{Y_t} d\ln(T_t)$$

Under constant returns to scale $\theta Lt = (1\text{-}\theta Kt)$.

([30]) In perfectly competitive markets, no market participants have the power to influence the prices of the goods and services that they buy or sell. In the case of perfectly competitive labour markets, the wages received by workers correspond to their marginal products. When production functions are homothetic in nature, the marginal rate of substitution between production inputs depends solely on the relative prices of those inputs.

Equation A.2 refers to continuous time which is not observable. The implementation of this equation in discrete time requires specification of a production function. For example, it is common to assume a translog functional form as this has attractive properties including time-varying elasticities of substitution between inputs and the fact that it nests the commonly used Cobb-Douglas production function. With a translog production function the growth accounting equation becomes:

(A.4) $$\Delta \ln Y_t = \bar{v}_t^K \Delta \ln K_t + \bar{v}_t^L \Delta \ln L_t + \Delta \ln A_t$$

where *Δ* denotes the change between periods *t-1* and *t*, $\bar{v}^i$ denotes the two-period average share of input *i* in nominal output defined for each year as:

(A.5) $$v_t^L = \frac{P_t^L L_t}{P_t^Y Y_t}; \quad v_t^K = \frac{P_t^K K_t}{P_t^Y Y_t}$$

and constant returns to scale imply that $\bar{v}^L + \bar{v}^K = 1$.

In most early growth accounting studies, labour quality or skills were not explicitly included in the production function and therefore the contribution of skills to output growth showed up in the residual category of TFP growth. However, as long as the shares of labour compensation awarded to different qualities or types of labour can be identified, a simple growth accounting framework can quantify the contribution of those different grades of labour input to GDP growth (Jorgenson and Griliches, 1967) and it is now common to account for skills in this way (e.g. Jorgenson et al., 2005; Timmer et al., 2010). Thus aggregate labour input can be specified as a Tornqvist quantity index of l individual labour types as follows:

(A.6) $$\Delta \ln L_t = \sum_l \bar{w}_{lt}^L \Delta \ln L_{lt}$$

where $\Delta \ln L_{lt}$ indicates the growth of hours worked by labour type l and weights are given by the period average shares of each type in the value of labour compensation. Subject to the assumption that relative wages reflect relative marginal products (Section 3.1), this approach to skill measurement has the advantage of taking account of uncertified as well as certified skills. Note that a similar expression can be derived for capital when assets are divided by type. The weighting procedures ensure that inputs which have a higher price also have a larger influence in the input index: doubling the hours worked by a high-skilled worker gets a bigger weight than doubling the hours worked by a low-skilled worker.

In terms of labour inputs, it is useful to split the volume growth of labour input L into the growth of hours worked (H) and the growth of measured skills (S). Let

Hlt indicate the hours worked by labour type l at time t, and Ht total hours worked by all types (summed over l). Then the change in labour input can be decomposed as follows:

(A.7) $$\Delta \ln L_t = \sum_l \bar{w}_{lt} \Delta \ln \frac{H_{lt}}{H_t} + \Delta \ln H_t = \Delta \ln S_t + \Delta \ln H_t$$

where $\bar{w}_{lt}$ is the period-average share of labour type l in total labour costs in industry j.

Finally it is useful to divide both sides of equation A.7 by hours worked to decompose the sources of ALP growth into those due to changes in capital per hour worked, skills and TFP. With the assumption of constant returns to scale, the decomposition of ALP becomes:

(A.8) $$\Delta \ln(\frac{Y_t}{H_t}) = \bar{v}_t^K \Delta \ln(\frac{K_t}{H_t}) + \bar{v}_t^L \Delta \ln S_t + \Delta \ln A_t$$

This is the basis of the decomposition of ALP growth set out in our growth accounting analysis in Chapter 4.

A.5 Regression-based analysis: empirical specifications

In our multivariate analyses we start with a similar specification to equation A.8 to estimate the impacts of capital and skills on labour productivity. This also has the advantage that a range of other influences on labour productivity can be included in the estimation. The baseline specification employed in the analysis is given for country j by:

(A.9) $$\ln(\frac{Y_{jt}}{H_{jt}}) = \beta_0 + \beta^K \ln(\frac{K_{jt}}{H_{jt}}) + \beta^S \ln S_{jt} + \sum \beta^Z Z_t + \varepsilon_{jt}$$

where the variables are as defined above, ε is the error term and Z is a vector of control variables such as the degree of openness of economies to trade and foreign investment, R&D spending and various dummy variables to control for country- and sector-specific characteristics and time-related influences on economic activity. Further details on these control variables are provided in the relevant sections below.

When dealing with long time series such as the 27-year period covered by our two data sets, we need to be concerned about the variables of interest being non-stationary (such as trending upwards over time) which may lead to spurious regression results if equation A.9 is estimated in levels. A common way of dealing with this issue is to estimate an error correction model (ECM) version of equation A.9 which takes the following form (country subscripts are omitted for simplicity):

$$\text{(A.10)} \quad \Delta \ln(Y/H)t = b + b1\,[\ln(Y/H)t\text{-}1 - b2\ln(K/H)t\text{-}1 - b3\ln(S/H)t\text{-}1] + b4\Delta\ln(Y/H)t\text{-}1 + b5\Delta\ln(K/H)t\text{-}1 + b6\Delta\ln(S/H)t\text{-}1 + b7\Delta\ln(Y/H)t\text{-}2 + b8\Delta\ln(K/H)t\text{-}2 + b9\Delta\ln(S/H)t\text{-}2 + b10\Delta\ln(K/H)t + b11\Delta\ln(S/H)t + \varepsilon t$$

where Δ is the first-difference operator, $b1$ is the error correction coefficient, and $b2$ and $b3$ are long-run parameters on the capital and skill variables. The term 'error correction' here refers to the fact that $b1$ represents the extent to which the values of the capital and skill variables fall short of those which would apply when the relationships between these variables are in long-run equilibrium ([31]). As suggested by Pesaran and Shin (1999), this approach allows us to derive unbiased estimates of the long-run relationships between key variables, and their standard errors, regardless of whether the underlying explanatory variables are integrated of order zero or one ([32]).

We make use of two different measures of skills in our analyses. When using the first wage-weighted measure of skills ($S*$), we make use of the full 27-year time series and all analyses are carried out using ECMs of the kind shown in equation A.10. However, our second skill measure is derived by combining unweighted measures of qualification group shares of employment with our measures of training capital stocks estimates. Since these training capital estimates are only available for the period 1995-2007, it is not feasible for them to be used with the relatively small macro-level data set; our analysis with this skill measure is confined to using the country/sector-level data set. Whenever the much shorter time period is involved, we move away from ECMs and use fixed effects panel data methods which have the advantage of controlling for time-invariant heterogeneity between the cross-sectional units (country/sector units in this case).

In these fixed effects analyses we begin with the following general production function:

([31]) Variables are said to be in long-run economic equilibrium when their values are stable and would only change if induced to do so by changing external circumstances.

([32]) A time series is integrated of order zero if it is stationary, i.e. it fluctuates around a constant mean over time and its variance is independent of time. A time series is integrated of order one if taking first differences produces a stationary series.

(A.11) $Yijt = AijtF(Kijt, Hijt, Sijt, TCijt)$

where Y is output, K is total capital services, H is the total number of hours worked, S is an unweighted measure of certified skills, TC is a measure of intangible training capital, A is a technology shift parameter and i, j and t denote industries, countries and time respectively. Assuming a Cobb-Douglas production function, disaggregating S and TC, dividing through by H and taking logarithms, equation A.11 can be rewritten as follows:

(A.12) $$\ln(Y/H)ijt = \alpha + \beta1\ln(K/H)ijt + \beta2\ln(S1/H)ijt + \beta3\ln(S2/H)ijt + \beta4\ln(TC1/H)ijt + \beta5\ln(TC2/H)ijt + \varepsilon ijt,$$

where $S1$ and $S2$ denote the employment shares of skill groups 1 and 2 and$TC1$ and $TC2$ represent the stocks of training capital accumulated in relation to those two skill groups.

The skill measure combining certified skills with training capital is developed by multiplying the relevant variables for each skill group to produce ‘interaction’ terms. If the coefficient on the interaction between $S1/H$ and $TC1/H$ turns out to be positive and statistically significant, this can be interpreted as evidence that, all else being equal, the impact of $S1$ on ALP is not only positive but is enhanced the more that the certified skills denoted by $S1$ are combined with employer-provided training as denoted by $TC1$. The reverse inference may also be drawn; the impact of TC1 on ALP is not only positive but is enhanced the more that such employer-provided training is accompanied by certified skills held by the workers receiving training.

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Macroeconomic benefits of vocational education and training

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Improvements in workforce skills are essential for European countries to attain higher economic growth and to compete effectively on product markets. Literature indicates a positive relationship between levels of education and productivity growth; this report builds on and expands this body of research in two ways. First, it investigates the differential impact of various skill types – higher (academic), upper-intermediate vocational, lower-intermediate vocational, lower-intermediate general, and low – on labour productivity. Then it accounts for the stock of uncertified skills (i.e. those built through training). The analysis is carried out in six EU Member States – Denmark, Germany, France, the Netherlands, Sweden and the UK – representing different modes of VET (and for which data were available). The analysis suggests that general and vocational skills complement each other and that the effect of (certified) skills on productivity is stronger when certified skills are reinforced by training.

Europe 123, 570 01 Thessaloniki (Pylea), GREECE
Postal address: PO Box 22427, 551 02 Thessaloniki, GREECE
Tel. +30 2310490111, Fax +30 2310490020
E-mail: info@cedefop.europa.eu

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