I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 10457

Sectoral Cognitive Skills, R&D, and Productivity: A Cross-Country Cross-Sector Analysis

Simone Sasso
Jo Ritzen

DECEMBER 2016

DISCUSSION PAPER SERIES

IZA DP No. 10457

Sectoral Cognitive Skills, R&D, and Productivity: A Cross-Country Cross-Sector Analysis

Simone Sasso
UNU-MERIT, Maastricht University

Jo Ritzen
IZA and UNU-MERIT, Maastricht University

DECEMBER 2016

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Sectoral Cognitive Skills, R&D, and Productivity: A Cross-Country Cross-Sector Analysis[1]

We focus on human capital measured by education outcomes (skills) and establish the relationship between human capital, R&D investments, and productivity across 12 OECD economies and 17 manufacturing and service industries. Much of the recent literature has relied on school attainment rather than on skills. By making use of data on adult cognitive skills from the Programme for the International Assessment of Adult Competences (PIAAC), we compute a measure of sectoral human capital defined as the average cognitive skills in the workforce of each country-sector combination. Our results show a strong positive relationship between those cognitive skills and the labour productivity in a country-sector combination. The part of the cross-country cross-sector variation in labour productivity that can be explained by human capital is remarkably large when it is measured by the average sectoral skills whereas it appears statistically insignificant in all our specifications when it is measured by the mere sectoral average school attainment. Our results corroborate the positive link between R&D investments and labour productivity, finding elasticities similar to those of previous studies. This evidence calls for a focus on educational outcomes (rather than on mere school attainment) and it suggests that using a measure of average sectoral cognitive skills can represent a major step forward in any kind of future sectoral growth accounting exercise.

JEL Classification: I21, J24, O47

Keywords: sectoral cognitive skills, productivity, R&D, human capital, knowledge stock

Corresponding author:
Jo Ritzen
IZA
Schaumburg-Lippe-Str. 5-9
53113 Bonn
Germany
E-mail: Ritzen@iza.org

1 We would like to thank Pierre Mohnen, Bart Verspagen, and Eddy Szirmai for the valuable suggestions provided during the development of this paper. We are also grateful to Anja Perry and Jan Paul Heisig for the useful information on the PIAAC data design generously shared at the PIAAC Workshop in Cologne. All errors remain our own. Financial support from IZA is gratefully acknowledged.

1. Introduction

The key source of modern economic growth is productivity growth (e.g. Maddison, 2007) which is ultimately determined by technological progress (Solow, 1957). Innovation and technological progress are driven by people's knowledge and skills which, in turn, are fostered by education and by research and development activities (R&D). Education – by equipping individuals with knowledge and skills – enables workers to use more efficiently existing technologies as well as to generate new ideas and, as a result, to stimulate innovation and technical change. Similarly, research and development activities deliberately aim at increasing the stock of knowledge and ideas and to find new solutions.

Since the advent of endogenous growth theories (e.g. Romer, 1986, 1990; Lucas 1988) education as well as the stock of ideas present in the economy have been formally added to the traditional inputs of physical capital and labour as a determinant of economic growth. Shortly after, from the seminal works of Barro (1991) and Mankiw, Romer and Weil (1992), empirical research on the relationship between human capital, productivity and growth has expanded tremendously. Most research has measured education through input-variables - namely through school-attainment or school-enrolment (e.g. Barro and Lee, 1993, 2013) - rather than through output-variables able to capture the actual knowledge and skills that education provides to individuals. This has led to some quite contrasting results on the role of human capital on productivity and growth. In recent years, a few studies - by making use of internationally comparable tests to assess students' cognitive skills - have started to measure human capital through educational outcome indicators. Hanushek and Woessmann (2008, 2012, 2015, 2016) found that the cross-country variation in GDP per capita growth that can be explained by human capital rises drastically when the country average of test scores are taken as a regressor instead of the country average years of schooling. However, to the best of our knowledge, no study has yet computed and used the average cognitive skills that the workforce in each sector of the economy has, i.e. a more precise measure of the human capital that is actually available in each sector.

In parallel, since the seminal work of Griliches (1979), economists have widely analysed to which extent the output of a firm, a sector, or an economy is related to its stock of R&D (Hall et al., 2010). However, considerably fewer studies have investigated how the impact of R&D on productivity varies across economic sectors (e.g. Ortega-Argilés et al., 2015; Verspagen, 1995) and no systematic study has yet looked at the joint impact of R&D and cognitive skills on productivity across different industries and countries.

Our paper aims to combine and cross-fertilise these strands of research in order to understand the interrelation of human capital, R&D investments and productivity across sectors and countries. The structural equation for the analysis is derived from a standard production function (e.g. Mankiw, Romer and Weil, 1992; Hall and Mairesse, 1995) where a measure of the average sectoral cognitive skills is taken as an additional right-hand factor for human capital, next to the traditional measures of fixed capital, labour stocks, and R&D investments.

Our results indicate a strong positive association between the cognitive skills of each country-sector combination and its productivity. The part of labour productivity that can be explained by human capital is remarkable large when it is measured by the actual skills of the different workforce, whereas it shows up statistically insignificant in all our specifications when measured by the sectoral average school attainment of the workforce. Our regressions confirm the positive link between R&D investments and labour productivity, finding very similar elasticities to those of previous studies (e.g. Verspagen, 1995; Bartelsman, 1990).

The rest of the paper is structured as follows. Section 2 discusses the theoretical background explaining the education-R&D-productivity relationship. Section 3 presents the empirical evidence on the returns to education and R&D. Section 4 describes the data used in our analysis and our sample. Section 5 explains our econometric estimation Model. Section 6 discusses the distributions of skills, R&D and productivity across the 12 countries and 17 sectors of our analysis. Section 7 presents the results. Finally, section 8 concludes and discusses our findings.

2. Theoretical background: how education and R&D affect productivity

Education, by equipping people with skills and knowledge, makes individuals more productive in performing their tasks as well as in adopting and using existing technologies; furthermore, it enables them to generate new ideas that, in turn, foster innovation and technological progress (Woessman, 2016). Similarly, R&D investments and the resulting innovation can boost productivity by improving the quality or reducing the average production costs of existing goods or by widening the range of final goods or intermediate inputs available (Hall et al, 2010).

In spite of their importance, human capital and the stock of ideas present in the economy have not been formally included into growth Models until the Nineties when endogenous growth theories rose. The so-called “new-growth theories” included these elements into two sets of Models; one set of theories emphasized the importance of R&D activities while another one focused on the key role played by human capital. According to the first strand of growth Models (e.g. Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991), R&D activities – by intentionally aiming to increase the stock of knowledge and ideas to find new solutions – generate technological progress and therefore increase economic output. The other approach (e.g. Lucas, 1988; Romer, 1986) stressed the idea that skilled human capital – by using existing technologies in a more efficient way and, at the same time, by generating new ideas, new processes or products – could spur innovation and, therefore, increase economic output.

Some scholars, by combining these two approaches, have pointed at the complementary link that characterises R&D and skills. In fact, R&D activities cannot *per se* be conducive to innovation if the firms’ employees are not adequately skilled. Nevertheless, the causality of this link can plausibly run two-ways. An increase of R&D investments and a leap in technological progress can be considered both the cause and the consequence of an increase in the skill endowment present in a certain country/sector/firm. On the one hand, economists have largely put forward the idea of *skill-biased technical change* to indicate that the improvements in ICTs and in the production technologies that occurred since the 1970s have been conducive to labour upskilling (e.g. Autor et al, 1998; Machin and Van Reenen, 1998). They stressed the idea that mundane activities have been increasingly automatized and performed by machines with a consequent decrease in unskilled-labour demand; at the same time, using, mastering and creating the new technologies has required more skilled-workers, resulting in an increase in the demand of skilled workers and in relative wages. In other words, innovation and the demand of highly-skilled individuals are mutually reinforcing: innovation increases the demand for non-routine jobs which, in turn, generate new products and processes (Levy and Murnane, 2012). On the other hand, one might expect that an initial high endowment of skilled individuals can increase the expected returns from R&D and, therefore, encourage firms to further invest in R&D. This is why a few authors have put forward the idea of *induced-bias* technological change (e.g. Accemoglu, 1998; Piva and Vivarelli, 2009).

3. Empirical evidence

Several empirical studies have tested the role that R&D and human capital play on increasing economic output at the micro-, meso- and macro- level.

Since the seminal work of Griliches (1979), which was published a decade before the surge of new growth theories, economists have widely analysed to which extent the output of a firm, of a sector, or of an economy is related to its R&D capital stock (for comprehensive reviews at the different scales of analysis see Griliches, 2001; Hall et. all, 2010). The literature on the topic is solid and, in general, has found that the returns of R&D investments are strongly positive and usually higher than the ones on physical capital[2]. Nevertheless, relatively fewer studies have investigated the R&D-productivity relationship at the sectoral level (e.g. Bartelsman, 1990; Ortega-Argilés et al., 2015; Verspagen, 1995) and, when they have done so, they have mostly concentrated on manufacturing industries. Analysing the returns of R&D at the firm level offers a limited perspective because it does not capture the effects of knowledge spillovers which may be generated from the R&D stock present in the industry. Furthermore, looking only at manufacturing may represent a rather restrictive analysis giving the increasing importance that R&D activities have assumed in the service sector, i.e. a sector which comprises about three-quarters of the GDP of developed countries (Jorgenson and Timmer, 2011).

[2] Note that recent meta-regression analyses (Ugur et al, 2016; Møen and Thorsen, 2015) – which have combined the results coming from several primary studies on R&D investments and firm/sector productivity – have pointed out that the average returns to R&D are positive but smaller than the ones that are reported in most of the literature. This occurs because of two main biases: a publication selection and a sample selection. The former occurs when the authors look for samples, estimation methods or specifications that allow them to have statistically significant estimates; the latter occurs when the reviewers rely on specific "representative" or "preferred" sub-samples rather than on the full available information.

In parallel, the impact of human capital on productivity and growth has been widely tested in the past decades. Empirical studies have relied almost exclusively on education input-measures - e.g. school attainment or school enrolment ratios (e.g. Barro and Lee, 2013) - rather than on output-variables able to capture the actual knowledge and skills that education provides to individuals. Findings have been mixed especially at the macro level. On the one hand – since the seminal works of Barro (1991) and the augmented-Solow Model tested by Mankiw et al (1992) - several studies found a positive relationship between education and economic growth (for a broad review see Sianesi and van Reenen (2003)). Ciccone and Papaioannou (2009) found not only that countries with higher initial education levels experience faster value-added growth, but also that more educated countries experience faster growth in skill-intensive industries.

On the other hand, other similar cross-country studies (e.g. Pritchett, 2001; Benhabib and Spiegel, 1994) found no significant association between educational attainment and productivity or growth. Only recently, empirical research has started using outcome measures of education, showing that – when measured by the actual skills that the people have learned and developed – human capital appears to be a (if not the most) central determinant of country's long-run economic growth. Hanushek and Woessmann (2008, 2012, 2015, 2016) – by using internationally comparable test scores measuring cognitive skills – found that the cross-country variation in GDP per capita growth that can be explained by human capital rises drastically when the country average of test scores (in math and science) are taken as a regressor instead of the country average years of schooling. Furthermore, when they include the initial average school attainment of each country in the regression Model, the years of education remain statistically insignificant suggesting that what matters for economic growth is what people know and not how many school years it took them to acquire those skills. These results have been further corroborated with a set of robustness checks to address possible problems of reverse causality and omitted variables. Hanushek and Woessmann (2015), after instrumenting the average test scores (by using characteristics of each national schooling system) or, for a subsample of countries, relating within country variations in growth and in average test scores, confirmed the causal link between human capital and growth.

The effects of the distribution of skills in the population are not yet clear. Hanushek and Woessmann (2015) found that improving both ends of the distribution is beneficial and complementary: a sound basic achievement skill level for the population at large is crucial to increase the average productivity of the country; at the same time, the extent to which a country has outstanding performances at the very top can be fundamental in order to have "rocket scientists" who are the engine of new ideas and technologies (Woessmann, 2016). At the same time, results by Coulombe et al. (2004) – who analyse labour productivity growth (measured as GDP per worker growth) and relate that to the average literacy scores of the population aged 17 to 25 in fourteen OECD countries – suggest that labour productivity is mainly influenced by the average cognitive skills of the entire workforce, rather by the ones of the highly-skilled workers.

These studies paved the way for a more extensive use of educational outcome measures to analyse the impact of human capital on economic results. So far, the recent studies relating cognitive skills to GDP growth (e.g. Hanushek and Woessmann, 2008, 2012, 2015, 2016) have generally relied on students' assessments of cognitive skills[3]. These measures can be good indicators of the quality of education; however, since they reflect only the knowledge that (secondary education) students have, they do not represent the human capital that is embodied in the workforce. Their skills of the workers operating in the various industries are shaped not only by the formal education that they received, but also by the several experiences and trainings that they have gone through their working life. In our analysis, by making use of data on cognitive skills from the Programme for the International Assessment of Adult Competences (PIAAC), we compute the average sectoral cognitive skills of the workforce operating in 12 economies and 17 economic sectors.

4. Data and sampling

Data for our study comes from three different sources. The socio-economic satellite accounts of the *World Input-Output Database* (WIOD) provides a set of sectorally-broken-down national accounts, including capital stocks and labour measures for a wide set of countries and for 35 industries (which largely reflect the International Standard Industrial Classification of All Economic Activities Rev.3.1)[4].

The OECD's *Analytical Business Enterprise Research and Development Database* (ANBERD) offers the state-of-the-art on business R&D expenditures broken down by sector (1 or 2 digit ISIC rev.4 or ISIC rev. 3) for OECD countries. Business R&D expenditures include all R&D activities carried out in the business sector, regardless of the origin of funding (private or public). Finally, our primary data source is represented by the OECD's Programme for the International Assessment of Adult Competencies (PIAAC). Given the novelty and the originality of the latter data, we concentrate mainly on describing the PIAAC micro-database and the way in which we computed our sectoral measures of cognitive skills.

4.1. The PIAAC data

The PIAAC survey provides internationally comparable data on cognitive skills of the adult population in 24 countries or sub-national regions[5]. In each country, a selected sample of 16-65 year-old population has been interviewed between August 2011 and March 2012. Different sampling schemes have been used and re-aligned with post-sampling weightings to meet the real population counts.

---

[3] Recently, Valente et al. (2016) have looked at the relationship between work-based cognitive skills and economic performance in European countries. They found that countries where workplaces require and strengthen advanced cognitive skills tend to have higher economic growth. It is worth noting that the measure of workplace cognitive skills adopted in the study relies on workers' self-assessment, which is likely to be more imprecise and culturally biased than the one based on internationally comparable cognitive skills tests.

[4] More details on the database and its construction can be found in Dietzenbacher et al (2013) and at www.wiod.org.

[5] The 24 countries and sub-national regions which participated in the first wave of the survey are the following: Australia, Austria, Canada, Cyprus, Czech Republic, Denmark, England/Northern Ireland (UK), Estonia, Finland, Flanders (Belgium), France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United States. Note that data for Australia is not publicly available whereas data on Cyprus and the Russian Federation is considered subject to change and not representative of their respective populations (see OECD (2013b: 21)). Therefore these three countries have not been considered in our analysis.

PIAAC assesses three domains of cognitive skills, i.e. literacy, numeracy and problem solving in technology-rich environments. Prior to the skills assessment, PIAAC respondents have been asked to complete a background questionnaire which provides key extensive information on respondents' education, employment, work experience, health, family and workplace characteristics[6]. The indicators of skills proficiency have been constructed by making use of adaptive testing and Item Response Theory (ITR), deriving ten plausible values on a 500-points scale and 80 replicate weights for each participating individual[7]. The OECD has divided the population into 6 proficiency levels, according to the score associated to their test (see Table A in Appendix and OECD, 2013a). As pointed out by the OECD (2013a), skill proficiencies of the three domains appear highly correlated with each other. Since questions on *problem solving in technology-rich environment* have been posed only to about two-thirds of the respondents – namely to those respondents who reported to have some computer experience[8] – we excluded this domain from our analysis. Literacy is defined as "understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (2013b:470). Numeracy is defined as "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (2013b:474). The test scores in these two skills appear to be strongly correlated[9]. Given the high correlation coefficient (r>0.9), in our main analysis we make use only of numeracy scores[10]. Thanks to the workplace information contained in the background questionnaire, we could identify the economic sector of activity of the respondents and calculate the average sectoral cognitive skills in each country-sector combination. In order to have the most accurate measures, our average sectoral cognitive skills have been calculated by taking into account all the plausible values available for each individual participating in the PIAAC survey and the replicate weights associated to him/her[11].

[6] In all participating countries, some individuals (usually less than 5% of the total sample) have been unable to fill in the background questionnaire because they had difficulties reading or writing or had mental or learning disabilities. In these cases only the age, the gender and, at times, the educational attainment of these individuals is known. No information on the employment status is known, nor on the industry where these individuals might work. Therefore, these individuals have not been included in the computation of the average sectoral cognitive skills. For details on literacy related non-response bias, see OECD (2013b:56).

[7] As it is customary in international large-scale assessments, to minimize individuals' response burden, each PIAAC respondent has been asked to answer only a limited number of test items. The scores of the items that have not been responded have been predicted based on the answers to the test and to the background questionnaires of similar individuals, generating a distribution of values and of associated probabilities with ten plausible values randomly obtained for each individual and implementing jackknife method (with 80 replicate weights) to take into account proper standard errors. For this reason, PIAAC data are ideal to estimate cognitive skills for each country population or for sub-groups of populations (e.g. in our case, all respondents working in the same sector of activity), whereas the accuracy of the competencies assessment is considerably lower for the individual level (see OECD, 2013b: 409). For details on PIAAC survey design and methodology, see OECD (2013b); for extensive information on plausible values and ITR, see von Davier et al (2009).

[8] Therefore, the sample truncation is not random and could lead to upward-biased estimates of the average scores in problem solving in technology rich environments across the various country-sector combinations.

[9] This high correlation is in line with expectations and with previous studies. By analyzing the test scores of all individuals (i.e. those who are employed as well as those who are not) in all the countries that participated into the PIAAC survey, proficiency in literacy and in numeracy are correlated with a coefficient of 0.86 (OECD, 2016: 56). Even higher correlation coefficient (i.e. r = 0.93) was found between prose literacy and numeracy in the International Adult Literacy Survey (IALS) (*ibidem*).

[10] We have repeated the same analysis also using literacy scores, reaching similar results.

[11] For a detailed discussion on the possible pitfalls connected to the use of single plausible values, see Rutkowski et al (2010) and OECD (2013b).

4.2 Data trimming

The presence of inconsistent or incomplete information and the fact that PIAAC data has been collected only in one wave forced us to use a rather parsimonious specification. The PIAAC database contains information on the sector where the workers are working at 2-digit ISIC rev.4 level[12]; the ANBERD database provides information on R&D investments broken down at 2-digit ISIC rev.3 level or 2-digit ISIC rev.4 level; the WIOD socio-economic satellite accounts provides information on labour, fixed assets, and value added for 35 industries which largely follow the ISIC rev. 3.1 classification. After controlling for the different classifications, we identify 12 countries and 17 sectors of activity, both in manufacturing and in services, resulting into 204 country-sector combinations. As reported in Table 1, all major industries and 12 principal OECD countries are part of this sample.

Table 1. Countries and sectors of analysis.

Countries		Industries	
1.	Belgium	1.	Food
2.	Czech Republic	2.	Textiles
3.	Germany	3.	Wood & Paper
4.	Spain	4.	Chemicals & Pharmaceuticals
5.	France	5.	Rubber & Plastics
6.	Italy	6.	Other Minerals
7.	Japan	7.	Metals
8.	Korea	8.	Machinery & Equipment
9.	Netherlands	9.	Electrical & Optical Equipment
10.	Poland	10.	Motor Vehicles
11.	United Kingdom	11.	Other Manufacturing
12.	Unites States	12.	Utilities
		13.	Construction
		14.	Sale & Trade
		15.	Transportation, Storage & Communication
		16.	Finance & Insurance
		17.	Other Professional & Business Services

Different from other international cognitive skill tests – most notably international students' achievement tests such as PISA and TIMSS – cognitive skills tested in PIAAC measure skills of the actual labour force. In this way they take into account also the skills that have been developed during adulthood through work experience or on-the-job training. Therefore, they represent a more accurate measure of the actual human capital that is present in the different workforces across different countries and sectors. Differently from other studies (e.g. Coulombe et al., 2004 who take average test scores of the population aged 17 to 25 or Hanushek and Woessmann, 2015 who use test score of secondary-education students) we analyse the test scores of the individuals that are employed in one of the 17 sectors of our analysis.

[12] Note that even if the PIAAC survey has been the same one for all the countries, appropriately translated into the official language or languages of each participating countries, several countries which have participated in PIAAC have not collected any sectoral information in their PIAAC survey (e.g. Austria, Canada, Estonia, or Finland).

5. Econometric estimation Model

We define our estimation Model by taking an extended Cobb-Douglas production function (e.g. Griliches, 1986; Mankiw, Romer and Weil, 1992) as follows

$$(1) \qquad Q_{ij} = A\, L_{ij}^{\alpha_1}\, C_{ij}^{\alpha_2}\, RD_{ij}^{\alpha_3} SKILLS_{ij}^{\alpha_4} e^{\varepsilon_{ij}}$$

where Q_{ij} is the output in country i, sector j measured by total value added, L_{ij} is labour measured by the total number of workers, C_{ij} is physical capital[13]; RD_{ij} is the knowledge capital measured by expenditure in R&D[14], and $SKILLS_{ij}$ is the average cognitive skills, i.e. the two key variable of interest in our analysis.
The parameters α_1, α_2, α_3, α_4 are elasticities, whereas ε_{ij} is a random disturbance term.
Taking logs of (1) we get

$$(2) \qquad \ln Q_{ij} = \ln A + \alpha_1 \ln L_{ij} + \alpha_2 \ln C_{ij} + \alpha_3 \ln RD_{ij} + \alpha_4 SKILLS_{ij} + \varepsilon_{ij}$$

Dividing (2) by the total stock of workers of each country-sector combination, we get our measure of labour productivity defined as

$$(3) \qquad \ln \frac{Q_{ij}}{L_{ij}} = \ln A + \alpha_2 \ln \frac{C_{ij}}{L_{ij}} + \alpha_3 \ln \frac{RD_{ij}}{L_{ij}} + \alpha_4 \ln SKILLS_{ij} + (\alpha_1 + \alpha_2 + \alpha_3 - 1) \ln L_{ij} + \varepsilon_{ij}$$

Using value added per worker relaxes possible restrictions on constant returns to scale (Hall et al, 2010); the term $(\alpha_1 + \alpha_2 + \alpha_3 - 1)$ measures the possible deviation from constant returns to scale. Since only one observation in time is available for the average sectoral cognitive skills, we are limited to adopt a cross-sectional setting. Our measure of average sectoral cognitive skills – which has been computed from the PIAAC micro-database – refers to 2011/12[15]. However, we use value added, labour, capital stock, and R&D flows values of 2007 (in USD dollars at fixed prices of 1995). First, economic indicators of year 2007 have not been affected by the crisis and therefore are closer to the current sectoral performances than those from 2011/12. Second, the WIOD database provides detailed information for fixed capital stock for 2007; using newer data would have implied a significant loss of observations in our analysis, as more recent years contain only for a few country-sector combinations. Third, we assume that the average cognitive skills present in a sector is rather stable and does not significantly change in the short-to-medium term; therefore, the average skills present in a certain sector in 2011 can be considered a good proxy of the average level of skills present in the same sector four years before.

---

[13] As common practice, note that in the WIOD database physical capital stocks have been computed by using the perpetual inventory method. In practice, the following formulas have been applied: $C_{i,0} = I_{i,0}/(g+\delta)$ and $C_{i,t} = C_{i,t-1}\,(1-\delta) + I_{i,t}$ where I is the gross investment in fixed assets, g is the average growth rate of the capital stock and δ is then depreciation rate. For further details see Erumban et al., 2012.

[14] Note that in our analysis R&D here refers to the R&D investments of the year of analysis (i.e. 2007). Since we deal with a cross-section setting and we use pre-crisis R&D expenditures, the elasticities of R&D investment do not significantly differ from the ones that one would obtain by using R&D capital stocks.

[15] PIAAC survey has been conducted between 2011 and 2012; the exact month/year varies across countries. For details, see OECD (2013b).

In order to have comparable values, by using the detailed sectoral information contained in the WIOD database, we build country-sector specific deflators defined as

$$(4) \qquad PI_{ijt} = \frac{\sum VA_{izt}}{\sum VA\_FX_{izt}}$$

where *j* identifies the 22 sectors of our analysis, *z* represents the 33 sectors available in the WIOD database, VA_{izt} is the total value added at current prices of country *i*, sector *z* and year *t*, and VA_FX_{izt} is the total value-added at fixed prices of 1995[16].

6. Descriptive statistics

In today's knowledge-economy, acquiring skills and knowledge has become increasingly important across virtually all sectors of activity.

However, this occurs at different scales, depending on the sector. When we compare the average sectoral numeracy scores across the 17 industries of our analysis, substantial heterogeneity emerges across sectors. As showed in Figure 1, out of a 0-500 scale, we find that the average sectoral numeracy score lies between 259 points and 294.5 points. Six (out of seventeen) sectors employ, on average, workers which have rather advanced numerical skills (i.e. they can recognize and work with mathematical relationships, patterns, and proportions as well as interpret and analyze data and statistics which may be less explicit not always familiar, and represented in more complex ways[17] (OECD, 2013b: 523)). The remaining 11 sectors employ workers that on average have medium-low numeracy (i.e. they can only apply a few steps or processes involving simple calculation with whole numbers and common decimals, percents, and fractions[18] (OECD, 2013b:522)).

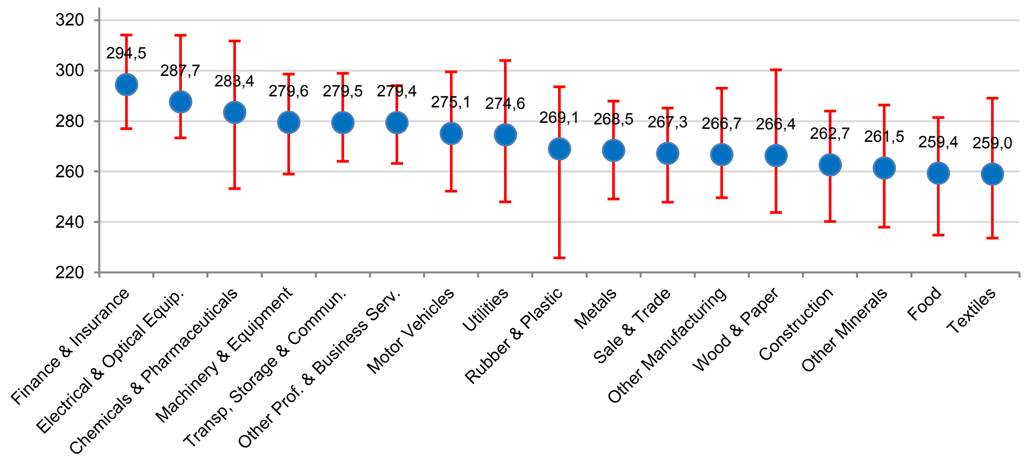
Our analysis shows that the financial and insurance sector is the most skill-intensive industry. This is in line with the findings from Jorgenson and Timmer (2011). Our data allow us to show more fine-grained variations in the sectoral skill distribution than previous analysis. For instance, Jorgenson and Timmer (2011) show manufacturing to be among the least skill-intensive industry. Our results consistently point out that only part of the manufacturing industries (i.e. low-tech manufacturing) is among the least skill-intensives sectors. High-tech manufacturing industries (e.g. electrical and optical equipment) in contrast are high-skill sectors.

[16] Note that to run the analysis in the same currency (i.e. USD), we use market exchange rates. The alternative is to use purchasing power parities (PPP) which measure the relative prices of the same basket of consumption goods in different countries. We have opted for market exchange rates for two main reasons. First, PPP conversion rates are not available at the sectoral level of aggregation required by our analysis: as recently pointed out by Van Biesebroeck (2009), cross-country cross-sector productivity comparisons done through aggregate PPP rates conduce to persistent sectoral biases and deviations which are not necessarily minor than the ones created by using market exchange rates. Second, as all the 12 countries of our analysis are advanced economies, the difference between market exchange rates and PPP rates tend to be small.

[17] This corresponds to Proficiency Level 3 as defined in the OECD PIAAC Technical Report. For further details, see Table A in appendix or OECD (2013b).

[18] This corresponds to Proficiency Level 2 as defined in the OECD PIAAC Technical Report.

Figure 1. Average sectoral numeracy scores by sector.



Sectors are ranked in descending order of mean score in numeracy (on a 0-500 scale). Blue dots indicate the cross-country sectoral mean, whereas the two whiskers indicate the maximum and the minimum country average numeracy within each particular industry. Source: own calculations based on the OECD Survey of Adult Skills PIAAC (2013).

The red bars of Figure 1 show that the cross-country within-sector variation is quite remarkable: for instance, the rubber and plastic industries employs workers that have on average medium-high numeracy scores in Japan and low numeracy scores (i.e. workers can perform only basic arithmetic operations or understand simple percentages and fractions[19] (OECD, 2013b: 521)) in Italy.

Internationally comparable data on the distribution of average school attainment by sector is limited[20]. The PIAAC micro dataset allows us to compute the average years of schooling across sectors. The sectoral distribution of schooling only partly reflects the distribution of numeracy skills. The financial and insurance sector is the sector where workers have both the highest average cognitive skills and the highest average school attainment. Electrical and optical equipment industries are second in terms of average numeracy skills (Figure 1), whereas they are only forth in terms of average years of school (Table 2).

Table 2. Average years of school of workers across sectors

Industry	Mean	s.d.	s.e.	Min	Max
Finance & Insurance	14.50	0.50	0.15	13.96	15.55
Other Professional & Business Services	13.72	0.61	0.19	12.56	14.62
Chemicals & Pharmaceuticals	13.67	1.02	0.31	11.91	15.56
Electrical & Optical Equipment	13.32	1.02	0.31	11.19	14.56

[19] This corresponds to Proficiency Level 1 or low Proficiency Level 2 as defined in the OECD PIAAC Technical Report.

[20] The measures of educational attainment by industry available have been mostly built using direct or extrapolated values coming from labour force surveys or census data. For some countries no detailed information on the educational attainment of the workforce by sector is available; these are imputed based on the distribution of sectoral educational attainment of other similar countries (e.g. Malta in Erumban et al, 2012). At the European level, data on educational attainment by sector has been collected in 2014 through the European Union Structure of Earnings Survey (SES). The SES uses a more aggregate sectoral level (i.e. NACE Rev. 2, one digit level) than the one used in our analysis; this results into having all manufacturing industries grouped together in one category (whereas our analysis includes twelve different manufacturing industries). Eurostat-SES data reveal that manufacturing industries are among those with the lowest percentage of tertiary educated workers (e.g. according to these statistics, only approximately 22% of the total workforce in manufacturing has completed at least a short-cycle tertiary education or a bachelor degree, whereas over 52% of the workers of the financial and insurance sector have obtained a higher education degree). Therefore, this kind of data is not able to catch the very different average school attainment levels that are present within the manufacturing industries.

Transportation, Storage & Communication	12.99	0.83	0.25	11.09	13.88
Machinery & Equipment	12.85	0.77	0.23	10.89	13.98
Utilities	12.75	0.85	0.26	11.40	14.02
Motor Vehicles	12.62	0.88	0.26	10.80	14.07
Sale & Trade	12.35	0.74	0.22	11.04	13.10
Other Minerals	12.13	1.58	0.48	9.26	15.04
Food	12.04	0.66	0.20	10.60	12.75
Metals	12.01	1.12	0.34	9.82	12.98
Other Manufacturing	11.92	1.10	0.33	9.50	13.38
Wood & Paper	11.92	1.09	0.33	9.33	13.10
Rubber & Plastic	11.91	1.37	0.41	8.93	13.77
Textiles	11.89	1.46	0.44	9.46	14.25
Construction	11.70	0.99	0.30	9.74	12.68

Source: Own calculations based on the OECD Survey of Adult Skills PIAAC (2013).

When we look at the average distribution of skills for the workers in the 17 industries of our analysis, some remarkable cross-country differences emerge. In line with what pointed out by the OECD (2013a, 2016b), overall the countries with the highest educated population are Japan, Belgium and the Netherlands, whereas at the lower end, we find Spain and Italy. However, as shown in Table 3, the sectoral distribution of skills within each country varies significantly. The workers of the sector with the highest numeracy in Korea have on average almost the same score as the ones of the sector with the lowest average numeracy in Japan. In most countries of our sample (8 countries out of 12) finance and insurance is the sector where the workers with highest numeracy cluster. For all countries, medium- and low- tech industries (e.g. textiles or the food industries) are the sectors with the average lowest numeracy scores.

Table 3. Minimum and maximum average sectoral cognitive skills by country.

Country	Min		Max	
Belgium	273.9	(Other Minerals)	314.1	(Finance & Insurance)
Czech Republic	254.2	(Other Minerals)	298.8	(Finance & Insurance)
France	236.5	(Textiles)	293.5	(Finance & Insurance)
Germany	250.8	(Textiles)	303.1	(Finance & Insurance)
Italy	225.7	(Rubber & Plastics)	288.6	(Finance & Insurance)
Japan	276.7	(Food)	310.8	(Chemicals & Pharmaceuticals)
Korea	246.4	(Textiles)	279.4	(Utilities)
Netherlands	256.6	(Other Manufacturing)	311.8	(Chemicals & Pharmaceuticals)
Poland	244.2	(Other Minerals)	291.4	(Finance & Insurance)
Spain	233.6	(Textiles)	282.6	(Finance & Insurance)
United Kingdom	244.7	(Food)	295.4	(Finance & Insurance)
Unites States	234.8	(Food)	283.1	(Electrical & Optical Equip.)

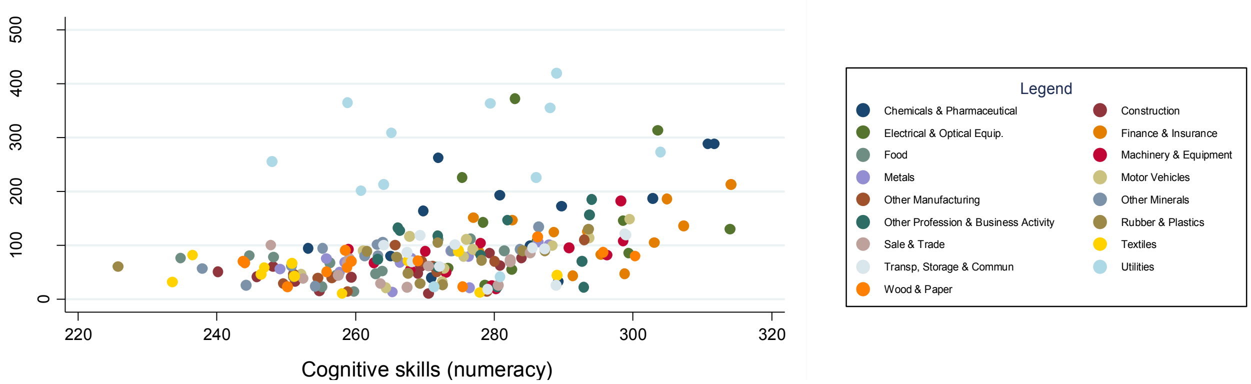
Source: Own calculations based on the OECD Survey of Adult Skills PIAAC (2013).

The distribution of business R&D expenditure by industry varies across countries and it is highly connected to the specific economic structure and industrial specialization of each country. In all our 12 countries, a limited number of sectors account for a large share of R&D investments. Three sectors (i.e. electrical and optical equipment, chemicals and pharmaceuticals, and motor vehicles) are the main industries where R&D activities are performed. Japan and the States are the countries of our sample with the highest expenditures in R&D across sectors, whereas Czech Republic and Poland are the ones with the lowest ones. Further details on the distribution of R&D business expenditure in our sample of analysis are available in Tables B and C in appendix. Finally, a breakdown of our measure of labour productivity by sector highlights a few industries that play a crucial role for the overall country productivity performances. Four sectors – i.e. utilities, chemicals and pharmaceuticals, electrical and optical equipment, and the financial and insurance sectors – stand out in terms of labour productivity. Japan, Belgium, and the Unites States are the three countries of our sample with the highest labour productivity across sectors. Further details on the distribution of labour productivity across countries and sectors are available in Tables D and E in the Appendix.

7. Results

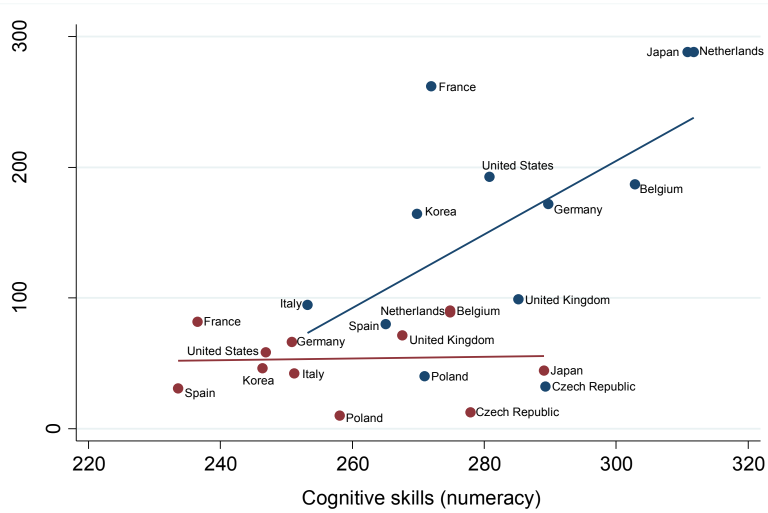
Substantial heterogeneity emerges across industries with respect to the relationship between the average cognitive skills of their workers and their average productivity. Figure 2 plots this relation for the seventeen industries included in our analysis. As it appears even more clearly in Figure 3, the correlation between cognitive skills and productivity varies substantially across sectors: it is strongly positive for high-tech industries and knowledge-intensive business services (e.g. chemicals and pharmaceuticals, dark blue in Figure 2, and electrical and optical equipment, dark green in Figure 2), whereas it does not turn out statistically meaningful for low-tech industries (e.g. textiles).

Figure 2. Correlation between sectoral average cognitive skills (numeracy) and sectoral labour productivity.



Average sectoral numeracy skills (on a scale 0-500) and average sectoral labour productivity (value added per worker in thousand USD at constant 1995 prices). Each colour represents one sector of activity. Source: Own calculations based on the OECD Survey of Adult Skills PIAAC (2013) and on WIOD data (2013).

Figure 3. Correlation between sectoral average cognitive skills (numeracy) and sectoral labour productivity in high-tech and low-tech sectors.



Average sectoral numeracy skills (on a scale 0-500) and average sectoral labour productivity (value added per worker in thousand USD at constant 1995 prices). Blue and magenta dots refer to the chemical and pharmaceutical industry and to the textile one respectively. The bold lines are the best linear predictions for the two sectors. Source**:** Own calculations based on the OECD Survey of Adult Skills PIAAC (2013) and on WIOD data (2013).

The regression Table below (Table 4) shows our results. In Model 1 we include the key variables of the analysis, noting that the average sectoral numeracy present in each sector, as well as its R&D expenditure and capital stocks are positively and significantly associated with productivity; the coefficient of labour indicates a small (positive) deviation from constant returns to scale.

In Model 2, we control for country specific effects: the statistical significance of R&D expenditures vanishes, whereas the average sectoral cognitive skills present in each sector-country combination still remains positive and significant. This Model explains almost 85% of the cross-country cross-sector variation in labour productivity. When we control for sectoral specific effects (Model 3), the reverse happens, i.e. the association between R&D flows and labour productivity appears to be positive and statistically meaningful, whereas skills do not appear to be statistically significantly correlated with productivity. This clearly reveals that skills are strongly associated to sectoral specificities[21]. In Model 4 we run the same specification of Model 1 and we substitute our measure of average sectoral cognitive skills with a more commonly used measure of human capital (i.e. average years of schooling); we see that human capital does not appear to be significantly associated to labour productivity. When, in Model 5, we include both these human capital variables - despite the high positive correlation between them[22] - the average sectoral cognitive skills measure remains positively and significantly associated with productivity, whereas the average school attainment does not. In line with previous studies which looked

[21] In a separate Model (that we have not included in Table 4), we control for both sector and country specific effect. The results of that Model are very similar to those of Model 3. However, giving the relatively low number of observations, including both country and sector dummies leads to a loss of a relevant number of degrees of freedom.

[22] Note that average years of education and average numeracy are – as expected – positively correlated (correlation coefficient = 0.67).

at the relationship between schooling, cognitive skills, and GDP growth, these results suggest that "school attainment has no independent effect over and above its impact on cognitive skills" (Hanushek and Woessmann 2008: 639).

Table 4. Regression Table . Log-log OLS Models on labour productivity.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
log Labour	0.058***	-0.077***	0.065**	0.044*	0.053**	0.058***	0.047*
	-0.022	-0.029	-0.027	-0.023	-0.024	-0.022	-0.024
log (Capital per worker)	0.418***	0.324***	0.546***	0.441***	0.431***	0.417***	0.423***
	-0.038	-0.033	-0.068	-0.039	-0.040	-0.037	-0.034
log (R&D per worker)	0.123***	0.023	0.163***	0.126***	0.123***	0.383	0.117***
	-0.022	-0.018	-0.038	-0.023	-0.024	-1.408	-0.017
log PIAAC numeracy	1.240**	2.879***	0.203		1.059*	1.237**	-0.392
	-0.508	-0.555	-0.534		-0.618	-0.501	-1.033
log (avg years of school)				0.499	0.076		-0.000
				-0.334	-0.380		-0.421
log R&D x log PIAAC						-0.046	
						-0.251	
% of workers in Lev 4							0.016*
							-0.008
Sectoral dummies			YES				YES
Country dummies		YES					
Constant	-5.054*	-13.050***	-0.042	0.599	-4.273	-5.031*	3.929
	-2.838	-3.042	-3.029	-0.879	-3.089	-2.785	-5.411
Observations	204	204	204	187	187	204	187
R-squared	0.690	0.849	0.836	0.687	0.691	0.690	0.697

Coefficients are reported with robust standard errors. ***, **, * indicates significance at the 1, 5, and 10 percent level respectively.

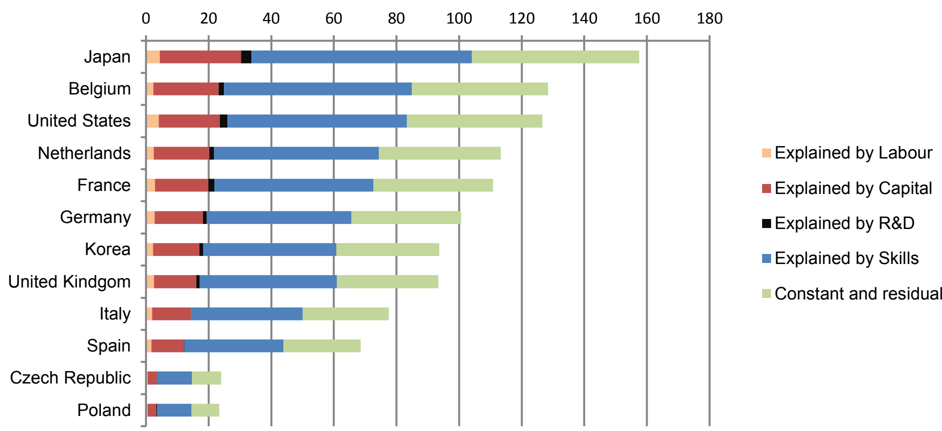
In Model 6, we control for possible complementarities between R&D and skills. The Model shows no significant super-modularity property between R&D and cognitive skills, but it confirms the strong positive association between average sectoral cognitive skills and productivity.

In Model *7* we look at the distribution of skills within each sector. As already mentioned, PIAAC scores are on a 0-to-500 scale; the OECD has divided the population into 6 proficiency levels (see Table A in appendix), according to the score associated to their test. In Model 7 – in order to test if the sectoral average labour productivity is associated not only to the sectoral average numeracy, but also to the distribution of the cognitive skills within each sector – we include the percentage of workers with the highest proficiency level[23] across the different country-sector combinations. We note that the percentage

[23] Since the percentage of people with proficiency level 5 is extremely small, we consider proficiency level 4 as the highest proficiency level in our distribution of cognitive skills. Note that in a separate Model (not reported in this article, available under request), we control for the shares of individuals in all the five proficiency levels, finding that none of them appears to be statistically significant.

of workers with the highest numeracy proficiency level is positively correlated with labour productivity also when we include sectoral dummies; the correlation still holds also when we include schooling (i.e. average years of education) and average sectoral numeracy scores.

Figure 4. Ranking of labour productivity.



Average cross-sectoral labour productivity (value added per worker in thousand USD at constant 1995 prices) by country. Source**:** Own calculations based on the OECD Survey of Adult Skills PIAAC (2013) and on WIOD data (2013).

By making use of Model 1 and of the real values observed in each country-sector combination, we analyse how much of the productivity of each country may be explained by - or, more appropriately, appears to be associated with - the four key factors of our analysis. Figure 4 shows the cross-sectoral average productivity of each country. The length of each segment bar represents the country cross-sectoral average productivity. Each segment is divided into 5 sub-parts which show our research efforts to find possible sources for the different productivity performances. The first four sub-bars show how much each of the four key variables of our analysis is estimated to be associated with the average (cross-sectoral) labour productivity of each country. The last sub-bar is given by the sum of two components, namely the constant and the residual (i.e. the part of the average sectoral productivity that is not explained by our Model). It is important to underline that the calculations used for Figure 4 are illustrative rather than conclusive for different reasons. First, several other factors may influence the productivity and the key explanatory variables that we have included in our Models. This means that the variables we use may take credit from other factors and un-measurable conditions. Furthermore, there might be a reverse causality: for example, a sector characterized by high labour productivity may push firms to further invest in their skilled personnel and increase their R&D expenditure. The fact that internationally comparable workers' cognitive skills measures are available just for one point in time allows us to show the magnitude of the relationship between skills and productivity, but not to infer possible statements about its causality. The development of different waves of adult cognitive skill tests and the creation of a longitudinal dataset is key to go beyond correlational evidence and to better inform policymakers.

Keeping in mind these limitations, our Model 1 shows that the average level of cognitive skills present in a sector, as well as its R&D investments, its fixed assets and the size of its workforce are together associated to 69 percent of the variation in labour productivity across sectors and countries. Furthermore, the positive association between skills and productivity remains strong even after allowing for the average sectoral school attainment, suggesting that the level of cognitive skills matter for labour productivity over and above the numbers of years spent in education.

8. Conclusions, discussion and policy recommendations.

We present here the first study at a sectoral level relating productivity of workers to their skills. The relationship between sectoral cognitive skills and sectoral productivity is found to be positive and strong, especially in high-tech sectors, i.e. in those sectors where innovation is most central. Average school attainment in a sector is not related statistically to sectoral productivity. But R&D investments per worker, capital per worker and the size of the labour force in the sector bear a significant relationship with sectoral productivity.

Education and the resulting human capital –the knowledge and skills of individuals – may contribute reaching many goals which are central in virtually all policymakers' agendas. These include increasing health consciousness, improving tolerance and civicness or reducing crime rates. Beyond these advantages, the evidence that we presented here suggests that human capital of workers can increase the productivity of the sectors they work in.

To the best of our knowledge, all research on human capital at the sectoral level relied on direct or extrapolated measures of workers' school attainment. However, this measure of human capital suffers from two major shortcomings. First, equal amount of years spent in school can lead to very different quantities and qualities of skills, both across countries and within a country, depending on the quality and the type of schools. Second, skills development continues also after school. In particular, learning at work, through formal training or through learning-by-doing, is crucial to acquire less easily codifiable knowledge, as well as to maintain the skills already developed and to keep up with organizational and technical change (Borghans et al, 2001; Hanushek and Woessmann, 2016).

This is confirmed by global statistics. In recent years, several countries have experienced a remarkable increase in their average education attainments. Today, in OECD economies, more than one in three 25-to-64-year-old individuals have received a tertiary education (OECD, 2016a). At the same time, relatively large shares of the population have weak cognitive skills. Paradoxically, some of the countries with the highest proportions of tertiary educated people have, at the same time, very high shares of innumerate or illiterate men and women. The United States is a clear example. Even if the proportion of the population with tertiary education is significantly higher than the average of other developed economies (i.e. 45% against, on average, 35% in OECD economies), also the percentage of those who are innumerate is much higher (9.1% in the US against, on average 5% in OECD countries) (OECD, 2013a).

Our analysis confirms that there is no correlation between increasing the years of education of the workforce and the increase in workers' productivity. Furthermore, we found a strong positive relationship between sectoral labour productivity and sectoral human capital when human capital is measured by the actual skills of the workforce. On the contrary, the relationship results statistically insignificant in all our specifications when it is measured by the mere average school attainment of the workforce present in each industry. The productivity-premium for skills remains strong even after allowing for the average sectoral school attainment of the workforce.

Our analysis confirms that internationally comparable cognitive skills tests offer a better approach to measure human capital and to understand its relationship with productivity. Compared to recent studies (e.g. Hanushek and Woessmann, 2008, 2012, 2015) that have used internationally comparable cognitive skills test scores, our research presents two main novelties. First, to the best of our knowledge, none of these studies has looked at the distribution of cognitive skills are across sectors. Second, most of them, by being based on students' test scores, do not consider the competences that have been developed after formal education and, in particular, in the workplace. Additionally, they do not consider that students can receive their education in one country and end up working in another one; therefore their skills might not stick to the country where they have been measured at the time when they were in secondary schools. In our analysis, we compute a measure of sectoral human capital based on the test scores of the actual workforce present in the different sectors. Results show that this measure is strongly associated with labour productivity, suggesting that using the actual average sectoral cognitive skills can represent a step forward in any kind of future growth accounting exercise.

All in all, these results confirm a need for reforms which aim to improve cognitive skills of the population as "investing in further schooling without ensuring commensurate improvements in cognitive skills does not lead to economic returns" (Hanushek and Woessman, 2015: 44). University autonomy (particularly in terms of academic approach, staffing, internal organization, and financial management) (Ritzen, 2016) and adequate funding for education (Cathles and Ritzen, 2017) are crucial for reaching higher levels of competences. Future measures to strengthen cognitive skills should be accompanied by sound assessments (Vignoles, 2016) and match financial incentives for schools and teachers with skill achievements. Having said this, it is still central to keep in mind that preparing individuals for a productive employment is just one of the goals that education can and must serve. Preparing students to be critical thinkers, developing their tolerance and civicness as well as enabling them to successfully shape their personal development and wellbeing is of paramount importance and must be considered in any future educational reform.

Bibliography

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *Quarterly Journal of Economics*, 1055-1089.

Aghion, P., & Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, *60*(2).

Autor, D.H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: have computers changed the labor market?. *The Quarterly Journal of Economics*, *113*(4), 1169-1213.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2), 407-443.

Barro, R. J., & Lee, J. W. (1993). International comparisons of educational attainment. *Journal of Monetary Economics*, *32*(3), 363-394.

Barro, R. J., & Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104, 184-198.

Bartelsman, E. J. (1990). *R&D spending and manufacturing productivity: An empirical analysis* (Working Paper No. 122). Board of Governors of the Federal Reserve System (US).

Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, *34*(2), 143-173.

Borghans, L., Green, F., & Mayhew, K. (2001). Skills measurement and economic analysis: an introduction. *Oxford Economic Papers*, 53, 375-384.

Cathles, A. & Ritzen, J. (2017). Educational Investments' Contribution to Adult Competencies (forthcoming IZA Research Paper).

Ciccone, A., & Papaioannou, E. (2009). Human capital, the structure of production, and growth. *The Review of Economics and Statistics*, *91*(1), 66-82.

Cohen, D., & Soto, M. (2007). Growth and human capital: good data, good results. *Journal of economic growth*, 12(1), 51-76.

Coulombe, S., Tremblay, J. F., & Marchand, S. (2004). *Literacy scores, human capital and growth across fourteen OECD countries* (pp. 89-552). Ottawa: Statistics Canada.

Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., & De Vries, G. (2013). The construction of world input–output Tables in the WIOD project. *Economic Systems Research*, *25*(1), 71-98.

Erumban, A., Gouma, R., de Vries, G., de Vries, K. & Timmer, M. P. (2012). *WIOD Socio-Economic Accounts(SEA) :Sources and Methods*. Growth and Development Centre, University of Groningen.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 92-116.

Griliches, Z. (1986). Productivity, research-and-development, and basic research at the firm level in the 1970s. *American Economic Review*, *76*(1), 141-154.

Griliches, Z. (2001). A perspective on what we know about the sources of productivity growth. In *New Developments in Productivity Analysis* (pp. 609-612). University of Chicago Press.

Grossman, G. M., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, *58*(1), 43-61.

Hall, B. H., & Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics*, 65(1), 263-293.

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the Returns to R&D. *Handbook of the Economics of Innovation*, *2*, 1033-1082.

Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46 (3), 607-668.

Hanushek, E. A., & Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, *17*(4), 267-321.

Hanushek, E. A., & Woessmann, L. (2015). *The knowledge capital of nations: education and the economics of growth*. MIT Press, Cambridge (MA).

Hanushek, E. A., & Woessmann, L. (2016). Knowledge capital, growth, and the East Asian miracle. *Science*, 351(6271), 344-345.

Jorgenson, D. W., & Timmer, M. P. (2011). Structural change in advanced nations: a new set of stylised facts. *The Scandinavian Journal of Economics*, *113*(1), 1-29.

Levy, F., & Murnane, R. J. (2012). *The new division of labor: How computers are creating the next job market*. Princeton University Press, Princeton.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3-42.

Machin, S., & Van Reenen, J. (1998). Technology and changes in skill structure: evidence from seven OECD countries. *Quarterly Journal of Economics*, 113 (4), 1215-1244.

Maddison, A. (2007). *Contours of the world economy 1-2030 AD: Essays in macro-economic history*. Oxford University Press, Oxford.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics*, *107*(2), 407-437.

Møen, J., & Thorsen, H. S. (2015). Publication bias in the returns to R&D literature. *Journal of the Knowledge Economy*, 1-27.

OECD (2013a). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD Publishing, Paris.

OECD (2013b). *Technical Report of the Survey of Adult Skills (PIAAC)*. OECD Publishing, Paris.

OECD (2016a). *Education at a glance 2016*. OECD Publishing, Paris.

OECD (2016b). *Skills Matter: Further Results from the Survey of Adult Skills*. OECD Publishing, Paris.

Ortega-Argilés, R., Piva, M., & Vivarelli, M. (2015). The productivity impact of R&D investment: are high-tech sectors still ahead?. *Economics of Innovation and New Technology*, *24*(3), 204-222.

Piva, M., & Vivarelli, M. (2009). The role of skills as a major driver of corporate R&D. *International Journal of Manpower*, *30*(8), 835-852.

Pritchett, L. (2001). Where Has All the Education Gone?. *The World Bank Economic Review*, 367-391.

Ritzen, J. (2016). University autonomy: Improving educational output. *IZA World of Labor*, 240.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 1002-1037.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5), 71-102.

Rutkowski, L., Gonzalez, E., Joncas, M., & von Davier, M. (2010). International large-scale assessment data issues in secondary analysis and reporting. *Educational Researcher*, *39*(2), 142-151.

Sakurai, N., Papaconstantinou, G., & Ioannidis, E. (1997). Impact of R&D and technology diffusion on productivity growth: empirical evidence for 10 OECD countries. *Economic Systems Research*, *9*(1), 81-109.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Ugur, M., Trushin, E., Solomon, E., & Guidi, F. (2016). R&D and productivity in OECD firms and industries: A hierarchical meta-regression analysis. *Research Policy*, on line.

Valente, A. C., Salavisa, I., & Lagoa, S. (2016). Work-based cognitive skills and economic performance in Europe. *European Journal of Innovation Management*, *19*(3), 383-405.

Van Biesebroeck, J. (2009). Disaggregate productivity comparisons: sectoral convergence in OECD countries. *Journal of Productivity Analysis*, *32*(2), 63-79.

Verspagen, B. (1995). R&D and productivity: A broad cross-section cross-country look. *Journal of Productivity Analysis*, *6*(2), 117-135.

Vignoles, A. (2016). What is the economic value of literacy and numeracy?. *IZA World of Labor*.

von Davier, M., Gonzalez, E., & Mislevy, R. nd. What are Plausible Values and why are they useful. *IERI Monograph Series: Issues and Methodologies in Large Scale Assessments*, *2*.

Woessmann, L. (2016). The economic case for education. *Education Economics*, *24*(1), 3-32.

Zachariadis, M. (2004). R&D-induced Growth in the OECD?. *Review of Development Economics*, *8*(3), 423-439.

Appendix

Table A. Numeracy proficiency levels

Score	Level	Task Description
0-175	Below 1	Concrete, familiar contexts. Tasks require simple processes, counting, sorting, basic arithmetic.
176-225	Level 1	Tasks usually require simple one-step or two-step processes involving basic arithmetic operations.
226-275	Level 2	Tasks tend to require the application of two or more steps or processes involving calculation with whole numbers and common decimals, percents and fractions.
276-325	Level 3	Tasks require to understand mathematical information which may be less explicit not always familiar, and represented in more complex ways.
326-375	Level 4	These tasks involve undertaking multiple steps and choosing relevant problem-solving strategies and processes.
376-500	Level 5	Tasks in this level require a broad range of mathematical information that may be complex, abstract or embedded in unfamiliar contexts.

Source: OECD PIAAC Technical Report (2013).

Table B. Business R&D expenditures (2007) by sector (in USD of 1995)

Industry	Mean	s.d.	Min	Max
Electrical & Optical Equipment	30.03	33.1	0.33	95.77
Chemicals & Pharmaceuticals	26.73	24.12	0.68	73.76
Motor Vehicles	11.84	9.38	0.32	25.88
Machinery & Equipment	5.8	5.36	0.27	20.4
Rubber & Plastic	2.79	2.7	0.16	7.45
Other Manufacturing	1.78	3.88	0.04	13.87
Other Minerals	1.55	1.7	0.04	6.23
Utilities	1.27	1.53	0.02	4.58
Textiles	1.16	1.04	0.02	3.5
Food	1.02	0.74	0.04	2.21
Metals	0.97	0.79	0.04	2.77
Other Professional & Business Services	0.83	0.63	0.05	2.1
Transportation, Storage & Communication	0.54	0.35	0.02	1.16
Wood & Paper	0.46	0.43	0.01	1.42
Finance & Insurance	0.33	0.31	0	1.08
Construction	0.11	0.13	0.01	0.34
Sale & Trade	0.1	0.09	0	0.26
Total	5.14	13.39	0	95.77

Source: Own calculations based on the OECD ANBERD database (2016).

Table C. R&D expenditures (2007) by country (in USD of 1995)

Country	Mean	s.d.	Min	Max
Japan	14.83	26.68	0.01	91.67
Unites States	11.4	25.4	0.02	95.77
France	8.68	16.35	0.06	60.16
Korea	5.25	11.45	0	46.68
Belgium	5.15	8.55	0.14	28.37
Netherlands	5	9.94	0.05	31.91
Germany	4.23	7.04	0.04	21.06
United Kingdom	3.96	7.3	0.01	25.87
Spain	1.36	1.72	0.06	6.25
Italy	1.21	1.81	0.02	6.66
Czech Republic	0.44	0.66	0.01	2.43
Poland	0.13	0.18	0	0.68
Total	5.14	13.39	0	95.77

Source: Own calculations based on the OECD ANBERD database (2016).

Table D. Labour productivity by sector.

Industry	Mean	s.d.	Min	Max
Utilities	253.6	123.9	22.8	419.4
Chemicals & Pharmaceuticals	158.4	90.7	32.1	288.3
Electrical & Optical Equipment	140.2	111.3	24.5	372.9
Finance & Insurance	120.5	51.2	43.5	212.8
Other Professional & Business Services	99.4	52.5	21.6	184.8
Transportation, Storage & Communication	84.1	34.5	18.5	121.5
Motor Vehicles	83.8	38	21.5	148
Machinery & Equipment	80.5	43.4	19.1	182.6
Other Minerals	78.7	32.3	24	134.2
Rubber & Plastic	71.4	31.6	26.2	129.2
Wood & Paper	67.2	26.5	22.9	115.7
Metals	66.7	28.6	12.5	105.5
Food	66.2	31.2	14.1	111.5
Sale & Trade	57.3	25.3	22.2	99.5
Textiles	53.6	27.5	9.9	90.4
Other Manufacturing	53.5	30.4	13.8	109.7
Construction	48.3	22.5	9.8	85.3
Total	93.1	73.5	9.8	419.4

Average sectoral value added per worker of 2007, in thousand USD at constant 1995 prices.
Source: Own calculations based on the WIOD database (2013).

Table E. Labour productivity by country.

Country	Min		Max	
Belgium	70.1	(Other Manufacturing)	354	(Utilities)
Czech Republic	9.8	(Construction)	46.8	(Finance & Insurance)
France	59.8	(Construction)	262	(Chemicals & Pharmaceuticals)
Germany	50.4	(Other Manufacturing)	226	(Utilities)
Italy	42.1	(Textiles)	201	(Utilities)
Japan	44.3	(Textiles)	419	(Utilities)
Korea	28.1	(Sale & Trade)	363	(Utilities)
Netherlands	39.6	(Other Manufacturing)	288	(Chemicals & Pharmaceuticals)
Poland	9.9	(Textiles)	43.5	(Finance & Insurance)
Spain	28.9	(Other Manufacturing)	255	(Utilities)
United Kingdom	44.4	(Sale & Trade)	365	(Utilities)
Unites States	41.5	(Construction)	373	(Electrical & Optical Equip.)

Average sectoral value added per worker of 2007, in thousand USD at constant 1995 prices. Source: Own calculations based on the WIOD database (2013).