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

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Abstract

Skills are widely recognised as central to absorptive capacity, that is, firms' ability to identify and make effective use of knowledge, ideas and technologies that are generated elsewhere. But identification of the specific levels 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. Drawing on a cross-country industry-level dataset, we retain separate measures of key components of absorptive capacity, namely, skills, R&D investments and openness to foreign trade and investment. We then estimate a system of structural equations in order to evaluate the extent to which different levels of skill contribute to innovative output (measured by growth in patenting) and subsequently to growth in productivity. 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 output. In final stages of production (making use of innovative output), productivity growth in countries near to the technological frontier is enhanced not just by high-level and upper intermediate skills but also by the skills of the workforce as a whole.

Keywords

Productivity; innovation; skills; absorptive capacity

Word count

10916

1. Introduction

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, even for firms attempting to imitate innovations developed 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.

But which specific levels of education and skills contribute most to the development of absorptive capacity (AC) and subsequently to innovation and productivity growth? The answers to these questions are highly relevant to understanding cross-country differences in 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 (Van Ark et al. 2008).

In this context, 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 et al. 2012) as well as the impact of complementarities and interdependence between high-level skills and other skills (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. [1] In this paper we address this issue 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 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. These countries were chosen to include a wide variety of education and training systems, with some more reliant on higher education than others and some more involved in vocational training at intermediate skill levels than others.

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. Sections 5-6 present our main findings and report on 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 (Lundvall 1992; Griffith et al. 2004; Cameron et al. 2004). Such transfers are often facilitated by inter-firm mobility of engineers and scientists and the personal networks built up by researchers (Mason et al. 2004).

Many spillover effects of this kind derive from foreign direct investment (FDI) and exposure to foreign competition through trade (Keller 2004; Newman et al. 2015), especially imports of new technology-based 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 et al. 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 et al. 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; Eisenhardt and Martin 2001; Teece 2007). The resources and capabilities which underpin AC derive in large part from 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 levels 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 levels 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) may also depend in many ways on intermediate-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). Recent evidence for Swiss manufacturing firms suggests that a strong presence of apprentice-trained workers alongside university graduates contributes positively to product innovation (Bolli et al. 2018). [2]

As discussed above, many earlier studies have been unable 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, Franco et al. (2014) find that skills interact with a 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). [3] 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. [4] The deployment of skilled workers may also contribute to the effectiveness of steps taken by firms to convert PAC into RAC, for example, improvements in internal communications, knowledge-sharing and departmental coordination (Jansen et al. 2005; Engelen et al. 2014).

In order to explore the contribution of skills at all stages of the innovation process, we adopt an alternative approach which recognises that, while RAC can be adequately proxied by different measures of innovative output, it is hard to find any single adequate measure of PAC. Therefore we 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.

Furthermore, our use of a cross-country industry-level dataset 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 (FDI) – both 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 to trade and FDI. 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 [5]

In addition to contributing to growth in innovative output through AC-related mechanisms, different levels of skill may also contribute to growth in final output at country/industry level by facilitating the adoption and diffusion of foreign technologies which help lagging countries to catch up with technology leaders (Bernard and Jones 1996; Cameron et al. 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 productivity gap between themselves and the world leader.

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 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). Their empirical results suggest that, while growth in multi-factor productivity (MFP) is negatively related to proximity to the technological frontier, it is positively related to the interaction between proximity and high-level (tertiary) skills. However, the interaction between proximity and lower-level skills is not significantly related to MFP growth. These findings imply that tertiary-educated workers are indeed more important than lower-skilled workers for countries closer to the frontier.

In related analysis Ang and Madsen (2015) find that the relationship between tertiary education and proximity to the technological frontier in OECD countries 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). [6]

The MFP and skills literature thus strongly suggests that high-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 levels 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 productivity performance. First, we investigate the extent to which workers with different skill levels 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 which skills help most to adapt and exploit external knowledge in improving production efficiency; the latter effect potentially has a direct influence on MFP growth. To this aim, we adopt a multi-equation regression framework in the spirit of the structural model proposed by Crepon et al. (1998).

We make use of industry-level data for eight countries between 1995-2007 (described below in Section 4). 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, the dependent variable is a measure of openness to foreign trade and 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:

$$(1) \qquad Openness_{ij,t} = \alpha_{ij0} + \alpha_1 \ln \bar{A}^f_{it} + \alpha_2 \ln TradeInvestmentBarriers_{jt}$$
$$+\alpha_3 \ln IndustrySize_{jt} + TD + \epsilon_{ijt}$$

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), the second equation of the model is based on a knowledge production function which relates innovative output to a measure of R&D effort adjusted for product expansion and the stock of existing patented knowledge. Thus R&D input is corrected to take account of the potentially negative effects of product proliferation on the effectiveness of R&D as R&D expenditure is spread over a larger number of product innovation projects (see Venturini 2012a). This makes R&D expenses per product line stationary over time. Knowledge production is modelled as follows (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, A is the existing stock of ideas and their ratio thus 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, reflecting the extent to which the generation of new ideas depends on existing knowledge.[7]

In this context, we estimate a log-linearized version of the above knowledge production function extended to account for the effects of skills and openness. [8] The dependent variable (innovation output) is approximated by $\Delta \ln \dot{A}$ (see Madsen 2008; Madsen et al. 2010):

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

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

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 external knowledge sourcing opportunities.

The third equation uses a distance-to-frontier framework to model 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) $$\Delta \ln MFP_{ijt+2} = \alpha_{ij0} + \alpha_1 \Delta \ln MFP_{iFt+2} + \alpha_2 PROX_{ijt+1} + \alpha_3 \ln Skills_{ijt+1}$$

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

Except for the frontier growth term, all the right-hand side variables are one-year lagged with respect to the dependent variable. In this case a positive and significant coefficient on the interaction term (α_5) would suggests that the skills in question contribute more to MFP growth in industries closer to the productivity frontier than they do in lagging industries.

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 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 external instruments in robustness tests described in Section 6. In addition we discuss results obtained using a two-stage least squares (2SLS) estimator to check whether results might be 'contaminated' by any of the equations in the system being misspecified.

In all analyses estimates are weighted by the share of each country-industry pair in total labour compensation to mitigate distortions related to different industry sizes.

4. Data sources

4.1 Data description

Our country/industry dataset has been assembled from a variety of sources and covers seven industries in eight countries (Denmark, France, Germany, Netherlands, Spain, Sweden, UK, US) for 1995-2007. As is standard in analyses dealing with R&D and patent data, we focus solely on manufacturing industries: Food, drink and tobacco (ISIC Rev 3.1:15-16); 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).

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. 3.1 classification, using the concordance table of intellectual property classes 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 the extent to which each country's institutional setting is favourable to internationalization, we use a country-level OECD measure of the strength of policy barriers to foreign direct investment (FDI), tariff barriers, differential treatment of foreign suppliers and barriers to trade facilitation. [9]

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 inflow and outflow series are derived from the OECD FDI statistics database.[10] 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.[11]

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). R&D expenditure is taken from the OECD ANBERD database while industry value added is derived from the EU KLEMS database (O'Mahony and Timmer 2009).

Other variables derived from the EUKLEMS database are:

(1) Multi-factor productivity, *MFP,* obtained assuming a multi-country translog production function based on value added, capital and labour.
(2) Gross value added expressed in constant-price 1997 US dollars converted on the basis of industry power purchasing parities; see Inklaar and Timmer (2008).
(3) Capital stocks derived through the perpetual inventory method from series on gross fixed capital formation (constant-price 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 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. [12] 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.

We obtain an internationally comparable measure of aggregate skill levels by taking the ratio of the EUKLEMS measure of quality-adjusted labour inputs (QAL_{ij}) to the total number of hours worked (L_{ij}):

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

As described above, this measure of aggregate skills takes some account of uncertified skills as well as certified skills through its *QAL* component. In our analysis it is systematically compared 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) $higher_{ij} = (L_{ij\_high}/L_{ij})$

that is, the proportion of total hours worked by persons with Bachelor degree qualifications or postgraduate university qualifications (L_{ij_high});

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

the proportion of total hours worked by persons 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

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

the proportion of total hours worked by persons with certified lower intermediate level skills (L_{ij_lower}) including high school diplomas in the US and craft-level qualifications in the European countries.

Further details of the classification of qualifications in each country and national data sources on qualifications are available in an on-line supplement to this paper. [13] Due to marked differences between US and European qualification systems, in Section 6.2 below we also report on robustness tests which assess the effects of making different assumptions regarding the allocation of US qualifications to different skill categories.

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. [14] In the case of Germany, France and Spain, medium-low estimates of openness reflect the net effect of considerable exposure to foreign trade being 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. In Sweden this shows up in a relatively high ranking on innovative output (average patent stocks per hour worked) but the same is not true for the US. 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 ($skills_{ij}$) were highest in the US at both the start and end of the 1995-2007 period. 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.

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. 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. 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).

5. Econometric findings

Results from three-stage least squares estimates of Equations 1-3 are reported in Table 1. 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 workers in different skill groups to the conversion of opportunities for external knowledge sourcing (openness) into innovative output and the extent to which each skill group influences MFP growth.

5.1 Openness to foreign knowledge sources

Across all 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 regressions. As expected, the coefficient on the country-level measure of policy barriers to trade and FDI (*TradeInvestmentBarriers*) is negatively-signed in all 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 skill measures, 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

In line with theoretical expectations, estimates of the knowledge production function (Equation 2) 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 (Table 1). 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 baseline estimates without interactions (Table 1, Columns 1, 3, 5 and 7), 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.

TABLE 1 ABOUT HERE

The significantly positive coefficients attached to R&D intensity are roughly in line with the values reported in earlier comparable studies using cross-country or cross-industry data (Ang and Madsen 2011; Venturini 2012a). A one pp increase in the ratio of R&D expenditure to value added (*RD/Y*) raises the rate of growth in patented knowledge by approximately 0.02% in the following year. The relatively small size of this estimated R&D impact may reflect the detrimental effect of product variety expansion (*Y*) with R&D effort being diluted across a larger number of product projects (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 1, Equation 2, Column 1, a one pp increase in the high-skilled share of hours worked is associated with an increase in the rate of growth in patented knowledge of 0.04% in the following year. This may underestimate the impact of high-skilled workers in R&D departments because a large proportion of R&D expenditure takes the form of researchers' wages, around 50% according to OECD estimates of R&D costs.[15] To the extent that researchers' productivity is fully reflected in their wages, the share of hours worked by highly educated workers will not capture the impact of human capital employed in R&D labs as the latter will already be captured by the R&D intensity measure. Thus the coefficient on the high-skilled labour share may only reflect positive effects of high-skilled R&D labour to the extent that their productivity exceeds their wages, plus 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, our estimates 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 negatively related to lower intermediate skills and the aggregate skills measure. These 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 patent growth in the baseline estimates of direct skills effects (Table 1, Column 3). In robustness tests reported in Section 6 below, we find that external instruments for upper intermediate skills are positively related to patenting performance (Table 3, Column 2); this is consistent with the relevant coefficient in our baseline estimates being attenuated due to measurement error.

At the same time, in our 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. Thus the main contribution by technicians and other intermediate-skilled workers may well take 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. While 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.

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

Table 1 also displays estimates for the MFP growth model (Equation 3), based on the distance-to-frontier approach. 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. 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.

MFP growth is also positively related to increases in RAC (innovative output) in the previous year, significantly so in a majority of specifications. 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.

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 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).

Notably, the aggregate skills/proximity interaction also has a positive significant effect on MFP growth. The aggregate skills measure takes account of both formal qualifications and uncertified skills (for example, those acquired through informal on-the-job training and work experience). Thus the positive coefficients on both the aggregate skills measure and the aggregate skills/proximity interaction in Table 1, Equation 3, Columns 7-8 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. Moreover, our results accord with evidence of a negative relationship between skill losses during unemployment and MFP performance at country level (Ortego-Marti 2017).

6. Robustness tests

6.1 Endogeneity issues

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 in Equations 2 and 3, for example, the possibility that 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 (institutional) variables relating to R&D policy and employment protection legislation (EPL) along with some deterministic elements. The predicted values of these variables are then utilised in re-estimating the full system of equations. Full details of the derivation of external instruments are provided in supplementary estimates for this paper, available on-line. [16]

Table 2 reports the first-stage estimates. As expected, R&D intensity is found to be significantly negatively related to measures of both the R&D tax price and R&D service regulation (Column 1). Both the high-skilled and upper intermediate-skilled 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). All skill shares are negatively related to the R&D tax price.

TABLE 2 ABOUT HERE

In order to check whether our sets of instruments satisfy the relevance condition (that is, our external variables are correlated with the potentially endogenous regressors), Table 2 reports the values of F-tests of joint significance of instruments in the first-stage estimates, for which the null hypothesis is that the instruments are jointly insignificantly related to the dependent variable. In each regression, the test value always exceeds the rule-of-thumb value of 10 identified by Stock et al. (2002), which provides assurance that the relevance condition is satisfied.

Table 3 shows the second-stage results in which R&D intensity is instrumented using the predicted values from Table 2, Column 1; higher skills and upper intermediate skills are instrumented using the predicted values from Table 2, Columns 3 and 5 respectively (based on EPL for temporary contracts); and lower intermediate skills are instrumented using the predicted values from Table 2, Column 6 (based on EPL for regular contracts)[17]. To check that each pair of external instruments satisfies the orthogonality condition (that is, instruments are uncorrelated with the dependent variable in each equation), we run auxiliary second-stage regressions which include both predicted regressors and external instruments and then test the joint insignificance of the latter variables. The p-values associated with this test show that, in each IV regression, the external instruments are jointly uncorrelated with the dependent variable.

TABLE 3 ABOUT HERE

In order to assess 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 3, 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 3, 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).

6.2 Other robustness tests

Our main inferences concerning Hypotheses 1 and 2 also prove to be robust to checks on other important econometric and measurement issues. Full details of these robustness test results are available in our on-line supplementary estimates. [18]

(1) In tests for strong cross-sectional dependence, we seek to purge the effects of common unobserved factors by including cross-sectional means of dependent variables and regressors in the system of equations while excluding time dummies, following the Pesaran (2006) common correlated effects (CCE) approach. The results are broadly in line with our main estimates in Table 1.

It should be noted that, when using the CCE approach to check for the presence of cross-sectional dependence, we are also controlling for unobservable sources of cross-industry, cross-country spillovers (such as localized R&D or human capital spillovers) having asymmetric effects among the panel units (see the discussion in Eberhardt et al. 2013).

(2) To test whether our 3SLS estimates have been contaminated by misspecification of one or more of the equations (which may lead to inconsistent estimates across the system as a whole), we re-estimate key specifications shown in Table 1 with 2SLS and compare these estimates with those yielded by 3SLS through a Hausman test. In all cases, the differences in coefficients between the consistent estimator (2SLS) and the efficient estimator (3SLS) prove to be statistically insignificant.

(3) In our main analysis we deploy a single measure of openness which is derived through a factor analysis of three different variables relating to trade and FDI: export share of sales, import penetration and the ratio of FDI flows to gross output. This use of a single

measure of openness is justified by the fact that all three component variables are highly correlated with each other and pass all relevant tests for factor analysis (see Section 4.1). Nonetheless, it remains of empirical interest to investigate whether international trade and FDI have different impacts on the knowledge production function.[19] We therefore carry out sensitivity tests using each of the three component variables in turn as indicators of openness. Our main findings in terms of hypothesis testing prove to be robust in all three cases. In general, the export and FDI measures appear to be more strongly linked to knowledge production than is the case with the import penetration measure. This is a plausible finding since mere purchasing of imports is less likely to provide opportunities for learning and innovation in host countries than is involvement in exporting and FDI activities.

(4) Due to marked differences between US and European qualification systems, we carry out additional analyses under different assumptions regarding the allocation of US qualifications to upper and lower intermediate skill categories. The results show that our main patterns of inference in relation to intermediate skills are robust to wide variations in these assumptions.

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 levels of education and skill 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.

Fourth, we carry out an extensive econometric analysis, based on a system estimator, which enables us to evaluate the extent to which different levels of skill contribute to innovative output (measured by growth in patenting) and subsequently to growth in productivity.

Our main findings are:

1. The conversion of opportunities for external knowledge sourcing (openness) into innovative output is positively related to employment of both high-skilled workers and upper intermediate-skilled workers.
2. Both high-level skills and upper intermediate-level skills contribute positively to multi-factor productivity (MFP) growth in countries and industries which are relatively close to the technological frontier (and thus tend to be more engaged in producing innovations than in imitating them).
3. The translation of innovative output into productivity performance in final stages of production also depends on the skills of the workforce as a whole, including skills acquired through informal on-the-job training and work experience, not just through formal education and training.

These findings are robust to tests for endogeneity and other important econometric and measurement issues. The key role of high-skilled (university graduate) workers in enhancing AC and growth in innovative output and productivity is expected given previous research findings in this field. However, our findings shed new light on the strong positive contributions made at each stage of innovation and production processes by upper intermediate-skilled workers. This category includes technicians who often play important support roles in new product design and development and in production management.

We also find evidence of positive links between workforce skills as a whole and innovation-driven productivity growth. This may partly reflect skilled workers' contributions to efficiency improvements but, in the context of firms' utilisation of externally-sourced knowledge, it could also reflect (among other things) the greater effectiveness of firms' efforts to improve inter-departmental communications, knowledge-sharing and coordination when overall skill levels are relatively high in all departments concerned. Such developments would be consistent with the literature on human capital spillovers within firms and industries which suggests that individual workers' productivity is stimulated by interactions with skilled co-workers (Moretti 2004; Kirby and Riley 2008).

In future research on the links between skills, absorptive capacity and firm performance, particular attention should be paid to the specific mechanisms by which externally-sourced knowledge is diffused and put into practice within firms – and how different skills facilitate that process. In addition, it would be useful to investigate other dimensions of skill besides those explored in this paper. For example, more account could be taken of cross-country differences in the proportion of graduates in STEM (science, technology, engineering and mathematics) subject areas as compared to non-STEM graduates, so long as the required data can be obtained at country and industry level. [20]

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Supplementary estimates and appendices

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Table 1: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity, analysed by skill level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-skilled		Upper intermediate-skilled		Lower intermediate-skilled		Aggregate skills	
(1) Dependent variable: Openness (t)								
ln foreign patent stocks per hour worked (t)	0.4031***	0.3822***	0.4035***	0.3775***	0.4181***	0.3594***	0.3893***	0.3606***
	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]
ln trade_investment barriers (t)	-0.0696*	-0.0845**	-0.0645*	-0.0770**	-0.0356	-0.1026***	-0.0806**	-0.1043***
	[0.036]	[0.036]	[0.036]	[0.036]	[0.035]	[0.036]	[0.036]	[0.036]
ln industry size (t)	-0.0776	-0.1114*	-0.0802	-0.1149*	-0.0388	-0.1579***	-0.1030*	-0.1527**
	[0.061]	[0.061]	[0.061]	[0.061]	[0.060]	[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)	-0.1029***	-0.1366***	-0.1007***	-0.1728***	-0.1117***	-0.1443***	-0.0922***	-0.0893***
	[0.021]	[0.026]	[0.021]	[0.027]	[0.022]	[0.021]	[0.020]	[0.018]
ln R&D intensity (t)	0.0173***	0.0195***	0.0203***	0.0279***	0.0171***	0.0191***	0.0191***	0.0203***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
ln skills (t)	0.0403***	0.0806***	-0.0349**	0.1656***	0.0112	-0.1752***	0.1176	0.3698**
	[0.014]	[0.021]	[0.014]	[0.049]	[0.023]	[0.039]	[0.105]	[0.156]
openness (t)	0.0594	0.1883**	0.0619	0.8127***	0.1303***	-0.2933***	0.0257	-0.5918**
	[0.039]	[0.074]	[0.039]	[0.181]	[0.043]	[0.058]	[0.039]	[0.297]
ln skills * openness (t)		0.0975**		0.3598***		-0.3170***		0.9600*
		[0.038]		[0.083]		[0.061]		[0.504]
(3) Dependent variable: growth in multi-factor productivity (t+2)								
Δ ln lead-country MFP (t+2)	0.7147***	0.7146***	0.7102***	0.7092***	0.7059***	0.7059***	0.7006***	0.7003***
	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]	[0.032]
ln proximity (t+1)	-0.0657***	-0.0656***	0.0477	0.0511	-0.0815***	-0.0826***	-0.1527***	-0.1563***
	[0.023]	[0.023]	[0.039]	[0.039]	[0.026]	[0.026]	[0.034]	[0.034]
Δ ln patent stocks per hour worked (t+1)	0.1404	0.1678*	0.2172**	0.1950**	0.1183	0.1235	0.1655*	0.1715*
	[0.090]	[0.090]	[0.088]	[0.088]	[0.094]	[0.094]	[0.090]	[0.089]
ln skills (t+1)	0.0398**	0.0399**	0.1052***	0.1071***	-0.0104	-0.0107	0.2740***	0.2755***
	[0.019]	[0.019]	[0.025]	[0.025]	[0.028]	[0.028]	[0.101]	[0.101]
ln skills * ln proximity (t+1)	0.0228**	0.0233**	0.0743***	0.0756***	0.0207	0.0209	0.0960*	0.0994*
	[0.009]	[0.009]	[0.018]	[0.018]	[0.021]	[0.021]	[0.052]	[0.052]
Observations	571	571	571	571	571	571	571	571
R-squared - Eqn 1	0.973	0.973	0.973	0.973	0.973	0.973	0.973	0.973
R-squared - Eqn 2	0.525	0.536	0.522	0.412	0.468	0.546	0.531	0.496
R-squared - Eqn 3	0.792	0.792	0.795	0.796	0.791	0.791	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 country/industry share of total employee compensation. Standard errors in brackets. All equations include country-by-industry fixed effects and year dummies.

Table 2: Instrumenting R&D intensity and skills with external (institutional) variables: 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 include country-by-industry fixed effects and year dummies. The null hypothesis for the F-test is that the external instruments are jointly insignificantly related to the dependent variable in each equation.
The R&D tax price measure is derived from Thomson (2013) combined with data on innovation intensity (R&D expenditure over value added) at country/industry level (Vartia 2008). The R&D service regulation measure is taken from the OECD index of service regulation pertaining to engineering professional services. Measures of the strictness of EPL (employment protection legislation) are taken from the OECD employment protection database (Venn 2009).

Table 3: Three-stage least squares estimates of openness, growth in innovative output and growth in multi-factor productivity - 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]
F-test on exclusion restrictions [p-value]	[0.180]	[0.502]	[0.216]
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 country/industry share of total employee compensation. Bootstrapped standard errors shown in brackets (200 replications). All equations include country-by-industry fixed effects and year dummies. Predicted values of R&D intensity and skills are derived from first-stage estimates reported in Table 2. The null hypothesis for the F-test on exclusion restrictions, described in the main text, is that the external instruments are jointly insignificantly related to the dependent variables in Equations 2 and 3 in each model, thus satisfying the orthogonality condition for instruments.

NOTES

[1] See Lane et al. (2006) for a detailed discussion of AC measurement difficulties.
[2] Bolli et al. (2018) focus specifically on the impact of 'vertical education diversity' on innovation performance rather than on the contributions made by different skill groups (the focus of the present paper). However, as Bolli et al. note (pp 127-128), in Switzerland vertical education diversity is strongly related to the relatively large proportions of workers at firm level who have been trained in the country's high-quality vocational education and training system.
[3] 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.
[4] 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.
[5] 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'.
[6] 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.
[7] If ϕ is unitary, this points to constant returns to scale in knowledge production. If ϕ is less than unity, this implies decreasing returns, whilst the reverse holds when ϕ is greater than one.
[8] Logs are not taken for the openness measure since, as described in Section 4 below, it is derived from data on foreign trade and FDI as a factor score with mean zero and standard deviation of one.
[9] 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.
[10] FDI flows and total gross output are aggregated to three-year periods because of unevenness in annual FDI flows at country/industry level.
[11] 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: $p<0.001$***
[12] Under this assumption a measure of quality-adjusted total labour input is obtained by weighting each different skill group (as signified by qualification levels) by the share that each skill group occupies in total labour compensation (see, for example, Jorgenson et al. 2005).
[13] Supplementary estimates and appendices are available at: https://works.bepress.com/francesco_venturini/60/
[14] Full descriptive statistics are available in an on-line supplement to this paper (see Note 13)
[15] Source: OECD Research and Development Statistics.
See http://stats.oecd.org/Index.aspx?DataSetCode=ONRD_COST
[16] See Note 13.
[17] In these second-stage regressions, standard errors are bootstrapped with 200 replications.
[18] See Note 13.
[19] We are grateful to a referee for this journal for making this suggestion.
[20] Considerable resources have recently been invested in cross-country comparisons of STEM graduate supplies by organisations such as the OECD and the US National Science Foundation.
See http://www.oecd.org/sti/oecd-science-technology-and-industry-scoreboard-20725345.htm ;
https://www.nsf.gov/statistics/2018/nsb20181/report/sections/overview/workers-with-s-e-skills .
However, upon investigation, these comparisons have so far focussed exclusively on annual output (*flows*) of different kinds of graduate for entire countries. By contrast, in the present paper our analysis relies on the availability of data on the *stocks* of workers with different qualifications at industry level in each country concerned.