Which skills contribute most to absorptive capacity, innovation, and productivity performance? Evidence from the US and Western Europe

Geoff Mason, Ana Rincon-Aznar and Francesco Venturini

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Geoff Mason*, Ana Rincon-Aznar and Francesco Venturini*****

***Centre for Research on Learning and Life Chances (LLAKES), UCL Institute of Education, London**

**** National Institute of Economic and Social Research, London**

***** University of Perugia, Italy**

List of Contents

Abstract ... 3

1. Introduction ... 4

2. Skills and absorptive capacity: theory, measurement issues and hypotheses ... 7

3. Empirical specification ... 13

4. Data sources and descriptive statistics ... 17

   4.1 Data description ... 17

   4.2 Summary statistics ... 20

5. Econometric findings ... 22

   5.1 Openness to foreign knowledge sources ... 22

   5.2 The contributions of skills, R&D intensity and openness to growth in innovative output ... 23

   5.3 The contributions of skills and realised absorptive capacity to growth in multi-factor productivity ... 26

6. Robustness tests ... 32

   6.1 Endogeneity issues ... 32

   6.2 Assessing the role of cross-sectional dependence ... 38

   6.3 Assessing the impact of varying assumptions made in the calculation of US skill measures ... 41

7. Summary and assessment ... 43

References ... 47

Appendix A: Descriptive statistics at country/industry level: openness, R&D spending, patent stocks and skills ... 53

Appendix B: Classification of educational qualifications ... 57

List of Tables

Table 5.1: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using higher skills measure ... 28

Table 5.2: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using upper intermediate skills measure ... 29

Table 5.3: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using lower intermediate skills measure ... 30

Table 5.4: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using aggregate skills measure 31

Table 6.1: Instrumenting R&D intensity and skills with external (institutional) variables, Western European and US manufacturing industries, 1995-2007: first-stage estimates.........36

Table 6.2: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 - Instrumenting R&D intensity and skills...37

Table 6.3: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 – Including common correlated effects to assess the impact of cross-sectional dependence...40

Table 6.4: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 – With different allocations of US workers in the ‘Some college, no degree’ category to Upper intermediate and Lower intermediate skill groups....................................42

List of Figures

Figure A1: Summary measure of openness, total manufacturing, eight countries, 1995 and 2007...53

Figure A2: R&D expenditure as percentage of total sales, total manufacturing, eight countries, 1995 and 2007 53

Figure A3: Patent stocks per hour worked, total manufacturing, eight countries, 1995 and 2007...54

Figure A4: Estimated aggregate skill levels in total manufacturing, eight countries, 1995 and 2007...54

Figure A5: High-skilled workers (holding Bachelor or higher degrees) as % of total hours worked, total manufacturing, eight countries, 1995 and 2007...55

Figure A6: Upper intermediate-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007...55

Figure A7: Lower intermediate-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007...56

Figure A8: Low-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007 56

Abstract

Skills are widely recognised as central to firms' and national industries' 'absorptive capacity', that is, their ability to identify and make effective use of knowledge, ideas and technologies that are generated elsewhere. But identification of the specific kinds of education and skills that contribute most to the development of absorptive capacity is often hampered by the use of skill measures as proxies for absorptive capacity itself. In this study, drawing on a cross-country industry-level dataset, we retain separate measures of key components of absorptive capacity – skills, R&D investments and openness to foreign trade and investment – in order to examine the strength of their respective contributions to innovation and ultimately to productivity growth. We find important roles for both high-level skills and upper intermediate (technician-level) skills in converting the knowledge sourcing opportunities provided by openness into innovative outputs (such as new ideas for products and processes). When these innovations are combined with other inputs into the production of final goods and services, productivity growth is enhanced not just by high-level skills and upper intermediate skills but also by other types of skill, including uncertified skills (for example, skills acquired through informal on-the-job training and work experience).

1. Introduction [1]

Knowledge and understanding of innovation processes have been greatly enhanced by research on 'absorptive capacity', that is, the ability of firms to identify and make effective use of knowledge, ideas and technologies that are generated elsewhere (Cohen and Levinthal, 1989, 1990; Zahra and George, 2002; Jansen et al, 2005). As a direct result of this literature, it is now well understood that, for firms even to attempt to imitate the results of innovation carried out by other firms, it is necessary for the would-be imitator firms to have acquired skills and knowledge relevant to research, development and innovation and to the translation of innovation results into improved productivity performance.

Thus skills are widely recognised as central to firms' absorptive capacity (AC), either in the form of skills and knowledge held by individual employees or skills and knowledge that are collective in nature and come into play only through the combined efforts of employees. Furthermore, just as skills and AC represent important intangible assets at firm level, so the combined skills and AC of firms in different industries and countries can also be expected to affect innovation and productivity performance at those levels of aggregation. Indeed, recent research by Andrews, Criscuolo and Gal (2015) suggests that the ability of leading national firms to narrow the productivity gaps between themselves and leading global firms at industry level is positively related to the quality of national education systems. [2] Ang and Madsen (2015) identify strong links between innovation performance and educated workers in OECD countries.

But which specific kinds of education and skills contribute most to the development of AC and subsequently to innovation and productivity growth? The answers to these questions are potentially highly relevant to understanding cross-country differences in

[1] The research for this paper has been supported by the Economic and Social Research Council (grant reference ES/J019135/1) via the Centre for Research on Learning and Life Chances (LLAKES), UCL Institute of Education, London. We are grateful to the ESRC and LLAKES for their financial support and to LLAKES seminar participants for helpful comments on previous versions of this paper. Responsibility for remaining errors is ours alone.

[2] Education quality is here measured through students' performance in international tests of cognitive skills such as mathematics and science.

economic performance because of marked differences in national education and training institutions.

For example, some researchers have argued that specialized vocational education in some European countries is less well suited to developing the skills needed to make use of new ideas and technologies than general or academic education which is more common in the US (Krueger and Kumar, 2004). This may help explain why the US has tended to outperform European countries in terms of productive applications of Information and Communication Technologies (ICTs) and the estimated contribution of ICTs to growth in labour productivity (O'Mahony and van Ark, 2003; Van Ark, O'Mahony and Timmer, 2008). [3]

In this respect the US is notable for a relatively high share of university graduates and several comparative studies focussing on the links between skills, innovation and growth at country or country/industry level have measured skills by the proportion of employees with tertiary education (for example, Griffith et al, 2004; Vandenbussche et al, 2006). However, there is increasing evidence that, in assessing the role of skills in the development of AC and in supporting innovation and growth, account also needs to be taken of contributions made by intermediate-skilled workers and by uncertified skills (Mason, O'Leary and Vecchi, 2012) as well as the impact of complementarities and interdependence between high-level skills and other types of skill (CEDEFOP, 2014; Rincon-Aznar et al, 2015).

Empirical investigation of the links between skills and AC has long been clouded by the absence of direct measures of AC which has often been proxied by measures of R&D intensity (a relatively narrow measure of innovation input) or even by measures of skills themselves. [4] In this paper we address this problem by constructing indicators of different components of AC which enable the separate contributions of skills, R&D intensity and other relevant variables to be distinguished and evaluated. We then draw on detailed

[3] Marsh, Rincon-Aznar, Vecchi and Venturini (2017) show that US firms endowed with a large base of absorptive capacity were better-equipped to accommodate the arrival of the new digital economy in the mid-1900s and, compared to other firms, were able to exploit industry-level spillovers associated with the diffusion of ICT. In their paper AC is measured as the cumulative value of R&D spending.

[4] See Lane, Koka and Pathak (2006) for a detailed discussion of AC measurement difficulties.

estimates of the composition of workforce skills at industry level in the US and seven European countries – which enable us to distinguish between high-level and intermediate skills – in order to explore the links between skills, AC, innovation and productivity performance in depth.

The paper is ordered as follows: Section 2 discusses relevant theory and measurement issues and sets out the main hypotheses to be tested. Section 3 outlines our main empirical specifications. Section 4 describes our data sources and presents descriptive statistics for key variables. Sections 5-6 present our main findings and associated robustness tests. Section 7 concludes.

2. Skills and absorptive capacity: theory, measurement issues and hypotheses

Theorising on AC is closely linked to the concept of knowledge spillovers – whereby knowledge created within one firm becomes available to other firms. Several potential transmission mechanisms have been identified in the literature, for example, the diffusion of new technologies and management practices and the spread of ideas and 'solutions to problems' up and down business supply-chains. Such transfers are often facilitated by inter-firm mobility of engineers and scientists and the personal networks built up by engineers and scientists (Griliches, 1992; Lundvall, 1992; Guellec and van Pottelsberghe de la Potterie, 2001; Bottazzi and Peri, 2007; Mason, Beltramo and Paul, 2004).

Many spillover effects of this kind derive from foreign direct investment (FDI) and exposure to foreign competition through trade (Keller, 2004), especially imports of new technology-based imports of intermediate and capital goods (Van Pottelsberghe de la Potterie and Lichtenberg, 2001; Madsen, 2008). At industry level, openness to FDI and foreign trade may also help speed up the diffusion of new technologies within each country from high-productivity multinational firms to lower-productivity domestic firms (Griffith, Redding and Simpson, 2009).

However, the creation of learning opportunities through international openness does not in itself ensure that potential recipient firms can take advantage of those opportunities. For example, the impact of spillovers through investment by multinational enterprises may be reduced if home-country firms lack the ability to absorb new knowledge and technologies, or are unable to withstand the increase in competition (Aitken and Harrison, 1999; Harris and Robinson, 2004).

Factors enabling technology and knowledge transfer are often described as the 'antecedents' of AC within firms, that is, the resources and capabilities built up by firms over time which enable them to identify and make effective use of external knowledge (Van den Bosch et al, 2003; Jansen et al, 2005; Fosfuri and Tribo, 2008; Franco, Marzucchi and Montresor, 2014). This emphasis on capability development draws on resource- and knowledge-based theories of the firm which seek to explain heterogeneity in firm performance (Teece et al, 1997; Phelan and Lewin, 2000; Eisenhardt and Martin, 2001; Teece, 2007). The resources and capabilities which underpin AC can only be developed over time through prior investments in R&D and innovation, in knowledge search activities and in skills acquisition and development.

In order to assess the role of particular types of skill in developing AC, it is useful – following Zahra and George (2002) – to distinguish between *potential absorptive capacity* (the ability to recognise, acquire and assimilate useful external knowledge) and *realised absorptive capacity* (the ability to transform and apply acquired knowledge effectively within organisations). 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 – different types of skill may be required. 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 (i.e., realise their absorptive capacity) will depend in many ways on intermediate-skilled employees 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 (Mason and Wagner, 2005; CEDEFOP, 2014).

As discussed above, many earlier studies have found it difficult to distinguish clearly between AC and its antecedents such as R&D spending and skills because indicators of R&D intensity and/or skills have themselves been used – separately or in combination – as proxy measures of AC. A key advantage of distinguishing between potential absorptive capacity (PAC) and realised absorptive capacity (RAC) is that it allows for deeper investigation of the role of skills at different stages of the innovation process.

For example, making a clear distinction between PAC and RAC, Fosfuri and Tribo (2008) and Franco et al (2014) derive estimates of PAC from Community Innovation Survey (CIS) data on external knowledge sources and external R&D cooperation. They then explore the effects of skills and other 'integration mechanisms' which might help translate PAC into RAC within firms, with RAC being proxied by different measures of innovative output. Integration mechanisms here refer to the resources and modes of organisation deployed by which firms to help them 'integrate, assimilate and exploit' external knowledge (Franco et al, 2014: 333). In addition to the deployment of skilled workers, other examples of integration mechanisms relevant to the conversion of PAC into RAC include steps taken by firms to improve internal communications, knowledge-sharing and departmental coordination (Jansen et al, 2005; Engelen et al, 2014).

These studies shed light in particular on the moderating effects of skills in relation to innovation performance. For example, Franco et al (2014) find that skills interact with their measure of PAC (based on external knowledge sourcing patterns) to have significant positive effects on RAC (defined as the share of output attributable to innovative products new to the market). [5] This is consistent with Escribano et al (2009) who find a positive moderating contribution to innovative performance by AC as a whole when different measures of skill are included as components of proxy measures of AC. [6]

From our perspective – aiming to explore the contribution of skills at all stages of the innovation process – an alternative approach which might be fruitful is to recognise that, while RAC can be adequately proxied by different measures of innovative output, it may be harder to find any single adequate measure of PAC. This seems all the more likely if we take account of Lane et al (2006)'s distinction between two different types of learning associated with the accumulation of PAC, namely, exploratory learning (helping to recognise potentially valuable external knowledge) and transformative learning (helping to assimilate such knowledge within each firm).

In this context we propose to retain separate measures of recognised components of PAC – in particular, skills and R&D investments – in order to examine the strength of their respective contributions to the accumulation of PAC and its translation into RAC. In so doing we make use of a cross-country industry-level dataset which enables us to take account of a key dimension to PAC that is hard to measure at firm level, namely, differences between economic units in the *opportunities* to acquire useful external knowledge. Specifically, we develop measures of openness at country/industry level which are derived from data on foreign trade and foreign direct investment – both

[5] Franco et al (2014) define skills as the presence of innovation-related training programmes at firm level and/or no reported problems due to lack of qualified workers.
[6] Specifically, Escribano et al (2009) derive AC as the principal component of four variables, two related to R&D spending, one related to training provision and one related to the employment share of engineers and scientists.

activities which, as discussed above, economic theory suggests are central to potential knowledge spillovers across national borders.

These data enable us to evaluate the extent to which different skills contribute to innovative output by enhancing the ability of firms in each country/industry to take advantage of the opportunities presented by openness. Bearing in mind the potential contributions of both high-skilled and intermediate-skilled workers noted above, we submit the following hypothesis to empirical scrutiny:

H1: The conversion of opportunities for external knowledge sourcing (openness) into innovative output (RAC) is positively related to:

(A) employment of high-skilled workers

(B) employment of intermediate-skilled workers such as technicians and craft-skilled workers [7]

In addition to contributing to growth in innovative output through AC-related mechanisms, different types of skill may also contribute to growth in final output at country/industry level by facilitating the adoption and diffusion of foreign production technologies which help technologically lagging countries to catch up with technology leaders (Bernard and Jones, 1996; Cameron, Proudman and Redding, 2005). In this context productivity growth may be positively related to a country's distance from the technology frontier so long as it has sufficient levels of skill to identify and make use of technologies developed elsewhere. Deploying models of this kind, Benhabib and Spiegel (1994) find that human capital stocks are positively associated with individual countries' ability to narrow the gap between themselves and the world-leading nation in terms of productivity.

With regard to the specific level of skills that are required, Vandenbussche et al. (2006) develop a theoretical model in which high-level skills contribute more to productivity the closer a country is to the technological frontier. In their work high-skilled workers are

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[7] Using a proxy measure of skills based on formal qualifications, a common definition of 'intermediate' refers to certificates or diplomas which lie below university graduate (Bachelor degree) level but are above proficiency levels regarded as 'semi-skilled'.

defined as tertiary-educated workers (a category which includes some workers with post-secondary intermediate-level education as well as university graduates). They argue that technologically advanced countries are more likely to engage in innovation (requiring high-level skills) than they are in imitation (requiring lower levels of skills) because advanced countries have fewer opportunities for imitation than less advanced countries. Their empirical results suggest that, while growth in multi-factor productivity (MFP) [8] is negatively related to proximity to the technological frontier, it is positively related to the interaction between proximity and high-level skills. However, the interaction between proximity and lower-level skills is not significantly related to MFP growth. These findings imply that highly skilled workers are indeed more important than lower-skilled workers (including many with intermediate-level skills) for countries closer to the frontier.

In related analysis Ang and Madsen (2015) find a strong positive relationship between MFP growth and the interaction between proximity to the technological frontier in OECD countries and employment of tertiary-educated workers. Similar to Vandenbussche et al. (2006), they find no significant relationship between MFP growth and the interaction between secondary education and proximity to the technological frontier.

Of particular interest, Ang and Madsen find that the relationship between tertiary education and proximity is strengthened by the contributions made by older tertiary-educated workers, perhaps reflecting the value of job experience and the advantages that older workers tend to have in crystallised intelligence relative to younger workers whose strengths tend to lie in fluid intelligence (Horn and Cattell, 1962; Salthouse and Maurer, 1996). [9]

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[8] Growth in MFP is defined residually as the increase in output that cannot be attributed to increases in the measured quantity of production inputs such as physical capital or labour and the measured quality of those inputs (referring to skills in the case of labour inputs). Thus, among other things, MFP captures the extent to which growth in output derives from more efficient deployment of existing resources and the effects of 'disembodied' technical change, that is, technical improvements and innovations which are not embodied in measured capital inputs. Other variables which may be picked up by an MFP measure include economies of scale, capacity utilisation and measurement errors of different kinds.

[9] Horn and Cattell (1962) define fluid intelligence as reflecting the impact on intellectual abilities of heredity and injury (such as impairment with age) while crystallised intelligence reflects the impact on abilities of learning acquired over time, for example, through work experience and continuing education and training, whether formal or informal in nature.

The MFP and skills literature thus strongly suggests that tertiary-level skills contribute more than lower-level skills to MFP growth in countries and industries where previous innovation has narrowed the gap with technology leaders. In our analysis at country-industry level we track the contribution made by innovative output (RAC) to MFP growth in the form of innovation inputs to final production and, as indicated above, we are able to distinguish clearly between high-level and intermediate skills (discussed further in Section 4). We are thus able to test the following hypothesis relating to the contributions of different types of skill to growth in final output:

H2: All else being equal, after controlling for the contribution of growth in innovation inputs to growth in productivity, the proximity of MFP levels to the technological frontier is:

(A) positively related to employment of high-skilled workers

(B) *not* significantly related to employment of intermediate-skilled workers

3. Empirical specification

We seek to identify the impact of skills in developing absorptive capacity by looking at two possible channels of transmission through to industry-level productivity performance. First, we investigate the extent to which different kinds of skill help to exploit external knowledge in developing new innovations, here measured by patent counts; this effect feeds through to productivity growth only indirectly, as patentable innovations are incorporated into final outputs. Second, we assess the role of different kinds of skill in helping to adapt and exploit external knowledge in improving production efficiency; the latter effect potentially has a direct influence on growth in multi-factor productivity (MFP). To this aim, we adopt a multi-equation regression framework in the spirit of the model proposed by Crepon et al (1998). This structural approach has been extensively used to study the effect of R&D effort on patenting, innovation and in turn MFP growth, mainly using firm-level data.

In the present paper, we make use of cross-industry, cross-country data for eight countries between 1995-2007 (see Section 4 below for further details of this dataset). We estimate a simultaneous system of three equations, modelling the impact of key components of PAC – openness, skills and R&D spending – on a measure of RAC (that is, innovative output, here measured as growth in patents per hour worked) and the subsequent contributions of innovative output and skills to MFP growth.

In the first equation of the system, the dependent variable is a measure of openness to foreign trade and foreign direct investment (FDI). The key independent variables reflect the institutional setting which helps shape trade relations between countries and the potential for cross-border knowledge exchange and transfer through trade and investment:

$$(1) \quad Openness_{ij,t} = \alpha_{ij0} + \alpha_1 \ln \bar{A}^f_{it} + \alpha_2 \ln TradeInvestmentBarriers_{jt}$$

$$+\alpha_3 \ln IndustrySize_{jt} + TD + \epsilon_{ijt}$$

in which, for industry *i* in country *j* in period *t*, $\bar{A}^f$ is the sum of patent stocks per worker in industry *i* in foreign countries. Building on Bottazzi and Peri (2007), $\bar{A}^f$ is proportional to the volume of technologically advanced ideas which are patented in the same industry in foreign countries and thus serves as a measure of the foreign knowledge sourcing opportunities to which each domestic industry may gain access through trade and FDI.

TradeInvestmentBarriers is a country-level indicator reflecting the strength of policy barriers to trade and FDI in each country. *IndustrySize* (proxied by total hours worked) is expected to capture an inverse relationship between involvement in trade and the size of domestic markets. α_{ij0} are country-by-industry fixed effects capturing unobserved time-invariant characteristics of the sector *ij* which are relevant to openness such as industry structure. TD are common time dummies and ε are spherical errors. α_1 is a semi-elasticity predicting the proportion of foreign knowledge which is potentially available to each country-industry pair.

Following the latest (second-generation) developments of Schumpeterian growth theory (Ha and Howitt 2007), in the second equation of the model we adopt a knowledge production function which takes account of the potentially negative effects of product proliferation on the effectiveness of R&D. Innovative output is assumed to depend on a measure of R&D effort adjusted for product expansion and the stock of existing patented knowledge. Thus R&D input is corrected to account for the effect of increasing consumer demand for product varieties which leads to R&D expenditure being spread over a larger number of product innovation projects (see Venturini, 2012a). This makes R&D expenses per product line stationary over time. The idea production function is modelled as follows (time and industry subscripts omitted for simplicity):

$\frac{\dot{A}}{A} = \lambda \left(\frac{RD}{Y}\right)^{\sigma} A^{\phi-1}$ where $\dot{A}$ is the flow of new patented ideas while A is the existing stock of ideas. Hence their ratio identifies the growth in patent stock. Product expansion can be approximated by the value of production and hence adjusted R&D input can be measured by the intensity of R&D expenses over output, *RD/Y*. λ is an exogenous (poissonian) parameter of research productivity, while σ is the elasticity of innovation output to R&D effort. ϕ measures inter-temporal returns to scale in innovation, in essence capturing the extent to which the generation of new ideas depends on existing knowledge.[10]

[10] If ϕ is unitary, this points to constant returns to scale in knowledge production, that is, in generating new ideas. If ϕ is less than unity, this implies decreasing returns, whilst the reverse holds when ϕ is greater than one.

In this context, we estimate a log-linearized version of the above knowledge production function which is extended to account for the effect of skills and openness. [11] The dependent variable (innovation output) is approximated by $\Delta \ln \dot{A}$ as in Madsen (2008) and Madsen et al (2010):

$$(2) \qquad \Delta \ln A_{ijt+1} = \alpha_{ij0} + \alpha_1 \ln A_{ijt} + \alpha_2 \ln \frac{RD}{Y}_{ijt} + \alpha_3 \ln Skills_{ijt}$$

$$+\alpha_4\, Openness_{ijt} + \alpha_5 [\ln Skills_{ijt} * Openness_{ijt}] + TD + \epsilon_{ijt}$$

All right-hand side variables are one-year lagged relative to the dependent variable. On the basis of the underlying theory, we expect α_1 to be negative and α_2 to be positive. Positive values for α_3 and α_4 would indicate that growth in patent stocks is facilitated by direct effects from, respectively, openness and skills. At the same time, if the coefficient on the skills/openness interaction term (α_5) is positive and significant, this would point to an additional positive and indirect effect of skills on patenting by enhancing the ability of industry *i* to take advantage of the external knowledge sourcing opportunities associated with openness.

The third equation uses a distance-to-frontier framework to model multi-factor productivity (MFP) growth at country/industry level as a function of MFP growth at the technological frontier (denoted by F), innovation output, skills and the proximity of each industry to the frontier. To capture the role of skills in facilitating technology transfers from the frontier, we interact the proximity terms with various measures of skill:

$$(3) \qquad \Delta \ln MFP_{ijt+2} = \alpha_{ij0} + \alpha_1 \Delta \ln MFP_{iFt+2} + \alpha_2 PROX_{ijt+1} + \alpha_3 \ln Skills_{ijt+1}$$

$$+\alpha_4 \Delta \ln A_{ijt+1} + \alpha_5 [\ln Skills_{ijt+1} * PROX_{ijt+1}] * +TD + \epsilon_{ijt}$$

Except for the frontier growth term, all the right-hand side variables are one-year lagged with respect to the dependent variable. If the coefficient on the interaction term (α_5) is positive and significant, this suggests that the skills in question contribute more to MFP growth in industries closer to the productivity frontier than they do in lagging industries (Griffith et al, 2004; Islam et al, 2014).

[11] Note that in this specification logs are not taken for our openness measure since, as described in Section 4 below, it is derived from data on foreign trade and foreign direct investment as a factor score with mean zero and standard deviation of one.

In the analysis that follows, Equations 1-3 are jointly estimated by three-stage least squares (3SLS) which is a well-known means of taking account of interdependence in the relationships between economic variables. Simultaneity issues are addressed by the series of lag structures built into the three equations.

In principle, 3SLS estimates should provide consistent and more efficient estimates than two-stage Instrumental Variables (IV) methods of dealing with endogeneity problems because 3SLS is able to take account of any correlation between cross-equation error terms (Pindyck and Rubinfeld, 1981). As a further check on potential endogeneity issues, we also explore the use of instrumental variables in robustness tests reported in Section 6.

4. Data sources and descriptive statistics

4.1 Data description

Our country/industry dataset has been assembled from a variety of sources and covers seven manufacturing industries in eight countries (Denmark, France, Germany, Netherlands, Spain, Sweden, UK, US) for 1995-2007. The seven industries are (with ISIC Rev 3.1 classification codes):

- Food, drink and tobacco (15-16)
- Chemicals and related industries (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)

The analysis focusses on manufacturing industries in order to be able to use patent applications as a measure of innovative output.

As a measure of the endowment of technological knowledge (ideas), patent stock, A, is derived from applying the permanent inventory method to the annual flow of fractional patent applications at the European Patent Office (source: OECD EPO patent database). A depreciation rate of 15% is applied. Patent applications are assigned to industries, identified on the basis of the two-digit ISIC Rev. 3 classification, using the concordance table of intellectual property classes (IPC) developed by Schmoch et al (2003). $\bar{A}^f$ is defined as the unweighted sum of patent stocks across countries at industry level (excluding the reference country j).

To characterise each country's institutional setting with regard to internationalization, *TradeInvestmentBarriers*, we use a country-level OECD measure, which reflects the strength of policy barriers to foreign direct investment (FDI), tariff barriers, differential treatment of foreign suppliers and barriers to trade facilitation. [12]

[12] Source: https://www.oecd.org/eco/growth/indicatorsofproductmarketregulationhomepage.htm#indicators
Copies of the relevant files accessed in 2016 are also available from the authors on request.

We derive a measure of openness at country/industry level through a factor analysis of data on exports, import penetration and FDI inflows and outflows (all expressed as a proportion of gross output). Trade figures are taken from the OECD Bilateral Trade database whilst FDI inflows and outflows series are derived from the OECD FDI statistics database.[13] The factor analysis yields a single factor which explains 67% of the total variation in export, import and FDI measures and is readily interpretable as a summary measure of openness.[14]

As a measure of R&D effort adjusted for product variety, we use the ratio of R&D expenses over value added (both expressed at current prices) as described in Section 3. R&D expenditure is taken from the OECD ANBERD database while industry value added is derived from the EU KLEMS database.

The following variables are derived from the EUKLEMS database as described in O'Mahony and Timmer (2009):

(1) Multi-factor productivity, *MFP*, obtained assuming a multi-country translog production function based on value added, capital and labour.
(2) Levels of gross value added (at basic prices) and capital stock are expressed in constant prices (1997 US dollars converted on the basis of industry power purchasing parities; see Inklaar and Timmer 2008).
(3) Capital input is defined as the flow of productive services provided by capital assets employed in production (derived through a perpetual inventory method using national accounts data on gross fixed capital formation; constant prices, 1997 US dollars)
(4) Labour input (unadjusted for skill): Total hours worked by persons engaged (employees plus self-employed)
(5) Quality-adjusted labour (QAL) input: Total hours worked by persons engaged multiplied by a labour quality index derived from EUKLEMS labour composition estimates which take account of workforce heterogeneity in terms of formal educational qualifications, average hourly pay, gender and age. These estimates

[13] FDI flows and total gross output are aggregated to three-year periods because of unevenness in annual FDI flows at country/industry level.
[14] Factor test scores: Cronbach's alpha measure of internal reliability: 0.696; Kaiser-Meyer-Olkin measure of sampling adequacy: 0.510; Bartlett's test of sphericity: $p<0.001$***

rely on an assumption of perfectly competitive markets in which a firm will hire an additional hour of labour up to the point where the worker's marginal productivity equals his/her marginal cost. [15] Thus, implicitly, the estimates take account of uncertified skills which contribute to individual productivity levels as well as skills which are certified by possession of formal qualifications.

In order to obtain skill measures which are comparable across countries, we first define a measure of aggregate skill levels by taking the ratio of the EUKLEMS measure of quality-adjusted labour inputs in industry i and country j (QAL_{ij}) to the total number of hours worked (L_{ij}):

(4) $$skills_{ij} = \left(\frac{QAL_{ij}}{L_{ij}} \right)$$

This measure of aggregate skills, which (as described above) takes some account of uncertified skills as well as certified skills through its *QAL* component, is then systematically compared in our analysis against three other skill measures which only take account of certified skills (formal qualifications) but – in contrast to input measures of education such as years of schooling – do measure educational attainments.

These qualification-based skill measures (derived from Labour Force Surveys for European countries and the Current Population Survey for the US) are:

(5) $$higher_{ij} = (L_{ij\_high}/L_{ij})$$

defined as the number of hours worked by persons with Bachelor degree qualifications or postgraduate university qualifications (L_{ij_high}), divided by the total number of hours worked (L_{ij});

(6) $$upperint_{ij} = (L_{ij\_upper}/L_{ij})$$

defined as the proportion of worker-hours with certified upper intermediate level skills (L_{ij_upper}) such as Associate degrees in the US and technician-level qualifications in the European countries; and

[15] Under this assumption a measure of quality-adjusted total labour input is obtained by weighting each different type of labour input (as signified by qualification levels) by the share that each type of labour occupies in total labour compensation (see, for example, Jorgenson et al, 2005).

(7) $lowerint_{ij} = (L_{ij\_lower})/L_{ij})$

defined as the proportion of worker-hours with certified lower intermediate level skills (L_{ij_lower}) including high school diplomas in the US and craft-level qualifications in the European countries. [16]

4.2 Summary statistics

Comparisons across all eight countries show the Netherlands and Denmark well ahead on the openness indicator, reflecting relatively high levels of exposure to both trade and FDI in manufacturing in those two countries, while the US ranks last, in large part due to its relatively low exposure to foreign trade (Appendix Figure A1). In the case of Germany, France and Spain, medium-low estimates of openness reflect the fact that their considerable exposure to foreign trade is offset by comparatively low levels of FDI flows in most branches of manufacturing.

By contrast, countries such as the US and Sweden which rank fairly low on the openness measure turn out to be relatively heavily engaged in R&D spending (Figure A2). [17] In Sweden this shows up in a relatively high ranking on a measure of innovative output (average patent stocks per hour worked) but the same is not true for the US (Figure A3). Overall, the Netherlands ranks highest on this measure of innovative output in both 1995 and 2007, with Germany ranked second in 1995 and Sweden second in 2007.

Aggregate skills (that is, $skills_{ij}$, the ratio of quality-adjusted labour inputs to total hours worked) were highest in the US at both the start and end of the 1995-2007 period, with Spain ranked second and France third while Denmark was ranked last in both years (Figure A4). Information on formal qualification levels suggests that the US lead was largely based on higher shares of both university graduates and holders of upper intermediate qualifications across all branches of manufacturing (Figures A5-6).

[16] See Appendix B for further details of the classification of qualifications in each country and national data sources on qualifications.

[17] In Figure A2 R&D expenditure and total sales are aggregated to three-year periods because of unevenness in annual R&D spending flows at country/industry level.

By contrast, Germany was strongest in terms of the lower intermediate share of total hours worked, with Denmark ranked second, reflecting the relative strength of apprenticeship training in both those countries (Figure A7). In Germany this lead on lower intermediate skills applied across all branches of manufacturing while in Denmark it applied mainly to metal goods, mechanical engineering and vehicle manufacturing. The lowest employment shares of lower intermediate-skilled workers were found in Spain and Sweden which contributes to those two countries recording the highest shares of low-skilled workers in both 1995 and 2007 (Figure A8).

In their different ways both Spain and Sweden exemplify countries which rely almost wholly on school-based vocational education and training (rather than on work-based training) and are sometimes criticised for the relatively weak links between vocational education and employment (Kuczera et al, 2008; OECD, 2007). However, as noted above, Spain in particular ranks second only to the US on the aggregate skills measure which takes some account of uncertified skills as well as formal qualifications.

5. Econometric findings

Results from three-stage least squares estimates of Equations 1-3 are reported in Tables 5.1-5.4. These estimates make use in turn of the following four skill measures:

(1) high-skilled employment share

(2) upper intermediate employment share

(3) lower intermediate employment share

(4) aggregate skills

The aggregate skills measure is derived as shown in Equation 4. Other skill measures are qualification group shares of total hours worked (derived as shown in Equations 5-7).

In order to test Hypotheses 1 and 2, we pay particular attention to the contributions of different types of skill to the conversion of opportunities for external knowledge sourcing (openness) into innovative output and the extent to which each type of skill influences MFP growth.

5.1 Openness to foreign knowledge sources

Across all four sets of estimates of Equation 1, our measure of openness (derived from trade and FDI data) is significantly positively related to foreign patent stocks per hour worked, with an effect that varies very little across each regression (Tables 5.1-5.4). As expected, the coefficient on the country-level measure of policy barriers to trade and FDI (*TradeInvestmentBarriers*) is significantly negative in a majority of specifications and the same is true for *IndustrySize* which is used as an indicator of domestic market size.

In estimates of Equation 2, where the dependent variable is growth in patent stocks per hour worked (our measure of innovative output, that is, RAC), the openness measure on its own is not significantly related to innovative performance in three of the four sets of estimates. However, as we now go on to discuss, when openness is interacted with different types of skill and with R&D intensity, the results suggest that – conditional on the skills and R&D spending deployed by firms in different country/industry units – the degree of openness to foreign trade and investment is strongly indirectly related to innovative performance.

5.2 The contributions of skills, R&D intensity and openness to growth in innovative output

With regard to estimates of Equation 2, Tables 5.1-5.4 again show separate regressions for each skill measure in turn. Column 1 in each of these tables presents baseline estimates without interactions. The specifications in Columns 2-3 admit singly the interactions between openness and skills and openness and R&D respectively, while Column 4 includes both sets of interactive terms.

In line with theoretical expectations, the baseline estimates all show that growth in the patented knowledge stock is positively and significantly related to the intensity of R&D effort in the previous year but is inversely related to the existing stock of patents in that year. The latter finding is consistent with diminishing technological opportunities in knowledge generation due to apparent declines in research productivity in many contexts. For example, recent research by Bloom et al (2017: 1) suggests that 'ideas are getting harder and harder to find' (see also Segerstrom, 1998 and Venturini 2012b). Focussing on Equation 2, Column 1 in each table, a one percentage point (pp) increase in the stock of patents is associated with a lower rate of growth in patented knowledge of 0.09-0.11% in the following year.

The significantly positive coefficients attached to R&D intensity are roughly in line with the values reported in earlier comparable studies; see Ang and Madsen (2011) for a cross-country analysis and Venturini (2012a) for an industry-level study focussed on the US. A one pp increase in the ratio of R&D expenditure to value added (*RD/Y*) is associated with faster rate of growth in patented knowledge of approximately 0.02% in the following year. The fact that this estimated R&D impact is not larger may reflect the detrimental effect of product variety expansion (*Y*), that is, the dilution of R&D effort across a larger number of product projects which puts downward pressure on aggregate rates of innovation (Madsen, 2008).

With regard to skills, the estimates of Equation 2 without interactions suggest that innovative output – growth in patent stocks per hour worked – is positively and significantly related to high-level skills. However, it is significantly negatively related to upper intermediate skills and not significantly related to lower intermediate skills or the aggregate skills measure.

As shown in Table 5.1, Equation 2, Column 1, a one pp increase in the high-skilled share of hours worked is associated with faster rate of growth in patented knowledge of 0.04% in the following year. To some extent this may underestimate the impact of high-skilled workers in R&D departments because a large proportion of R&D expenditure (perhaps as much as 50%) takes the form of researchers' wages.[18] To the extent that researchers' productivity is fully captured by their wages, the share of hours worked by highly educated workers will not capture the impact of human capital employed in R&D labs. Thus the coefficient on the high-skilled labour share is likely to capture:

(1) positive effects of high-skilled R&D labour to the extent that their productivity exceeds their wages, plus
(2) the contributions made by high-skilled workers outside R&D departments which are complementary to the efforts of researchers, engineers and scientists directly employed in R&D. Examples of contributions to innovative output by high-skilled non-R&D workers may include roles in strategic management and involvement in feedbacks from production and design departments to R&D project aims and methods.

In addition to the apparent direct positive contribution of high-skilled labour to innovative performance, the results shown in Tables 5.1-5.4, Equation 2, Columns 3-4 shed light on Hypothesis 1 which posited the existence of potential *indirect* effects of skills on innovative performance by facilitating the conversion of opportunities for external knowledge sourcing (openness) into innovative output.

Growth in patent stocks per hour worked is positively and significantly related to the interacted skills/openness variable for the previous year in the case of both high-level skills and upper intermediate skills. However, the skills/openness interactions are non-significant in relation to lower intermediate skills and the aggregate skills measure. These

[18] Source: OECD Research and Development Statistics.
See http://stats.oecd.org/Index.aspx?DataSetCode=ONRD_COST

findings provide strong support for Hypothesis 1A that high-level skills have positive effects on each country/industry's ability to convert opportunities for external knowledge sourcing into innovative output. But there is only partial support for Hypothesis 1B regarding the indirect effects of intermediate skills on innovative output, with support confined to the upper end of the intermediate skills spectrum.

As noted above, upper intermediate skills were associated with a slower rate of knowledge growth in the baseline estimates of direct skills effects (Table 5.2, Equation 2, Column 1). However, on the basis of the extended model taking account of interactions between skills and openness, upper intermediate skills are found to make a strong positive indirect contribution to future patenting performance by helping to adapt and implement external knowledge. This is consistent with the main contribution of technicians and other intermediate-skilled workers taking the form of support for high-skilled R&D workers in areas such as new product design and development as opposed to intermediate-skilled workers playing an independent role. At the same time, the estimated coefficient on the upper intermediate skills/openness interacted variable is substantially higher than that attached to the interaction between high-level skills and openness. This may reflect the underestimation of high-skilled workers' contributions discussed above.

Growth in patent stocks per hour worked is also found to be positively and significantly related to the interacted R&D intensity/openness variable for the previous year, suggesting that, alongside higher and upper intermediate skills, R&D spending contributes positively to the conversion of opportunities for external knowledge sourcing into innovative output.

These results are broadly confirmed when the empirical model is extended to include both the interaction between openness and R&D intensity and the interaction between openness and skills (Tables 5.1-5.4, Equation 2, Column 4). Notably, in this specification, the indirect contribution of skills predominates over the indirect R&D contribution in the case of both high-level skills and upper intermediate skills. However, the R&D/openness interactions predominate when skills are represented by the lower intermediate category and the aggregate skills measure. These findings strengthen support for Hypothesis 1A but support for Hypothesis 1B remains partial, being confined to upper intermediate skills.

5.3 The contributions of skills and realised absorptive capacity to growth in multi-factor productivity

Tables 5.1-5.4 also display estimates for the MFP growth model (Equation 3), based on the distance-to-frontier approach. In line with theoretical expectations, the rate of MFP growth is found to be positively and significantly related to productivity growth at the frontier, indicating that when the frontier moves outward, new opportunities for further productivity improvements by laggards are created. MFP growth is also positively related to increases in RAC (innovative output) in the previous year, significantly so in half of the specifications but falling short of statistical significance while remaining positively signed in the remaining models. [19] Overall, these findings are consistent with growth in innovative output translating into better productivity performance due to factors such as cost reductions, efficiency increases and/or helping to secure greater market shares for new products.

In line with many previous studies, MFP growth is negatively and significantly related to proximity to the technological frontier in a large majority of specifications, confirming that country/industry units far from the frontier typically benefit most from the scope for knowledge transfers from technological leaders.

When different measures of skills are interacted with the proximity measure, the resulting coefficients are positive significant in the case of high-level skills, upper intermediate skills and the aggregate skills measure while being non-significant in the case of lower intermediate skills. These findings provide strong support for Hypothesis 2A which posited that, after controlling for the contribution of growth in innovation inputs to growth in productivity, employment of high-skilled workers is positively related to the proximity of MFP levels to the technological frontier. However, we do not find support for

[19] In the case of models where skills are represented by high-level skills (Table 5.1), the lack of statistical significance attached to the positive coefficients on growth in innovative output (patents per hour worked) may partly reflect the high degree of overlap between the effects of innovative output and the effects of skills.

Hypothesis 2B (suggested by the existing literature) that employment of intermediate-skilled workers is *not* significantly related to the proximity of MFP levels to the technological frontier.

Indeed, the positive coefficient on the upper intermediate skills/proximity interaction suggests that, even when country/industry units are relatively close to the technological frontier, MFP growth benefits not just from high-level skills but also from high-level skills being complemented by upper intermediate skills to some extent. By facilitating the adoption of best practices, new business models and investment in other intangible assets, upper intermediate-skilled workers may contribute to spillovers that increase productivity levels (Corrado et al. 2015).

At the same time the positive significant coefficient on the aggregate skills/proximity interaction is notable since the aggregate skills measure not only covers all sections of the workforce but also takes account of uncertified skills (for example, those acquired through informal on-the-job training and work experience), not just formal qualifications. Thus the positive coefficients on both the aggregate skills measure and the aggregate skills/proximity interaction in Table 5.4, Equation 3 imply that the translation of RAC into productivity performance in the production of final goods and services depends on the skills of the workforce as a whole – unlike in the production of innovative outputs (such as patents) where high-level and upper intermediate skills are more important than lower levels of skill. Since the aggregate skills measure also takes account of the age of workers as an indicator of work experience (see Section 2 above), the positive interaction between aggregate skills and proximity to the frontier is consistent with the strong positive relationship found by Ang and Madsen (2015) between MFP growth and the interaction between proximity to the technological frontier and employment of older tertiary-educated workers in OECD countries.

Table 5.1: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using higher skills measure

	(1)	(2)	(3)	(4)
(1) Dependent variable: openness (t)				
ln foreign patent stocks per hour worked (t)	0.4031***	0.3989***	0.3822***	0.3812***
	[0.043]	[0.042]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0696*	-0.0161	-0.0845**	-0.0862**
	[0.036]	[0.033]	[0.036]	[0.036]
ln industry size (t)	-0.0776	-0.0089	-0.1114*	-0.1145*
	[0.061]	[0.057]	[0.061]	[0.061]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)				
ln patent stocks per hour worked (t)	-0.1029***	-0.1614***	-0.1366***	-0.1307***
	[0.021]	[0.025]	[0.026]	[0.026]
ln R&D intensity (t)	0.0173***	0.0452***	0.0195***	0.0246***
	[0.006]	[0.012]	[0.006]	[0.008]
ln higher skills (t)	0.0403***	0.0414***	0.0806***	0.0746***
	[0.014]	[0.015]	[0.021]	[0.021]
openness (t)	0.0594	0.2861***	0.1883**	0.1688**
	[0.039]	[0.060]	[0.074]	[0.073]
ln R&D * openness (t)		0.0491**		0.0095
		[0.019]		[0.011]
ln higher skills * openness (t)			0.0975**	0.0818**
			[0.038]	[0.040]
(3) Dependent variable: growth in multi-factor productivity (t+2)				
Δ ln lead-country MFP (t+2)	0.7147***	0.7148***	0.7146***	0.7154***
	[0.032]	[0.032]	[0.032]	[0.032]
ln proximity (t+1)	-0.0657***	-0.0654***	-0.0656***	-0.0675***
	[0.023]	[0.023]	[0.023]	[0.023]
Δ ln patent stocks per hour worked (t+1)	0.1404	0.1459	0.1678*	0.1235
	[0.090]	[0.090]	[0.090]	[0.089]
ln higher skills (t+1)	0.0398**	0.0407**	0.0399**	0.0406**
	[0.019]	[0.019]	[0.019]	[0.019]
ln higher skills * ln proximity (t+1)	0.0228**	0.0232**	0.0233**	0.0227**
	[0.009]	[0.009]	[0.009]	[0.009]
Observations	571	571	571	571
R-squared - Eqn 1	0.973	0.972	0.973	0.973
R-squared - Eqn 2	0.525	0.341	0.536	0.539
R-squared - Eqn 3	0.792	0.792	0.792	0.792

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Three stage least squares estimates of Equations 1-3, weighted by average country/industry share of total employee compensation. Standard errors in brackets. All equations allow for country/industry fixed effects and include year dummies.

Table 5.2: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using upper intermediate skills measure

	(1)	(2)	(3)	(4)
(1) Dependent variable: openness (t)				
ln foreign patent stocks per hour worked (t)	0.4035***	0.3939***	0.3775***	0.3784***
	[0.043]	[0.042]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0645*	0.0022	-0.0770**	-0.0777**
	[0.036]	[0.033]	[0.036]	[0.036]
ln industry size (t)	-0.0802	-0.013	-0.1149*	-0.1147*
	[0.061]	[0.057]	[0.061]	[0.061]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)				
ln patent stocks per hour worked (t)	-0.1007***	-0.1643***	-0.1728***	-0.1671***
	[0.021]	[0.025]	[0.027]	[0.026]
ln R&D intensity (t)	0.0203***	0.0490***	0.0279***	0.0278***
	[0.006]	[0.013]	[0.007]	[0.009]
ln upper intermediate skills (t)	-0.0349**	-0.0260*	0.1656***	0.1523***
	[0.014]	[0.015]	[0.049]	[0.050]
openness (t)	0.0619	0.3152***	0.8127***	0.7584***
	[0.039]	[0.062]	[0.181]	[0.182]
ln R&D * openness (t)		0.0518**		0.0012
		[0.020]		[0.012]
ln upper intermediate skills * openness (t)			0.3598***	0.3352***
			[0.083]	[0.086]
(3) Dependent variable: growth in multi-factor productivity (t+2)				
Δ ln lead-country MFP (t+2)	0.7102***	0.7101***	0.7092***	0.7102***
	[0.032]	[0.032]	[0.032]	[0.032]
ln proximity (t+1)	0.0477	0.0503	0.0511	0.0485
	[0.039]	[0.038]	[0.039]	[0.039]
Δ ln patent stocks per hour worked (t+1)	0.2172**	0.2048**	0.1950**	0.1638*
	[0.088]	[0.088]	[0.088]	[0.088]
ln upper intermediate skills (t+1)	0.1052***	0.1062***	0.1071***	0.1056***
	[0.025]	[0.025]	[0.025]	[0.025]
ln upper intermediate skills * ln proximity (t+1)	0.0743***	0.0755***	0.0756***	0.0748***
	[0.018]	[0.018]	[0.018]	[0.018]
Observations	571	571	571	571
R-squared - Eqn 1	0.973	0.972	0.973	0.973
R-squared - Eqn 2	0.522	0.290	0.412	0.429
R-squared - Eqn 3	0.795	0.795	0.796	0.796

Notes: See Table 5.1

Table 5.3: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using lower intermediate skills measure

	(1)	(2)	(3)	(4)
(1) Dependent variable: openness (t)				
ln foreign patent stocks per hour worked (t)	0.4181***	0.3712***	0.3594***	0.3683***
	[0.043]	[0.041]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0356	0.0129	-0.1026***	-0.0969***
	[0.035]	[0.031]	[0.036]	[0.036]
ln industry size (t)	-0.0388	-0.035	-0.1579***	-0.1423**
	[0.060]	[0.056]	[0.061]	[0.061]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)				
ln patent stocks per hour worked (t)	-0.1117***	-0.1739***	-0.1443***	-0.1333***
	[0.022]	[0.025]	[0.021]	[0.022]
ln R&D intensity (t)	0.0171***	0.0615***	0.0191***	0.0218**
	[0.006]	[0.014]	[0.006]	[0.009]
ln lower intermediate skills (t)	0.0112	0.0763**	-0.1752***	-0.1260***
	[0.023]	[0.030]	[0.039]	[0.043]
openness (t)	0.1303***	0.4579***	-0.2933***	-0.1905***
	[0.043]	[0.070]	[0.058]	[0.070]
ln R&D * openness (t)		0.0796***		0.0056
		[0.023]		[0.012]
ln lower intermediate skills * openness (t)			-0.3170***	-0.2350***
			[0.061]	[0.065]
(3) Dependent variable: growth in multi-factor productivity (t+2)				
Δ ln lead-country MFP (t+2)	0.7059***	0.7060***	0.7059***	0.7061***
	[0.032]	[0.032]	[0.032]	[0.032]
ln proximity (t+1)	-0.0815***	-0.0813***	-0.0826***	-0.0829***
	[0.026]	[0.026]	[0.026]	[0.026]
Δ ln patent stocks per hour worked (t+1)	0.1183	0.1209	0.1235	0.1139
	[0.094]	[0.094]	[0.094]	[0.094]
ln lower intermediate skills (t+1)	-0.0104	-0.0106	-0.0107	-0.0104
	[0.028]	[0.028]	[0.028]	[0.028]
ln lower intermediate skills * ln proximity (t+1)	0.0207	0.0205	0.0209	0.0205
	[0.021]	[0.021]	[0.021]	[0.021]
Observations	571	571	571	571
R-squared - Eqn 1	0.973	0.972	0.973	0.973
R-squared - Eqn 2	0.468	0.028	0.546	0.558
R-squared - Eqn 3	0.791	0.791	0.791	0.791

Notes: See Table 5.1

Table 5.4: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007, using aggregate skills measure

	(1)	(2)	(3)	(4)
(1) Dependent variable: openness (t)				
ln foreign patent stocks per hour worked (t)	0.3893***	0.3993***	0.3606***	0.3887***
	[0.043]	[0.042]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0806**	-0.0077	-0.1043***	-0.0838**
	[0.036]	[0.033]	[0.036]	[0.036]
ln industry size (t)	-0.1030*	-0.0235	-0.1527**	-0.1059*
	[0.061]	[0.058]	[0.061]	[0.061]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)				
ln patent stocks per hour worked (t)	-0.0922***	-0.1528***	-0.0893***	-0.0871***
	[0.020]	[0.024]	[0.018]	[0.018]
ln R&D intensity (t)	0.0191***	0.0476***	0.0203***	0.0536***
	[0.006]	[0.013]	[0.006]	[0.013]
ln aggregate skills (t)	0.1176	-0.0919	0.3698**	-0.2399
	[0.105]	[0.121]	[0.156]	[0.176]
openness (t)	0.0257	0.2918***	-0.5918**	0.8139**
	[0.039]	[0.062]	[0.297]	[0.321]
ln R&D * openness (t)		0.0522***		0.0591***
		[0.020]		[0.020]
ln aggregate skills * openness (t)			0.9600*	-1.2445**
			[0.504]	[0.514]
(3) Dependent variable: growth in multi-factor productivity (t+2)				
Δ ln lead-country MFP (t+2)	0.7006***	0.7006***	0.7003***	0.7006***
	[0.032]	[0.032]	[0.032]	[0.032]
ln proximity (t+1)	-0.1527***	-0.1511***	-0.1563***	-0.1492***
	[0.034]	[0.034]	[0.034]	[0.034]
Δ ln patent stocks per hour worked (t+1)	0.1655*	0.1516*	0.1715*	0.1419
	[0.090]	[0.090]	[0.089]	[0.089]
ln aggregate skills (t+1)	0.2740***	0.2762***	0.2755***	0.2755***
	[0.101]	[0.101]	[0.101]	[0.101]
ln aggregate skills * ln proximity (t+1)	0.0960*	0.0946*	0.0994*	0.0893*
	[0.052]	[0.052]	[0.052]	[0.052]
Observations	571	571	571	571
R-squared - Eqn 1	0.973	0.972	0.973	0.973
R-squared - Eqn 2	0.531	0.329	0.496	0.476
R-squared - Eqn 3	0.792	0.793	0.792	0.793

Notes: See Table 5.1

6. Robustness tests

In this section we describe a series of robustness checks designed to test the sensitivity of our main findings to:

1. Potential endogeneity of key regressors
2. Cross-sectional dependence
3. Variation of assumptions made in the calculation of selected skill measures

6.1 Endogeneity issues

As discussed in Section 3, by using a 3SLS estimator and appropriate lags in analysis of our multi-equation system, we have addressed one type of potential endogeneity, namely, simultaneity between external knowledge sourcing, innovative processes and the translation of innovation outputs into productivity gains. However, concerns still remain about potential reverse causality between dependent and independent variables in Equations 2 and 3, in particular, the relationships between:

a) firms' decisions to invest in R&D and their ability to increase knowledge stocks (proxied here by patent stocks)
b) firms' decisions to employ skilled workers and their performance in respect of growth in knowledge stocks and/or productivity levels

In other words, firms that perform well in terms of patenting and/or productivity may also be more likely to invest heavily in R&D and/or employ more high-skilled workers.

To investigate this type of endogeneity, we adopt a two-stage instrumental variable (IV) regression strategy in which, following Bloom et al (2013), the potentially endogenous variables of interest – R&D intensity and skill shares of employment – are first regressed on a set of external (policy) variables (along with some deterministic elements) and then the predicted values of these variables are utilised in re-estimating the system of equations.

As external instruments for each endogenous variable, we use time-varying country-by-industry indicators of R&D policies and labour market regulation. Following Rajan and Zingales (1998), each external instrument has been obtained as an interaction between a country-level, time-varying policy indicator and an industry-specific (benchmark) variable reflecting the intensity in industry use of the factor that is the target of the policy (the so-called treated factor). The benchmark variable is time-invariant and is taken at the initial year of the analysis (1995). To further reduce the bias associated with the use of a benchmark external to the sample, the intensity in industry use of the treated factor is computed as a cross-country mean (see Ciccone and Papaioannou 2016):

(10) $$INST_{ij,t} = \omega_{i\bar{j}} \times POLICY_{jt}$$

Here *i* refers to industries, *j* to countries. The bar denotes the average intensity share for our set of eight countries (*ω*). The share refers to the initial year of observation and hence should exclude the possibility of reverse causation such as the intensity in use of the factor under examination changing in response to a variation in the policy. The policy indicator, *POLICY*, is available at country level and changes over time.

The impact of R&D intensity is predicted by means of a) the fiscal incentives to R&D; and b) an indicator capturing the extent of regulation on R&D services:

a) R&D tax credits are measured in terms of the tax price component of R&D user cost, taken from Thomson (2013). [20] The higher are fiscal incentives to R&D, the lower is the tax price (Wilson, 2009; Minniti and Venturini, 2017). The R&D tax price, here denoted by *RDTAX*, is multiplied by the innovation intensity of sector *i* across eight countries, defined as R&D expenditure over value added (Vartia, 2008).

(11) $$INST1_{ij,t} = \omega1_{i\bar{j}} \times RDTAX_{jt} \qquad \omega1_{i\bar{j}} = 1/n \sum_{j=1}^{N} \frac{RD_{ij,95}}{Y_{ij,95}}$$

b) We use an indicator of the regulation of R&D services which tends to be inversely related to the cost for firms of outsourcing R&D tasks. The strictness of such regulation

[20] This measure of fiscal incentives is also known as the 'B index', defined by the OECD (2009, Section 2.14) as 'the present value of before tax income necessary to cover the initial cost of R&D investment and to pay corporate income tax, so that it is profitable to perform research activities'. Thus the amount of tax subsidy for R&D can be calculated as 1 minus the B index (Warda, 2001). An extensive literature shows that R&D tax credits are positively associated with the intensity of research activity (Thomson 2015; Bloom et al, 2002).

is measured by means of the OECD index of service regulation pertaining to engineering professional services (RDREG). This index is available for certain benchmark years (1998, 2003 and 2008) and hence intermediate time observations have been interpolated. This index of regulation, available at country level, is multiplied by the share of purchases of professional engineering services in total intermediate input purchases by each industry *i*. [21]

$$(12) \qquad INST2_{ij,t} = \omega 2_{i\bar{j}} \times RDREG_{jt} \qquad \omega 2_{i\bar{j}} = 1/n \sum_{j=1}^{N} \frac{PROFSERV_{ij,95}}{PURCHASES_{ij,95}}$$

The second set of endogenous variables to be considered are the shares of each skill category in total hours worked. Predicted values of these variables are generated by regressing them on measures of the strictness of employment protection legislation (EPL) for workers on regular (open-ended) and temporary contracts, taken from the OECD employment protection database (Venn, 2009). These measures are interacted with the cross-country average of labour share, i.e. the ratio between labour compensation and value added.

$$(13) \qquad INST3_{ij,t} = \omega 3_{i\bar{j}} \times RDREG_{jt} \qquad \omega 3_{i\bar{j}} = 1/n \sum_{j=1}^{N} \frac{LAB_{ij,95}}{Y_{ij,95}}$$

Previous research findings suggest that the harder it is to dismiss workers on temporary contracts, the greater are the incentives for firms to develop and seek to retain high-skilled workers on regular contracts while tending to reduce employment of lower-skilled workers (OECD, 2013, Chapter 2). Conversely, stricter EPL for workers on regular contracts increases incentives for employers to make use of temporary employment but some types of firm – especially those engaged in innovation – also respond by providing more training to upgrade the skills of existing employees (Pierre and Scarpetta, 2013).

Table 6.1 reports the first-stage estimates. As expected, R&D intensity is found to be significantly negatively related to both the R&D tax price and the measure of R&D service regulation (Column 1). Both the high-skilled and upper intermediate-skilled

[21] Source: World Input-Output Database (WIOD), http://www.wiod.org/home (Timmer et al, 2015)

shares of employment are significantly positively related to the strictness of EPL on temporary contracts (Columns 3 and 5). The employment share of lower intermediate-skilled workers is significantly negatively related to the strictness of EPL on regular contracts and unrelated to EPL on temporary contracts (Columns 6-7).

Table 6.2 shows the second-stage results in which R&D intensity is instrumented using the predicted values from Table 6.1, Column 1; higher skills and upper intermediate skills are instrumented using the predicted values from Table 6.1, Columns 3 and 5 respectively (based on EPL for temporary contracts); and lower intermediate skills are instrumented using the predicted values from Table 6.1, Column 6 (based on EPL for regular contracts). (In these second-stage regressions, standard errors are bootstrapped with 200 replications). In order to check the robustness of our main findings in relation to Hypothesis 1, we focus on specifications in which each skill category is interacted in turn with the openness measure.

In general, the IV results are highly consistent with our main estimates reported in Section 5. In line with Hypothesis 1A, high-level skills are found to make a positive contribution to each country/industry's ability to convert opportunities for external knowledge sourcing into innovative output, as shown by the significant positive coefficient attached to the interaction between higher skills and openness in Table 6.2, Equation 2, Column 1. Similarly, we continue to find partial support for Hypothesis 1B regarding the indirect contribution of intermediate skills to innovative output, with a significantly positive interaction between upper intermediate skills and openness (Column 2) while the equivalent coefficient relating to lower intermediate skills is significantly negative (Column 3).

Importantly, the IV results also support our main findings in respect of Hypothesis 2. After controlling for the contribution of growth in innovation inputs to growth in MFP, employment of high-skilled workers is found to be positively related to the proximity of MFP levels to the technological frontier (Table 6.2, Equation 3, Column 1) as is also the case for employment of upper intermediate-skilled workers (Column 2) but not lower intermediate-skilled workers (Column 3).

Table 6.1: Instrumenting R&D intensity and skills with external (institutional) variables, Western European and US manufacturing industries, 1995-2007: first-stage estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**ln R&D intensity (t)**	**ln higher skills (t)**	**ln higher skills (t)**	**ln upper inter-mediate skills (t)**	**ln upper inter-mediate skills (t)**	**ln lower inter-mediate skills (t)**	**ln lower inter-mediate skills (t)**
R&D tax price	-0.6758***	-0.7121***	-0.3847***	-0.6655***	-0.5425***	-0.5863***	-0.3287***
	[0.253]	[0.116]	[0.103]	[0.106]	[0.099]	[0.065]	[0.069]
R&D service regulation	-0.2707***						
	[0.088]						
EPL - regular contracts		-0.7190**		0.0496		-1.8972***	
		[0.290]		[0.265]		[0.163]	
EPL - temporary contracts			0.4895***		0.2736***		0.0115
			[0.044]		[0.042]		[0.029]
F-test for joint significance	15.6***	18.9***	80.7***	22.6***	45.0***	82.9***	12.4***
Observations	676	728	728	728	728	728	728
Adj. R-squared	0.969	0.955	0.962	0.931	0.935	0.978	0.974

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
OLS estimates. Standard errors in brackets. All equations allow for country/industry fixed effects and include year dummies.

Table 6.2: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 - Instrumenting R&D intensity and skills

	(1)	(2)	(3)
Skill measure:	**Higher**	**Upper intermediate**	**Lower intermediate**
(1) Dependent variable: openness (t)			
ln foreign patent stocks per hour worked (t)	0.3837***	0.3778***	0.3612***
	[0.054]	[0.057]	[0.057]
ln trade_investment barriers (t)	-0.0878**	-0.0906**	-0.0992***
	[0.043]	[0.037]	[0.036]
ln industry size (t)	-0.1109**	-0.1218**	-0.1508***
	[0.051]	[0.053]	[0.050]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)			
ln patent stocks per hour worked (t)	-0.1574***	-0.1978***	-0.1417***
	[0.034]	[0.048]	[0.032]
ln R&D intensity_predicted (t)	0.1829**	0.1821**	-0.0789
	[0.072]	[0.089]	[0.114]
ln skills_predicted (t)	0.1571***	0.2195***	-0.1488
	[0.040]	[0.065]	[0.099]
openness (t)	0.2318**	0.7775*	-0.3905***
	[0.093]	[0.410]	[0.141]
ln skills_predicted * openness (t)	0.1085**	0.3610*	-0.5204***
	[0.047]	[0.187]	[0.161]
(3) Dependent variable: growth in multi-factor productivity (t+2)			
Δ ln lead-country MFP (t+2)	0.7094***	0.7095***	0.7051***
	[0.067]	[0.068]	[0.067]
ln proximity (t+1)	-0.0503	0.0656	-0.0547
	[0.031]	[0.053]	[0.040]
Δ ln patent stocks per hour worked (t+1)	0.0712	0.0684	0.019
	[0.159]	[0.150]	[0.136]
ln skills_predicted (t+1)	0.06	0.1318*	-0.1233
	[0.043]	[0.073]	[0.089]
ln skills_predicted * ln proximity (t+1)	0.0370***	0.0898***	0.0529
	[0.011]	[0.025]	[0.035]
Observations	571	571	571
R-squared - Eqn 1	0.973	0.973	0.973
R-squared - Eqn 2	0.537	0.523	0.547
R-squared - Eqn 3	0.795	0.796	0.794

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Three stage least squares estimates of Equations 1-3, weighted by average country/industry share of total employee compensation. Bootstrapped standard errors shown in brackets (200 replications). All equations allow for country/industry fixed effects and include year dummies. Predicted values of R&D intensity and skills are derived from first-stage estimates reported in Table 6.1, as described in the main text.

6.2 Assessing the role of cross-sectional dependence

In our main analysis we used a set of year dummies to control for common time effects that may be caused by, for instance, technology shocks or other sources of fluctuation in economic activity.

As Pesaran (2006) points out, this procedure is effective in purging time effects only when there is weak cross-sectional dependence among sample units. It assumes that time-related shocks affect all sample units to the same extent. However, using time dummies is ineffective in the presence of strong cross-sectional dependence that may be caused by shocks and other unobservable effects that affect national economies or industries asymmetrically. Such shocks may yield inefficient estimates if they are orthogonal to explanatory variables or even generate inconsistent estimates if they are correlated with regressors.

In order to assess how much main findings have been affected by cross-sectional dependence, we seek to purge the effects of common unobserved factors by including cross-sectional means of dependent variables and regressors in our system of equations, following the common correlated effects (CCE) approach developed by Pesaran (2006). The results of including CCE terms (obtained on a yearly basis) are reported in Table 6.3, again using three different skill measures in turn (higher, upper intermediate and lower intermediate). The impact of these terms is assumed to be equal across all country/industry units in the sample.

The results are in line with our main findings in respect of Hypothesis 1A with a positive significant coefficient attached to the interaction between higher skills and openness when we take account of CCEs (Table 6.3, Equation 2, Column 1). Similarly, we continue to find only partial support for Hypothesis 1B with the interaction between upper intermediate skills and openness being positive significant (Column 2) while the equivalent coefficient relating to lower intermediate skills is negative significant (Column 3), consistent with our main findings.

Turning to Hypothesis 2 relating to skills and MFP growth, when we take account of CCEs, the results are consistent with our main findings. On the one hand, we find a positive significant interaction between higher skills and proximity to the technological frontier, thus providing support for Hypothesis 2A (Table 6.3, Equation 3, Column 1). On the other hand, we continue to find no support for Hypothesis 2B with the coefficient on the interaction between upper intermediate skills and proximity to the frontier remaining positive significant (Column 2), as in our main estimates.

Table 6.3: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 – Including common correlated effects to assess the impact of cross-sectional dependence

	(1)	(2)	(3)
Skill measure:	Higher	Upper intermediate	Lower intermediate
(1) Dependent variable: openness (t)			
ln foreign patent stocks per hour worked (t)	0.3831***	0.3772***	0.3624***
	[0.043]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0823**	-0.0775**	-0.0999***
	[0.036]	[0.036]	[0.036]
ln industry size (t)	-0.0903	-0.0986	-0.1415**
	[0.060]	[0.060]	[0.060]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)			
ln patent stocks per hour worked (t)	-0.1570***	-0.1940***	-0.1548***
	[0.026]	[0.028]	[0.022]
ln R&D intensity (t)	0.0223***	0.0295***	0.0214***
	[0.006]	[0.007]	[0.006]
ln skills (t)	0.0915***	0.2139***	-0.1780***
	[0.022]	[0.052]	[0.041]
openness (t)	0.2549***	0.9730***	-0.2721***
	[0.076]	[0.189]	[0.061]
ln skills (t) * openness (t)	0.1265***	0.4282***	-0.3100***
	[0.039]	[0.087]	[0.065]
(3) Dependent variable: growth in multi-factor productivity (t+2)			
Δ ln lead-country MFP (t+2)	0.7224***	0.7180***	0.7108***
	[0.033]	[0.032]	[0.033]
ln proximity (t+1)	-0.0747***	0.0138	-0.0895***
	[0.023]	[0.038]	[0.026]
Δ ln patent stocks per hour worked (t+1)	0.0174	-0.0334	-0.0377
	[0.075]	[0.076]	[0.074]
ln skills (t+1)	0.0438**	0.0859***	-0.0027
	[0.019]	[0.026]	[0.029]
ln skills (t+1) * ln proximity (t+1)	0.0218**	0.0629***	0.0188
	[0.009]	[0.018]	[0.021]
Observations	571	571	571
R-squared - Eqn 1	0.972	0.973	0.973
R-squared - Eqn 2	0.462	0.300	0.487
R-squared - Eqn 3	0.785	0.787	0.782

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Three stage least squares estimates of Equations 1-3, weighted by average country/industry share of total employee compensation. Standard errors in brackets. All equations include CCE terms as described in the main text and allow for country/industry fixed effects.

6.3 Assessing the impact of varying assumptions made in the calculation of US skill measures

As described in Appendix B, our four different skill categories – higher, upper intermediate, lower intermediate and low-skilled – have been defined on the basis of formal qualifications held by workers in each country. For the seven European countries, information to support the classification of qualifications to each skill category was derived from CEDEFOP and UNESCO information which gave us some confidence about the comparability of different qualifications across those countries. However, in the case of the US, workforce qualifications data obtained from the Current Population Survey included a 'Some college, no degree' category which has no counterpart in any of the European countries under investigation. We therefore made use of US Census Bureau estimates of enrolments at different levels to propose the following allocation of US qualifications to upper and intermediate skill levels:

- Upper intermediate – Associates degrees plus 50% of persons classified to the 'Some college, no degree' category
- Lower intermediate – High school graduates plus 50% of persons classified to the 'Some college, no degree' category

In order to assess the sensitivity of our main findings to variations in the assumed proportions of 'Some college, no degree' workers allocated to each intermediate skill category, we carried out additional analyses assuming, first, that the split was 60%/40% between upper and lower intermediate; and second, that the split was 40%/60%. The results show that our main patterns of inference in relation to intermediate skills are robust to both these variations in assumptions (Table 6.4).

Table 6.4: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, Western European and US manufacturing industries, 1995-2007 – With different allocations of US workers in the 'Some college, no degree' category to Upper intermediate and Lower intermediate skill groups

	(1)	(2)		(3)	(4)
Skill measure:	**Upper intermediate**	**Lower intermediate**		**Upper intermediate**	**Lower intermediate**
% of US workers in 'Some college, no degree' category allocated to each skill group	**60%**	**40%**		**40%**	**60%**
(1) Dependent variable: openness (t)					
ln foreign patent stocks per hour worked (t)	0.3775***	0.3600***		0.3780***	0.3588***
	[0.043]	[0.043]		[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0777**	-0.1025***		-0.0762**	-0.1027***
	[0.036]	[0.036]		[0.036]	[0.036]
ln industry size (t)	-0.1147*	-0.1574**		-0.1148*	-0.1584***
	[0.061]	[0.061]		[0.061]	[0.061]
(2) Dependent variable: growth in patent stocks per hour worked (t+1)					
ln patent stocks per hour worked (t)	-0.1798***	-0.1459***		-0.1621***	-0.1424***
	[0.028]	[0.022]		[0.025]	[0.021]
ln R&D intensity (t)	0.0275***	0.0192***		0.0280***	0.0190***
	[0.007]	[0.006]		[0.007]	[0.006]
ln skills (t)	0.1614***	-0.1632***		0.1645***	-0.1876***
	[0.048]	[0.037]		[0.050]	[0.041]
openness (t)	0.7857***	-0.2800***		0.8183***	-0.3069***
	[0.174]	[0.056]		[0.186]	[0.060]
ln skills (t) * openness (t)	0.3472***	-0.3021***		0.3627***	-0.3318***
	[0.080]	[0.059]		[0.086]	[0.064]
(3) Dependent variable: growth in multi-factor productivity (t+2)					
Δ ln lead-country MFP (t+2)	0.7102***	0.7058***		0.7080***	0.7060***
	[0.032]	[0.032]		[0.032]	[0.032]
ln proximity (t+1)	0.0493	-0.0816***		0.0517	-0.0836***
	[0.039]	[0.026]		[0.038]	[0.026]
Δ ln patent stocks per hour worked (t+1)	0.1878**	0.1251		0.2036**	0.1224
	[0.088]	[0.093]		[0.088]	[0.094]
ln skills (t+1)	0.1048***	-0.0083		0.1086***	-0.0129
	[0.026]	[0.028]		[0.025]	[0.029]
ln skills (t+1) * ln proximity (t+1)	0.0748***	0.0220		0.0758***	0.0197
	[0.018]	[0.021]		[0.017]	[0.021]
Observations	571	571		571	571
R-squared - Eqn 1	0.973	0.973		0.973	0.973
R-squared - Eqn 2	0.422	0.548		0.406	0.543
R-squared - Eqn 3	0.796	0.791		0.796	0.791

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Three stage least squares estimates of Equations 1-3, weighted by average country/industry share of total employee compensation. Standard errors in brackets. All equations allow for country/industry fixed effects and include year dummies. See main text for details of the different assumptions concerning the allocation of US workers in the 'Some college, no degree' category to different intermediate skill groups.

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7. Summary and assessment

Skills are widely recognised as central to firms' absorptive capacity (AC), that is, their ability to identify and make effective use of knowledge, ideas and technologies that are generated elsewhere.

But which specific kinds of education and skills contribute most to the development of AC and subsequently to innovation and productivity growth? In previous research, identification of the links between skills and AC has often been hampered by the use of skill measures as proxies for AC itself. Although the role played by high-skilled workers such as university-educated engineers and scientists has been taken for granted, little attention has been paid to the potential contributions made by intermediate-skilled workers (for example, technicians and apprentice-trained craft workers) and by workers with uncertified skills acquired through informal on-the-job training and experience.

In this paper we address these issues through analysis of a cross-country industry-level dataset which covers the US and seven Western European countries between 1995 and 2007.

First, we distinguish between potential absorptive capacity (PAC, the ability to recognise, acquire and assimilate useful external knowledge) and realised absorptive capacity (RAC, the ability to transform and apply acquired knowledge effectively within organisations).

Second, we construct separate indicators of key components of PAC – skills, R&D investments and openness to foreign trade and investment – in order to examine the strength of their respective contributions to innovative output (RAC) and ultimately to productivity growth.

Third, we draw on detailed estimates of the composition of workforce skills at country/industry level which enable us to distinguish between high-level, upper intermediate and lower intermediate skills in investigating the links between skills, AC, innovation and productivity performance.

By carrying out analysis at country/industry level, we are able to take account of a key dimension to PAC that is hard to measure at firm level, namely, differences between economic units in the opportunities to acquire useful external knowledge. Specifically, we develop measures of openness at country/industry level which are derived from data on foreign trade and foreign direct investment (FDI) – both activities which economic theory and empirical evidence suggests are central to potential knowledge spillovers across national borders.

Taken together these data enable us to evaluate the extent to which different skills contribute to innovative output and subsequently to growth in productivity by estimating a simultaneous system of three equations in which the dependent variables are, respectively: (1) our measure of openness to trade and FDI (2) growth in patent stocks per hour worked (innovative output) and (3) growth in multi-factor productivity (MFP).

We then test Hypothesis 1 that the conversion of opportunities for external knowledge sourcing (openness) into innovative output is positively related to:

(A) employment of high-skilled workers
(B) employment of intermediate-skilled workers such as technicians and craft-skilled workers

Our estimates show strong support for Hypothesis 1A in respect of high-skilled workers. Since our model also controls for R&D spending of which a large proportion takes the form of researchers' wages, we interpret the significant positive coefficient on the high-skilled labour share as partly comprising productivity contributions by high-skilled R&D workers in excess of their wages and partly the contributions made by high-skilled workers outside R&D departments which are complementary to the efforts of researchers, engineers and scientists directly employed in R&D.

We find partial support for Hypothesis 1B, in that the employment share of upper intermediate-skilled workers is also significantly positively related to the conversion of opportunities for external knowledge sourcing into innovative output. However, the same is not true of lower intermediate-skilled workers. Overall, the results are consistent with technicians and other upper intermediate-skilled workers playing key support roles in areas such as new product design and development.

In order to assess the contribution of different types of skill to MFP growth, we draw on the MFP and skills literature which strongly suggests that high-level skills contribute more than intermediate skills to MFP growth in countries and industries where previous innovation has narrowed the gap with technology leaders. In this context we test Hypothesis 2 which posits that, all else being equal, after controlling for the contribution of growth in innovation inputs to growth in productivity, the proximity of MFP levels to the technological frontier is:

(A) positively related to employment of high-skilled workers
(B) *not* significantly related to employment of intermediate-skilled workers

In line with theoretical expectations, we find MFP growth to be positively related to increases in innovative output (RAC) in the previous year, consistent with productivity benefitting from innovation-driven factors such as cost reductions, efficiency increases and/or helping to secure greater market shares for new products.

As found in many previous studies, MFP growth is negatively related to proximity to the technological frontier, confirming that country/industry units far from the frontier typically benefit most from the scope for knowledge transfers from technological leaders.

When different measures of skills are interacted with the proximity measure, the resulting coefficients are positive significant in the case of high-level skills, upper intermediate skills and the aggregate skills measure while being non-significant in the case of lower intermediate skills. These findings provide strong support for Hypothesis 2A but not for Hypothesis 2B.

Indeed, the positive coefficient on the upper intermediate skills/proximity interaction suggests that, even when country/industry units are relatively close to the technological frontier, MFP growth benefits not just from high-level skills but also from high-level skills being complemented by upper intermediate skills to some extent. By facilitating the adoption of best practices, new business models and investment in other intangible assets, upper intermediate-skilled workers may contribute to spillovers that increase productivity levels.

At the same time the positive significant coefficient on the aggregate skills/proximity interaction is notable since the aggregate skills measure not only covers all sections of the workforce but also takes account of uncertified skills (for example, those acquired through informal on-the-job training and work experience), not just formal qualifications. Our findings therefore imply that the translation of innovative output into productivity performance in the production of final goods and services depends on the skills of the workforce as a whole – unlike in the production of innovative outputs (such as patents) where high-level and upper intermediate skills are more important than lower levels of skill. Since the aggregate skills measure also takes account of the age of workers as an indicator of work experience, our findings are also consistent with the strong positive relationship found by other researchers between MFP growth and employment of older tertiary-educated workers in OECD countries.

All estimates relating to our main hypotheses are robust to alternative specifications which take account of potential endogeneity of key regressors, cross-sectional dependence and variation in key assumptions made in the calculation of selected skill measures.

Taken together, we believe our findings have proved encouraging in terms of our decision to avoid incorporating skills in proxy measures of AC and instead to retain separate measures of skills, R&D investments and openness in our analysis. This approach has helped to identify the ways in which different types of skill may be required at each stage of external knowledge sourcing, innovation and production processes. 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 (i.e. realise their absorptive capacity) appear to depend in many ways on intermediate-skilled employees as well as on high-skilled employees.

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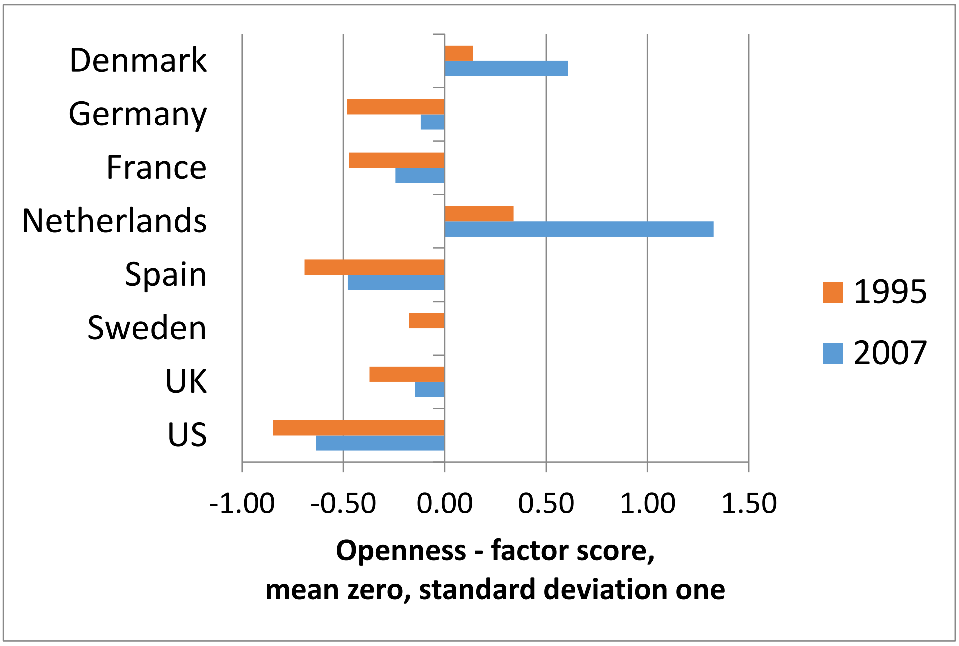
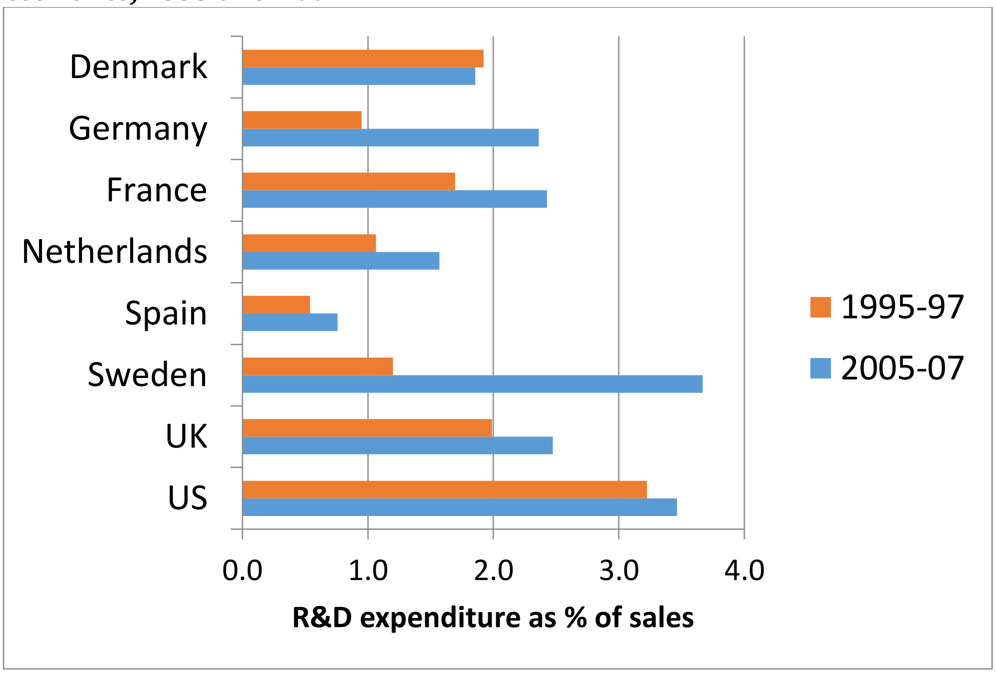
Appendix A: Descriptive statistics at country/industry level: openness, R&D spending, patent stocks and skills

Figure A1: Summary measure of openness, total manufacturing, eight countries, 1995 and 2007



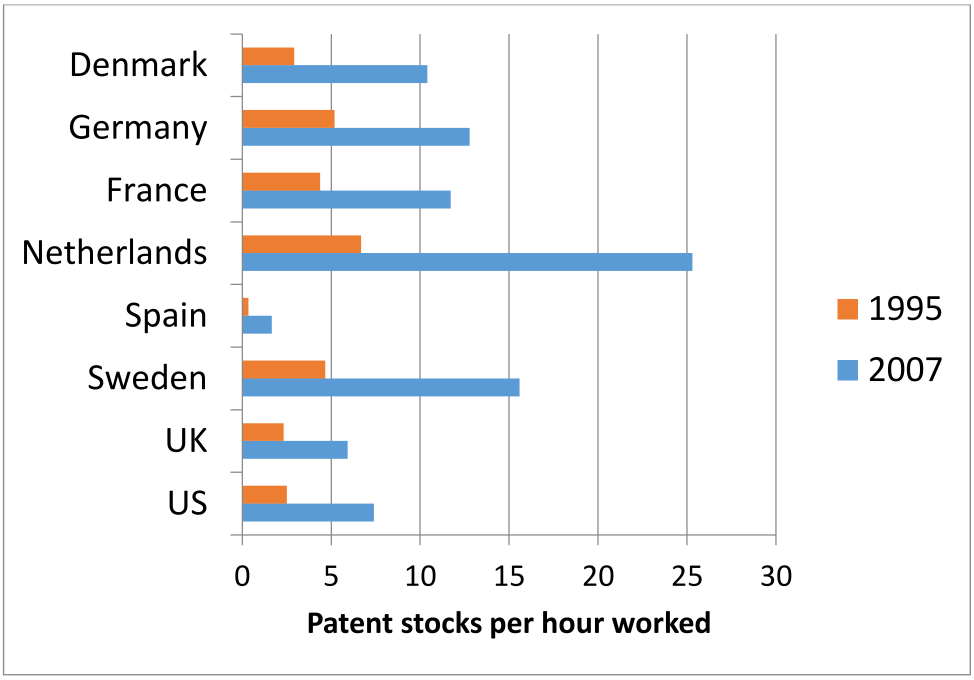
Source: Derived from OECD trade and FDI data (see main text).

Figure A2: R&D expenditure as percentage of total sales, total manufacturing, eight countries, 1995 and 2007



Source: Derived from OECD data on R&D expenditure (see text).

Figure A3: Patent stocks per hour worked, total manufacturing, eight countries, 1995 and 2007



Source: Derived from OECD/EPO data on patent applications (see main text).

Figure A4: Estimated aggregate skill levels in total manufacturing, eight countries, 1995 and 2007

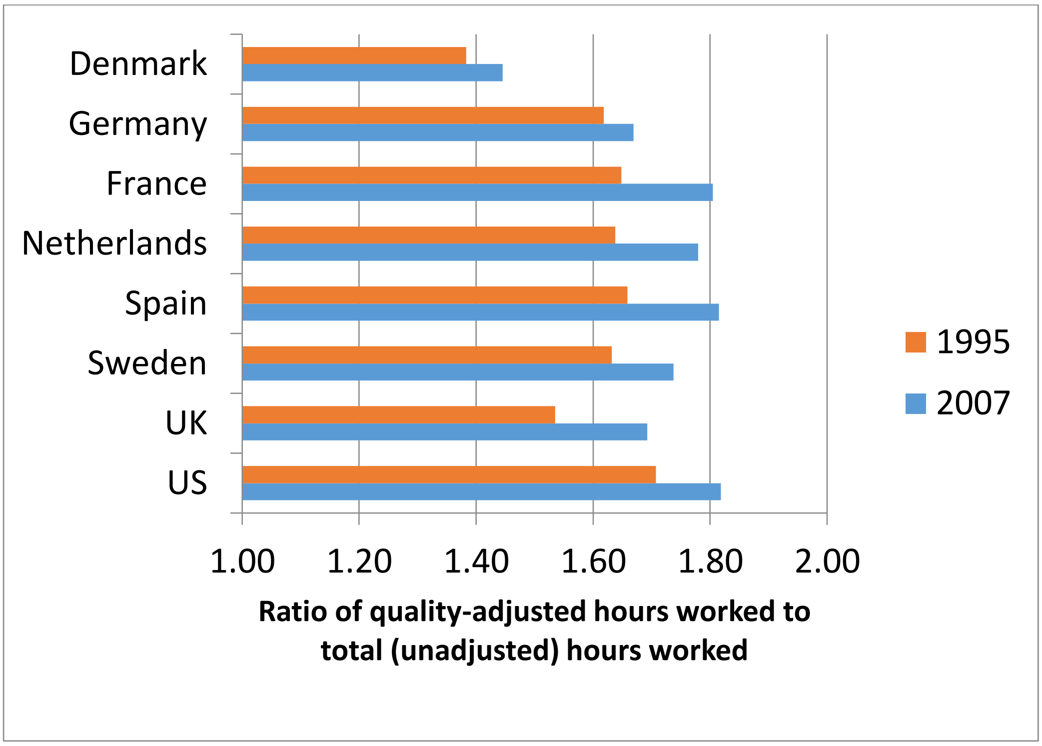


Figure A5: High-skilled workers (holding Bachelor or higher degrees) as % of total hours worked, total manufacturing, eight countries, 1995 and 2007

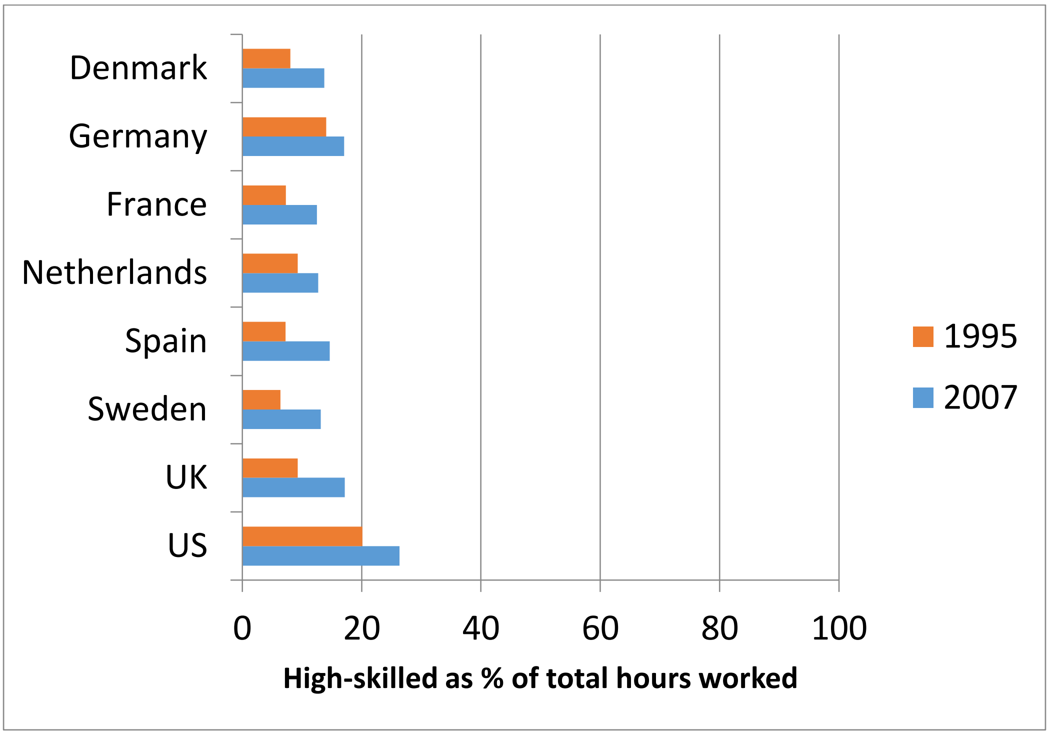


Figure A6: Upper intermediate-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007

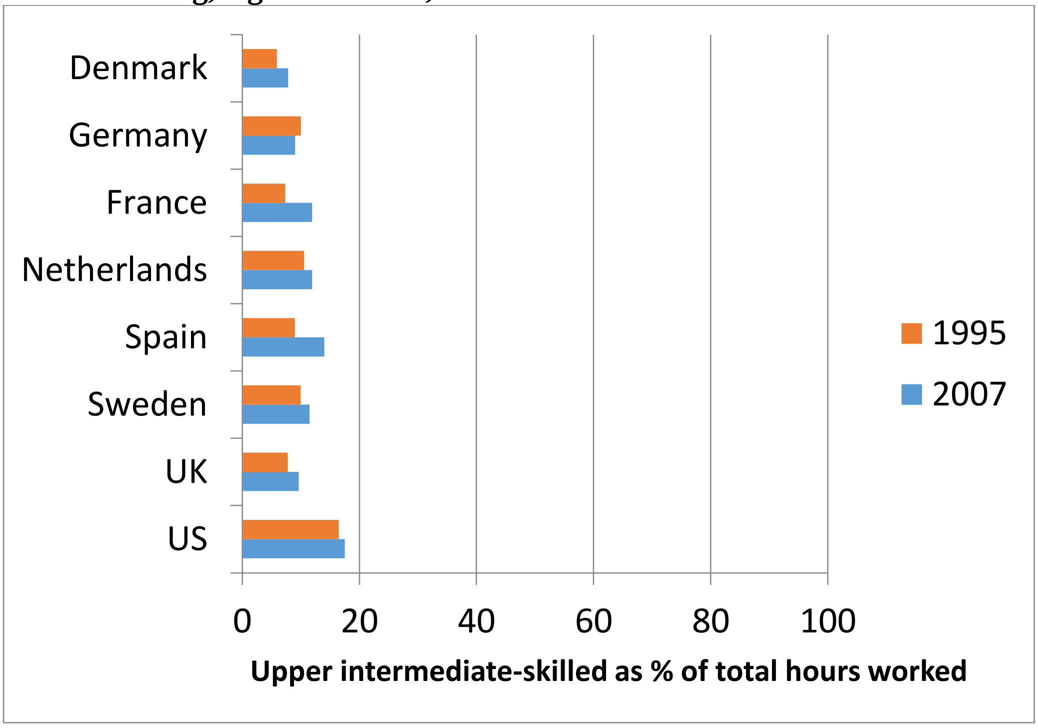


Figure A7: Lower intermediate-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007

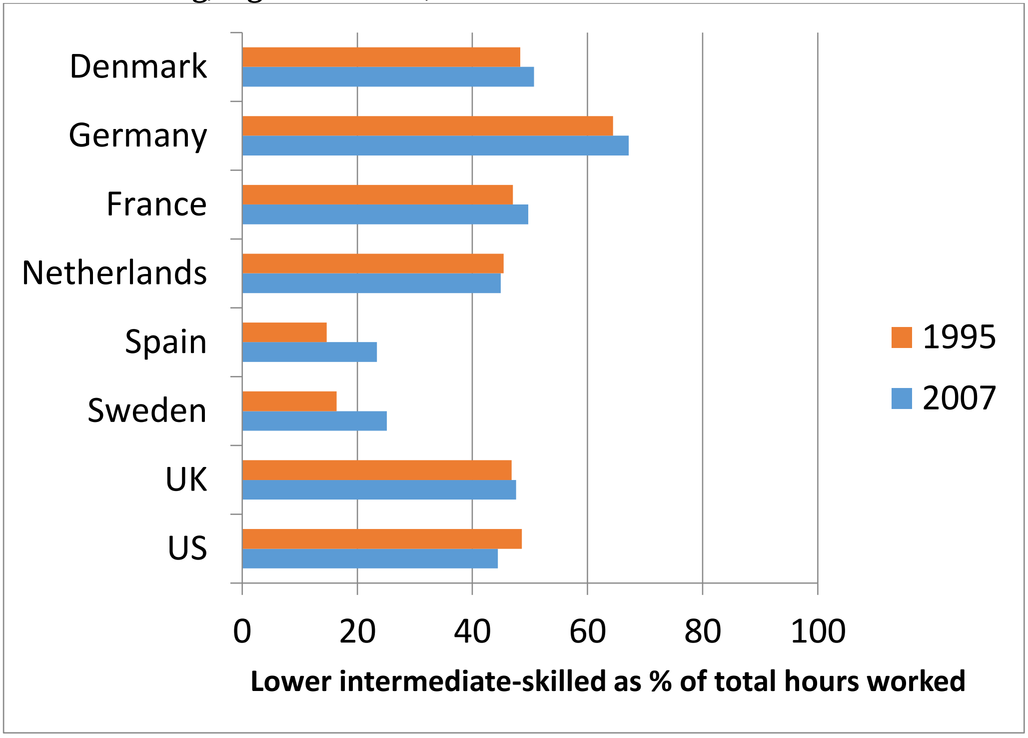
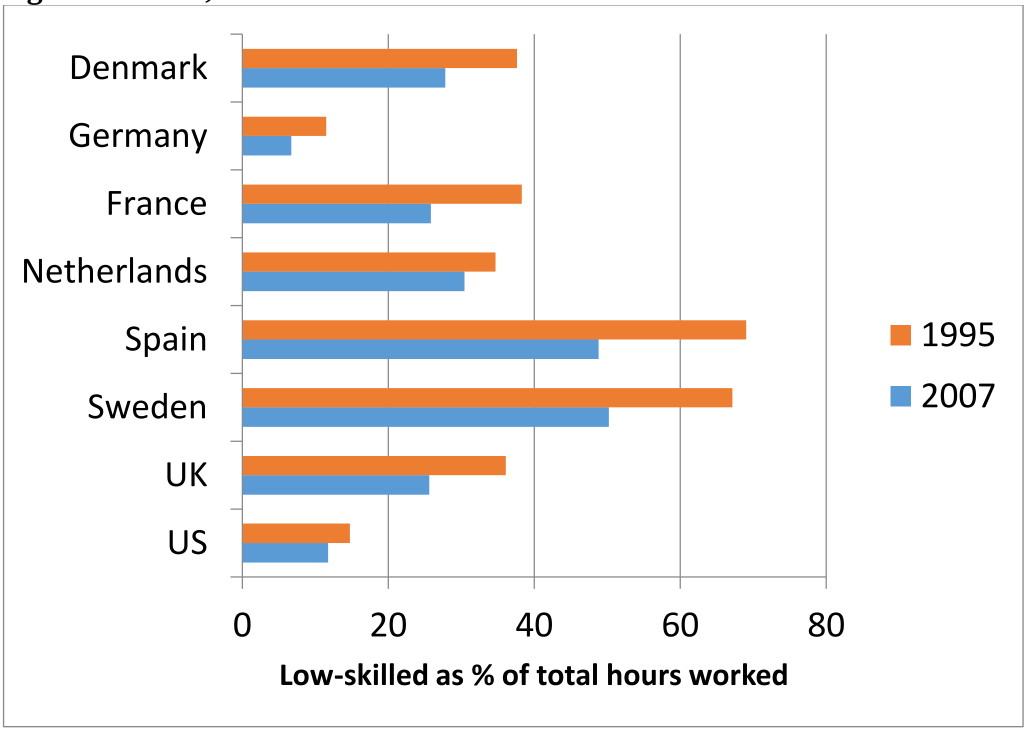


Figure A8: Low-skilled workers as % of total hours worked, total manufacturing, eight countries, 1995 and 2007



Appendix B: Classification of educational qualifications

In order to derive skill measures based on formal qualifications which are comparable across countries, we first define four different qualification groups in terms of different levels on the 1997 International Standard Classification of Education (ISCED) scale:

Qualification group	ISCED level
Higher	5A, 6
Upper intermediate	4, 5B
Lower intermediate	3A, 3B
Low-skilled	3C, 2 or lower

Notes on ISCED levels of education: [Derived from OECD, Education at a Glance, 2002, Glossary]
ISCED 5A: 'Tertiary-type A programmes [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. They have a minimum cumulative theoretical duration (at tertiary level) of three years' full-time equivalent, although they typically last four or more years'.
ISCED 5B: 'Tertiary-type B programmes [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'.
ISCED 4: 'Post-secondary non-tertiary education straddles the boundary between upper secondary and post-secondary education from an international point of view, even though it might clearly be considered upper secondary or post-secondary programmes in a national context. Although their content may not be significantly more advanced than upper secondary programmes, they serve to broaden the knowledge of participants who have already gained an upper secondary qualification. The students tend to be older than those enrolled at the upper secondary level'.
ISCED 3: 'Upper secondary education corresponds to the final stage of secondary education in most OECD countries. The entrance age to this level is typically 15 or 16 years. The typical duration of ISCED 3 programmes …. typically [ranges] from two to five years of schooling. ISCED 3 may either be "terminal" (i.e., preparing the students for entry directly into working life) and/or "preparatory" (i.e., preparing students for tertiary education)'. ISCED 3A and 3B programmes can enable direct access to tertiary education courses (ISCED 5) if students do not enter the labour market and typically signify a higher level of attainment than ISCED 3C programmes which do not enable access to tertiary education.

The division between the higher and upper intermediate groups corresponds to the boundary between long-cycle higher education (Bachelor and Higher degrees) and short-cycle higher education. In all seven European countries the bulk of upper intermediate education is vocational or occupation-specific in nature. The same is not true at lower intermediate level where there is usually a clear split between general and vocational education.

Information to support the classification of qualifications in this way was derived for European countries from CEDEFOP Country Reports showing how qualifications in each of the seven countries were allocated to different levels on the ISCED scale. [22] We also drew on summary files prepared by UNESCO for additional information on programme

[22] http://www.cedefop.europa.eu/en/publications-and-resources/country-reports/vet-in-europe-country-reports: United Kingdom. VET in Europe – Country Report 2009, ReferNet United Kingdom; France. VET in Europe – Country Report 2009, ReferNet France; Germany. VET in Europe – Country Report 2009, ReferNet Germany; Spain. VET in Europe – Country Report 2009, ReferNet Spain; Netherlands. VET in Europe – Country Report 2009, Karel Visser (ECBO, Netherlands); Denmark. VET in Europe – Country Report 2009; ReferNet Denmark; Vocational education and training in Sweden: short description, Cedefop Panorama series 180.

orientation (ie, whether they are general or vocational in nature). [23] However, UNESCO summary files for the US show a less detailed allocation to ISCED levels [24] than we had available for European countries. Therefore we make use of US Census Bureau estimates of enrolments at different levels in 2009 [25] and estimates derived from the US Current Population Survey to propose the following allocation of US qualifications:

- Higher – Bachelor and higher degrees
- Upper intermediate – Associates degrees plus 50% of persons classified to the 'Some college, no degree' category [26]
- Lower intermediate – High school graduates plus 50% of persons classified to the 'Some college, no degree' category
- Low-skilled – Did not graduate from high school

The following national data sources were used to obtain estimates of the proportions of the workforce holding different types of qualification:

- UK: Labour Force Survey
- US: Current Population Survey
- France: Enquête-Emploi
- Germany: Socio-Economic Panel
- Spain: Economically Active Population Survey
- Netherlands: Labour Force Survey, data obtained from Central Bureau of Statistics, Netherlands
- Denmark: Labour Force Survey, data obtained from Statbank Denmark
- Sweden: Labour Force Survey, data obtained from Statistics Sweden

[23] The weblinks for these UNESCO files are no longer readily accessible. Copies of the relevant files accessed in 2010 are available from the authors on request.

[24] http://www.uis.unesco.org/Education/ISCEDMappings/Pages/default.aspx [accessed 30.05.2017]

[25] Ryan and Siebens (2012).

[26] Our reasoning for deciding (as a rough approximation) to allocate half of persons in the 'Some college, no degree category' to the upper intermediate group and half to the lower intermediate group is as follows: US Census Bureau estimates for 2009 show approximately 70% of individuals aged over 25 in this category holding vocational certificates (below Associates degree level) from 1-2 years attendance at college. The remaining 30% are shown as holding vocational certificates from 12 months or less attendance at college. However, an unknown proportion of individuals in the 'Some college, no degree category' may not have acquired formal qualifications of any kind. Furthermore, earnings estimates derived from the US Current Population Survey suggest that, on average, gross hourly earnings for individuals in the 'Some college, no degree category' are closer to those of High School graduates than the earnings of Associates degree holders. It therefore seemed inappropriate to classify all persons in the 'Some college, no degree category' to the upper intermediate group but available data do not allow more than a rough division of persons in the 'Some college, no degree category' between the upper and lower intermediate groups. As discussed in Section 6, when we submit our main results to sensitivity tests regarding different options for the classification of US intermediate-level qualifications, the main patterns of inference remain unchanged (see Table 6.4 in main text).

For more information, please contact
ioe.llakescentre@ucl.ac.uk

LLAKES Centre
UCL Institute of Education
University College London
20 Bedford Way
London WC1H 0AL
U.K.

National Institute of Economic and Social Research

UNIVERSITY OF Southampton School of Education

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL