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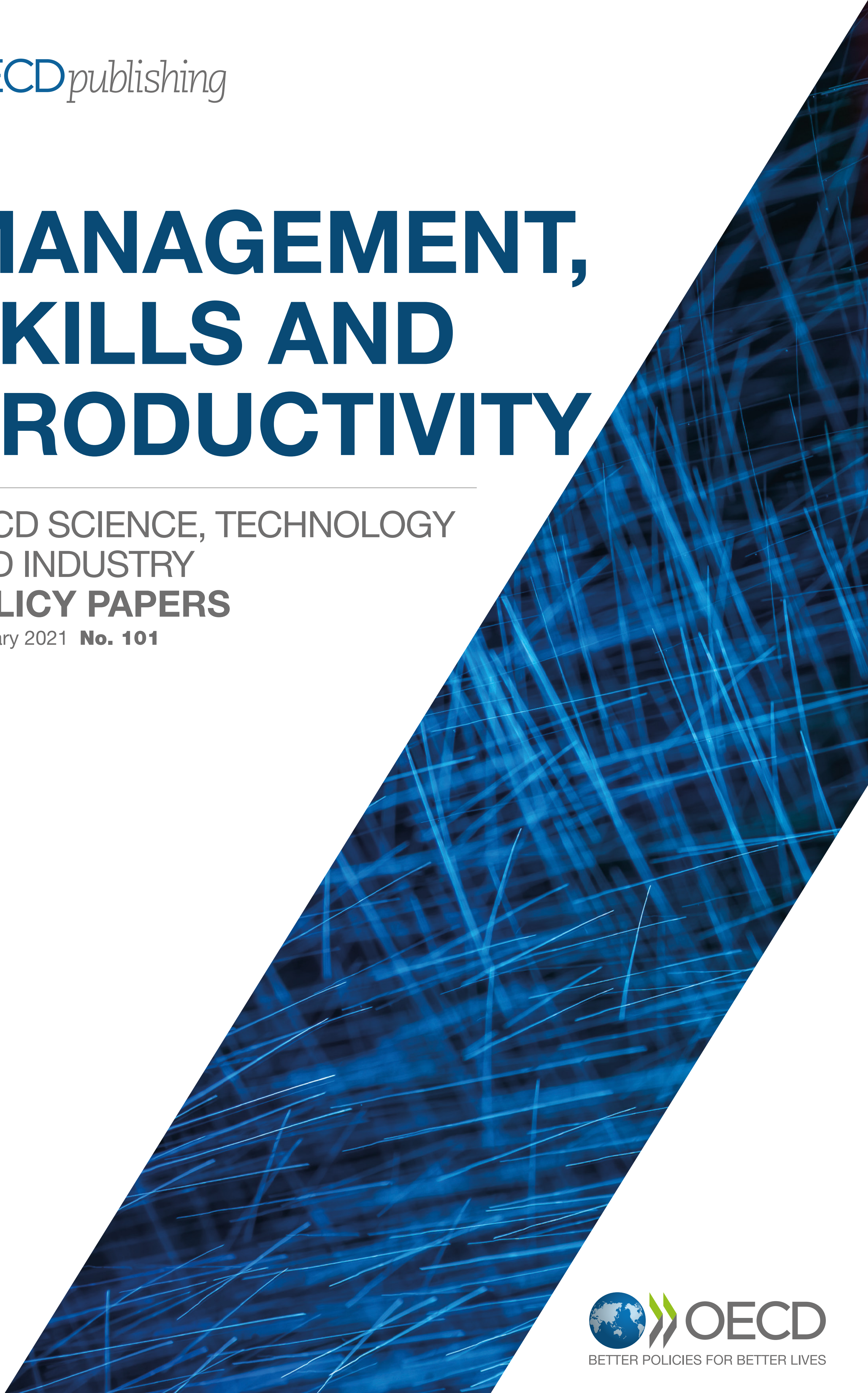

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Management, Skills and Productivity

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This paper studies how industries' investment in organisational capital (OC) and workforce skills relate to productivity, building on OECD estimates of OC, output data from the OECD Structural Analysis (STAN) database, and both cognitive and task-based skill indicators from the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The paper finds that at the industry level, workers' numeracy and endowment of skills related to science, technology, engineering and mathematics (STEM) correlate positively with productivity, and that the positive correlation of STEM skills with productivity is generally larger for OC workers. The paper also finds evidence that skills dispersion harms industry performance. A gap between the ICT skills of OC and non-OC workers seems to trigger a "lost in translation" type of mechanism, whereby communication and information flows become less fluid and impinge upon the economic performance of sectors, correlating negatively with productivity.

Keywords: Human Capital; ICT; Labour Productivity; Organisational Capital; Skills; STEM

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Table of contents

Tables

Figures

Executive Summary

This paper investigates the relationship between Organisational Capital (OC), workforce skills and labour productivity, at the industry level. In particular, it looks at the way numeracy skills, as well as task-based skills such as information and communication technology (ICT) and STEM skills influence productivity, and whether differences emerge in the way the skills of the OC workers and of the other workers relate to industry performance.

The work is motivated by the need to better understand the role of human capital in fostering economic performance, to put people and workers back at the centre of inclusive growth policies.

By looking at the complex interaction between OC, skills and productivity, the analysis contributes to shed light on the relationship between workforce and management skills, on the one hand, and industry performance, on the other hand; and on the way skills dispersion relate to productivity levels.

The work builds on OECD work estimating investment in OC (Le Mouel and Squicciarini, 2015[1]) and constructing cognitive and task-based skill-related indicators (Grundke et al., 2017[2]) using data from the Programme of the International Assessment of Adult Competencies (PIAAC). The analysis further exploits industry-level output information from the OECD Structural Analysis (STAN) database, and information from a number of other industry-level OECD datasets.

In addition to providing results based on controlled correlations, the analysis relies on a three-step model coupling a Heckman selection model with an instrumental variable approach, to address potential selection and endogeneity biases. The aim is, firstly, to control for the possible selection and self-selection of individuals with higher skills into larger firms, as the latter tend to be more productive and offer better salaries (Wagner, 1999[3]). Secondly, it addresses potential endogeneity problems related to reverse causality (e.g., more productive firms may give workers more opportunities to improve their skills) and omitted variable biases.

The main findings of the analysis and their implications for policymaking are:

- *Workers in OC-relevant occupations are better endowed with ICT as well as with STEM skills compared to non-OC workers.* The highest average scores are observed in ICT (J) and finance and insurance (K) industries. Sectors whose workforce is less endowed with such skills are: wholesale and retail (G), transport, accommodation and food (H&I) and other social and personal services (R&S).
- *Skill endowments appear very dispersed across countries and industries, especially with regards to ICT skills among non-OC workers.* Interestingly, the industries that stand out for their high average skill scores also exhibit relatively high levels of average labour productivity, while those with lower average scores show more often lower levels of productivity.
- *Cognitive skills display a positive and significant relationship with labour productivity when investment in net fixed assets, the share of OC workers, skills intensity (as proxied by average educational attainment), Research and Development (R&D) and differences between countries and industry clusters are taken into account*.

- *A positive relationship also exists between STEM skills and productivity, which is even larger in the case of OC workers*. A standard deviation increase in the STEM skill score for non-OC workers is associated with an 8.4-11.4 percent increase in productivity. This calls for the need to raise the bar, i.e. to endow all workers, including OC-workers, with sound cognitive skills, as these correlate positively with productivity (in line with early findings by Grundke et al. (2017[2])).
- *We also find evidence about skills dispersion hurting industry performance, especially when it comes to ICT task based skills.* When a gap between the ICT task-based skills of OC staff and of other workers (the non-OC workers) exists at the industry level, this correlates negatively with productivity.
- When STEM skill endowment is controlled for, the ICT task based skill endowment of people working outside OC relevant occupations is not associated with higher labour productivity.
- *A "lost in translation" type of mechanism seemingly exists, whereby differences in the ICT task-based skills of OC and non-OC-related workers impinge upon the economic performance of sectors*. By *"lost in translation"* mechanism we refer to the possibility that gaps in the ICT task-based skills of OC and non-OC workers reflect or create difficulties in communication, information flows and cooperation between OC and non-OC workers. This is likely to lead to relevant information being overlooked or underutilised, thus impinging upon industries' economic performance. Narrowing the ICT skill gap between OC and non-OC workers may lead to improved productivity. Such a mechanism may happen both within firms, if (different types of) workers do not succeed to communicate effectively, and between firms. Spillovers across firms may in fact be hindered by the lack of the relevant absorptive capacity, skills or by the lack or paucity of information sharing and networking possibilities.
- *Skill intensity, captured by educational attainment, is positively and significantly related to productivity.* This confirms that investment in education yields high returns through higher productivity.
- *Key results hold when addressing selectivity and endogeneity, to assess the causal nature of such productivity links.*
- *Economic performance enhancing policies should aim at improving cognitive numeracy and STEM scores for the full working population and at minimising dispersion of ICT skills.*

Among others, our results call for the need to know more about the role of training policies in upgrading STEM and ICT task-based skills, as well as about the mechanisms through which the skills of all workers, both OC and non-OC workers, affect productivity. In this respect, it is crucial to better understand how the different skills of OC and non-OC workers relate to innovation output and to higher productivity.

Section 1. Introduction

Most developed economies have experienced a slowdown in productivity growth since the Great Recession and even before it, with resumption to productivity convergence that has proved hard in many cases (Bergeaud, Cette and Lecat, 2015[4]; OECD, 2016[5]). Some countries have only recently managed to recover from the Great Recession and are now already facing a new, and perhaps even bigger, economic crisis due to the COVID-19 pandemic. Easing the tremendous economic, social and political tensions that economic crises may trigger calls for the need to identify, tap into and nurture the sources of productivity growth. In particular, it is important to understand the role that human capital plays in fostering economic performance, to put people and workers back at the centre of inclusive growth policies.

This paper contributes to shedding light on the productivity puzzle (OECD, 2015[6]; Remes, Mischke and Krishnan, 2018[7]) by studying how Organisational Capital (OC) and workforce skills relate to labour productivity at the industry level, with OC staff defined as the part of a firm's workforce whose knowledge and tasks[1] affect the long-term functioning of firms (Le Mouel and Squicciarini, 2015[1]).

The importance of human capital in contributing to firm productivity has been examined both, at the micro- and macro-level, and has been widely acknowledged (Jorgenson and Fraumeni, 1992[8]; Bloom and Van Reenen, 2006[9]; Philippou, 2019[10]). Many studies have investigated the link between firm level OC and productivity, or between workforce skills and productivity. However, to date, the complex interaction between all three components, i.e. OC, skills and productivity, remains largely unexplored. More needs to be known on the extent to which industries invest in their managerial and OC and on how workers' skills and OC relate to a number of economic performance metrics, such as sales' growth and productivity.

To shed light on these issues, this paper analyses the relationship between OC, cognitive and task-based skills,[2] and industry-level productivity. In particular, it investigates the relationship between overall workforce skills levels and productivity and whether differences emerge in the way the skills of the OC team and of the other workers relate to industry performance. Doing so, it contributes to the discussion on the importance of management in shaping firm and industry performance and on whether a greater skill endowment (or quality) of OC staff translates into better economic outcomes (Bloom and Van Reenen, 2006[9]; 2011[11]; Bloom, Sadun and Reenen, 2012[12]; Bender et al., 2018[13]). In addition, it contributes to inform the skills dispersion debate by assessing the extent to which differences in the skills endowment of OC workers and non-OC staff relate to productivity levels (Caroli and Van Reenen, 2001[14]; Grundke et al., 2018[15]).

This work builds on previous OECD work estimating investment in OC (Le Mouel and Squicciarini, 2015[1]). The cognitive and task-based skill-related indicators used in the present analysis are also constructed relying on earlier OECD work, following Grundke et al. (2017[2])[3] and using data from the Programme of the International Assessment of Adult Competencies (PIAAC[4]).

Cognitive skills are proxied using numeracy scores from PIAAC. Literacy scores are left outside of the analysis, since numeracy and literacy scores appear to be highly correlated[5] (OECD, 2016[16]) and adding them both in the analysis would not improve our understanding of the underlying dynamics[6]. We here prefer numeracy over literacy following Hoyles et al. (2002[17]) who argue that numeracy and mathematical skills are cognitive abilities conducive to business success because they are deployed to achieving goals such as improving efficiency, dealing with change and innovation, making informed decisions, remaining competitive, and maintaining operations.

As the digital transformation unfolds and digital technologies progressively penetrate all sectors, albeit at a different speed and in a different fashion (Calvino et al., 2018[18]), it is reasonable to expect that cognitive abilities such as numeracy will need to be complemented by skills related to the use of Information and Communication Technologies (ICT) at the workplace. This motivates our choice to rely on task-based skill components, such as STEM[7]-quantitative skills (here denoted as "STEM" in short), which mirror the frequency with which workers perform tasks requiring relatively advanced mathematical skills; and ICT task-based skills, mirroring the frequency with which workers perform tasks requiring ICT-related skills. Doing so we also align with recent literature, which underlies the growing importance of these skills for labour dynamics as well as economic performance (Forth and Mason, 2006[19]; Soriano and Abello, 2015[20]; Falck, Heimisch and Wiederhold, 2016[21]; Hagsten and Sabadash, 2017[22]).

We leave out of the analysis the other task-based skills identified in Grundke et al. (2017[2]) that may partially correlate with the type of occupations considered to be OC-related. These are "Managing and Communication", "Self-Organisation" and "Marketing and Accounting" skills[8].

The analysis further exploits industry-level output information from the OECD Structural Analysis (STAN) database, and information from a number of other industry-level OECD datasets[9]. Finally, as individuals with higher skills may self-select into larger firms that tend to be more productive and more productive firms tend to offer better salaries (Wagner, 1999[3]), as well as greater learning and training opportunities (Kotey and Folker, 2007[23]; Kim and Yoon, 2008[24]; World Bank, 2010[25]; Cunningham and Rowley, 2010[26]; Almeida and Aterido, 2010[27]; Shepherd et al., 2011[28])[1], a three-step model coupling a Heckman selection model with an instrumental variable approach is implemented in the present analysis, to address potential selection and endogeneity biases.

The first part of the analysis is exploratory in nature and relies on a simple Ordinary Least Square (OLS) approach that relates productivity with variables accounting for skills and OC, as well as industries' main features (e.g. investment in net fixed assets, NFA). The results show that greater educational attainment of the workforce, measured in terms of the share of highly educated workers in the industry - which can be considered as a proxy for "better" human capital - is always positively correlated with economic performance. A positive and significant correlation also emerges when looking at the role of STEM skills for labour productivity. Such a positive link emerges for those workers that are not involved in OC functions (here denoted as "non-OC workers") and is even larger in the case of OC workers. Taken together, results stress the need to raise the bar, in terms of endowing all workers with good STEM skills, and to have an even better skill endowed OC staff, given that labour productivity seemingly arises in a relatively more important fashion from their abilities.

Results further show that the ICT task-based skills and STEM skills may to some extent be related. For the bulk of the workforce, i.e. non-OC workers, ICT task-based skills do not emerge as being significantly associated with higher labour productivity when the STEM skills are taken into account. Moreover, differences in ICT task-based skills between OC and non-OC workers appear to negatively correlate with productivity: A 0.1 point increase in the ratio between the ICT skill of OC staff and non-OC workers corresponds to 2.34 percent less productivity. This suggests that in principle not all workers need being endowed with ICT skills. However, when ICT features prominently in the organisation of a company or industry (as captured by the ICT skills that OC staff needs to be endowed with), then (greater) differences in the ICT skills between OC and non-OC staff may trigger (more important) "*lost in translation*" type of mechanisms. These may lead to relevant information getting lost or overlooked, thus harming the economic performance of the industry.

As a caveat, it should be noted that, as the analysis is carried out at the country-industry, rather than at the firm level, we cannot look at ICT skills' dispersion at the within-firm level. Lost in translation mechanisms therefore refer here rather to dispersion between firms in the same industry, and that knowledge and information spillover effects may be hindered at the within industry level by differences in the ICT skills of workers in different occupations and functions.[10]

The second part of the paper explores the existence of causal links by addressing possible selection bias and the endogenous nature of skills through the implementation of a three-step estimation model. This combines a Heckman selection model with an instrumental variable approach and relies on two exclusion restrictions. The first captures the social mobility of workers and is used in relation to the cognitive ability of workers. The second accounts for the use of ICT at home by workers, and in particular for the ICT transactions done while being at home. This is done to account for the overall ICT ability of workers, irrespective of the extent to which the tasks that they perform on the job and the company's organisation rely on ICT.

These exclusion restrictions are used in a selection model that tries to address the possible selection and self-selection dynamics that may lead to having different type of workers sorting into different types of firms, which has long been established in the sorting literature (Burdett and Mortensen, 1998[29]; Shimer, 2001[30]; Menzio, Telyukova and Visschers, 2016[31]). Evidence in fact suggests that better skilled workers may be selected or may self-select into bigger firms (Idson and Feaster, 1990[32]; Rebitzer and Robinson, 1991[33]), as they are known to offer better remuneration packages and career opportunities (Wagner, 1999[3]; World Bank, 2010[25]; Shepherd et al., 2011[28]). In a third estimation step we add parental education and email use at home to instrument numeracy and ICT skill scores, to address the possible endogenous relationship that may exist between economic performance and skills of the workforce.

While overall results generally confirm the findings of the simple OLS regression, not all coefficients remain statistically significant. The majority of the model specifications confirms a negative and significant effect for the ratio between ICT scores for OC and non-OC workers and a positive significant effect for STEM skills, which is even larger for OC staff than for non-OC staff.

Finally, we explore different measures of labour productivity and replace our preferred measure of value added per employee with gross output per employee, to assess economic performance from a different perspective.[11] The ratio between ICT scores for OC and non-OC workers is again negative and significantly related with productivity, lending support to the "*lost in translation*" hypothesis. The ratio between STEM scores for OC and non-OC workers also remains significant and positively related to productivity, indicating that STEM scores are even more important for OC than for non-OC staff to obtain a better economic performance.

The reminder of the paper proceeds as follows. The next section frames the problem in existing literature. The following section defines OC and explains how the skill indicators have been constructed. Section 4 outlines the empirical methodology devised, whereas section 5 presents country-industry-level evidence on the relationship between OC, skills and productivity. Section 6 concludes.

Section 2. Framing the Problem

There is ample evidence suggesting that human capital is an important determinant for labour market prospects. Dang et al. (2001[34]) define human capital as the "knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being". This broad definition mirrors the complexity of the human capital concept and explains the many ways in which the literature has interpreted this locution. Many are also the indicators that have been used to proxy human capital, ranging from educational attainment to specific skills' assessment. Such a holistic and complex understanding of what human capital is and how to measure it goes beyond the economic literature and is also observed in the management and personnel economics literature but also in social science more broadly.

The present paper builds upon and aims to contribute to this vast literature, especially the one related to education, skills and economic performance, and the one focusing on organisations, knowledge-based capital and productivity.

2.1. At the Macro Level

One strand of the literature relevant to our work relates macro estimates of human capital to economic growth (Jorgenson and Fraumeni, 1992[8]; Cooray, 2009[35]). Here education is considered an investment into the knowledge and skills of individuals (Checchi, 2006[36]). Macro level estimates of human capital typically rely on quantitative measures of schooling (Topel, 1999[37]; Krueger and Lindahl, 2001[38]; Pritchett, 2006[39]) and, more recently, performance measures taken from internationally administered tests of cognitive abilities. These include the Programme for International Student Assessment (PISA), Trends in International Mathematics and Science Study (TIMSS) or Progress in International Reading Literacy Study (PIRLS) (Hanushek and Woessmann, 2012[40]; Altinok and Aydemir, 2017[41]; Balart, Oosterveen and Webbink, 2018[42]).

Existing evidence indicates that the association between cognitive skills and economic growth far exceeds the one with years of schooling[12]. Countries with a more skilled labour force experience faster growth in skill-intensive industries, and a more rapid adoption of new technologies and production processes (Ciccone and Papaioannou, 2009[43]). Both are essential to endogenous growth models that stress the importance of innovation and ideas (Romer, 1990[44]) and to models of technological diffusion and growth (Nelson and Phelps, 1966[45]).

In this work, we contribute to this macroeconomic literature by looking at the relationship between productivity and the share of medium and high-skilled workers, at the industry level. The measure of educational attainment used is taken from Horvát and Yamano (2019[46]), and is denoted as "skill intensity".

2.2. Absorptive Capacity

A second branch of the literature that is relevant to our purposes links human capital to the organisational theory literature. Among others, it proposes the concept of absorptive capacity, i.e. a firm's ability to recognise the value of new information, assimilate it and apply it to commercial ends (Cohen and Levinthal, 1989[47]; 1990[48]). The knowledge infrastructure, management support and relational capability of workers are all found to have a positive and significant impact on the absorptive capacity of firms. For instance, a vast strand of the literature has underlined the role of communication and interactions between workers on the performance of firms. Cooperation and interaction between employees result in fewer missed signals between employees, and reduce the time wasted carrying out redundant communications, searching for missing information, and waiting to hear from co-workers (Hamilton, Nickerson and Owan, 2003[49]; Gittell, Seidner and Wimbush, 2010[50]). Important in this respect is also the role of investment in Research and Development (R&D) activities. On the one hand, they are key for innovation; on the other hand, investment in R&D helps nurturing the absorptive capacity of firms, making the human capital of firms more receptive and able to absorb the possible knowledge spillovers that may be available (Cohen and Levinthal, 1989[47]; 1990[48]). Information technology (IT) further allows users of IT to invent new and valuable applications, rather than directly shifting the production-possibility frontier of the economy (Bresnahan, 2002[51]).

Recent studies further highlight the link between innovation, managerial practices and performance metrics, such as firm-level productivity, profitability and survival rates (Bloom and Van Reenen, 2007[52]; Bloom and Van Reenen, 2010[53]; Zou, Ertug and George, 2017[54]). All these concepts strongly relate to OC and jointly suggest OC to be an important factor in enhancing the performance of firms, which in turn should increase labour productivity. However, it is important to emphasise the fact that managers are not the sole to perform managerial tasks affecting the long-term functioning of firms, such as developing objectives and strategies, organising, planning, supervising production and managing human resources (Squicciarini and Le Mouel, 2012[55]; Le Mouel and Squicciarini, 2015[1]). Such findings support the arguments put forward by Caroli and Van Reenen (2001[14]) and von Krogh et al. (2011[56]) about the fact that tasks traditionally carried out by managers have been progressively devolved upon a wide array of non-managerial occupational profiles. This decentralisation of authority and delayering of managerial functions in turn suggests that firm-specific managerial skills and abilities should be assessed and compared across a wide array of occupational profiles, and not only with respect to managers.

This work contributes to this broad literature by studying the relationship between productivity and the skill endowment of workers in both, OC and non-OC related occupations. The relative importance of the OC staff skills as compared to the skills of non-OC workers also relates to the work of Caroli and Van Reenen (2001[14]). They argue that organisational change and skills are complements and find that organisational change leads to greater productivity increases when the initial skill endowment of the firm is comparatively larger.

2.3. Managers and Workers

Assigning workers to tasks based on their comparative advantages, i.e. optimally matching workers to job tasks, is one of the key channels through which (good) management drives productivity. Although we here intend management in a broad fashion, à la Le Mouel and Squicciarini (2015[1]), this work relates importantly to the literature on organisational and personnel economics that examines the relationship between managers and workers (Lazear and Oyer, 2007[57]; Lazear and Shaw, 2007[58]). Among others, this literature addresses the question of whether equally performing manager-worker pairs enhance productivity or if good managers are paired with poorly performing workers (Kremer, 1993[59]; Holmstrom and Tirole, 1989[60]; Garicano and Rossi-Hansberg, 2006[61]).

Garicano and Rossi-Hansberg (2004[62]) find that firms with high-skilled managers tend to hire high-skilled workers. Benson et al. (2019[63]) find that good managers strengthen the contributions of good workers through retention (Lazear, Shaw and Stanton, 2015[64]), effort elicitation (Frederiksen, Kahn and Lange, 2020[65]) and task assignment (Adhvaryu, Kala and Nyshadham, 2019[66]) and conclude that the skills of the two groups are not substitutable. Conversely, Adhvaryu et al. (2020[67]) find that better managers tend to match with less productive workers within firms, and vice versa, to avoid production and delivery delays, even though positive assortative matching of workers and managers would increase aggregate output by between 1 to 4 percent.

More generally, empirical estimates of sorting on the labour market depend on the shape of the underlying production function (Eeckhout and Kircher, 2011[68]) and most studies focusing on the sorting of workers across firms (Abowd, Kramarz and Margolis, 1999[69]; Card, Heining and Kline, 2013[70]; 2018[71]; Eeckhout, 2018[72]) identify in the existence of complementarities (or imperfect substitutability) between worker and manager skills the source of positive assortative matching[13] (Bandiera, Barankay and Rasul, 2007[73]; 2009[74]; Lazear, Shaw and Stanton, 2015[64]).

This paper contributes to this strand of the literature by investigating whether and to what extent the interaction between managers and workers' skills relate to economic performance. In particular, it looks at ICT and STEM task-based skill gaps between OC workers and non-OC workers and studies its effect on productivity. If we were to uncover a positive relationship, this study would lend support to the complementarity hypothesis.

2.4. Skills and Labour Market Returns

Another branch of the literature we build upon, and aim to contribute to, refers to human capital (at the micro level) and looks at the way skills relate to workers' payoffs. Existing evidence has in fact shown the existence of a positive relationship between skill endowment and labour market returns, although it is known that the size of the wage premium varies by skill type and across countries (Weinberger, 2014[75]; Hanushek et al., 2015[76]; Falck, Heimisch and Wiederhold, 2016[21]; Deming, 2017[77]; Deming and Kahn, 2017[78]; Grundke et al., 2018[15]). Hanushek et al. (2015[76]) and Lane and Conlon (2016[79])[14] find returns to general numeracy to be consistently higher than those to literacy. Hanushek et al. (2015[76]) find wages to increase by 18 percent with a one standard deviation increase in numeracy skills. Lane and Conlon (2016[79]) examine the incremental increase of skills and educational attainment and find that numeracy or literacy skills increase wages by 8 to 10 percent for those with upper secondary level education and below, and even up to 18 percent for those with tertiary education.

This literature also offers evidence about the relationship between skills heterogeneity and productivity outcomes. Grundke et al. (2018[15]) find that workers with higher levels of self-organisation and advanced numeracy skills are especially rewarded in digital intensive industries and that there is an additional wage premium if workers are endowed with both, a high level of numeracy skills and a high level of self-organisation or managing and communication skills. Iranzo et al. (2008[80]), considering the skill dispersion at the firm level, find productivity to be positively related to skill dispersions within occupational groups and negatively related to skill dispersion between these groups.

Furthermore, looking at the role of skills in determining participation in trade and global value chains (GVCs), it appears that the relative skill endowment as well as the dispersion of skills within a country may lead to having comparative advantages (OECD, 2017[81]). When skills development accompanies participation in GVCs, countries can achieve stronger productivity growth. Countries' dispersion of skills influences what industry they specialise in, as well as their competitiveness patterns. The OECD Skills Outlook 2017 (OECD, 2017[81]) provides plenty of evidence about the fact that even if two countries have identical average skills endowments, they will trade with each other depending on the properties of their human capital dispersion.

The present work thus takes into account skill levels and skill dispersion at the country-industry level, to shed light on whether greater skills dispersion may hamper productivity.

2.5. Measurement Issues, Endogeneity and Selection Bias

Empirically assessing the relationship between skills and labour market outcomes may entail having to deal with a number of challenges and biases. First, measuring skills is never easy and skill-related variables may often suffer from measurement error problems. Second, if employment patterns impact skill test scores over the lifecycle, i.e. people with better skills have better jobs, there may be issues related to reverse causality. For instance, some jobs may help reinforce certain skills (e.g. management skills) while employment breaks can depreciate them (Edin and Gustavsson, 2008[82]). Omitted variable bias may also impinge upon the accuracy of the estimates if e.g. the effect of family background, health or personality traits, among many others, on earnings are not accounted for. Finally, relying on cross-sectional skills data as we do here, given that PIAAC data has been collected only once in the countries considered (with the exception of the United States), may impinge upon the precision of the model's estimates.

A number of recent studies have increasingly attempted to tackle these concerns by employing instrumental variable approaches and exploiting exogenous variations in skills induced by changes in e.g. compulsory schooling laws. Their results often suggest that OLS estimates of skills premiums in terms of both wages and employment outcomes may well provide a lower-bound estimate of the true returns to skills. For instance, a common approach to addressing attenuation bias[15] in PIAAC's skill variables is to instrument one skill variable with another one. Both, Hanushek et al. (2015[76]) and Hampf et al. (2017[83]) instrument numeracy with literacy skill test scores. While this approach does not resolve all potential measurement errors, especially when such problems are common to both, literacy and numeracy test score measures, it exploits the variation that is common to both skill measures as the relevant cognitive dimension. When they use school attainment and family background, which are both determined prior to entering the labour market, to instrument skills and address potential reverse causality, returns to skills more than double compared to the OLS results. This is in line with existing literature on returns to school attainment, which often uses parental education to instrument schooling length (Ichino and Winter-Ebmer, 1999[84]). This paper adopts the in the literature commonly used approach (Hanushek et al., 2015[76]; Hampf, Wiederhold and Woessmann, 2017[83]) and elaborates on it in the methodology section.

To assess the existence of causal relationships, exogenous variation in skills induced by, for instance, changes in compulsory schooling laws, can be exploited (Acemoglu and Angrist, 2000[85]; Oreopoulos, 2006[86])[16]. Hanushek et al. (2015[76]) do so for the United States' sample in the restricted access PIAAC data and assign each individual a minimum school-leaving age according to their state of residence and birth cohort. If schooling is considered as an input into skill development, by attending school for longer, the stock of skills should grow. The authors find a confirmation for this hypothesis: Hanushek et al. (2015[76]) confirm that schooling is a strong instrument for numeracy skills with every additional year of compulsory schooling being associated with 2.7 percent of a standard deviation higher skills. They also find a substantial increase in the point estimate in the second stage, compared to the OLS approach, which is in line with existing literature on returns to school attainment.

Another natural experiment specifically related to the development of ICT skills was initially exploited by Falck et al. (2016[21]) and later adapted by Hampf et al. (2017[83]). While ICT skills are increasingly demanded in the labour market, the fact that these skills and a person's general ability are highly correlated makes it difficult to disentangle their effect on wages. For instance, individuals using computers at work tend to have unobserved skills that are not related to the computer itself but which increase productivity and, hence, wages (DiNardo and Pischke, 1997[87]). Falck et al. (2016[21]) and Hampf et al. (2017[83]) rely on the exogenous variation in broadband access at a very fine regional level across German municipalities[17] to instrument ICT skills and find instrumented coefficients that are twice the size of the corresponding OLS results.

While our data does not allow us to exploit a natural experiment, this paper attempts to control for these different sources of endogeneity by combining a Heckman selection model with an instrumental variable approach in a three-step approach. Therefore, it follows and builds on existing literature by using social mobility of workers and their overall ICT ability as exclusion restrictions in the selection model that addresses sorting into different types of firms. Parental education and email use at home are used to instrument skill scores.

Section 3. Construction of Skills and Organisational Capital Indicators

3.1. Programme for the International Assessment of Adult Competencies (PIAAC)

This analysis combines a wide range of datasets, drawing the main variables of interest, namely OC and skill scores, from the OECD Survey of Adult Skills. PIAAC is an international survey of individuals that now features three rounds of data collection. The first survey, completed in 2011-12, includes Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland) and the United States. The second data collection was conducted in 2014-15 and includes Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey. The most recent survey was completed in 2017 and includes Ecuador, Hungary, Kazakhstan, Mexico, Peru, as well as another round for the United States.

PIAAC is representative of the working population between the ages 16 to 65 and encompasses a wide range of information on individuals' skill sets. It tests adults' numeracy, literacy and problem solving abilities in technology rich environments, and asks questions aimed at assessing skill use and the performance of management, communication, organisation and planning-related tasks, as well as physical work. PIAAC further assesses workers' attitude towards learning and trust, among others. Finally, the survey gathers background information on educational attainment and job characteristics, namely occupation following the International Standard Classification of Occupations (ISCO 08) and the industry of activity, according to the International Standard Industrial Classification of All Economic Activities (ISIC).

In the present analysis countries are included independently of the round of PIAAC they belong to[18]. However, some may drop out when availability of information for variables from other datasets is limited. Also, country-industry level information is removed when sample size for OC relevant occupations goes below 20 observations in PIAAC (see notes of regression tables for details).

3.2. Defining Organisational Capital

The complex nature of OC has made it difficult to quantify or measure OC. This is reflected in the vast number of definitions and measurement approaches used in the literature, which, nevertheless, has mainly focused on management. Earlier work by Squicciarini and Le Mouel (2012[55]) defines OC as the firm-specific organisational knowledge resulting from the performance of tasks affecting the long-term functioning of firms, such as developing objectives and strategies; organising, planning and supervising production; and managing human resources. This work operationalises the task-based definition above using Occupational Information network (O*NET) data to identify those occupations that perform OC-related tasks to the highest extent, which are then denoted as being OC-related. Later work by the same authors (Le Mouel and Squicciarini, 2015[1]) validates the occupations identified in previous work by using data from PIAAC.

This paper builds on the more recent work carried out by Le Mouel and Squicciarini (2015[1]), which considers workers to be OC-related when they perform tasks, such as developing objectives and strategies; organising, planning and prioritising work; building teams, matching employees to tasks, and providing training; supervising and coordinating activities; and communicating across and within groups to provide guidance and motivation.

Based on this list of tasks, 20 ISCO 2008 occupations enter the OC group, and are supposed to generate own-account OC[19]. These 20 groups are all managerial, professional and associate professional occupations in business administration, science and engineering, health, and education.

Due to the small number of individuals in OC-relevant occupations in PIAAC, we employ a broader definition of OC and combine occupations that have been identified to generate OC in PIAAC as well as in O*NET. The final list of relevant occupations used in the present work is presented in Table 3.1.

Table 3.1. Selection of OC-related occupations

According to the PIAAC and to the ONET databases

ISCO 3 digit	ISCO Title	O*NET	PIAAC
110	Chief executives and legislators	X	X
121	Business services and administration managers	X	X
122	Sales, marketing and development managers	X	X
131	Production managers in agriculture		X
132	Manufacturing, mining, construction, and distribution managers	X	X
133	Information and communications technology service managers	X	X
134	Professional services managers	X	X
141	Hotel and restaurant managers	X	X
142	Retail and wholesale trade managers	X	X
143	Other services managers	X	X
213	Life science professionals	X	
214	Engineering professionals (excluding electrotechnology)	X	
216	Architects, planners, surveyors and designers	X	
220	Health professionals, except doctors	X	X
221	Medical doctors	X	X
232	Vocational education teachers		X
233	Secondary education teachers		X
234	Pre- and primary school teachers		X
242	Administration professionals	X	
243	Sales, marketing and public relations professionals	X	
252	Database and network professionals	X	
261	Legal professionals		X
262	Librarians, archivists and curators	X	
263	Social and religious professionals	X	X
312	Mining, manufacturing and construction supervisors	X	X
322	Nursing and midwifery		X
331	Financial and mathematical associate professionals	X	
334	Administrative and specialised secretaries	X	
343	Artistic, cultural and culinary associate professionals	X	
522	Shop salespersons	x	

Note: Based on PIAAC data, extracted June 2015, and O*NET data (version 16.0), extracted April 2012
Source: (Le Mouel and Squicciarini, 2015[1])

3.3. Skill Indicators

To study the relationship between skills, OC and labour productivity, we define and build a set of variables proxying cognitive as well as task-based skills of the workforce that are expected to relate to economic performance.

To this end, we follow the approach implemented by Grundke et al. (2017[2]) who use an advanced exploratory factor analysis based on Conti et al. (2014[88])[20] that assumes the existence of a number of unobserved latent variables, called factors, whose joined variation explains the correlation pattern of a larger set of observed variables (or items). Each factor is a weighted combination of the observed variables, whereby the weights are called factor loadings. It is important to note that the number of factors is a parameter of the model and needs to be chosen carefully using certain criteria established in the literature (Conti et al., 2014[88]; Costello and Osborne, 2005[89])[21]. Based on this methodology, the authors arrive at six task-based skill indicators, namely: ICT skills; STEM – quantitative skills; readiness to learn and creative problem solving; managing and communication; self-organisation; and marketing and accounting.

In this work, we apply Grundke et al.'s (2017[2]) methodology on all PIAAC surveys available and construct these indicators not only at the country-industry level as done before, but also by OC and non-OC occupations (see Table 3.1). We thus obtain OC-specific ICT as well as STEM skill scores at the country-industry level.

The PIAAC items included in the construction of these indicators are presented in Table 3.2 below. For a full list of indicators with the corresponding items, please see Grundke et al. (2017[2]).

Table 3.2. Indicators of job-related task and skill requirements

Indicator of job related skill requirements	Items included in the construction of the indicator
ICT skills	G_Q05e Frequency of excel use G_Q05g Frequency of programming language use G_Q05d Frequency of transactions through internet (banking, selling/buying) G_Q05a Frequency of email use G_Q05c Frequency of simple internet use G_Q05f Frequency of word use G_Q05h Frequency of real-time discussions through ICT Computer G_Q01b Frequency of Reading letters, emails, memos G_Q02a Frequency of Writing letters, emails, memos G_Q06 Level of Computer Use required for the job F_Q06b Frequency of working physically over long periods
STEM-quantitative skills	G_Q03f Frequency of preparing charts and tables G_Q03g Frequency of Use simple algebra and formulas G_Q03h Frequency of Use complex algebra and statistics

Note: Compilation based on PIAAC.
Source: (Grundke et al., 2017[2])

3.4. Cluster Analysis

Due to small sample sizes (260 observations in our preferred model), average skill scores at the country-industry level cannot always be computed reliably for the group of OC-relevant occupations. To address this shortcoming, a multi-step procedure is implemented in order to impute missing values. This is based on information obtained from countries that are similar in terms of overall skills profile and have enough observations to construct reliable scores. The assumption made here is the following: if workers in the same occupation in a considered cluster perform similar sets of tasks with similar frequencies, their occupational characteristic and skill endowment can, ceteris paribus, be expected to be similar. This cluster analysis approach leads to the grouping of countries presented in Table 3.3.

First, countries are grouped in clusters according to the similarity of their skill score distributions in each of the nine-digit occupation groups. Second, these clusters are used to construct weighted ratios of ICT and STEM skill scores of the OC and non-OC group. Weights are based on the country-industry specific sample size with a minimum threshold of 20 observations per cell. For instance, if a country cluster features three countries and two have large enough cells but one of the countries, say country A, has a sample size of only five observations, a weight of 5/20=0.25 is given to the ratio of that country. The remaining weight of 0.75 is given to the skill score ratio emerging from all the other countries in the cluster, pooled together. As a result, the skill score ratios, and therefore the skill scores themselves, of the two countries for which good data are available, does not change. Instead, their skill score ratios feed into the imputed skill score ratio of country A. The weighting mechanism devised avoids pure imputations from the other countries in the cluster and exploits to the maximum extent the country-specific information available. The newly imputed skill value of the OC-group in country A is the non-OC groups' skill score times the newly constructed weighted ratio. A numeric example is provided in 0.

Despite our best efforts, though, data coverage for some industries remains insufficient and does not allow implementing the country cluster approach described above. As a result, agriculture (A), mining (B), electricity, gas, steam and air conditioning supply (D), water supply; sewerage, waste management and remediation activities (E), and real estate activities (L) are dropped from the analysis[22].

Table 3.3. Country clusters used for skill score imputation

	Countries
Cluster 1	Australia, Great Britain, Canada, Ireland, New Zealand, United States
Cluster 2	Denmark, Finland, Norway, Sweden
Cluster 3	Austria, Belgium, Czech republic, Estonia, Germany, Hungary, Netherlands
Cluster 4	France, Greece, Israel, Italy, Poland, Slovenia, Spain,
Cluster 5	Kazakhstan, Lithuania, Slovakia, Turkey
Cluster 6	Korea, Japan, Singapore
Cluster 7	Chile, Ecuador, Mexico, Peru

Note: A numerical example of the methodology is provided 0.
Source: Authors' own compilation based on PIAAC data and following Bechichi et al. (2018[90])

Section 4. Methodology

4.1. Estimation of Conditional Correlations

The relationship between OC, human capital (proxied by educational attainment, task-based skills as well as cognitive skills), and labour productivity is first explored using a simple OLS regression at the country-industry level. The paper employs labour productivity in value added terms (i.e. value added in Million USD per employee) as the dependent variable:

$$\ln(LP)_{i,k} = a_0 + a_1 \overline{ICT}^{non-OC}{}_{i,k} + a_2 ICTratio_{i,k} + a_3 \overline{STEM}^{non-OC}{}_{i,k} + a_4 STEMratio_{i,k} + a_5 \overline{numeracy}_{i,k} + a_6 numeracy10/90_{i,k} + a_7 OCshare_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \quad (1)$$

For country *i*, industry *k* and industry cluster *c*.

The independent variables $\overline{ICT}^{non-OC}$ and $\overline{STEM}^{non-OC}$ represent the average ICT and STEM skill score, respectively, at the country-industry level for non-OC occupations, i.e. the part of the workforce that is supposed not to contribute to the generation and accumulation of OC.

The variables $ICTratio$ and $STEMratio$ are the ratio between the average skill scores of the OC-relevant and the OC-non-relevant occupations, at the country-industry level.

Cognitive skills and their dispersion are accounted for using the average numeracy skill score, $\overline{numeracy}$, as well as the ratio between the top and the bottom 10 percentile of the numeracy score at the country-industry level. Since numerous surveys find that cognitive skills are highly correlated with one another (OECD, 2016[16]) and numeracy appears to be most relevant for the accumulation of ICT and STEM skills, literacy, which is also measured in PIAAC, is excluded from this model.

Although problem solving skills, which are also measured in PIAAC, are arguably relevant for accumulating ICT and STEM skills, they are not used either because they relate to technology rich environments, and therefore represent a subset of more general problem solving skills. In addition, if we were to consider problem solving in technology rich environments, we would need to leave Italy, France and Spain out of the analysis, given that such module is not present in the respective PIAAC survey data. Finally, and to facilitate comparison of the skill related coefficients, all skill indicators are rescaled and defined following a 0 to 100 scale.

In order to control for the quality as well as the quantity of the OC in an industry, the model also includes the variable $OCshare$, which captures the proportion of OC-relevant occupations in total employment at the country-industry level.

In addition, and to account for a number of factors known to shape economic performance and for the complementarity of investment in other knowledge-based assets, the proposed model features the following country-industry specific variables:

- Physical capital intensity, measured as net fixed assets in Thousands USD per worker (in log terms) from the OECD's Annual National Accounts database.

- Skill intensity, defined as the share of medium and high-skilled workers, as measured by educational attainment, obtained from Horvát and Yamano (2019[46]).
- Expenditure in R&D in Billion USD, taken from the OECD ANBERD database.

Finally, all regressions include country (μ_i) and industry cluster (δ_c) fixed effects to control for unobserved characteristics at the country and the industry (that are similar across countries) level, respectively. By controlling for unobserved country characteristics (that are similar across industries), the analysis takes into account cultural differences known to affect organisational and managerial practices (Bloom et al., 2007[91]; Bloom et al., 2012[92]).The use of industry cluster dummies, in addition, helps shedding light on how changes in skills and OC within each industry relate to the labour productivity of industries, on average in the cluster.

Robust standard errors are clustered at the country level and fewer than 20 observations in a country-industry cell of PIAAC are imputed (where possible) or otherwise excluded from the analysis, to reduce possible measurement error in the skill variables.

4.2. Exploring Causality

As previous sections have discussed, the model is likely to suffer from selection bias and endogeneity. Firstly, individuals with higher skills may self-select into larger firms that tend to be more productive and to pay comparatively higher wages. This being the case, we would be facing selection biases. Existing empirical evidence supports such a hypothesis and shows that comparatively larger firms offer career prospects and fringe benefits that seemingly attract better-educated school leavers, in particular (Wagner, 1999[3]). Conversely, small and micro firms generally cannot offer comparable remuneration and career prospects and may thus appear less attractive employment-wise (Kelliher and Reinl, 2009[93]). Secondly, there is evidence that more productive firms tend to be larger and to provide training more frequently (Kotey and Folker, 2007[23]; Kim and Yoon, 2008[24]; Almeida and Aterido, 2010[27]; Cunningham and Rowley, 2010[26]; World Bank, 2010[25]; Shepherd et al., 2011[28])[23] whereas small firms tend to rather rely on informal processes to develop the skills of their workforce (Ashton, 2008[94]; Kitching, 2008[95]; Bishop, 2012[96]; 2017[97]). This being the case, our model would suffer from reverse causality, as better skills would be conducive to better economic performance, in the same way as better economic performance would be conducive to better skills.

Finally, if other unobserved factors that affect both, skills and productivity, such as socio-economic background, perceived opportunities and social expectations, are omitted from the model, estimates may suffer from omitted variable bias. The paper attempts to control for these different sources of endogeneity by combining a Heckman selection model with an instrumental variable approach in a three-step approach consisting of up to five equations.

The first stage determines the probability of self-selecting into a large or a small firm type of employer. It is composed of one equation with two different exclusion restrictions and is estimated using a probit model (Heckman, 1979[98]).

$$Prob(firmsize = 1 \mid ICTxOC, ICTratio, STEMxOC, STEMratio, numeracy, numeracy10/90, exclusion, x)$$
$$= a_0 + a_1\overline{ICT}^{non-OC}{}_{i,k} + a_2 ICTratio_{i,k} + a_3\overline{STEM}^{non-OC}{}_{i,k} + a_4 STEMratio_{i,k} + a_5\overline{numeracy}_{i,k} +$$
$$a_6 numeracy10/90_{i,k} + a_7\overline{exclusion}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \tag{2}$$

For country i, industry k and industry cluster c.

The decision to join either a small or a large firm is a discrete event and therefore reflected in a binary variable at the individual level. However, the analysis is carried out at the industry-country level and therefore, this binary variable, is converted into proportions. Consequently, a dependent variable $firmsize$ is constructed and coded one if the country-industry specific share of medium-to-large firms exceeds the country-specific median, and zero otherwise.

Furthermore, the model is estimated with two different exclusion restrictions $exclusion$, which either capture network and social mobility effects ($samepath$) or ICT use at home ($ICTtrans$). The former is measured as the share of workers who have a high-skilled occupation (i.e. ISCO 2008 1-digit level groups 1 to 3) and who have at least one parent with tertiary education (ISCED 5 or 6). It can be argued that this variable encompasses network effects, social mobility and parents' expectations and therefore may influence the choice of their children's employment (OECD, 2018[99]), but not impact labour productivity directly. An equally valid exclusion restriction can be the use of ICT at home, which is captured by the share of workers making transactions on the internet (e.g. buying/selling products or services, or banking) in their every-day life, at least once a month. The fact that workers use ICT at home may help shape their ICT skills, but not their productivity at work directly. The selection model includes country fixed effects but only three industry clusters to make sure that there is enough variation across industries to capture selection into larger firms. The three industry clusters include manufacturing (C), other businesses (F-N, R&S) and public sector services (O&P&Q)

This first step allows estimating an Inverse Mills Ratio (IMR), which is then used as an additional control variable in the second and third step, to control for selectivity in the instrumental variable approach.

Since skills are likely to be endogenous, in the second step we attempt to address such a concern by instrumenting these variables one after the other. We instrument numeracy and both ICT skill variables, using parental education and email use at home, respectively. This should help obtain more accurate estimates for the returns to STEM[24] skills: controlling for numeracy and ICT more adequately shall improve the precision of the STEM-related coefficient, by helping to disentangle the effects of these different skill types.

Although parental education is widely acknowledged to be a suitable instrument for children's educational attainment and their skills (Hanushek et al., 2015[76]; Hampf, Wiederhold and Woessmann, 2017[83]), we are aware that the assumption that parental education shapes labour productivity only through its effect on people's numeracy scores may be heroic and subject to violation. For instance, school attainment may mirror some non-cognitive components of the human capital that contribute to shape earnings but are not captured by the numeracy score. Equally, if family ties (and therefore family background in the wider sense) help to obtain better jobs, the link between skills and earnings does not only reflect the causal effect of skills. As a result, family background may rather act as a further explanatory variable. These caveats notwithstanding, we use such variables in the analysis in line with earlier studies and are aware of the data limitations that impinge upon identifying fully exogenous instruments.

As mentioned, we hold that using emails at home is correlated with ICT task-based skills (Kuhlemeier and Hemker, 2007[100]), but does not impact labour productivity directly.[25] We do so following a similar logic to the one behind using parental education to instrument cognitive skills. Using email at home is expected to affect productivity primarily through the ability to perform ICT task-based skills but not directly. ICT task-based skills also depend on the organisational and information structure of a firm. A worker can perform certain ICT tasks at work if and only if the firm has the infrastructure and organisational arrangements for the worker to do so. We thus hold that being able to perform certain ICT tasks, as demonstrated by the ability of a person to do so at home, is not a sufficient condition for the worker to be able to shape the productivity of the firm where she works.

Moreover, as home-based email usage can be observed for both, OC and non-OC workers, we instrument average ICT task-based skills of non-OC workers with the share of workers in non-OC occupations that use emails in their every-day life at least once a month. The ratio between ICT skills of OC workers and non-OC workers is instrument by the share of OC workers using emails frequently. As a result, we estimate up to three equations for this step.

$$\overline{numeracy}_{i,k} = a_0 + a_1\overline{ICT}^{non-OC}_{i,k} + a_2 ICTratio_{i,k} + a_3\overline{STEM}^{non-OC}_{i,k} + a_4 STEMratio_{i,k} + a_5 numeracy10/90_{i,k} + a_6\hat{\lambda}_{i,k} + a_7\overline{parent}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \tag{3}$$

$$\overline{ICT}^{non-OC}_{i,k} = a_0 + a_1 ICTratio_{i,k} + a_2\overline{STEM}^{non-OC}_{i,k} + a_3 STEMratio_{i,k} + a_4\overline{numeracy}_{i,k} + a_5 numeracy10/90_{i,k} + a_6\hat{\lambda}_{i,k} + a_7\overline{email}^{non-OC}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \tag{4}$$

$$ICTratio_{i,k} = a_0 + a_1\overline{ICT}^{non-OC}_{i,k} + a_2\overline{STEM}^{non-OC}_{i,k} + a_3 STEMratio_{i,k} + a_4\overline{numeracy}_{i,k} + a_5 numeracy10/90_{i,k} + a_6\hat{\lambda}_{i,k} + a_7\overline{email}^{OC}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \tag{5}$$

Finally, the labour productivity model is estimated again incorporating the instrumented skill variables as well as the previously estimated IMR from the first step (equation 2).

$$\ln(LP)_{i,k} = a_0 + a_1\overline{ICT}^{non-OC}_{i,k} + a_2 ICTratio_{i,k} + a_3\overline{STEM}^{non-OC}_{i,k} + a_4 STEMratio_{i,k} + a_5\overline{numeracy}_{i,k} + a_6 numeracy10/90_{i,k} + a_7\hat{\lambda}_{i,k} + x_{i,k}'\beta + \mu_i + \delta_c \tag{6}$$

We remove R&D and the share of OC workers from the model to avoid overfitting problems caused by having too many control variables in a model relying on relatively few observations. We later show that results are robust to the inclusion or exclusion of R&D and share of OC workers in the regression model.

As a robustness check, the model is estimated using gross output rather than value added per employee as a measure of labour productivity. Due to the fact that richer countries have fewer but better skilled managers (Esfahani, 2019[101]), who are a significant component of OC and tend to operate in larger plants (Bento and Restuccia, 2016[102]), gross output is expected to be related with firms size and their organisational structure. Therefore, the share of OC enters the model as an additional explanatory variable.

Section 5. The Relationship between Organisational Capital, Skills and Productivity

5.1. Descriptive Statistics: Organisational Capital and Task-Based Skills

Before assessing econometrically the relationship between OC, skills and labour productivity, it may be helpful to statistically characterise the link between OC and skills.

Figure 5.1 portrays the median score of ICT (panel A) and STEM (panel B) skills and highlights the cross-country as well as cross-industry differences that emerge in the skill endowment of the workforce. In the panels shown, workers are subdivided into two groups, with workers in OC-relevant occupations depicted in navy, and workers in non-OC occupations shown in orange. The height of each bar represents the cross-country dispersion of median scores and displays the minimum and maximum average country-specific value within each industry.

It becomes apparent that, regardless of the skill type or industry considered, workers in OC-relevant occupations are relatively better endowed with ICT as well as STEM skills, on average. The highest ICT skills scores for both groups are found in the case of the ICT (J) as well as the finance and insurance (K) industries. While these industry groups also exhibit the highest STEM skill scores for non-OC occupations, the highest average STEM scores of workers in OC-relevant occupations are observed in manufacturing of chemicals and metals (CC-CH) and in manufacturing of computers, electronics, transport equipment, other manufacturing and repair and installation of machinery (CI-CM).

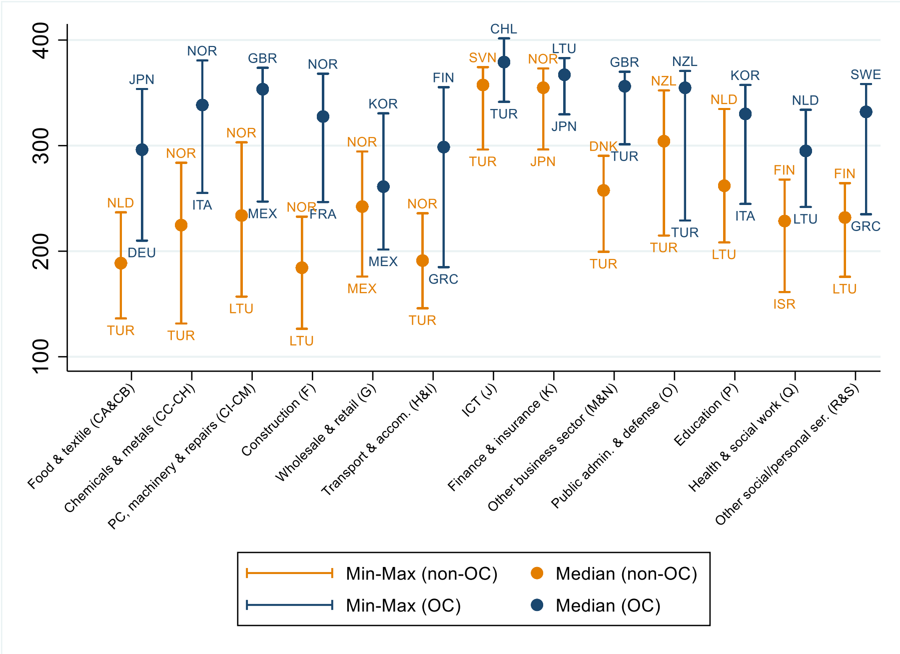
The difference between the two occupational groups is particularly apparent in manufacturing (C), construction (F), transportation and accommodation (H&I), and other business sectors (M&N) as well as public services (O&P&Q) and other social and personal services (R&S). It is not only less apparent in ICT (J) as well as in finance and insurance (K), but also in wholesale and retail (G).

Both graphs also show that endowments are very dispersed across countries and that dispersion varies by industry as well as by occupational group. The largest heterogeneity in ICT skill endowments across countries is observed among the OC-relevant occupations in the transport and accommodation sector (H&I). While a comparable pattern presents itself for the STEM skills, a similar level of dispersion is observed for the same group in the manufacturing sector (C) and in construction (F).

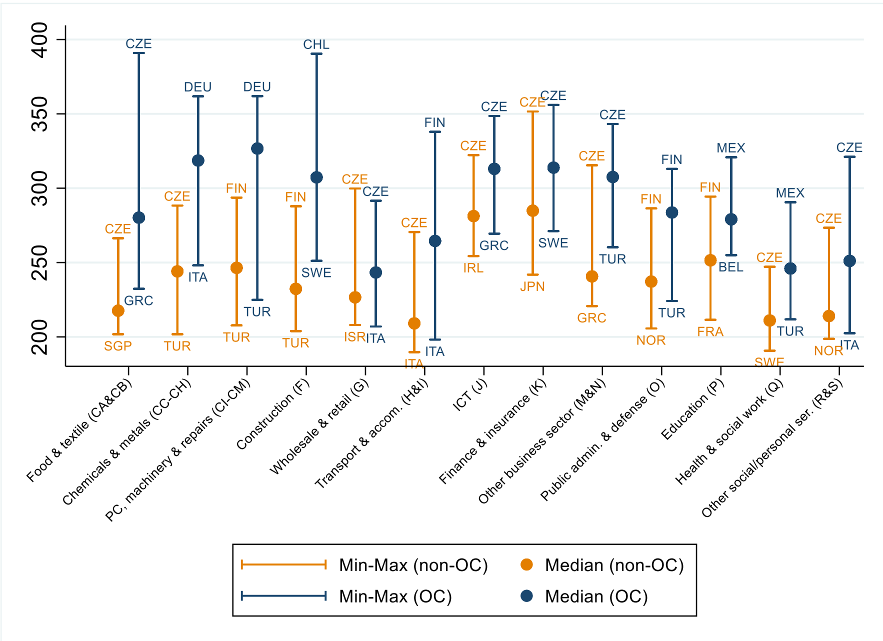
The only exception where skill endowment varies to a lesser extent across countries and the two occupation groups is, again, ICT (J). While ICT skills also appear less heterogeneous in finance and insurance (K), STEM skills exhibit less variation in the human health and social care sector (Q).

Figure 5.1. Median skill scores by industry

A) ICT task-based skill scores



B) STEM-quantitative skill scores



Note: Figures are based on country specific averages by industry. Countries included in the analysis: AUT, BEL, CAN, CHL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, MEX, NLD, NOR, NZL, POL, SGP, SVK, SVN, SWE, TUR and first wave of USA. The sample consists of 402 and 401 observations when examining ICT and STEM skills, respectively. Sample sizes are too small to construct median ICT task-base skill scores for food & textile (CA&CB) in Korea and other social & personal services (R&S) in Turkey, and too small to construct STEM skills for ICT in Turkey.
Source: Authors' own compilation based on PIAAC data.

5.2. Descriptive Statistics: Skills, Digital Intensity and Labour Productivity

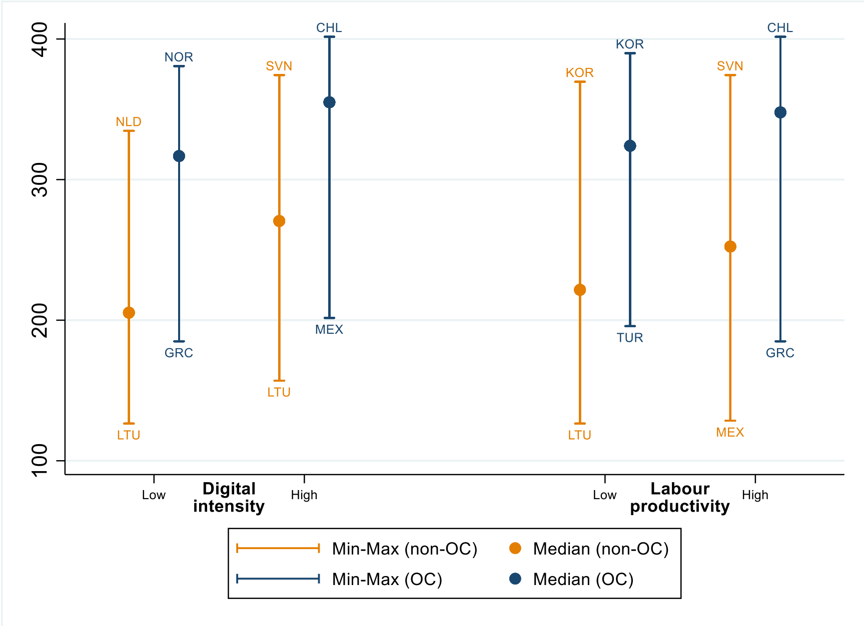
Figure 5.2 portrays the median score of ICT (panel A) and STEM (panel B) skills by industries' level of digital intensity as well as by labour productivity. Levels are divided into "low" and "high", with "low" identifying the bottom half and "high" the top half of the distribution of labour productivity and digital intensity. The digital intensity of sectors is defined following Calvino et al. (2018[18]).

The graphs show again that, regardless of the type of skill considered or the dimension over which the skill endowment is studied, OC-relevant occupations perform better on average. They also highlight the fact that both, ICT and STEM skills, are higher for OC- and non-OC workers in industries that are more digitally intensive or more productive.

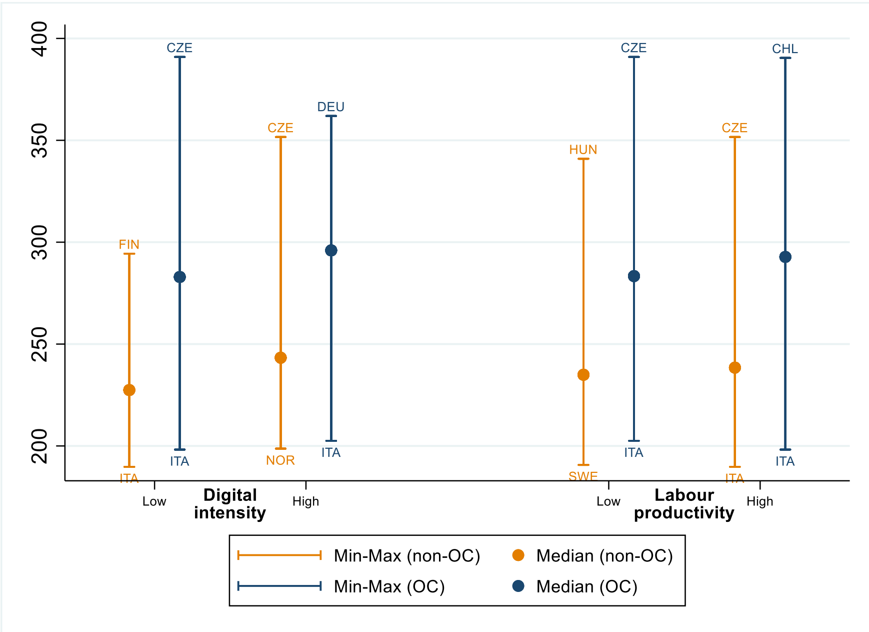
This is in line with Grundke et al. (2018[15]) who find that digital intensive industries especially reward workers having relatively higher levels of self-organisation and advanced numeracy skills. They further observe advantages of skill bundles for workers in digital intensive industries where workers endowed with a high level of numeracy skills receive an additional wage premium, if they also show high levels of self-organisation or managing and communication skills.

Figure 5.2. Median skill scores by digital intensity and labour productivity

A) ICT task-based skill scores



B) STEM-quantitative skill scores



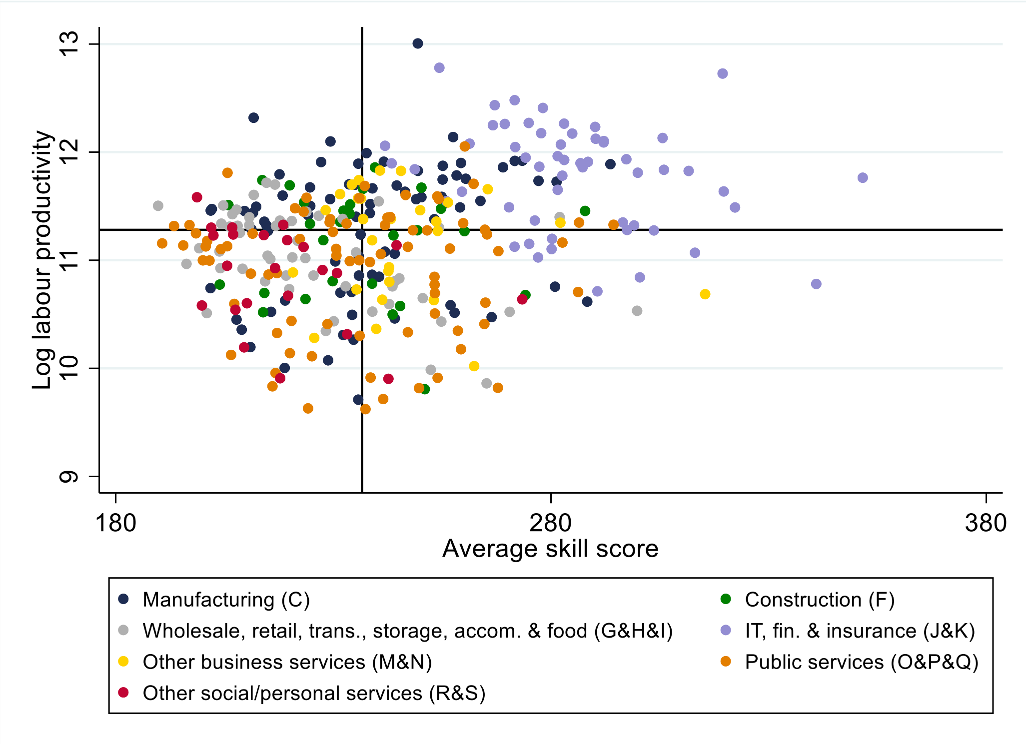
Note: Figures are based on country specific averages by digital intensity or labour productivity. Countries included in the analysis: AUT, BEL, CAN, CHL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, MEX, NLD, NOR, NZL, POL, SGP, SVK, SVN, SWE, TUR and first wave of USA. The sample consists of 402 and 401 observations when examining ICT and STEM skills, respectively. Sample sizes are too small to construct median ICT skill scores for food & textile (CA&CB) in Korea and other social & personal services (R&S) in Turkey, and too small to construct STEM skills for the ICT sector (J) in Turkey. In panel A) and B), "High" identifies sectors in the top half and "Low" in the bottom half of the distribution of labour productivity and digital intensity. For more information on how digital intensity is defined, please see Calvino et al. (2018[18]).

Source: Authors' own compilation based on PIAAC data.

Figure 5.3 shows the relationship between STEM skill scores of non-OC workers and labour productivity. Each dot represents a country-industry's average STEM score and average productivity level. The colours of the dots reflect the related industry-cluster, while the black horizontal and vertical lines represent the median values of labour productivity and STEM skill scores, respectively, dividing the figure into four quadrants. The industry cluster containing IT, finance and insurance (J&K) stands out with almost all dots located in the high STEM score and high productivity quadrant. The industry cluster containing other social and personal services (R&S), on the other hand, stands out for having almost all dots in the low STEM score and low productivity quadrant. The dots related to the other industry clusters are more evenly distributed across the quadrants. The dots related to the industry clusters consisting of public services (O&P&Q) and wholesale, retail, transportation, storage, accommodation and food (G&H&I) are relatively often observed in the low skills and low productivity quadrant. For manufacturing (C) a large spread across both dimensions is observed, with high levels of STEM scores and productivity for some countries. Most countries feature less dispersed average skill scores around the median for other business services (M&N), but differences in productivity between different countries are larger for this industry cluster. Finally, the country-industry averages for construction (F) are almost equally distributed over the quadrants.

Figure 5.3. Scatter plot: mean STEM-quantitative skill scores of non-OC workers

Median labour productivity and median skill score presented by horizontal and vertical black lines, respectively



Note: Figures are based on country specific averages by industry. Industries are colour-coded by industry clusters to aid the reader. Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, NLD, NOR, NZL, POL, SVK, SVN, SWE, TUR and first wave of USA. However, some industries are missing for EST, ISR, JPN, NZL, and TUR. The sample consists of 343 observations. Scatter plots presenting the relationship between STEM-quantitative skills and labour productivity for workers in OC-relevant occupations as well as between ICT task-based skills and labour productivity for non-OC and OC workers are provided in Annex B.
Source: Author's own compilation

Scatter plots presenting the relationship between STEM skills and labour productivity for workers in OC-relevant occupations as well as between ICT task-based skills and labour productivity for non-OC and OC workers are provided in Annex B. The differences between the different industry clusters are even more pronounced for the ICT skill scores, especially for non-OC workers.

Table 5.1 shows the descriptive statistics of the variables from the regression model. The first column shows the variable name, the second column the definition of the variable and the next columns present the mean, 90th percentile and 10th percentile. Labour productivity is measured as the log of value added (or gross output) in Million USD per employee. The skill scores are measured on a 0-100 scale.

Table 5.1. Descriptive statistics of variables from the regression models

All variables are at the country-industry level

Variable	Definition	Mean	90th percentile	10th percentile
Log of VA	Log of labour productivity measured as value added in Million USD per employee	11.22	11.90	10.42
Log of GO	Log of labour productivity measured as gross output in Million USD per employee	11.93	12.89	10.90
ICT score (non-OC)	Average ICT skill score of non-OC occupations	51.38	71.01	36.84
ICT score ratio (OC/non-OC)	Ratio between the average ICT skill scores of the OC-relevant and the OC-non-relevant occupations	1.33	1.65	1.04
STEM score (non-OC)	Average STEM skill score of non-OC workers	48.75	57.51	41.42
STEM score ratio (OC/non-OC)	Ratio between the average STEM skill scores of the OC-relevant and the OC-non-relevant occupations	1.19	1.35	1.05
Numeracy score	Average numeracy skill score of all workers	55.90	60.58	50.98
Numeracy score (Perc10/Perc90)	Ratio between the top and the bottom 10 percentile of the average numeracy score of all workers	0.65	0.71	0.59
Share of OC	Proportion of OC-relevant occupations in total employment	33.15	55.18	14.67
Log of net fixed assets per employee	Physical capital intensity measured as log of net fixed assets in Thousands USD per worker	11.30	12.53	10.31
R&D expenditure (lagged)	Expenditure in R&D in Billion USD lagged by one year	1.65	2.41	0.00
Skill intensity	Skill intensity defined as the share of medium and high-skilled workers	0.86	0.98	0.69
Samepath	Share of workers who have a high-skilled occupation (ISCO 2008 major groups 1 to 3) and who have at least one parent with tertiary education (ISCED 5 or 6)	18.49	36.89	4.14
ICT transactions	Share of workers that conduct transactions on the internet (e.g. buying/selling products or services, or banking) in their every-day life at least once a month	36.84	57.12	16.47
One parent educated	Share of workers who have at least one parent with secondary or tertiary education (ISCED 3, 4, 5 or 6)	69.22	89.19	47.49
ICT email use (non-OC)	Share of workers in OC-non-relevant occupations that use emails in their every-day life at least once a month	70.46	89.35	50.80
ICT email use (OC)	Share of workers in OC-relevant occupations that use emails in their every-day life at least once a month	81.92	94.25	66.20
Firmsize	One if the country-industry specific share of medium-to-large firms exceeds the country-specific median, and zero otherwise	0.47	1.00	0.00

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. Descriptive statistics are presented for the sample used in the preferred regression models using 260 observations. R&D expenditure (lagged) is available for 213 out of the 260 country-industries, mostly missing for the public sector.
Source: Authors' own compilation

5.3. Estimation Results

Table 5.2 shows the conditional correlations that emerge between (OC and non-OC) skills and labour productivity, controlling for unobserved country and industry cluster[26] characteristics. These correlations show the industry-specific relationship between skill endowment and labour productivity.

The specification in the first column (model 1) presents the base model, which only includes skill indicators, share of OC workers, net fixed assets as well as country and industry cluster fixed effects. The second column (model 2) further controls for the share of workers with high educational attainment, which we here denote as "skills intensity", for short. Model 3 controls for R&D expenditure but not for skill intensity, while model 4 controls for both, R&D and skills intensity. Finally, model 5 gives the preferred specification, which controls for skill intensity, but not for R&D nor for the share of OC workers.

The results are very similar regardless of the specification employed. However, by removing R&D expenditure and skills intensity (as shown in model 1) the number of observations increases from 213 to 284, reducing the margin of error. Since the results for the different model specifications are very similar, it is preferred to remove R&D and the share of OC workers from the model to avoid overfitting problems caused by having too many control variables in a model relying on relatively few observations. Although R&D expenditure is highly significant, by removing it from the model, the number of observations increases by 47. We remove the share of OC because the coefficient is zero (and insignificant), and so it does not add much to the discussion.

A significant and positive correlation emerges between productivity and numeracy proficiency, where a one-point increase in the numeracy score relates to a 1.8-2.4 per cent increase in productivity which is comparable to the effect size found in Grundke et al. (2017[2]). This result suggest that a one standard deviation (3.4) increase in numeracy skills relates to a 6.1-8.2 per cent increase in productivity, which is smaller than the effect of 18 percent increase in wages with a one standard deviation increase in numeracy skills found in Hanushek et al (2015[76]). However, it confirms that a greater cognitive skills endowment of the workforce is indeed related to better economic performance. The analysis conversely does not allow us to say anything about the extent to which cognitive skills dispersion may hamper productivity, as the coefficient for the dispersion of the numeracy score, which compares the top and the bottom ten percentile of the distribution, is negative but statistically insignificant.

The ICT skill score of the non-OC group does not appear to be correlated with labour productivity when controlled for STEM skills.[27] However, the ratio between ICT skill scores for OC workers and that of non-OC workers is negatively correlated, although significance levels vary. This suggests that while greater ICT skills of all non-OC workers may not always be needed to increase labour productivity, too big differences in the ICT abilities of OC workers and non-OC workers may indeed harm economic performance. One possible explanation might be that a larger gap in the ICT skills between OC workers and non-OC workers may reflect or create difficulties in communication and cooperation between OC and non-OC workers as well as hiccups in the flow of information - we call this the "*lost in translation*" hypothesis. As the analysis is at the country-industry level, the negative effect of dispersion in ICT skills' dispersion could be explained by both, dispersion within firms and dispersion between firms. The latter suggests paucity of knowledge spillovers between firms/workers featuring high levels of ICT task-based skills and firms/workers with low levels of such skills.

Finally and differently from the ICT case, STEM skill scores of the non-OC workforce emerge as being positively and highly significantly correlated with productivity in models 1 to 3 and model 5. The relevant coefficient only turns insignificant in model 4, i.e. the one where we control for both, R&D and skill intensity (which also features the lowest number of observations). The coefficient varies between 0.014-0.019 suggesting that a one-point increase in the STEM score (non-OC) is related to a 1.4-1.9 percent increase in labour productivity. Since the STEM skill score is also defined on a 0-100 scale, a standard deviation of 6 suggests that a standard deviation increase in the STEM skill score for non-OC workers is associated with an 8.4-11.4 percent increase in productivity, which is surely non-negligible as an effect.

The coefficient for the ratio between the STEM score for OC workers and non-OC workers is positive and highly significant in all five models, suggesting that the STEM score is even more important for the OC workers than it already is for the other workers. However, the coefficient for the ratio of the STEM scores becomes statistically insignificant when the ratio of the ICT score is dropped from the model, suggesting that the positive correlation between the ratio of STEM and productivity is conditional on the ratio between ICT skill scores for OC and non-OC occupations.

No statistically significant association between the share of OC and labour productivity is found either.

A one percent increase in net fixed assets per employee relates to a 0.15-0.16 percent higher labour productivity and a one-percentage point increase in the share of high-educated workers is related to a 0.77-0.85 percent higher productivity. For R&D, a one Billion USD increase in R&D is associated with a 0.2 percent higher labour productivity. This is clearly a lower bound estimate because R&D consists for a large part of a human capital component, which is expected to be partly absorbed by our different skill variables. Unfortunately, it is impossible to fully disentangle this human capital component of R&D from our skill variables, which gives us lower estimates compared to the literature. However, our estimates are comparable to the findings of Grundke et al. (2017[2]) who find an estimate of 0.5 percent higher labour productivity for every one Billion USD in R&D expenditure when controlling for skills. Studies that use micro-data and employ rigorous econometric methods to address endogeneity problems typically find larger effects of R&D on innovation output and thereby productivity (Crepon, Duguet and Mairesse, 1998[103]; OECD, 2009[104]).

Tests show results to be robust for the models 1 to 5, suggesting that overfitting should not be much of a concern, because the number of observations increases by dropping R&D expenditure and skill intensity. Although R-square values are relatively high for all specifications, suggesting that the models explain around 90-93 percent of the variation in labour productivity, a predicted R-square of similar magnitude provides further support of overfitting not being an important issue.

Table 5.2. Estimation results: Correlations between skill indicators, OC and labour productivity

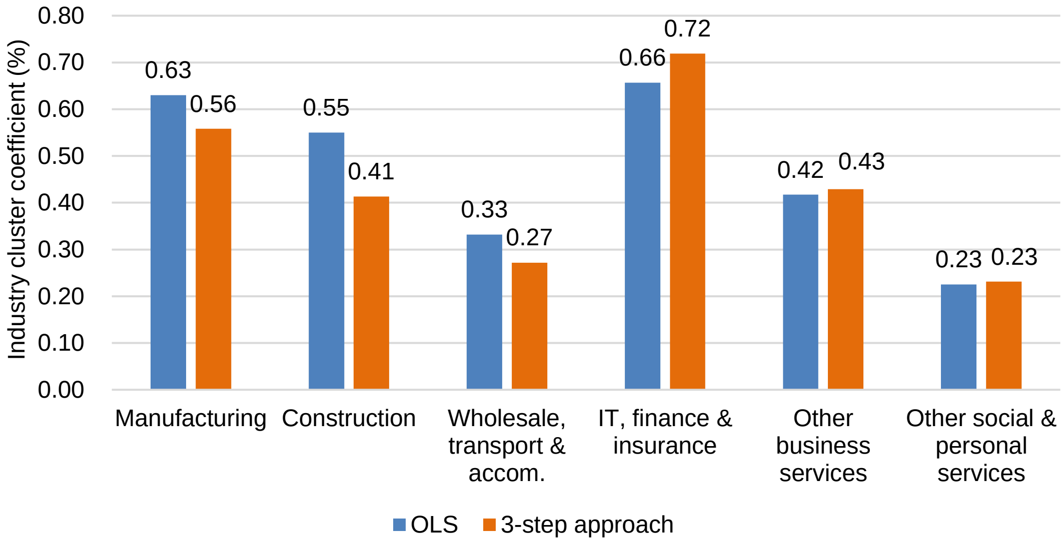
	Model 1	Model 2	Model 3	Model 4	Model 5
Numeracy score	0.024***	0.018**	0.031***	0.029**	0.018**
	(0.008)	(0.009)	(0.010)	(0.010)	(0.008)
ICT score (non-OC)	-0.004	-0.003	-0.005	-0.006	-0.003
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
ICT score ratio (OC/non-OC)	-0.234*	-0.246*	-0.256*	-0.275**	-0.242**
	(0.127)	(0.123)	(0.134)	(0.125)	(0.112)
STEM score (non-OC)	0.019***	0.014***	0.017**	0.012	0.014***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.005)
STEM score ratio (OC/non-OC)	0.384**	0.299**	0.416***	0.301**	0.302**
	(0.147)	(0.125)	(0.129)	(0.113)	(0.128)
Numeracy score (Perc10/Perc90)	-0.606	-0.848	-0.555	-0.781	-0.843
	(0.635)	(0.599)	(0.585)	(0.515)	(0.600)
Log of net fixed assets per employee	0.163***	0.160***	0.147***	0.156***	0.160***
	(0.020)	(0.022)	(0.027)	(0.028)	(0.021)
Share of OC	0.000	-0.000	-0.000	-0.001	
	(0.001)	(0.001)	(0.001)	(0.001)	
Skill intensity		0.771**		0.850**	0.769**
		(0.281)		(0.360)	(0.284)
R&D expenditure (lagged)			0.002**	0.002***	
			(0.001)	(0.000)	
Constant	7.206***	7.349***	7.116***	7.000***	7.341***
	(0.404)	(0.378)	(0.578)	(0.517)	(0.379)
Observations	284	260	232	213	260
R-squared	0.908	0.917	0.918	0.927	0.917
Country FE	YES	YES	YES	YES	YES
Industry cluster (7 groups) FE	YES	YES	YES	YES	YES

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. Since there is no data available for the skills intensity variable for ISR, JPN and KOR, they are dropped in model 2, 4 and model 5. More observations are dropped when R&D is added to the model, mostly because R&D expenditure is often not available for the public sector. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author's own compilation

Annex D provides a more extensive presentation of the results in Table 5.2, in which the coefficients for the different country and industry-cluster dummies are presented. Figure 5.4 shows the industry coefficients in a bar chart, to facilitate comparison between different industries. When using the public sector as the reference industry, manufacturing (C), construction (F) and IT, finance and insurance (J&K) stand out among the most productive industries in comparison to the public sector (as a matter of fact, all industry clusters exhibit positive coefficients, i.e. greater productivity than the public sector). As the largest coefficients emerge in relation to what also other studies find to be the most productive sectors, we may be confident that we properly control for industry differences and that our results are not driven by a few industries like IT, finance and insurance. When looking at the country fixed effects and taking Greece as the reference country, Ireland, Italy and Norway exhibit relatively high levels of labour productivity conditional on the control variables used and the inclusion of industry cluster fixed effects.

Figure 5.4. Industry clusters' coefficients

Coefficient sizes from OLS and 3-step approach in comparison



Note: Figures are based on regression results presented in Annex D (OLS) and Annex E (3-step approach). The public sector is used as the reference industry.
Source: Author's own compilation

5.4. Exploring Causality: Disentangling Endogeneity and Selectivity

Table 5.3 shows the estimation results when endogeneity and selectivity issues are addressed. As discussed, selectivity can occur when individuals with higher skills self-select into larger firms that tend to be more productive. Endogeneity can be caused by reverse causality, as more productive (often larger) companies may offer better learning and training opportunities. Endogeneity can also be caused by other unobserved factors that affect both skills and productivity, such as socio-economic background, perceived opportunities and social expectations. This section of the paper attempts to control for these different sources of selectivity and endogeneity by combining a Heckman selection model with an instrumental variable approach. Table 5.3 shows the following results: 1) OLS; 2) selection model; 3) first stage(s); 4) second stage. This structure is repeated using the different combinations of exclusion restrictions and instruments discussed in previous sections.

Column 1 repeats the OLS results that were presented in column 2 of Table 5.2 in which the model controls for 7 industry clusters and skill intensity, but not for R&D. The selection model is presented in column 2 from which the IMR is derived, which is then used to control for selectivity in the two stage least squares (2SLS) regression model in the two subsequent columns.

The selection model captures selection into larger firms using firm size as the dependent variable. The 'samepath' variable is used as the exclusion restriction and is measured as the share of workers in a high-skilled occupation (ISCO 2008 major groups 1-3; Managers, Professionals and Technicians) who have at least one parent with tertiary education (ISCED 5 or 6). The selection model shows that the exclusion restriction is not statistically significant. At the same time, ICT skills for both OC and non-OC workers positively relate to firm size, whereas STEM skills are negatively related.

Column 3 shows the first stage of the 2SLS model in which numeracy is instrumented by the proportion of workers whose parent(s) have obtained at least secondary education. Parental education is strongly positively correlated with numeracy skills, which is in line with Hanushek et al. (2015[76]) and Hampf et al. (2017[83]), suggesting a strong first stage, which is also confirmed by the F-statistic (14.87) being larger than the threshold of 10.

The second stage's results, presented in column 4, show that the IMR is small and insignificant, indicating that the selection effect might not be a major problem, possibly because it is already sufficiently absorbed by the fixed effects and other control variables. The effect of numeracy on labour productivity turns insignificant when instrumented with parental education. This finding contrasts the results of Hanushek et al. (2015[76]) and Hampf et al. (2017[83]) who find larger effects on wages when numeracy is instrumented with parental education. Nevertheless, similar effects to the OLS results remain for the ICT and STEM skill scores.

Columns 5 to 7 repeat the estimations shown in columns 2 to 4 but this time the share of people who carry out ICT transactions at home is used as an exclusion restriction in the selection equation, shown in column 5. A positive and highly significant coefficient for ICT transactions suggests that this exclusion restriction is perhaps more relevant than the 'samepath' variable. Column 6 displays the first stage results using the share of email use at home for non-OC workers to instrument ICT skill scores for non-OC workers. It presents a positive and highly significant effect of the instrument, email use at home, on ICT skills for non-OC workers. The results of the second stage, column 7, show that the coefficient for ICT skills for non-OC workers remains insignificant for labour productivity. In addition, the IMR is also small whilst statistically insignificant. The negative coefficient of ICT ratio becomes even more negative, while the coefficients for STEM skills of non-OC workers, the ratio of STEM skills between both types of workers and numeracy become even more positive.

Columns 8 to 11 combine the previous steps by considering both 'samepath' and ICT transactions as exclusion restrictions and both parental education and ICT email use at home as instruments for numeracy and ICT non-OC workers, respectively. The results remain robust across the selection model and the first stages. The multiple F-test statistics are larger than 10 and the IMR is not significant in the second stage. The results of the second stage are still very similar to the OLS estimates, except for numeracy that is not statistically significant, albeit with a comparable, even slightly larger, coefficient.

Finally, columns 12 to 16 add the share of email use at home by OC workers as an instrument for the ratio between ICT skills for OC and non-OC workers. Column 15 shows that the share of email use by OC workers is indeed positively and significantly related with the ICT ratio variable, with a multiple F-test statistic larger than 10. Column 16 presents the second stage results including all exclusion restrictions in the selection model and all three instruments for numeracy, ICT non-OC and the ICT ratio. The IMR remains positive, but small and statistically insignificant, which has been the case across the different model specifications. This may mean that no selection effect remains that is not absorbed by the instrumental variables, fixed effects and other controls. Column 16 presents the first labour productivity results in which both the ICT and STEM ratio variables turn statistically insignificant, but the coefficients remain almost identical to the OLS estimates.

Using two exclusion restrictions and three instruments may perhaps look too ambitious given the limited number of observations. Nevertheless, the coefficients for the skill ratio variables remain very stable across the different model specifications.

Finally, the coefficient for STEM for non-OC workers is 0.026 and still statistically significant, suggesting that a one-point increase in the STEM score (non-OC) is related to a 2.6 percent increase in labour productivity. This effect is larger than the OLS estimate and is consistent with Hampf et al. (2017[83]) and Hanushek et al. (2015[76]) who find that the OLS estimates provide a lower bound of the true returns to skills in the labour market. However, neither of the authors interprets these instrumented estimates as causal because the exclusion restriction is impossible to prove and might be violated.

All together, the results, taking into account selection bias and endogeneity, can be interpreted as additional evidence confirming the OLS results, but they are not sufficient to claim causality with any certainty. Annex E provides a more extensive presentation of the results in Table 5.3.

Table 5.3. Estimation results of skills on value added per employee

Stages	**OLS**	Selection	First	**Second**	Selection	First	**Second**	Selection	First	First	**Second**	Selection	First	First	First	**Second**
Dependent variable	VA (1)	Firm size (2)	Numeracy (3)	VA (4)	Firm size (5)	ICT non-OC (6)	VA (7)	Firm size (8)	Numeracy (9)	ICT non-OC (10)	VA (11)	Firm size (12)	Numeracy (13)	ICT non-OC (14)	ICT ratio (15)	VA (16)
Samepath		0.002						0.012				0.009				
		(0.023)						(0.020)				(0.020)				
ICT trans.					0.099***			0.104***				0.097***				
					(0.032)			(0.033)				(0.033)				
Parent edu.		-0.056*	0.055***					-0.046	0.059***	0.041		-0.050*	0.056***	0.024	-0.001	
		(0.030)	(0.014)					(0.030)	(0.015)	(0.043)		(0.030)	(0.015)	(0.052)	(0.002)	
Email non-OC					-0.029	0.110***		-0.018	-0.003	0.103***		-0.027	-0.003	0.135***	-0.003**	
					(0.025)	(0.036)		(0.025)	(0.012)	(0.029)		(0.026)	(0.011)	(0.045)	(0.002)	
Email OC												0.017	0.011	0.032	0.004***	
												(0.020)	(0.011)	(0.037)	(0.001)	
IMR			0.133	0.026		0.634**	0.034		0.098	0.633*	0.028		0.088	0.318	0.017	0.027
			(0.120)	(0.018)		(0.311)	(0.021)		(0.120)	(0.332)	(0.022)		(0.121)	(0.360)	(0.011)	(0.020)
Numeracy	0.018**			0.005	0.146	0.367**	0.026**				0.029					0.026
	(0.008)			(0.042)	(0.116)	(0.146)	(0.010)				(0.060)					(0.058)
ICT non-OC	-0.003	0.224***	0.038**	-0.002			-0.020				-0.021					-0.018
	(0.004)	(0.052)	(0.018)	(0.005)			(0.015)				(0.020)					(0.019)
ICT ratio	-0.242**	5.647***	-0.172	-0.241**	1.390	-15.32***	-0.517**	1.315	-0.788	-15.63***	-0.520*					-0.334
	(0.112)	(1.572)	(0.626)	(0.100)	(1.169)	(2.110)	(0.228)	(1.141)	(0.610)	(2.128)	(0.273)					(0.444)
STEM non-OC	0.014***	-0.140**	0.161***	0.016**	-0.020	0.684***	0.028**	0.020	0.194***	0.751***	0.027***	0.009	0.191***	0.780***	-0.005	0.026***
	(0.005)	(0.063)	(0.036)	(0.008)	(0.051)	(0.067)	(0.011)	(0.044)	(0.034)	(0.059)	(0.009)	(0.045)	(0.037)	(0.085)	(0.003)	(0.008)
STEM ratio	0.302**	-5.111**	2.108*	0.336**	-3.025	10.750***	0.503**	-1.865	2.562**	11.660***	0.497**	-1.384	1.330	-7.346***	1.016***	0.309
	(0.128)	(2.198)	(1.218)	(0.136)	(1.960)	(2.028)	(0.214)	(1.883)	(1.169)	(2.031)	(0.201)	(1.802)	(0.892)	(2.421)	(0.150)	(0.434)
Num. ratio	-0.843	-0.877	22.980***	-0.548	-3.429	10.380	-0.655	0.00779	23.85***	18.83**	-0.743	0.498	24.340***	27.860***	-0.552*	-0.637
	(0.600)	(3.941)	(3.449)	(1.006)	(4.616)	(9.353)	(0.638)	(3.700)	(3.628)	(8.411)	(1.073)	(3.847)	(3.697)	(10.04)	(0.294)	(1.136)
Log NFA	0.160***	0.297	0.316***	0.164***	0.470**	1.696***	0.193***	0.525**	0.397***	1.846***	0.192***	0.501**	0.404***	2.042***	-0.0149	0.190***
	(0.021)	(0.241)	(0.074)	(0.024)	(0.206)	(0.286)	(0.027)	(0.209)	(0.075)	(0.258)	(0.025)	(0.207)	(0.083)	(0.275)	(0.011)	(0.021)
Skill intensity	0.769**	12.680***	1.811	0.808***	11.960***	2.254	0.817***	13.210***	1.903	2.627	0.808***	12.990***	2.299	7.016*	-0.156	0.840***
	(0.284)	(3.385)	(1.880)	(0.276)	(3.185)	(2.832)	(0.265)	(3.169)	(1.920)	(3.170)	(0.272)	(3.149)	(1.828)	(4.216)	(0.138)	(0.303)

Constant	7.341***	-16.26***	19.620***	7.572***	-17.59***	-29.96***	6.707***	-15.35***	18.640***	-23.01***	6.640***	-14.01***	17.930***	-36.12***	0.816***	6.656***
	(0.379)	(4.554)	(2.743)	(0.960)	(4.897)	(6.612)	(0.703)	(4.523)	(2.599)	(6.232)	(1.706)	(4.310)	(2.754)	(5.800)	(0.267)	(1.679)
Observations	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260
R-squared	0.917			0.917			0.913				0.912					0.913
Ind. cluster (3)		YES			YES			YES				YES				
Ind. cluster (7)	YES		YES	YES		YES	YES		YES	YES	YES		YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-stat.			14.87			9.20			7.76	6.78			6.92	3.54	4.31	
Multi. F-stat.			14.87			9.20			15.97	17.13			15.95	16.00	15.98	

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). The three industry clusters include manufacturing (C), other businesses (F-N, R&S) and public sector services (O&P&Q). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author's own compilation.

5.5. Robustness Analysis: the Effects of Skills on Gross Output per Employee

Table 5.4 shows the estimation results using gross output per employee as the dependent variable instead of value added per employee. These robustness results are presented for the OLS model and for the most comprehensive three-step model, using both exclusion restrictions and all instruments. Hence, it can be compared to the results in columns 1 and 12 to 16 in Table 5.3 when value added per employee is used as a measure of labour productivity.

The only additional control variable we add in the gross output models is the share of OC workers. It was dropped from the value added regression model because the coefficient was close to zero and statistically insignificant (see Table 5.2). However, gross output is expected to be more related to firm size and organisational structure than value added because of e.g. economies of scale and scope, and we thus reintroduce the share of OC in the models.

In the OLS results, displayed in column 1, a negative and statistically significant correlation emerges between the ICT ratio and gross output, providing additional evidence for the "*lost in translation*" hypothesis. The coefficients for numeracy, STEM for non-OC workers and the STEM ratio are similar to the results when using value added per employee in Table 5.3, but are now statistically insignificant. Columns 2 to 5 show the results for the most comprehensive model including all exclusion restrictions in the selection model and all three instruments in the 2SLS model. The results for the selection model and first stages are very similar to the results of the same model for value added, presented in columns 12 to 15 of Table 5.3. The second stage results, presented in column 5, show that the IMR becomes positive and significant for gross output, indicating the importance of controlling for self-selection into bigger firms. The coefficient of -0.676 for the ICT ratio remains statistically significant, suggesting that a 0.1 point increase in the ratio between ICT scores for OC and non-OC workers would translate into a 6.8 percent decrease in gross output. This provides robust evidence for the "*lost in translation*" hypothesis. Finally, the STEM ratio coefficient is 0.692 and becomes statistically significant again, indicating that STEM skills remain even more important for OC-workers than for non-OC workers. Annex F provides a more extensive presentation of the results in Table 5.4.

Table 5.4. Estimation results of skills on gross output per employee

Stages	**OLS**	Selection	First	First	First	**Second**
Dependent variable	GO (1)	Firm size (2)	Numeracy (3)	ICT non-OC (4)	ICT ratio (5)	GO (6)
Samepath		0.017				
		(0.021)				
ICT trans.		0.096***				
		(0.033)				
Parent edu.		-0.047	0.050***	0.022	0.000	
		(0.030)	(0.015)	(0.053)	(0.002)	
Email non-OC		-0.035	0.004	0.137***	-0.005***	
		(0.026)	(0.011)	(0.044)	(0.001)	
Email OC		0.018	0.010	0.031	0.005***	
		(0.021)	(0.011)	(0.037)	(0.001)	
IMR			0.130	0.234	0.012	0.052**
			(0.110)	(0.376)	(0.009)	(0.021)
Numeracy	0.025					0.013
	(0.019)					(0.081)
ICT non-OC	-0.009*					-0.018
	(0.004)					(0.025)
ICT ratio	-0.316**					-0.676*
	(0.134)					(0.360)
STEM non-OC	0.007	0.017	0.191***	0.778***	-0.005	0.018
	(0.007)	(0.045)	(0.0337)	(0.0847)	(0.003)	(0.011)
STEM ratio	0.346	-1.983	2.617***	-6.834**	0.813***	0.692*
	(0.223)	(1.848)	(0.923)	(3.039)	(0.137)	(0.402)
Num. ratio	-0.606	0.889	23.56***	27.54***	-0.430*	-0.187
	(1.050)	(3.852)	(3.522)	(10.11)	(0.260)	(1.738)
Log NFA	0.200***	0.430**	0.517***	2.083***	-0.033***	0.218***
	(0.024)	(0.216)	(0.076)	(0.292)	(0.010)	(0.036)
Skill intensity	0.399	14.10***	1.690	6.727	-0.061	0.460
	(0.273)	(3.287)	(1.749)	(4.195)	(0.142)	(0.283)
Share of OC	-0.004***	-0.022*	0.023***	0.010	-0.004***	-0.005*
	(0.001)	(0.013)	(0.005)	(0.016)	(0.001)	(0.002)
Constant	7.730***	-13.01***	15.16***	-37.03***	1.252***	7.892***
	(0.259)	(4.387)	(2.767)	(6.906)	(0.272)	(1.968)
Observations	260	260	260	260	260	260
R-squared	0.929					0.928
Ind. cluster (3)		YES				
Ind. cluster (7)	YES		YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
F-stat.			5.55	3.81	6.55	
Multi. F-stat.			10.31	13.04	27.31	

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). The three industry clusters include manufacturing (C), other businesses (F-N, R&S) and public sector services (O&P&Q). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author's own compilation

Section 6. Conclusion

Although it is widely accepted that OC, workforce skills and firm productivity go hand in hand, very little is known on the extent to which workers' skills and OC relate to labour productivity. To shed light on these issues, the paper analyses this relationship building on OECD estimates of OC, output information from the STAN dataset and cognitive and task-based skill indicators based on PIAAC data.

The results show that workers in OC-relevant occupations are better endowed with ICT as well as with STEM skills, with the highest average scores being observed in ICT (J) and finance and insurance (K) industries. Sectors that are less endowed with such skills are wholesale and retail (G), transport, accommodation and food (H&I) and other social and personal services (R&S).

At the same time, skill endowments appear very dispersed across countries and industries, especially with regards to ICT skills among non-OC workers. Interestingly, the aforementioned industries that stand out for their high average skill scores also experience relatively high levels of average labour productivity, while the industries with lower average scores show more often lower levels of productivity.

The regression analysis shows that ICT skill endowment for people working outside OC relevant occupations is not associated with higher labour productivity (if STEM skill endowment is controlled for), but that a larger gap in ICT skills between OC and non-OC workers is negatively correlated with productivity. We refer to this result as a "*lost in translation*" mechanism, whereby the relatively poorer ICT skills of non-OC workers may lead to overlooking or underutilising relevant information, thus negatively correlating with productivity. In addition to skill dispersion often observed within firms, we argue skill dispersion to hinder knowledge flows and spillovers between firms, i.e. that ICT skill dispersion curbs the possible positive effects of knowledge spillovers also across firms within the same industry.

A contrasting picture emerges when examining the role of workers' STEM skill endowments. Here, STEM skill proficiency is positively correlated with productivity for non-OC workers, but even more for workers within OC relevant occupations. This calls for the need to raise the bar, i.e. to endow all workers, including OC-workers, with sound cognitive (measured by numeracy) skills, as these correlate positively with productivity (in line with some early findings by Grundke et al. (2017[2])).

The paper also explores causality by disentangling potential selection bias and the endogenous nature of skills. When employing a three-step procedure with a Heckman selection model and an instrumental variable approach similar coefficient sizes are observed. While this indicates robust estimates, we are cautious in interpreting them as causal for a number of reasons. Firstly, we use parental education to instrument numeracy skills, which is likely to encompass some non-cognitive components of human capital that contribute to earnings but are not captured by the numeracy score. Equally, if family ties (and therefore family background in the wider sense) help to obtain better jobs, the link between skills and earnings does not reflect the causal effect of skills, at least not only, and, as a result, family background should rather act as a further explanatory variable. Secondly, we instrument ICT skills with email use at home and assume that the instrument is related to labour productivity only through its effect on people's ICT scores. Although both instruments are likely to violate the exclusion restriction, we see them best fit given the data limitations and are aware of the task-based nature of the skills indicators used.

Finally, while these effects are estimated using value added per employee as a measure of labour productivity, we carry out a further robustness check and use gross output per employee instead. The findings from the OLS and the three-step procedure are largely robust. The findings confirm the "*lost in translation*" hypothesis and the fact that STEM skill proficiency is even more important for OC than for non-OC staff to obtain a higher productivity.

This work brings together the complex interaction of OC, skills and productivity, which so far remains largely unexplored. Our findings stress the need to raise the bar, in terms of endowing all workers with good STEM skills, and to have even better STEM-endowed OC staff, as labour productivity depends in a relatively more important fashion on their STEM ability. At the same time, for ICT the focus should be on narrowing the ICT skill gap between OC and non-OC workers.

Our results call for the need to know more about the extent to which industries invest in managerial and OC, and on how workers' skills and OC relate to productivity. In addition, more research needs to be conducted on the role of training policies in upgrading STEM and ICT task-based skills, as well as on the mechanisms through which the skills of all workers, both OC and non-OC workers, affect productivity. More specifically, it is crucial for policy makers to learn more about how the different skills of OC and non-OC workers relate to innovation output and may lead to higher productivity.

Endnotes

[1] These include developing objectives and strategies; organising, planning and supervising production; and managing human resources. According to this definition, OC includes, but is not limited to, managers.

[2] Cognitive skills or abilities have multiple facets and relate to the ability of an individual to perform various mental activities associated with learning (Kautz et al., 2014[110]). Task-based skills are defined as the skills that workers need to perform their job task. See Grundke et al. (2017[2]) for more details.

[3] Grundke et al. (2017[2]) also provides some initial evidence on the relation between cognitive and non-cognitive skills and productivity.

[4] Also known as the "Survey of Adult Skills".

[5] Little if any additional learning would in this case happen at the expenses of the parsimony of our estimating model, given the relatively small number of industry-level observations we rely upon. See further details about the type and number of observations in the data section.

[6] While in principle extremely relevant to the present analysis, we do not exploit the information related to problem solving contained in PIAAC for two main reasons. First, problem solving skills tested in PIAAC relate to technology rich environments, and therefore represent a subset of more general problem solving skills. Second, no information about problem solving are available for Italy, France and Spain and these countries would thus need to be left aside of the analysis, in case.

[7] STEM is the acronym corresponding to Science, Technology, Engineering, and Mathematics. The OECD Skills Outlook (OECD, 2017[81]) refers to task based skills as those skills that relate to the performance of business tasks at work. The full locution used in the case of STEM skills in Grundke et al. (2017[2]) is "STEM – quantitative skills". STEM-quantitative task based skills relate to the performance of numeric tasks such as 'Use simple algebra or formulas' or 'Use advanced math or statistics', as captured in the OECD Survey of Adult Skills and are broadly interpreted as skills necessary for Science, Technology, Engineering and Mathematics.

[8] In addition, Grundke et al. (2017) identify "Readiness to learn and creative problem solving" among the task based skills that emerge following a Baysian-like type of approach. However, since readiness to learn appears to be more of a personality trait rather than a skill per se, this indicator is left out of the analysis.

[9] Further data were obtained from the OECD's Annual National Accounts and the OECD's ANBERD database. Estimates of skill intensity were constructed and provided by Horvát and Yamano (2019[46]).

[10] In addition to firm level data, this analysis would benefit from information on location and mobility of workers to further explore these relationships. However, given the data constraints, we have to limit ourselves to drawing conclusions at the industry level.

[11] In addition to gross output per employee, our results remain robust when using value added per hour worked as a dependent variable. They are available from the authors upon request.

[12] Recent evidence highlights the role of non-cognitive skills in the relationship between tests scores and economic growth (Bartel, Ichniowski and Shaw, 2007[106]; Borghans and Schils, 2012[107]) and suggests that it is an important omitted variable.

[13] Assortative matching can be defined as the tendency of agents with similar characteristics to interact with one another in isolation of others. See, e.g. Durlauf and Seshadri (2003[109]).

[14] Although, in theory, these studies (Hanushek et al., 2015[76]; Lane and Conlon, 2016[79]; Falck, Heimisch and Wiederhold, 2016[21]) also examine the role of ICT skills, these skills are in fact proxied by problem solving skills in technology rich environments. Therefore, their findings and our analysis are not comparable.

[15] Attenuation bias refers to the fact that a regression's slope may go towards zero, i.e. may be biased towards an underestimation of its absolute value because of errors in the independent variables.

[16] Both papers instrument years of schooling with minimum school-leaving ages that were a result of compulsory schooling requirements that US states changed at different times.

[17] While internet access itself is not random, Germany upgraded copper wires of the traditional voice-telephony network to provide fast internet access by means of the so-called DSL technology at different times due to costly but necessary earthworks. For more detail, please refer to Falck et al. (2016[21]).

[18] There are currently two waves of data for the Unites States available and this paper uses the first one (2011-2012) only.

[19] This work cannot say anything about OC purchased from, e.g. consultants, or through external collaborations.

[20] Conti et al. (2014[88]) develop a Bayesian factor analysis that jointly determines the number of factors and the model's most important parameters using several test statistics. At the time of Grundke et al.'s (2017[2]) paper the algorithm was not available and the authors implemented the basic features of the Bayesian factor analysis described in Conti at el. (2014) by means of applying classical factor analysis tools.

[21] For a detailed description of the methodology, please refer to Grundke et al. (2017[2]).

[22] In addition to these industries, three economies are not considered in the analysis: Australia, as PIAAC only provides information at the two digit ISCO 2008 occupation level and thus prevents us from identifying OC staff; Cyprus and Russia due to small sample sizes. Evidently, the second data collection made for the United States is not considered in the present work, as it would lead to a greater weight of the United States in the analysis. Countries are later dropped from the analysis if no control variables are available.

[23] There are exceptions, such as in Germany and Austria, where small employers often engage in particular types of training and apprenticeships (OECD, 2010[108]).

[24] There are two main reasons why STEM is not instrumented: 1) given the dataset's limitations, it is difficult to find a suitable instrument; 2) the effect of STEM is already partly captured by the (instrumented) numeracy score, and the STEM variable captures task-based skills, while numeracy does not.

[25] To recap, we use social mobility of workers and their overall ICT ability as exclusion restrictions in the selection model and parental education and email use at home to instrument skill scores."

[26] Manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S).

[27] Annex C shows the correlation matrix for the different variables in our model. ICT skills and STEM skills are, as expected, positively correlated with each other and with productivity. However, when we include both, ICT and STEM skills in our model, STEM skills appear to drive this positive relationship. The correlation matrix also shows that the correlation between STEM and ICT skills is not high enough to be concerned about multicollinearity problems.

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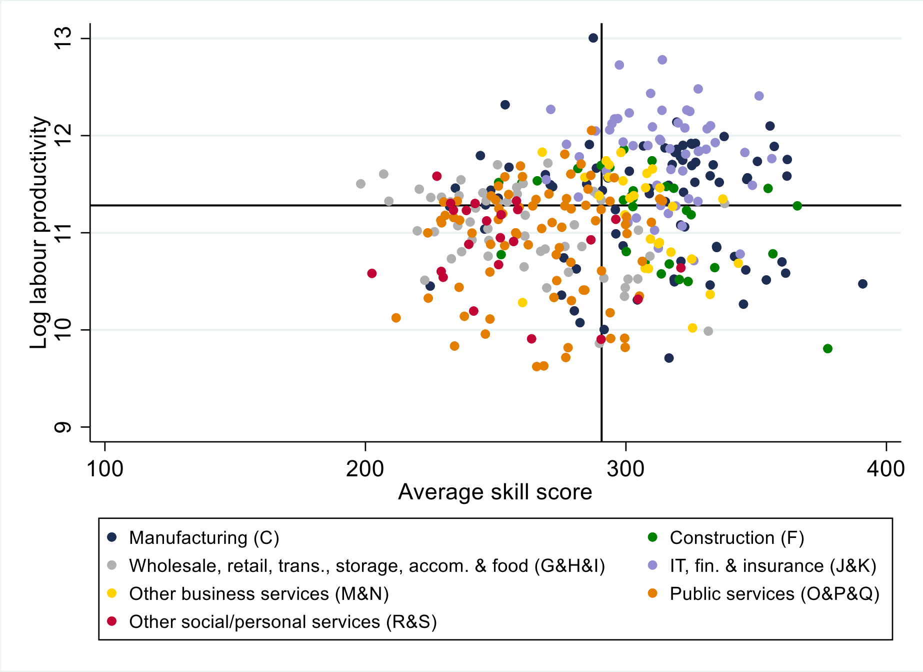
Annex A. Skill Indicators

Country	Sample size OC	Sample size Non-OC	Skill score OC	Skill score Non-OC	1 Ratio between OC and non-OC group	2 Sample weight	Revised ratio between OC and non-OC group	Revised skill score for OC group
A	5	25	240	**230**	1.04	$\frac{5}{20}=\frac{1}{4}$	$(\frac{1}{4}\,1.04) + (\frac{3}{4}\,1.15) = 1.12$ 4	230 * 1.12 = **257.60**
B	25	40	**250**	**205**	1.22		*unchanged* 3	*unchanged*
C	30	50	**270**	**250**	1.08		*unchanged*	*unchanged* 5
B, C (combined)					$\frac{1.22+1.08}{2}=1.15$	$1-\frac{1}{4}=\frac{3}{4}$		

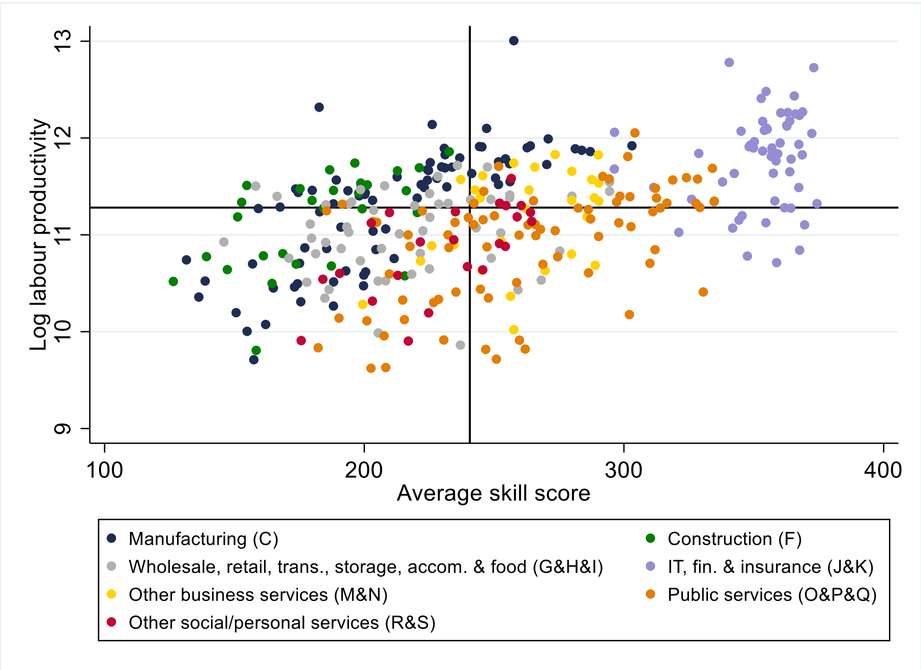
1. The ratios of skill scores for OC and non-OC workers are constructed.
2. These ratios are weighted according to the sample size. If the sample size for the non-OC groups in country A is 5, a weight of 5/20=0.25 is attached to country A's ratio. The remaining weight of 0.75 is given to all the other countries within the cluster combined, i.e. country B and country C have together a weight of 0.75.
3. Since N of country B and country C is large enough, their skill scores are not changed but their skill scores feed into the imputed skill score of country A.
4. The original skill ratio of country A is weighted by 0.25, while the remaining 0.75 are coming from the average skill ratio of country B and country C.
5. The newly imputed skill score of the OC-group in country A is the non-OC groups' skill score times the newly constructed weighted ratio.

Annex B. Scatter Plots

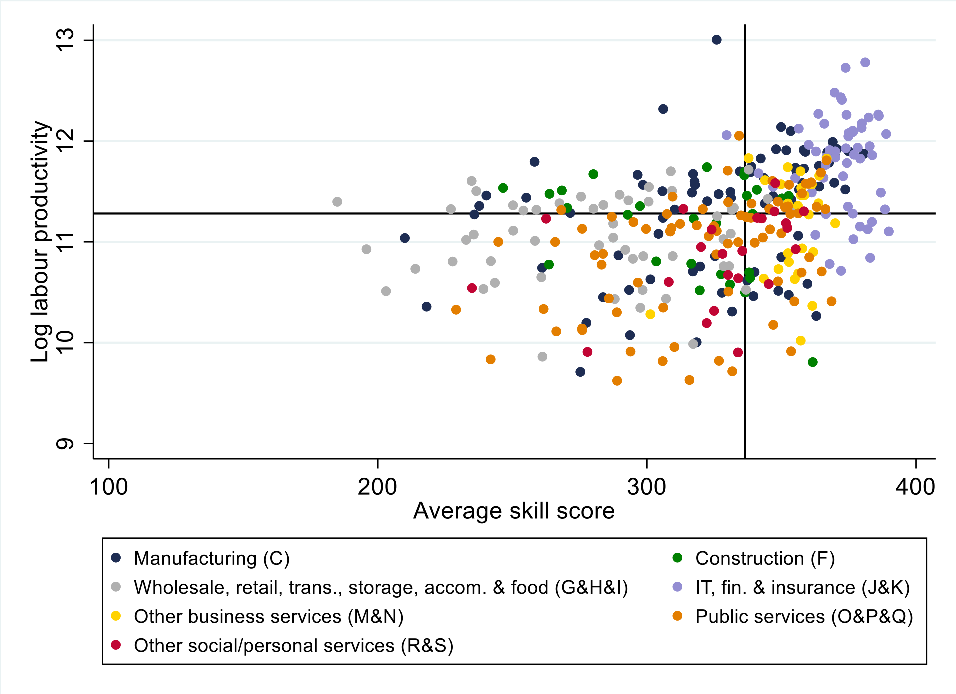
Mean STEM-quantitative skill scores of OC workers



Mean ICT task-based skill scores of non-OC workers



Mean ICT task-based skill scores of OC workers



Note: Figures are based on country specific averages by industry. Industries are colour-coded by industry clusters to aid the reader. Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, NLD, NOR, NZL, POL, SVK, SVN, SWE, TUR and first wave of USA. However, some industries are missing for EST, ISR, JPN, NZL, and TUR (also KOR when estimating ICT skill scores). The sample consists of 343 observations.
Source: Author's own compilation

Annex C. Correlation Matrix

	Log of VA/emp	Log of GO/emp	ICT (non-OC)	ICT ratio (OC/non-OC)	STEM (non-OC)	STEM ratio (OC/non-OC)	Numeracy	Numeracy (Perc10/Perc90)	Share of OC	Log of NFA/emp	Skill intensity	Same-path	ICT trans-actions	One parent edu.	ICT email (non-OC)	ICT email (OC)	Firm size
Log of VA/emp	1.00																
Log of GO/emp	0.90	1.00															
ICT (non-OC)	0.47	0.21	1.00														
ICT ratio (OC/non-OC)	-0.32	-0.05	-0.79	1.00													
STEM (non-OC)	0.20	0.14	0.69	-0.43	1.00												
STEM ratio (OC/non-OC)	-0.07	0.14	-0.52	0.76	-0.36	1.00											
Numeracy	0.31	0.16	0.79	-0.51	0.68	-0.34	1.00										
Numeracy (Perc10/Perc90)	0.09	-0.02	0.58	-0.42	0.55	-0.39	0.77	1.00									
Share of OC	-0.06	-0.30	0.35	-0.57	0.15	-0.51	0.28	0.24	1.00								
Log of NFA/emp	0.46	0.28	0.53	-0.42	0.20	-0.28	0.40	0.35	0.03	1.00							
Skill intensity	-0.23	-0.40	0.46	-0.33	0.51	-0.23	0.48	0.44	0.36	0.08	1.00						
Samepath	0.10	-0.14	0.65	-0.46	0.42	-0.30	0.61	0.35	0.43	0.20	0.53	1.00					
ICT transactions	0.47	0.34	0.65	-0.43	0.44	-0.24	0.64	0.38	0.17	0.32	0.21	0.46	1.00				
One parent edu.	-0.17	-0.26	0.38	-0.24	0.49	-0.17	0.45	0.35	0.19	0.07	0.68	0.48	0.37	1.00			
ICT email (non-OC)	0.42	0.21	0.81	-0.62	0.49	-0.43	0.72	0.50	0.27	0.43	0.35	0.58	0.80	0.42	1.00		
ICT email (OC)	0.23	0.11	0.52	-0.17	0.31	-0.02	0.55	0.26	0.11	0.21	0.23	0.52	0.61	0.34	0.65	1.00	
Firm size	0.26	0.23	0.43	-0.27	0.31	-0.13	0.35	0.23	0.07	0.30	0.26	0.27	0.21	0.04	0.29	0.24	1.00

Note: The sample consists of 260 observations. R&D expenditure (lagged) is excluded as it is not available for the whole sample and not used in our main models.
Source: Author’s own compilation

Annex D. Estimation Results using Value Added, OLS

Correlations between skill indicators, OC and labour productivity at the country-industry level

	Model 1	Model 2	Model 3	Model 4	Model 5
Numeracy score	0.024***	0.018**	0.031***	0.029**	0.018**
	(0.008)	(0.009)	(0.010)	(0.010)	(0.008)
ICT score (non-OC)	-0.004	-0.003	-0.005	-0.006	-0.003
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
ICT score ratio (OC/non-OC)	-0.234*	-0.246*	-0.256*	-0.275**	-0.242**
	(0.127)	(0.123)	(0.134)	(0.125)	(0.112)
STEM score (non-OC)	0.019***	0.014***	0.017**	0.012	0.014***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.005)
STEM score ratio (OC/non-OC)	0.384**	0.299**	0.416***	0.301**	0.302**
	(0.147)	(0.125)	(0.129)	(0.113)	(0.128)
Numeracy score (Perc10/Perc90)	-0.606	-0.848	-0.555	-0.781	-0.843
	(0.635)	(0.599)	(0.585)	(0.515)	(0.600)
Log of net fixed assets per employee	0.163***	0.160***	0.147***	0.156***	0.160***
	(0.020)	(0.022)	(0.027)	(0.028)	(0.021)
Share of OC	0.000	-0.000	-0.000	-0.001	
	(0.001)	(0.001)	(0.001)	(0.001)	
Skill intensity		0.771**		0.850**	0.769**
		(0.281)		(0.360)	(0.284)
R&D expenditure (lagged)			0.002**	0.002***	
			(0.001)	(0.000)	
Manufacturing	0.531***	0.629***	0.505***	0.625***	0.630***
	(0.046)	(0.056)	(0.044)	(0.073)	(0.049)
Construction	0.400***	0.549***	0.375***	0.529***	0.550***
	(0.097)	(0.099)	(0.073)	(0.083)	(0.098)
Wholesale, transport & accom.	0.248***	0.331***	0.241***	0.331***	0.332***
	(0.049)	(0.056)	(0.051)	(0.068)	(0.054)
IT, finance & insurance	0.593***	0.657***	0.561***	0.630***	0.657***
	(0.064)	(0.059)	(0.077)	(0.064)	(0.059)
Other business services	0.355***	0.416***	0.305***	0.383***	0.417***
	(0.061)	(0.064)	(0.059)	(0.070)	(0.063)
Other social & personal services	0.192**	0.223***	0.098	0.143**	0.225***
	(0.069)	(0.071)	(0.069)	(0.065)	(0.070)
AUT	0.218***	0.207***	0.203***	0.177***	0.208***
	(0.022)	(0.024)	(0.027)	(0.038)	(0.024)
BEL	0.379***	0.412***	0.352***	0.370***	0.412***
	(0.028)	(0.039)	(0.036)	(0.044)	(0.039)
CAN	0.318***	0.260***	0.303***	0.250***	0.260***
	(0.031)	(0.034)	(0.029)	(0.032)	(0.035)
CZE	-0.615***	-0.653***	-0.613***	-0.671***	-0.65***
	(0.057)	(0.062)	(0.081)	(0.081)	(0.061)
DEU	0.037	0.019	0.029	-0.003	0.021
	(0.024)	(0.025)	(0.032)	(0.037)	(0.023)
DNK	0.316***	0.368***	0.273***	0.325***	0.368***
	(0.031)	(0.046)	(0.036)	(0.047)	(0.045)
EST	-0.547***	-0.583***	-0.571***	-0.605***	-0.58***

	(0.038)	(0.042)	(0.035)	(0.041)	(0.042)
FIN	0.108**	0.134***	0.089*	0.106**	0.136***
	(0.040)	(0.036)	(0.050)	(0.042)	(0.032)
FRA	0.384***	0.384***	0.376***	0.384***	0.384***
	(0.021)	(0.019)	(0.021)	(0.020)	(0.0178)
GBR	0.190***	0.182***	0.186***	0.181***	0.182***
	(0.023)	(0.023)	(0.022)	(0.024)	(0.0225)
HUN	-1.113***	-1.133***	-1.142***	-1.174***	-1.13***
	(0.034)	(0.039)	(0.038)	(0.041)	(0.038)
IRL	0.493***	0.465***	0.453***	0.416***	0.465***
	(0.018)	(0.020)	(0.025)	(0.034)	(0.020)
ISR	0.317***		0.294***		
	(0.050)		(0.046)		
ITA	0.429***	0.492***	0.435***	0.504***	0.492***
	(0.022)	(0.034)	(0.017)	(0.034)	(0.034)
JPN	0.308***		0.230***		
	(0.042)		(0.050)		
KOR	-0.245***		-0.256***		
	(0.036)		(0.036)		
LTU	-0.631***	-0.722***	-0.654***	-0.762***	-0.72***
	(0.030)	(0.047)	(0.038)	(0.061)	(0.048)
NLD	0.379***	0.446***	0.343***	0.423***	0.446***
	(0.031)	(0.052)	(0.037)	(0.058)	(0.052)
NOR	0.532***	0.551***	0.490***	0.506***	0.550***
	(0.029)	(0.036)	(0.034)	(0.043)	(0.036)
POL	-0.432***	-0.507***	-0.296***	-0.383***	-0.51***
	(0.028)	(0.045)	(0.039)	(0.052)	(0.045)
SVK	-0.464***	-0.529***	-0.339***	-0.450***	-0.53***
	(0.046)	(0.053)	(0.045)	(0.067)	(0.053)
SVN	-0.281***	-0.352***	-0.273***	-0.351***	-0.35***
	(0.022)	(0.042)	(0.028)	(0.048)	(0.041)
SWE	0.346***	0.334***	0.312***	0.283***	0.335***
	(0.036)	(0.039)	(0.046)	(0.057)	(0.038)
USA	0.264***	0.159***	0.295***	0.190***	0.159***
	(0.025)	(0.056)	(0.038)	(0.059)	(0.054)
Constant	7.206***	7.349***	7.116***	7.000***	7.341***
	(0.404)	(0.378)	(0.578)	(0.517)	(0.379)
Observations	284	260	232	213	260
R-squared	0.908	0.917	0.918	0.927	0.917
Country FE	YES	YES	YES	YES	YES
Industry cluster (7 groups) FE	YES	YES	YES	YES	YES

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, JPN, KOR, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. Since there is no data available for the skills intensity variable for ISR, JPN and KOR, they are dropped in models 2, 4 and 5. More observations are dropped when R&D is added to the model, mostly because R&D expenditure is often not available for the public sector. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author's own compilation

Annex E. Estimation Results using Value Added, Three-Step Approach

Stages Dependent variable	**OLS** VA (1)	Selection Firm size (2)	First Numeracy (3)	**Second** VA (4)	Selection Firm size (5)	First ICT non-OC (6)	**Second** VA (7)	Selection Firm size (8)	First Numeracy (9)	First ICT non-OC (10)	**Second** VA (11)	Selection Firm size (12)	First Numeracy (13)	First ICT non-OC (14)	First ICT ratio (15)	**Second** VA (16)
Samepath		0.002						0.012				0.009				
		(0.023)						(0.020)				(0.020)				
ICT trans.					0.099***			0.104***				0.097***				
					(0.032)			(0.033)				(0.033)				
Parent edu.		-0.056*	0.055***					-0.046	0.059***	0.041		-0.050*	0.056***	0.024	-0.001	
		(0.030)	(0.014)					(0.030)	(0.015)	(0.043)		(0.030)	(0.015)	(0.052)	(0.002)	
Email nonOC					-0.029	0.110***		-0.018	-0.003	0.103***		-0.027	-0.003	0.135***	-0.003**	
					(0.025)	(0.036)		(0.025)	(0.012)	(0.029)		(0.026)	(0.011)	(0.045)	(0.002)	
Email OC												0.017	0.011	0.032	0.004***	
												(0.020)	(0.011)	(0.037)	(0.001)	
IMR			0.133	0.026		0.634**	0.034		0.098	0.633*	0.028		0.088	0.318	0.017	0.027
			(0.120)	(0.018)		(0.311)	(0.021)		(0.120)	(0.332)	(0.022)		(0.121)	(0.360)	(0.011)	(0.020)
Numeracy	0.018**			0.005	0.146	0.367**	0.026**				0.029					0.026
	(0.008)			(0.042)	(0.116)	(0.146)	(0.010)				(0.060)					(0.058)
ICT nonOC	-0.003	0.224***	0.038**	-0.002			-0.020				-0.021					-0.018
	(0.004)	(0.052)	(0.018)	(0.005)			(0.015)				(0.020)					(0.019)
ICT ratio	-0.242**	5.647***	-0.172	-0.241**	1.390	-15.32***	-0.517**	1.315	-0.788	-15.63***	-0.520*					-0.334
	(0.112)	(1.572)	(0.626)	(0.100)	(1.169)	(2.110)	(0.228)	(1.141)	(0.610)	(2.128)	(0.273)					(0.444)
STEM nonOC	0.014***	-0.140**	0.161***	0.016**	-0.020	0.684***	0.028**	0.020	0.194***	0.751***	0.027***	0.009	0.191***	0.780***	-0.005	0.026***
	(0.005)	(0.063)	(0.036)	(0.008)	(0.051)	(0.067)	(0.011)	(0.044)	(0.034)	(0.059)	(0.009)	(0.045)	(0.037)	(0.085)	(0.003)	(0.008)
STEM ratio	0.302**	-5.111**	2.108*	0.336**	-3.025	10.750***	0.503**	-1.865	2.562**	11.660***	0.497**	-1.384	1.330	-7.346***	1.016***	0.309
	(0.128)	(2.198)	(1.218)	(0.136)	(1.960)	(2.028)	(0.214)	(1.883)	(1.169)	(2.031)	(0.201)	(1.802)	(0.892)	(2.421)	(0.150)	(0.434)
Num. ratio	-0.843	-0.877	22.980***	-0.548	-3.429	10.380	-0.655	0.00779	23.85***	18.83**	-0.743	0.498	24.340***	27.860***	-0.552*	-0.637
	(0.600)	(3.941)	(3.449)	(1.006)	(4.616)	(9.353)	(0.638)	(3.700)	(3.628)	(8.411)	(1.073)	(3.847)	(3.697)	(10.04)	(0.294)	(1.136)

Log NFA	0.160***	0.297	0.316***	0.164***	0.470**	1.696***	0.193***	0.525**	0.397***	1.846***	0.192***	0.501**	0.404***	2.042***	-0.0149	0.190***
	(0.021)	(0.241)	(0.074)	(0.024)	(0.206)	(0.286)	(0.027)	(0.209)	(0.075)	(0.258)	(0.025)	(0.207)	(0.083)	(0.275)	(0.011)	(0.021)
Skill intensity	0.769**	12.680***	1.811	0.808***	11.960***	2.254	0.817***	13.210***	1.903	2.627	0.808***	12.990***	2.299	7.016*	-0.156	0.840***
	(0.284)	(3.385)	(1.880)	(0.276)	(3.185)	(2.832)	(0.265)	(3.169)	(1.920)	(3.170)	(0.272)	(3.149)	(1.828)	(4.216)	(0.138)	(0.303)
Ind. C	0.630***	3.421***	0.204	0.632***	2.745***	-3.64***	0.555***	2.501***	0.024	-3.57***	0.553***	2.673***	0.048	-4.13***	0.073	0.558***
	(0.049)	(0.839)	(0.363)	(0.046)	(0.702)	(0.818)	(0.074)	(0.704)	(0.365)	(0.858)	(0.085)	(0.748)	(0.405)	(1.091)	(0.049)	(0.085)
Ind. F	0.550***		-1.12***	0.539***		-5.50***	0.433***		-1.45***	-6.00***	0.436***		-1.54***	-9.66***	0.301***	0.413**
	(0.098)		(0.427)	(0.073)		(1.135)	(0.153)		(0.415)	(1.184)	(0.130)		(0.427)	(1.407)	(0.071)	(0.163)
Ind. G&H&I	0.332***		-0.94***	0.325***		-4.07***	0.260***		-1.14***	-4.53***	0.262***		-1.02***	-4.21***	0.048	0.272***
	(0.054)		(0.174)	(0.051)		(0.414)	(0.082)		(0.169)	(0.476)	(0.071)		(0.185)	(0.664)	(0.032)	(0.073)
Ind. J&K	0.657***		0.194	0.652***		4.095***	0.723***		0.382	4.200***	0.726***		0.452*	5.031***	-0.030	0.719***
	(0.059)		(0.268)	(0.051)		(0.766)	(0.077)		(0.266)	(0.754)	(0.076)		(0.262)	(0.720)	(0.033)	(0.073)
Ind. M&N	0.417***		0.950***	0.430***		0.905	0.428***		0.984***	1.154	0.423***		1.029***	1.877*	-0.040	0.429***
	(0.063)		(0.269)	(0.076)		(0.822)	(0.060)		(0.281)	(0.803)	(0.083)		(0.275)	(0.991)	(0.037)	(0.084)
Ind. R&S	0.225***		0.121	0.237***		0.637	0.250***		0.143	0.582	0.247***		0.049	-1.090	0.099***	0.231***
	(0.070)		(0.351)	(0.073)		(0.845)	(0.063)		(0.365)	(0.923)	(0.070)		(0.357)	(0.847)	(0.030)	(0.077)
Ind. F-N,R&S		-1.59***			-1.71***			-1.59***				-1.47***				
		(0.417)			(0.382)			(0.398)				(0.404)				
AUT	0.208***	0.546	0.503	0.233***	-2.25***	0.514	0.231***	-0.909	0.513	0.199	0.224**	-0.723	0.473	-0.881	0.080	0.215**
	(0.024)	(1.149)	(0.465)	(0.088)	(0.865)	(0.481)	(0.030)	(1.094)	(0.471)	(1.311)	(0.098)	(1.110)	(0.475)	(1.543)	(0.053)	(0.103)
BEL	0.412***	-0.147	2.793***	0.458***	-3.68***	0.264	0.459***	-2.964**	2.977***	1.165	0.446***	-2.694**	2.827***	-0.486	0.058	0.441***
	(0.039)	(0.938)	(0.330)	(0.154)	(1.299)	(1.028)	(0.049)	(1.301)	(0.433)	(1.239)	(0.168)	(1.288)	(0.456)	(1.621)	(0.054)	(0.166)
CAN	0.260***	-0.034	-0.113	0.276***	-3.48***	2.482**	0.347***	-2.818**	0.074	2.087	0.343***	-2.443*	-0.0543	0.218	0.096*	0.321***
	(0.035)	(1.039)	(0.496)	(0.064)	(1.337)	(0.982)	(0.079)	(1.401)	(0.537)	(1.782)	(0.066)	(1.399)	(0.516)	(2.030)	(0.056)	(0.073)
CZE	-0.65***	1.642	-2.51***	-0.66***	-3.17***	-6.36***	-0.75***	-1.770	-2.82***	-8.05***	-0.74***	-1.321	-2.94***	-11.3***	0.249***	-0.76***
	(0.061)	(1.489)	(0.738)	(0.055)	(0.891)	(0.833)	(0.096)	(1.376)	(0.763)	(1.836)	(0.100)	(1.361)	(0.777)	(1.757)	(0.064)	(0.126)
DEU	0.021	1.449	-0.601	0.039	-2.648**	-0.877*	0.024	-1.027	-0.677	-1.846	0.019	-0.783	-0.693	-2.812	0.087	0.012
	(0.023)	(1.386)	(0.672)	(0.071)	(1.055)	(0.497)	(0.022)	(1.419)	(0.694)	(1.908)	(0.086)	(1.424)	(0.682)	(2.123)	(0.067)	(0.090)
DNK	0.368***	0.052	1.680***	0.403***	-2.713**	2.546**	0.458***	-1.868	1.927***	2.940**	0.449***	-1.714	1.761***	1.172	0.058	0.433***
	(0.045)	(1.054)	(0.433)	(0.120)	(1.270)	(1.032)	(0.079)	(1.316)	(0.497)	(1.485)	(0.107)	(1.314)	(0.518)	(1.957)	(0.065)	(0.106)
EST	-0.58***	0.223	0.240	-0.56***	-3.56***	0.030	-0.55***	-2.668**	0.299	-0.310	-0.55***	-2.278*	0.028	-4.318**	0.208***	-0.59***
	(0.042)	(1.108)	(0.525)	(0.091)	(1.197)	(0.855)	(0.033)	(1.278)	(0.564)	(1.545)	(0.092)	(1.248)	(0.580)	(1.683)	(0.063)	(0.134)
FIN	0.136***	-1.219	1.939***	0.162	-4.63***	-1.629**	0.131***	-4.45***	2.008***	-0.956	0.123	-4.14***	1.872***	-2.93***	0.102**	0.116

	(0.032)	(0.867)	(0.332)	(0.106)	(1.213)	(0.702)	(0.029)	(1.293)	(0.371)	(0.752)	(0.137)	(1.273)	(0.353)	(0.931)	(0.041)	(0.140)
FRA	0.384***	0.745	0.017	0.391***	-0.054	2.004***	0.453***	0.175	0.192	1.914*	0.451***	0.245	0.147	1.854	-0.026	0.447***
	(0.0178)	(0.932)	(0.236)	(0.026)	(0.927)	(0.764)	(0.062)	(0.950)	(0.292)	(1.045)	(0.051)	(0.959)	(0.282)	(1.334)	(0.035)	(0.047)
GBR	0.182***	-0.140	-0.652	0.189***	-3.75***	2.905***	0.267***	-2.953**	-0.483	2.304	0.266***	-2.612*	-0.516	2.015	0.006	0.255***
	(0.0225)	(1.031)	(0.471)	(0.0309)	(1.250)	(0.759)	(0.0792)	(1.387)	(0.491)	(1.592)	(0.0676)	(1.385)	(0.462)	(1.875)	(0.0516)	(0.0616)
HUN	-1.13***	0.759	0.644	-1.11***	-2.89***	-2.21***	-1.17***	-1.709	0.504	-2.514*	-1.18***	-1.416	0.348	-5.28***	0.166***	-1.19***
	(0.038)	(1.096)	(0.507)	(0.100)	(0.960)	(0.693)	(0.046)	(1.121)	(0.530)	(1.327)	(0.155)	(1.104)	(0.516)	(1.133)	(0.041)	(0.167)
IRL	0.465***	-0.161	-0.032	0.469***	-2.953**	1.536***	0.515***	-2.987**	0.0949	1.501***	0.514***	-2.683**	0.047	0.879	0.028	0.505***
	(0.020)	(0.866)	(0.193)	(0.020)	(1.150)	(0.399)	(0.043	(1.163)	(0.233)	(0.504)	(0.040)	(1.149)	(0.246)	(0.700)	(0.028)	(0.042)
ITA	0.492***	0.370	0.313	0.488***	1.046	2.546***	0.550***	0.425	0.494	2.966***	0.552***	0.263	0.332	0.932	0.087***	0.528***
	(0.034)	(0.916)	(0.330)	(0.037)	(0.884)	(0.517)	(0.053)	(0.983)	(0.362)	(0.804)	(0.075)	(0.992)	(0.367)	(0.798)	(0.019)	(0.073)
LTU	-0.72***	-0.173	0.402	-0.70***	-2.76***	-1.93**	-0.74***	-2.328**	0.332	-2.158*	-0.75***	-1.869**	0.101	-6.29***	0.248***	-0.77***
	(0.048)	(1.017)	(0.451)	(0.088)	(0.925)	(0.804)	(0.048)	(1.001)	(0.464)	(1.249)	(0.121)	(0.949)	(0.471)	(1.067)	(0.035)	(0.160)
NLD	0.446***	-0.919	3.224***	0.489***	-3.568**	1.795	0.535***	-3.469**	3.567***	3.178***	0.524***	-3.314**	3.330***	1.030	0.045	0.511***
	(0.052)	(0.879)	(0.281)	(0.144)	(1.409)	(1.269)	(0.080)	(1.407)	(0.492)	(1.169)	(0.134)	(1.400)	(0.554)	(1.770)	(0.063)	(0.131)
NOR	0.550***	-0.898	1.683***	0.587***	-4.58***	3.045***	0.644***	-3.581**	1.926***	3.376**	0.634***	-3.306**	1.772***	2.005	0.026	0.621***
	(0.036)	(1.044)	(0.464)	(0.121)	(1.350)	(0.953)	(0.086)	(1.410)	(0.496)	(1.537)	(0.109)	(1.402)	(0.499)	(1.924)	(0.062)	(0.108)
POL	-0.51***	1.307	-1.288**	-0.50***	-2.222**	-0.529	-0.50***	-1.051	-1.346**	-1.562	-0.50***	-0.767	-1.439**	-3.752**	0.154***	-0.52***
	(0.045)	(1.247)	(0.555)	(0.049)	(0.940)	(0.612)	(0.039)	(1.241)	(0.579)	(1.588)	(0.046)	(1.263)	(0.582)	(1.572)	(0.050)	(0.081)
SVK	-0.53***	0.028	0.365	-0.50***	-3.36***	-3.59***	-0.59***	-1.981*	0.175	-4.04***	-0.59***	-1.665	-0.014	-7.81***	0.243***	-0.61***
	(0.053)	(1.230)	(0.553)	(0.109)	(0.898)	(0.804)	(0.080)	(1.186)	(0.562)	(1.316)	(0.182)	(1.154)	(0.595)	(1.227)	(0.0527)	(0.207)
SVN	-0.35***	-0.223	-1.234**	-0.35***	-2.032**	0.971	-0.30***	-1.160	-1.157**	0.161	-0.30***	-0.998	-1.35***	-2.195	0.100**	-0.33***
	(0.041)	(1.098)	(0.481)	(0.039)	(0.845)	(0.700)	(0.062)	(1.028)	(0.502)	(1.438)	(0.065)	(1.018)	(0.477)	(1.520)	(0.048)	(0.082)
SWE	0.335***	-0.942	3.118***	0.383**	-1.889**	3.575***	0.435***	-1.183	3.428***	4.669***	0.423***	-1.028	3.277***	2.802*	0.0785	0.406***
	(0.038)	(0.868)	(0.333)	(0.157)	(0.963)	(0.988)	(0.088)	(0.888)	(0.385)	(1.101)	(0.145)	(0.897)	(0.410)	(1.427)	(0.0493)	(0.147)
USA	0.159***	0.118	-2.23***	0.151***	-4.25***	0.953	0.202***	-3.411**	-2.22***	-0.463	0.205**	-3.021**	-2.26***	-1.063	0.0328	0.193**
	(0.054)	(1.182)	(0.687)	(0.054)	(1.270)	(0.795)	(0.073)	(1.426)	(0.714)	(2.049)	(0.088)	(1.429)	(0.670)	(2.119)	(0.0502)	(0.0883)
Constant	7.341***	-16.26***	19.620***	7.572***	-17.59***	-29.96***	6.707***	-15.35***	18.640***	-23.01***	6.640***	-14.01***	17.930***	-36.12***	0.816***	6.656***
	(0.379)	(4.554)	(2.743)	(0.960)	(4.897)	(6.612)	(0.703)	(4.523)	(2.599)	(6.232)	(1.706)	(4.310)	(2.754)	(5.800)	(0.267)	(1.679)
Observations	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260	260
R-squared	0.917			0.917			0.913				0.912					0.913
3 ind. clusters		YES			YES			YES				YES				
7 ind. clusters	YES		YES	YES		YES	YES		YES	YES	YES		YES	YES	YES	YES

Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-stat.			14.87			9.20			7.76	6.78			6.92	3.54	4.31	
Multi. F-stat.			14.87			9.20			15.97	17.13			15.95	16.00	15.98	

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). The three industry clusters include manufacturing (C), other businesses (F-N, R&S) and public sector services (O&P&Q). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author’s own compilation

Annex F. Estimation Results using Gross Output, Three-Step Approach

Stages	**OLS**	Selection	First	First	First	**Second**
Dependent variable	GO (1)	Firm size (2)	Numeracy (3)	ICT non-OC (4)	ICT ratio (5)	GO (6)
Samepath		0.017				
		(0.021)				
ICT trans.		0.096***				
		(0.033)				
Parent edu.		-0.047	0.050***	0.022	0.000	
		(0.030)	(0.015)	(0.053)	(0.002)	
Email nonOC		-0.035	0.004	0.137***	-0.005***	
		(0.026)	(0.011)	(0.044)	(0.001)	
Email OC		0.018	0.010	0.031	0.005***	
		(0.021)	(0.011)	(0.037)	(0.001)	
IMR			0.130	0.234	0.012	0.052**
			(0.110)	(0.376)	(0.009)	(0.021)
Numeracy	0.025					0.013
	(0.019)					(0.081)
ICT nonOC	-0.009*					-0.018
	(0.004)					(0.025)
ICT ratio	-0.316**					-0.676*
	(0.134)					(0.360)
STEM nonOC	0.007	0.017	0.191***	0.778***	-0.005	0.018
	(0.007)	(0.045)	(0.0337)	(0.0847)	(0.003)	(0.011)
STEM ratio	0.346	-1.983	2.617***	-6.834**	0.813***	0.692*
	(0.223)	(1.848)	(0.923)	(3.039)	(0.137)	(0.402)
Num. ratio	-0.606	0.889	23.56***	27.54***	-0.430*	-0.187
	(1.050)	(3.852)	(3.522)	(10.110)	(0.260)	(1.738)
Log NFA	0.200***	0.430**	0.517***	2.083***	-0.033***	0.218***
	(0.024)	(0.216)	(0.076)	(0.292)	(0.010)	(0.036)
Skill intensity	0.399	14.10***	1.690	6.727	-0.061	0.460
	(0.273)	(3.287)	(1.749)	(4.195)	(0.142)	(0.283)
Share of OC	-0.004***	-0.022*	0.023***	0.010	-0.004***	-0.005*
	(0.001)	(0.013)	(0.005)	(0.016)	(0.001)	(0.002)
Ind. C	1.456***	2.421***	0.379	-4.004***	0.020	1.411***
	(0.0708)	(0.782)	(0.380)	(0.998)	(0.039)	(0.155)
Ind. F	1.014***		-1.194***	-9.534***	0.246***	0.967***
	(0.111)		(0.378)	(1.286)	(0.059)	(0.240)
Ind. G&H&I	0.603***		-0.855***	-4.161***	0.021	0.546***
	(0.063)		(0.171)	(0.643)	(0.029)	(0.089)
Ind. J&K	1.050***		0.580**	5.122***	-0.050	1.073***
	(0.072)		(0.284)	(0.739)	(0.031)	(0.110)
Ind. M&N	0.685***		1.092***	1.897*	-0.051	0.701***
	(0.078)		(0.258)	(0.990)	(0.033)	(0.111)
Ind. R&S	0.350***		0.534	-0.911	0.023	0.382***
	(0.069)		(0.328)	(0.955)	(0.032)	(0.118)
Ind. F-N,R&S		-1.711***				
		(0.436)				

AUT	0.232***	-0.749	0.641	-0.798	0.054	0.291**
	(0.031)	(1.128)	(0.479)	(1.578)	(0.046)	(0.136)
BEL	0.586***	-2.618**	2.668***	-0.531	0.083*	0.688***
	(0.058)	(1.295)	(0.413)	(1.593)	(0.048)	(0.216)
CAN	0.392***	-2.480*	0.0240	0.268	0.084*	0.479***
	(0.053)	(1.399)	(0.487)	(2.054)	(0.050)	(0.080)
CZE	-0.361***	-1.601	-2.510***	-11.11***	0.181***	-0.399**
	(0.073)	(1.391)	(0.802)	(1.847)	(0.059)	(0.161)
DEU	0.106***	-1.053	-0.346	-2.650	0.032	0.138
	(0.031)	(1.436)	(0.704)	(2.194)	(0.064)	(0.135)
DNK	0.445***	-1.611	1.791***	1.205	0.054	0.556***
	(0.044)	(1.318)	(0.483)	(1.966)	(0.059)	(0.142)
EST	-0.380***	-2.396*	0.202	-4.227**	0.181***	-0.294*
	(0.040)	(1.258)	(0.558)	(1.737)	(0.058)	(0.161)
FIN	0.339***	-4.233***	2.010***	-2.844***	0.080**	0.381*
	(0.045)	(1.279)	(0.357)	(0.953)	(0.038)	(0.201)
FRA	0.457***	0.405	-0.002	1.802	-0.003	0.507***
	(0.031)	(0.961)	(0.252)	(1.317)	(0.032)	(0.070)
GBR	0.255***	-2.628*	-0.496	2.041	0.003	0.316***
	(0.030)	(1.383)	(0.449)	(1.884)	(0.048)	(0.083)
HUN	-0.969***	-1.691	0.609	-5.154***	0.124***	-0.931***
	(0.056)	(1.126)	(0.538)	(1.189)	(0.039)	(0.245)
IRL	0.658***	-2.583**	-0.001	0.866	0.036	0.696***
	(0.019)	(1.162)	(0.225)	(0.690)	(0.026)	(0.056)
ITA	0.541***	0.474	0.255	0.898	0.100***	0.592***
	(0.042)	(1.000)	(0.370)	(0.799)	(0.019)	(0.087)
LTU	-0.713***	-2.302**	0.327	-6.185***	0.213***	-0.657***
	(0.055)	(0.999)	(0.468)	(1.128)	(0.034)	(0.216)
NLD	0.544***	-3.041**	3.099***	0.956	0.082	0.665***
	(0.055)	(1.401)	(0.506)	(1.727)	(0.056)	(0.170)
NOR	0.664***	-3.020**	1.585***	1.951	0.056	0.783***
	(0.055)	(1.407)	(0.463)	(1.890)	(0.054)	(0.133)
POL	-0.299***	-0.875	-1.202**	-3.641**	0.116**	-0.267***
	(0.052)	(1.272)	(0.588)	(1.632)	(0.046)	(0.084)
SVK	-0.382***	-1.838	0.225	-7.691***	0.206***	-0.343
	(0.046)	(1.187)	(0.597)	(1.288)	(0.044)	(0.269)
SVN	-0.129***	-0.963	-1.295***	-2.150	0.092**	-0.080
	(0.035)	(1.027)	(0.467)	(1.544)	(0.044)	(0.062)
SWE	0.385***	-1.007	3.267***	2.816**	0.080*	0.522**
	(0.069)	(0.887)	(0.366)	(1.423)	(0.044)	(0.203)
USA	0.263***	-3.150**	-2.177***	-1.005	0.020	0.286***
	(0.051)	(1.451)	(0.674)	(2.147)	(0.047)	(0.093)
Constant	7.730***	-13.01***	15.16***	-37.03***	1.252***	7.892***
	(0.259)	(4.387)	(2.767)	(6.906)	(0.272)	(1.968)

Observations	260	260	260	260	260	260
R-squared	0.929					0.928
3 ind. clusters		YES				
7 ind. clusters	YES		YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
F-stat.			5.55	3.81	6.55	
Multi. F-stat.			10.31	13.04	27.31	

Note: Countries included in the analysis: AUT, BEL, CAN, CZE, DEU, DNK, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, NLD, NOR, POL, SVK, SVN, SWE and first wave of USA. The seven industry clusters include: manufacturing (C); construction (F); wholesale, retail trade and repair of motor vehicles, transportation, storage and accommodation and food services (G&H&I); IT, financial and insurance activities (J&K); other business services (M&N); public services (O&P&Q) and other social and personal services (R&S). The three industry clusters include manufacturing (C), other businesses (F-N, R&S) and public sector services (O&P&Q). Robust standard errors are clustered at the country level. *, **, and *** indicate that coefficients are significant at the 10%, 5% and 1% levels, respectively.
Source: Author’s own compilation