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THE HUMAN SIDE OF PRODUCTIVITY: UNCOVERING THE ROLE OF SKILLS AND DIVERSITY FOR FIRM PRODUCTIVITY

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ABSTRACT/RÉSUMÉ

The Human Side of Productivity:

Uncovering the role of skills and diversity for firm productivity

Relying on linked employer-employee datasets from 10 countries, this paper documents that the skills and the diversity of the workforce and of managers – the *human side* of businesses – account on average for about one third of the labour productivity gap between firms at the productivity "frontier" (the top 10% within each detailed industry) and medium performers at the 40-60 percentile of the productivity distribution. The composition of skills, especially the share of high skills, varies the most along the productivity distribution, but low and medium skilled employees make up a substantial share of the workforce even at the frontier. High skills show positive but decreasing productivity returns. Moreover, the skill mix of top firms varies markedly across countries, pointing to the role of different strategies pursued by firms in different policy environments. We also find that managerial skills play a particularly important role, also through complementarities with worker skills. Gender and cultural diversity among managers – and to a lesser extent, among workers – is positively related to firm productivity as well. We discuss public policies that can facilitate the catch-up of firms below the frontier through skills and diversity. These cover a wide range of areas, exerting their influence through three main channels: the *s*upply, *u*pgrading and the *m*atching across firms (the *SUM*) of skills and other human factors.

Keywords: productivity, skills, diversity, managers, linked employer-employee data

JEL classification codes: D24, J24, M14

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La dimension humaine de la productivité :

Déterminer le rôle des compétences et de la diversité dans la productivité des entreprises

Se fondant sur des séries de données appariées employeurs-salariés couvrant 10 pays, le présent document montre que les compétences et la diversité des employés et des cadres – soit la *dimension humaine* des entreprises – contribuent pour environ un tiers en moyenne à l'écart de productivité du travail entre les entreprises situées à la frontière de productivité (c'est-à-dire le décile supérieur de chaque secteur détaillé) et celles à productivité moyenne, qui se trouvent entre le 40e et le 60e centiles de la distribution de la productivité. La composition des compétences, en particulier la proportion de compétences élevées, varie le plus en fonction de la distribution de la productivité, mais les salariés peu ou moyennement qualifiés représentent une part considérable des effectifs, même à la frontière. Des niveaux de compétences élevés entraînent des gains de productivité qui s'avèrent toutefois décroissants. De plus, la répartition des compétences dans les entreprises les plus productives varie sensiblement d'un pays à l'autre, mettant en évidence le rôle des diverses stratégies adoptées par les entreprises face à différents paramètres de l'action publique. Il ressort également de nos travaux que les compétences des cadres jouent un rôle particulièrement important, notamment en raison de leur complémentarité avec celles des employés. La parité hommes-femmes et la diversité culturelle parmi les cadres (et, dans une moindre mesure, parmi les employés) influent aussi positivement sur la productivité. Nous examinons des politiques publiques qui permettent de faciliter le rattrapage des entreprises situées en deçà de la frontière en promouvant les compétences et la diversité. Ces politiques portent sur un large éventail de domaines et exercent leur influence via trois principaux canaux : l'offre, l'amélioration et l'appariement des compétences et des autres facteurs humains au sein des entreprises.

Mots clés : productivité, compétences, diversité, cadres, données appariées employeurs-salariés

Classification JEL : D24, J24, M14

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The Human Side of Productivity: Uncovering the role of skills and diversity for firm productivity

By Chiara Criscuolo, Peter Gal, Timo Leidecker and Giuseppe Nicoletti[1]

1. Introduction

1. Productivity differences across firms are large and persistent in most countries and sectors, even within narrowly defined industries, as highlighted by a growing number of studies (Bartelsman and Doms, 2000[1]; Syverson, 2011[2]). The OECD and in particular its Global Forum on Productivity (GFP) has documented this phenomenon both at national (Berlingieri et al., 2017[3]) and at global levels (Andrews, Criscuolo and Gal, 2016[4]). Focusing on 10 GFP partner countries that contributed to this report, the presence of substantial and widespread productivity gaps across firms is confirmed (Figure 1): the typical "median performer" firm – at the 40-60 percentile of the productivity distribution –is about 1/3 as productive as the leading firm at the "frontier" – at the top 10% – within the same industry, with the gap doubling for "laggard" firms – at the bottom 10%.

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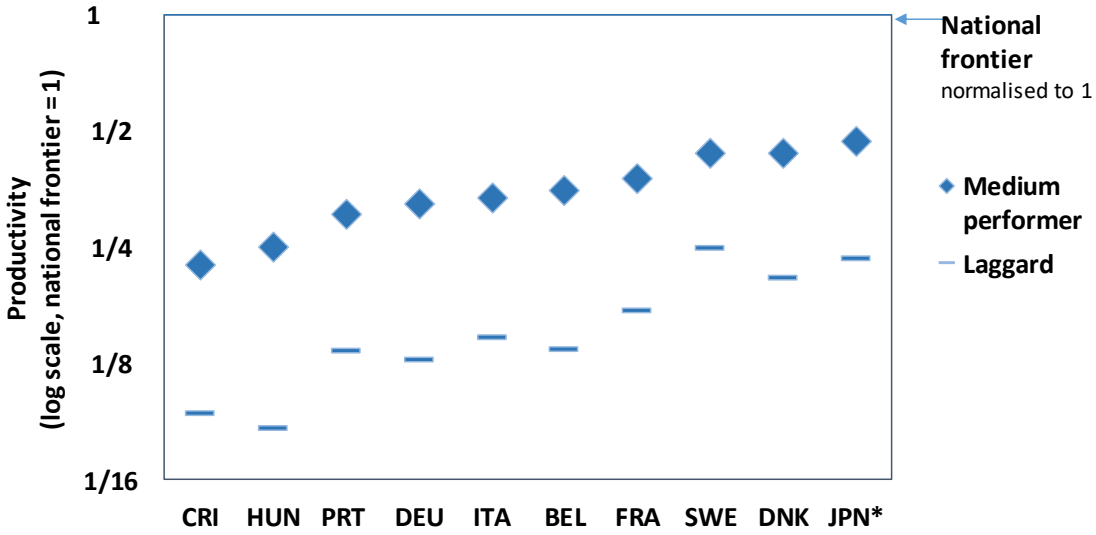
Figure 1. Productivity gaps across firms are large and widespread

Log-differences in value added based labour productivity between firms at the top 10% of the productivity distribution and at the median (40-60%) and at the bottom 10%.



Note: Averages across detailed industries and over years. For more details on the sample, see Annex A. Medium performer: average within the 40-60 percentile of the within industry productivity distribution; Laggard: average of the bottom 10% of the same distribution.
Source: OECD GFP calculations based on micro-aggregated linked employer-employee data.

2. Interestingly, within-industry cross-firm productivity gaps are larger in less advanced countries (Costa Rica, Hungary, Portugal) than in most developed ones (Sweden, Denmark, Japan), suggesting a link with aggregate performance; and previous work has shown that rising productivity dispersion at the firm level is associated with the slowdown in aggregate productivity (Andrews, Criscuolo and Gal, 2016[4]). Therefore, understanding the sources of productivity gaps and the scope for government intervention aimed at facilitating the catch-up of lagging companies is key for reversing the productivity slowdown that has plagued the global economy for more than two decades. A growing number of studies have focused on technology adoption, especially differences in digital diffusion, business dynamism, the business environment and the driver of innovative activities (Calligaris, Criscuolo and Marcolin, 2018[5]; Calvino, Criscuolo and Verlhac, 2020[6]; Andrews, Nicoletti and von Rueden, 2020[7]; Gal et al., 2019[8]).

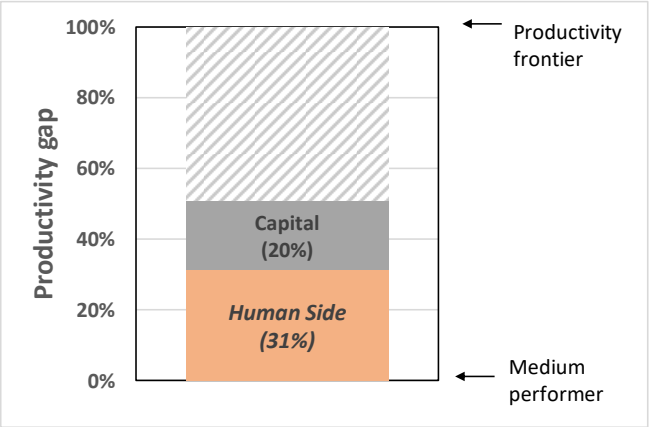
3. The focus of this report is on a less well-understood aspect of cross-firm productivity differences: the role of people – workers and managers – and their interactions, that is, the *Human Side* of firms. Thanks to the assembling of a new cross-country dataset on firm productivity and the characteristics of managers and workers, based on Linked Employer-Employee Data (LinkEED), our work sheds light on the role of their skills and their diversity in terms of gender and cultural background.

4. With this micro-based approach, our paper builds on two distinct strands of the literature. The more traditional, macroeconomic one, centred on endogenous growth models, focuses on the key role of human capital on economic growth, (see (Égert, Botev and Turner, 2020[9]) for recent empirical work). The more recent microeconomic one show that intangible assets, including prominently skills, management and organisational capital, are a key driver of multi-factor or labour productivity (Corrado et al., 2020[10]; Bloom

and Van Reenen, 2007[11]).[2] In essence, we focus on the Human Side of intangibles, including not only skills – which are traditionally included in human capital – but also diversity and the structure of the firm.[3]

5. The main upshot is that the labour productivity gap between a typical median performer and the frontier can be closed by nearly one-third through human factors, which is substantial when compared to the role of capital (20%) (Figure 2; and see Box 1 on the details of measurement). This still leaves a significant part of the productivity gap unexplained which is likely to be related to differences in other, harder to measure intangible assets, and to interactions between different types of capital – physical, intangible and human capital. For instance, new machinery often comes with new skill requirements; developing a brand, its design, or the culture of a company – which are also part of intangible capital – is due to the people – managers, engineers or marketing experts – inside the firm (Haskel and Westlake, 2018[12]). People and capital are thus closely intertwined; these interactions will be the focus of future work.

Figure 2. Upgrading the Human Side can help to close the productivity gap



Note: The figure shows the contribution of productivity enhancing adjustments of the workforce composition and capital intensity respectively to the catch up of a typical medium performer towards the productivity frontier in the same industry and country. Results are based on a firm-level regression controlling simultaneously for capital intensity and workforce composition among other variables and fixed effects. More details on the underlying analysis are provided in Box 1 and Annex A. All countries for which capital is measured have been included.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

6. What lies behind these substantial gains? In Section 2, we show that more productive firms generally rely more intensively on high-skill employees. On average across countries, high skilled employees account for about one third of the workforce in top performing firms, about twice as much as in the least productive firms. Our results also show that top performing firms employ a larger share of employees with high levels of *specific* cognitive (ICT) and non-cognitive skills (Management and communication) skills. In most countries, top performing firms have also become more intensive in high skills over time. However, medium and low-skilled employees remain indispensable for top performing firms as well. On average across countries, medium-skilled employees account for about half the workforce in the most productive firms, and low-skilled employees still account for about one fifth. Still, structural changes and digitalisation may contribute to making low and medium skills less important in the future.

7. Skill strategies adopted by top performing firms, how employees with different skills are combined to achieve high performance, vary substantially across sectors and countries. Besides reflecting the different technological requirements of sectors – with knowledge intensive services employing a much

[2] There are further country-specific studies over the few decades that document these links, for Germany (Bender et al., 2017[140]), the UK (Galindo-Rueda and Haskel, 2005[136]), New Zealand (Maré, Hyslop and Fabling, 2017[138]) and very recently for the United States as well (Cindy Cunningham, 2021[139]); see more also in Box 2.

[3] Box 1 and Box 3 provide details on the analysis and skill measures underlying results of this paper.

larger share of high skilled workers –, the different skill strategies of top firms across countries exemplify the potential for policies to shape the productive use of skills by firms. For instance, the most productive German firms are found to rely to a larger extent on medium skilled workers than other countries, possibly reflecting the effectiveness of its educational and training system in providing a good quality medium skilled workforce.

8. Section 3 documents that the most productive firms also stand out in terms of devoting relatively more of their labour resources to management and employing a more skill-intensive managerial workforce. We find that manager skills contribute disproportionately to firm productivity. However, to reap the full potential of skill-related productivity gains, the upskilling of managers should be complemented by adjusting the skill structure of non-managerial employees given that the large majority of the workforce is non-managerial.

9. Further, as we show in Section 4, a more diverse management – in terms of gender and cultural background, captured by the country of origin or nationality – is associated with higher productivity. This is also to case for non-managerial workers, although to a lesser extent. Section 5 provides an illustrative exercise to quantify the potential gains for productivity: our estimates suggest that, by adjusting its managerial workforce along the lines identified in the preceding Sections, the typical firm could close its productivity gap with the frontier by 16% (excluding complementarities) and by 35% if they additionally adjust their non-managerial workforce.

10. Section 6 discusses the various public policy areas that can facilitate productivity catch-up by focusing on the *Human Side* of median and laggard firms. We highlight that successful policy efforts need to rest on the ***SUM*** of three sets of measures: increasing skill ***s***upply, fostering ***u***pgrading and helping with better ***m***atching of jobs to workers. Bettering the educational system is key to raise the quality and supply of higher skills in the longer run. Improving the provision and quality of training, including vocational training and lifelong learning, is also critical for enhancing a broader range of general and specific skills in the shorter run, and for easing the adaptation of workers to changing skill demands due to structural change and technological progress. Skills also contribute to an increased resilience in the face of shocks, such as the reallocation needs induced by the COVID-19 pandemic, which likely involve not only within but cross-sectoral movements of employees (Criscuolo, 2021[13]).

11. To reach the full potential of productivity gains from the human side of businesses, policies should also raise awareness about the importance of good management and demographic diversity, increase the supply of managerial as well as worker skills, and facilitate restructuring through adult training or labour reallocation. Especially, activating hitherto underrepresented demographic groups could raise skill supply while simultaneously allowing to increase diversity.

12. Ongoing structural changes and the shock induced by the COVID-19 pandemic make the Human Side of companies even more relevant. Increased digitalisation, especially given the recent boost by the COVID19 pandemic (Criscuolo, 2021[13]), is associated with *winner-takes-most dynamics*, which further amplify the gains from getting the `right' mix of employees (Autor et al., 2020[14]). Many digital industries are characterised by high fixed and low marginal costs for production as well as network effects, suggesting that relatively small differences in quality or efficiency can result in large differences in market-share. Similarly, globalisation implies that firms often compete for larger markets, raising the gains for successful firms. As achieving high quality and efficiency depend crucially on the people the firm employs, differences in workforce composition may lead to very large differences in performance (Kaplan and Zoch, 2020[15]).

13. The successful adoption of digital technologies often requires complementary investments in *intangible capital*, whereby the firm's ability to make these investments rests importantly on the people it employs. This is because intangible capital, e.g. software, branding and designs, or corporate culture, is often firm-specific and developed in-house by the firm's employees. The abilities and characteristics of its employees are therefore an important factor in the firm's capacity to successfully invest in intangible capital and make effective use of advanced technologies (Haskel and Westlake, 2018[12]).

14. At the same time as the gains from the right mix of employees may have increased, getting access to them may have become more difficult, especially for low productivity firms or new entrants. Several trends witness the rising market power of successful incumbent firms: many OECD countries exhibit rising *industry concentration* and a *divergence of mark-ups*, together with *declining business dynamism* in terms of entry and job reallocation rates (Calligaris, Criscuolo and Marcolin, 2018[5]; Bajgar et al., 2019[16]; Calvino, Criscuolo and Verlhac, 2020[6]). To the extent that the increasing market power of successful firms affects their ability to hire and retain scarce talent, firms with weaker labour market power may find it more difficult to achieve catch-up through the Human Side (Marinescu, Ouss and Pape, 2021[17]). Indeed, industries with higher initial levels of business polarisation saw faster declines in job reallocation rates, compatible with economic inequalities being associated with less fluid labour markets. Getting access to the right employees may be further curtailed by *population ageing*, which decreases the overall size of the workforce.

15. Finally, a highly globalised economy implies that firms' ability to draw on a culturally diverse workforce is becoming an increasingly important advantage for achieving high firm performance. Operating in global markets requires successfully combining different country-specific knowledge and cultural competences (Lazear, 1999[61]). In addition, with high performance increasingly hinging on finding the right match for key positions, firms able to attract talent from across the globe can tap into a larger pool of candidates.

Box 1. Measurement and analysis of the Human Side of Productivity

The Human Side of Productivity is based on the analysis of a novel dataset containing information on the productivity and workforce characteristics of the universe of firms across a broad range of countries. This box briefly describes how this information was collected and analysed to derive the main results.

A collaborative approach with partners in the Global Forum on Productivity

This work would not have been possible without the support of partners in the network of Global Forum on Productivity, who helped to access and analyse the rich national micro-level databases on firms and their employees (Table 1). Indeed collecting the necessary information for the analysis of the Human Side – i.e. detailed information on firms and their employees across countries – required addressing two challenges: (1) data access is usually restricted by country-specific confidentiality requirements; (2) data need to be harmonized across countries.

To meet these challenges, the GFP applied, in close collaboration with country partners, a distributed microdata approach, building on OECD expertise from e.g. the OECD MultiProd and DynEmp projects: for *data harmonisation*, the GFP liaised with country partners on data preparation and shared a common code producing micro-aggregated results satisfying confidentiality requirements; *data access* was provided by country partners, who prepared data, implemented the code and shared results with the GFP Team for further cross-country analysis. The steps involved were (i) collecting metadata, (ii) developing a harmonised and flexible routine (Stata program code), (iii) preparing the national datasets in a format that matches the requirements of the routine (iv) running the routines to collect summary statistics and regression results (v) sending back the result to a centralised analysis at the OECD, ensuring that confidentiality requirements are met (vi) centralised analysis, in consultation with GFP partner countries.

This data collection effort resulted in a novel micro-aggregated dataset including information from 10 countries on firm productivity and detailed workforce characteristics – e.g. on skills, age, gender and foreign cultural background for managerial and non-managerial employees. For most countries, the underlying source is the universe of firms with at least 10 employees covering the 2000-2019 period or a subset within that. More details are provided in Annex A.

Quantifying the gains from upgrading the *Human Side* of firms

The project leverages this dataset to examine how top performing firms differ in terms of their Human Side, and how much medium performers stand to gain from imitating these firms. To quantify the gains, the project relied on regression analysis of the following *baseline model* to disentangle the contributions of different components of the Human Side to productivity:

$$Productivity_{it} = Skill\ structure_{it} + Demographics_{it} + Organisation_{it} + Controls_{it} + Error_{it} \quad (1)$$

The model estimates the link between productivity and the workforce composition. The baseline productivity measures is the log of value added per employee, which maximises cross-country and cross-sectoral coverage. A more refined variant that uses full time equivalent employment or hours worked yields similar results in those countries where data availability permits a comparison. Workforce composition is captured through the skill structure and demographic composition in terms of age, gender and foreign cultural background (place of birth or nationality) for managerial and non-managerial employees, as well as other firm organisation measures such as the manager-share and task diversity.

The model includes several controls, e.g. gender-specific shares of part-time employees, and industry-year as well as firm-size group fixed effects – implying that estimates are identified comparing firms within the same detailed industry, year and firm-size group. More details on the model are provided in Annex A.

These estimates allow computing how much higher productivity would be for a typical medium performer if that firm adjusted a specific component of the Human Side to match a typical firm at the productivity frontier – and thus how much adjusting the Human Side could contribute to closing the productivity gap.

These estimated gains may deviate from actual gains to some degree. One potential source of bias lies in the fact that firms may differ in characteristics not observed in the above model – but which affect productivity *and* co-vary with components of the Human Side. For instance, one important factor not included in the baseline model pertains to capital, and firms e.g. employing a more highly-skilled workforce may also be more capital intensive. Failing to control for differences in capital intensity, the productivity gains associated with adjusting the skill structure may partly reflect adjustments in capital. To check for this possibility, the model was re-estimated including measures for capital intensity for countries where information on firm-level capital stocks were available (France, Hungary, Portugal, Sweden). Reassuringly, the estimated productivity gains associated with the Human Side remained largely unchanged for these countries.

Table 1. Acknowledgments to partners in the GFP network for data access

The list of countries, institutions and colleagues who made it possible to access linked employer employee datasets

Belgium	*Central Bank*	Emmanuel Dhyne, Gert Bijnens
Costa Rica	*Central Bank*	Alonso Alfaro Urena, Catalina Sandoval Alvarado, Evelyn Munoz
Denmark	*Ministry of Industry, Business and Financial Affairs*	Søren Gaard, Katrine Bagge Thorball, Magnus Skafte-Larsen, Louis Konstantyner
France	*CASD*	
Germany	*IAB Nuremberg / HU Berlin*	Alfred Garloff

Hungary	*Ministry of Finance*	Peter Toth, Istvan Szabo, Andras Svraka, Katalin Horvath, Balint Van, Tibor Keresztely
Italy	*ISTAT;* *INAPP and University of Milan*	Caterina Viviano, Patrizia Cella, Maria Carla Congia, Fabio Bacchini; Giorgio Barba Navaretti, Anna Rosso, Camilla Andretta
Japan	*Institute of Economic Research, Hitotsubashi University*	Ryo Kambayashi
Portugal	*Ministry of Economy, Statistics Portugal*	Ricardo Alves
Sweden	*Growth analysis*	Pontus Mattsson, Ismail Ouraich
OECD	*Age Diversity project of the Employment, Labour and Social Affairs Directorate*	Alexander Hijzen, Oliver Denk, Wouter Zwysen

2. The role of workforce skills

16. The skill composition of a firm's workforce is an essential element of its human and organisational capital and a key driver of its productivity performance. It determines how well employees can perform their tasks and interact with their peers (e.g. in teamwork) or with managers. It also determines how well they can use physical capital and new technologies, given the firm's product specialisation. This Section focuses on the quality of cognitive and non-cognitive skills (i.e. human capital), across workers and managers alike, while the next chapter focuses more specifically on the occupational structure within the firm (i.e. the share and quality of managers) and their complementarity with workers' skills, which are more directly related to its organisational capital.

17. The use of advanced technologies increasingly relies on a *high-skill intensive workforce*. Digitalisation allows replacing many routine tasks with capital, e.g. computers, software or robots. This decreases the need for employees engaged in these tasks, who tend to be less skilled, and widens the scope for workers engaged in non-routine, more creative tasks – e.g. planning, research, or selling –, which often require more cognitive abilities. As digital technologies also raise the productivity of complementary tasks with higher skill requirements, the relative demand for high versus low-skilled labour increases (Autor, 2014[19]). Besides employing a workforce that is intensive in high skills, achieving high productivity performance also depends on exploiting *skill complementarities between employees* by combining various skills, which keep evolving due to digitalisation. For instance, digital technologies substituting for routine tasks may increase complementarities between high and low skilled employees engaged in non-routine tasks, e.g. programmers and warehouse clerks in online retail. Such changes in skill demand and skill complementarities are well documented, especially at the aggregate level (Box 2).

Box 2. The changing nature of skill demand: a short overview from the literature

Many countries exhibited labour demand shifts away from occupations performing mostly routine tasks towards occupations intensive in non-routine cognitive tasks (Autor, Levy and Murnane, 2003[20]; Goos, Manning and Salomons, 2014[21]; Acemoglu and Autor, 2011[22]). *Within* occupations, the complexity of tasks may also have increased, requiring higher skill levels, as shown for Germany (Spitz-Oener, 2006[23]). At the firm- or plant-level, the adoption of digital technologies and ensuing organisational changes have also been shown to increase demand for high skills (Caroli and Van Reenen, 2001[24]; Bresnahan, Brynjolfsson and Hitt, 2002[25]; Bartel, Ichniowski and Shaw, 2007[26]; Garicano and Heaton, 2010[27]). Conversely, firm-level productivity gains from adopting digital technologies are smaller when

complementary skills are harder to find, as indicated by recent OECD findings on the role of skill shortages (Gal et al., 2019[8]).

How employees complement each other depends on the production processes and organisational structure of the firm. For instance, highly interconnected production processes, where errors are very costly, may favour employing a more homogenously skilled workforce, e.g. in the production of luxury cars (Kremer, 1993[28]). More hierarchical organisational structures, where performance rests on a small number of "superstars", implies a more dispersed workforce, e.g. consultancies combining experienced partners with young associates (Rosen, 1981[29]). The combination of employees with different skill levels also depends on the firm's size and organisational structure, e.g. by affecting autonomy and thus skill requirements (Bloom et al., 2013[30]; Caliendo et al., 2020[31]). Some trends witness changes in the combination of skill groups, with varying patterns across countries. The USA, Germany, Sweden and Brazil saw a rising shares of employees with similar skills within firms (increased sorting) starting in the 1980s (Card, Heining and Kline, 2013[32]; Håkanson, Lindqvist and Vlachos, 2015[33]; Helpman et al., 2017[34]; Song et al., 2019[35]). However, other countries, such as Italy, saw no corresponding increase over this period, which, however, may reflect a relatively slow adoption of advanced technologies (Iranzo, Schivardi and Tosetti, 2008[36]). The relationship between skills and productivity also depend on the sector of economic activity, as well as on the nature of innovation carried out by firms, as shown for Germany and the Netherlands (Bartelsman, Dobbelaere and Peters, 2015[37]).

18. Aside from upgrading skills and exploiting skill complementarities, broadening the scope of workers' skills across several dimensions, such as cognitive and non-cognitive ones, has also been shown to be crucial for productivity, especially in the context of rapid technological progress. By complementing more creative and interactive tasks, advanced technologies have raised demand not only for a range of specific skills, but also for many soft skills – such as teamwork, communication and leadership. Both cognitive and non-cognitive skills have been found to exhibit high labour market returns, especially when combined. For instance, digital-intensive industries offer particularly high returns to workers juxtaposing several skill dimensions (Grundke et al., 2018[38]). For the US, labour demand increased particularly strongly for jobs requiring both cognitive and social skills (Deming, 2017[39]; Weinberger, 2014[40]), and job posting data demonstrate high demand for workers combining social (i.e. communicative and collaborative) and analytical skills, which in turn are linked to higher wages and firm performance (Deming and Kahn, 2018[41]). For Sweden, sorting increased strongly for both cognitive and non-cognitive skills (Håkanson, Lindqvist and Vlachos, 2015[33]).

19. Considering the crucial role of the firm's skill structure for performance, this Section provides systematic evidence on how the most productive firms differ in their use of skills from less productive firms, distinguishing between low, medium, and high skills as well as between general and specific skills (Box 3). We show that more productive firms exhibit a more high-skill intensive composition of tasks, even though low and medium skills always remain important ingredients of the skill mix. However, there are important differences in the combination of these three skill groups across sectors and countries along the productivity distribution, possibly reflecting how different technologies and policy environments shape complementarities between the various these *generic* skill levels. We also find evidence of a strong association between *specific* skills, notably ICT and management and communication skills, and productivity performance.

20. The chapter then explores how providing better access to skills for less productive firms may support their productivity catch-up. This involves enhancing a broad range of skills via policies that increase the supply of high skilled labour through the education system *and* improve the quality of medium and low general skills, as well as specific skills, through vocational education, training and lifelong learning.

Box 3. Measuring the firm's skill structure across countries

Skills – i.e. the capability to perform various tasks (Acemoglu and Autor, 2011[22]) – are an essential component of the Human Side, but their measurement is challenging, especially in a cross-country context and therefore this study uses a broad range of measures, which are discussed here.

What are the challenges of measuring skills across countries?

Skills are multi-faceted, which makes them difficult to capture comprehensively with a single measure: they can be *general or specific*, in that some of them are transferable across tasks, such as cognitive skills, while others are more task-specific, such as communication or ICT skills, which can make them specific to an industry or even a firm. Skills can also reflect either largely *immutable features of a person* (innate ability) or *can be acquired* through education, training or experience.

Capturing these different aspects in a reliable and comparable way is difficult, especially in a cross-country context. For instance, education and occupations are not reported in all countries with sufficient level of detail and in the same way, even after applying conversion tables to international classifications (ISCO or ISCED for occupations and education respectively). This implies a *trade-off between the quality of the measure* and its *cross-country coverage.*

Which skill measures are used in this paper?

To balance this trade-off as well as for robustness, the analysis uses a range of skill measures (for more details, see also Annex A):

1. ***Education-based:*** Educational attainment reflects mostly general skills, both innate and acquired, reflecting an employee's capability across a broad range of tasks. On the other hand, it captures other, relevant skills less well, such as those that are acquired later in life through training or on-the-job experience.
2. ***Occupation-based:*** Occupations reflect a set of tasks, which implies the presence of a given set of skills by the employees working in a particular occupation. Occupations can thus be used as an approximate measure for the skill levels of employees when ranked by cognitive performance (a) or task content (b).[4]

   a) Cognitive test score-based ranking: The OECD Survey of Adult Skills (PIAAC) measures cognitive abilities of individuals through test scores. We average these score results by country and occupation to arrive at a measure of *general skill* intensity, which is used to rank occupations within each country.

   b) Task-based ranking: PIAAC also collects information about the tasks carried out by employees, such as the use of computers or the nature of interactions with colleagues. Averaging the intensity of various tasks by occupations allows for a measure of *specific skills* that are typically needed in an occupation. In the grouping of tasks, we rely on Grundke et al. (2017[42]) for management and communication skills and Nedelkoska and Quintini (2018[43]) for ICT skills.

[4] Of course, occupations based measures rely on the assumption that employee skill levels are well characterised by their occupation, both across different firms and over time. Recent work for France is supportive of this in that it finds that employees are well matched to job skill requirements: e.g. employees in occupations with high cognitive scores are likely to be high-skilled for the majority of employees (Brun-Schammé and Rey, 2021[115]).

3. ***Wage-based*:** Employees working in occupations that on average command higher wages than other occupations are more likely to be high skilled, assuming that tasks requiring more capabilities are more highly paid.[5]

For each measure, we assign employees based on the ranking of their educational attainment or occupation to one of three skill levels: low, medium or high. In this way, we move beyond the simple dichotomy between low and high skills, motivated by findings in the literature about the idiosyncratic role of the medium skilled segment and "middle-class" jobs more generally (Acemoglu and Autor, 2011[22]).[6]

How do different skill measures affect the estimated link with productivity?

These measures may still understate the role of skills for firm productivity because (i) they do not capture skill differences *within* occupation or education categories (e.g. due to differences in innate ability, quality of education, or previous experience); and (ii) more productive firms may be *systematically* better at attracting those who are most skilled within each group. This may lead us to measure a weaker relationship between the *true unobserved* skill level of the workforce and the firm's productivity. To the extent that the skill measures are also noisy, regression estimates may further suffer from attenuation bias. Importantly, both factors work *against* finding a significant positive link between higher skill levels and productivity. In this sense, the strength of the relationship that we find may be considered a lower bound.

While the exact *magnitude* of the estimated link between skill structure and productivity for any single measure should thus be taken with a grain of salt, this array of measures is useful to establish the qualitative link between skills and productivity. In the analysis, we also test the robustness of our results to a rich set of controls for firm characteristics – including capital intensity – and more refined productivity measures, based on the number of hours worked. Consistency of results across skill measures, model specifications and definitions of productivity is reassuring.

2.1. More productive firms employ a more highly skilled workforce

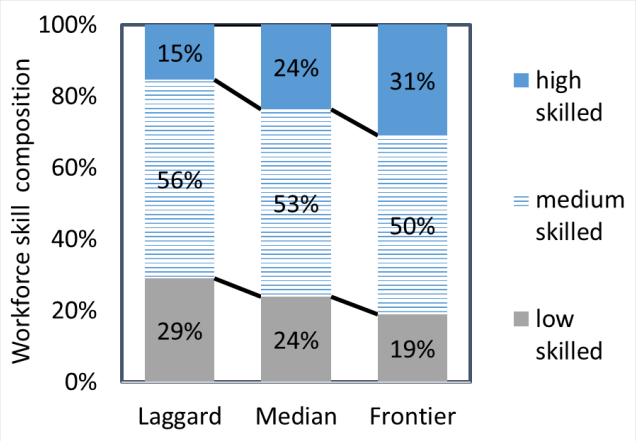
21. Using the occupation-based measure of skill levels, on average across countries, the more productive firms in our sample employ a workforce that is more intensive in high skills (Figure 3), a pattern that is robust to using the alternative skill measures described in Box 3 (see Annex B). High-skilled employees account for about a third of the workforce in the most productive firms, more than twice as many as in the least productive firms. Thus, employing a highly skilled workforce appears to be crucial for achieving high firm performance.

[5] A more refined alternative of the wage-based approach would be to rely on worker fixed effects in wage regressions, as proposed initially by (Abowd, Kramarz and Margolis, 1999[134]) and with more recent refinements, notably by (Bonhomme, Lamadon and Manresa, 2019[135]). However, their implementation is not straightforward especially in the current context of working remotely with various national datasets whose characteristics differ (tracking worker movements is possible or not, computational feasibility limits, etc.).

[6] Occupation-based rankings are generally country-specific. Where country-specific rankings were not possible because the country was not covered in PIAAC, country-averaged rankings were used. For more details on how exactly employees were assigned to skill groups see Annex A.

Figure 3. More productive firms employ a more high-skill intensive workforce

The share of different skill groups by firms at different segments of the productivity distribution



Note: The figure shows workforce skill composition along the productivity distribution. Workforce composition shown as firm-level shares of low, medium and high skilled employees. Firm-level shares are computed as average firm-level skill group shares by productivity group x STAN A38 industry x year x country; results shown are averaged by productivity group across STAN A38 industries x years x countries. Baseline skill measure is based on 2-digit ISCO08 occupations ranked by cognitive test scores from PIAAC; where occupational data in sufficient detail is not available, educational attainment is used. More details on the construction of skill groups can be found in Box 3 and in Annex A. Frontier, median and laggard firms refer to 90th, 40-60th and 10th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

22. While the most productive firms are more intensive in high skills, low and medium skills remain nonetheless indispensable. The higher share of high-skilled employees at more productive firms comes mostly at the expense of low-skilled employees, although also the share of medium-skilled employees decreases slightly as we get closer to the frontier. The combined share of low and medium skills declines from 85% to just under 70% going from least to most productive firms. Thus, even in the most productive firms, the overwhelming majority of employees is less than high skilled, with medium-skilled employees alone accounting for about half the workforce at the productivity frontier.

23. Obtaining similar results for skill measures based on occupations and educational attainment suggests that the firm's skill structure is closely intertwined with its organisational setup. In other words, more productive firms differ from less productive firms by both employing more high skilled employees *and* by performing more complex tasks. The close link between these two aspects implies that upskilling entails more comprehensive changes than simply employing more highly skilled employees. Indeed, improving productivity via upskilling requires firms to change *what they do* and *how* they carry out their activities in addition to *who* is doing them.

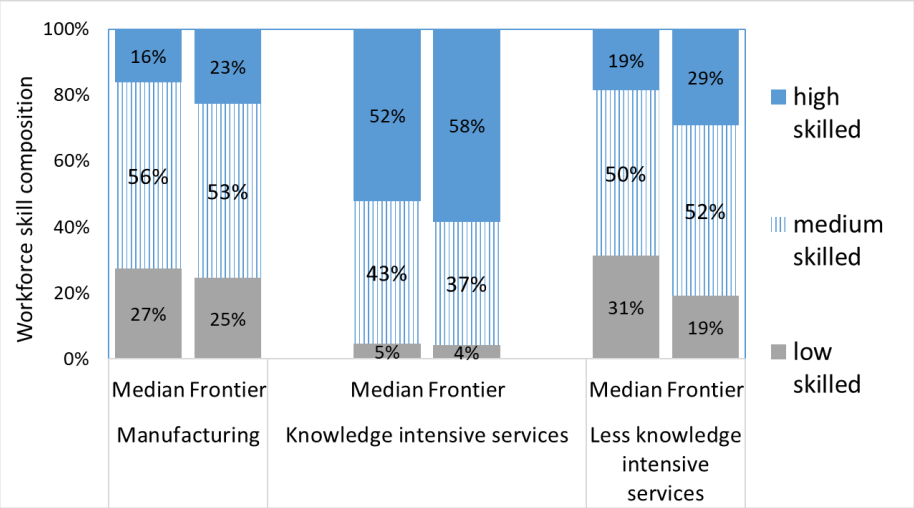
2.2. The combination of skills varies across countries, sectors and firms

24. The mix of high, medium and low skilled labour varies substantially across sectors, as shown in Figure 4. On average across countries, high skills are most important in knowledge-intensive services (ICT and professional services), while low and medium skills are most important in manufacturing and less knowledge intensive services (wholesale, retail, transport, hotels and restaurants), where they account for more than three quarters of the workforce across the productivity distribution. By contrast, knowledge intensive services rely much less on lower skill levels, with low and medium skilled employees combined accounting for less than one half of employees. Specifically, low skilled employees make up about one fourth of the workforce in manufacturing and between one-fifth and one-third of the workforce in less

knowledge intensive sectors. They are least important in knowledge intensive services, where they account for only about 5% of the workforce across the productivity distribution. These differences are likely to reflect mostly sector-specific capital intensities and technological patterns, with the implied differences in capital-labour complementarities.

Figure 4. Productivity and the skill composition of the workforce: varying patterns by sector

The share of different skill groups by firms at different segments of the productivity distribution



Note: Figure shows workforce skill composition along the productivity distribution by sector. Workforce composition shown as firm-level shares of low, medium and high skilled employees. Firm-level shares are computed as average firm-level skill group shares by productivity group x STAN A38 industry x year x country; results shown are averaged by productivity group across STAN A38 x years x countries by sector. The average employment share across countries for knowledge intensive services is about 46%, for manufacturing 18%, and for knowledge intensive services 15%. Baseline skill measure is based on 2-digit ISCO08 occupations ranked by cognitive test scores from PIAAC; where occupational data in sufficient detail is not available, educational attainment is used. More details on the construction of skill groups can be found in Box 3 and in Annex A. Frontier, median and laggard firms refer to 90th, 40-60th and 10th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

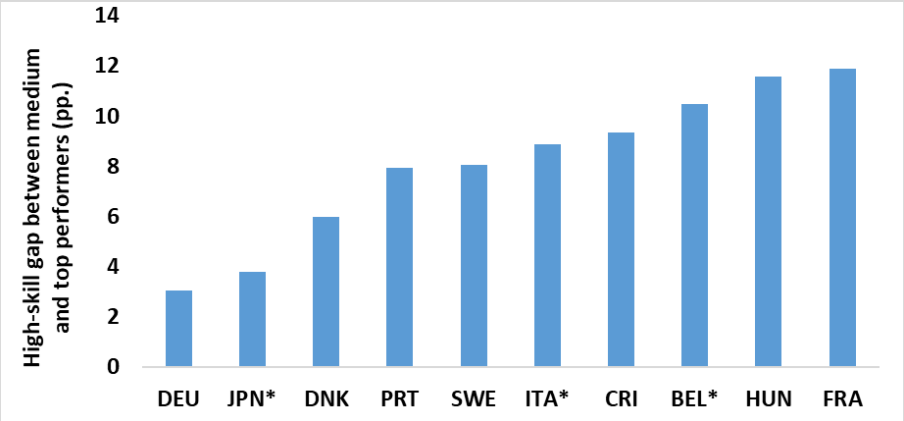
25. Top performing firms differ not only in their reliance on high skills, but also in how they combine high skilled with low and medium skilled employees to exploit potential complementarities. These differences are particularly noticeable in less knowledge intensive sectors. High and medium skills appear to be crucial for achieving high productivity in these sectors, with firms at the productivity frontier employing a 10 percentage point higher share of high skilled workers and actually relying *more* intensively on medium skilled employees – which account for 52% of the workforce – than less productive firms. Given that less knowledge intensive services constitute a large segment of the economy (nearly half of the non-farm, non-financial business sector), this underlines the importance for policies to improve the supply and quality of medium skills. In less knowledge intensive services, more productive firms also use less low skilled labour, but low skilled employees still account for about one fifth of the workforce at the productivity frontier.

26. Ongoing structural changes may worsen the prospects of the low skilled being employed in top performing firms in the future. In many countries, employment in manufacturing declines and employment in services increases. Sectoral shifts thus suggest low skilled labour becoming less important over time: low skilled labour appears most important in shrinking manufacturing, and less important in services, where it accounts for very small shares in knowledge intensive services and is used less often at more productive firms in less knowledge intensive services. In light of these particular challenges, policies should support low skilled employees in adapting to changing skill demands, e.g. through training and lifelong learning.

27. Large differences also exist across countries in how much top performing firms specialize on high skills and, conversely, how much they specialize on low and medium skills. Figure 5 shows the high skill gap, measured as the difference in the share of high skilled employees between the most productive firms and medium performers in each country. While the high skill intensity of top performing firms is a universal feature across countries, the magnitude of the skill gap varies substantially by country. Gaps are largest in France, where the most productive firms employ about 12 percentage points larger shares of high skilled employees than medium performers, and they are smallest in Germany, where firms at the productivity frontier employ only about 3 percentage points larger shares of high skilled workers than in other firms. Put differently, the high skill intensity of French top performing firms relative to medium performers is about 4 times as large in France than in Germany.

Figure 5. Firms at the frontier employ a larger share of the high skilled workforce in all countries but to varying degrees

The concentration of high skills, measured by the difference in the share of different skill groups between firms at the frontier and at the median productivity segment



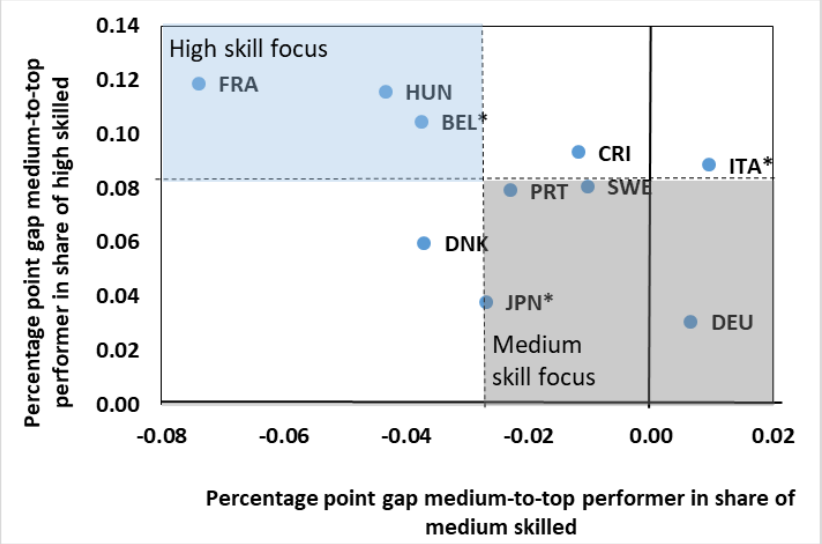
Note: Figure shows high skill gap at the productivity frontier, i.e. the difference in the share of high skilled employees at frontier versus median firms, by country. Results are based on average firm-level share of high-skilled employees by productivity group x STAN A38 industry x year x country cell. High skill gaps are computed as difference between share of high skilled employees averaged across industries by country. Baseline skill measure is based on 2-digit ISCO08 occupations ranked by cognitive test scores from PIAAC. Countries where skill measure is based on education levels because occupations were not available in sufficient detail are marked by asterisk (*). More details on the construction of skill groups can be found in Box 3 and in Annex A. Frontier and median firms refer to 90th and 40-60th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

28. The flipside of differences in high skill intensity at the productivity frontier are of course different combinations of low and medium skills. Figure 6 plots gaps in the share of high skilled employees between top and medium performers against the corresponding gap in the share of *medium* skilled employees by country. Countries fall roughly into two groups: those in which firms at the frontier specialise in the use of high skills and use much less of either medium and low skills (*high skill focus*), and countries in which firms at the frontier rely less intensively on high skills and relatively more on medium skills (*medium skill focus*). At one end of the spectrum lies France, which relies especially intensively on high skills and exhibits the largest negative gap with regard to medium skills (about minus 8 percentage points medium skill gap). The high skill intensity of French top performing firms thus comes at the expense of mostly medium but also low skilled employees. At the other end lies Germany, which exhibits a comparatively small high skill gap and a small but *positive* medium skill gap, implying that top performing firms in Germany rely *more* intensively on both high *and* medium skilled labour. Denmark lies in between these two extremes, implying that there are smaller high *and* medium skill gaps across firms with different productivity levels. This simple

descriptive finding is in line with a specific detailed study for Denmark, which showed that only a modest share of productivity dispersion across firms can be explained by various measures of firm-level human capital (Fox and Smeets, 2011[44]).

Figure 6. Firms at the frontier have different skill use strategies across countries

The relative concentration of high (vertical axis) and medium skilled (horizontal axis) at the productivity frontier, in percentage points



Note: Figure shows high skill gap at the productivity frontier, i.e. the difference in the share of high skilled employees at frontier versus median firms, plotted against the corresponding medium skill gap by country. Results are based on average firm-level share of medium- and high-skilled employees by productivity group x STAN A38 industry x year x country cell. Skill gaps are computed as difference between share of respective skill group averaged across industries by country. Baseline skill measure is based on 2-digit ISCO08 occupations ranked by cognitive test scores from PIAAC. Countries where skill measure is based on education levels because occupations were not available in sufficient detail are marked by asterisk (*). More details on the construction of skill groups can be found in Box 3 and in Annex A. Frontier and median firms refer to 90th and 40-60th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

29. Country-specific patterns in the combination of different skill types are likely to reflect mainly differences in countries' institutional and policy settings, since the results shown in the figures control for cross-country differences in sectoral specialisation. Potentially, they include educational systems, labour or product market settings and the tax benefit system, which may affect how firms best combine employees with different skills to achieve high productivity. Weaknesses in the educational system or less competitive markets make access to high skilled labour, especially for less productive firms, more difficult, and may thus widen gaps in the use of high skilled labour with respect to top performing firms. Conversely, well-functioning vocational training systems, such as in Germany, may be able to better equip for instance medium skills workers with relevant skills, thus allowing firms to achieve high productivity with larger shares of medium skilled employees. Overall, these patterns suggest an important role of policies to reduce productivity gaps by improving the quality of and providing better access to skills.

30. Detailed regression results from each country confirm that the share of high skilled workers is positively related to productivity at the firm level, controlling for a range of fixed effects (at the industry x year level and by firm size categories) and control variables (including the demographic structure, the intensity of part time work and further variables capturing the firm's organisation) (Table 2). However, the results also show decreasing returns for the share of high skills in most countries, and find no evidence for

complementarities between high and low skilled workers. Instead, the findings are compatible with complementarities between high and *medium* skilled employees.[7] This reflects the idea documented by the simple descriptive figures above that even top productivity firms rely crucially on employees with lower skill levels, typically at medium skilled level.

Table 2. The skills structure and productivity: country-by-country firm level regressions

Countries / Variables	BEL(1)	CRI	DEU	DNK	FRA	HUN	JPN(1)	ITA(1)	PRT	SWE
Share of high skilled	1.058*** (.03)	1.017*** (.104)	1.094*** (.167)	.42*** (.038)	.626*** (.015)	1.555*** (.048)	.551*** (.044)	.923*** (.021)	1.265*** (.045)	.38*** (.015)
Share of low skilled	-.326*** (.028)	-.295*** (.034)	-.103** (.046)	.037*** (.014)	-.292*** (.005)	-.18*** (.023)	.115 (.182)	-.599*** (.01)	-.213*** (.011)	-.059*** (.012)
High x high	.01 (.079)	-.245 (.193)	-1.13*** (.232)	-.568*** (.061)	-.303*** (.027)	-1.57*** (.105)	-.368** (.155)	-1.146*** (.054)	-1.335*** (.071)	-.17*** (.033)
High x low	.087 (.155)	-.492 (.329)	.314 (.534)	-.334** (.132)	-.983*** (.045)	-1.645*** (.168)	.858 (.64)	-1.114*** (.089)	-.876*** (.125)	-.242*** (.052)
Controls	Manager and worker demographics (share of old, young; share of women; share of foreign); share of part-time (2); occupation structure; manager/worker relative wage									
Industry x year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm size categories	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	.484	.503	.368	.689	.526	.537	.418	.32	.465	.414
Number of observations	325,476	49,927	25,483	115,852	1,356,840	122,737	13,376	272,599	256,161	307,439

Note: Results are based on the following specification run country by country (*c*) at the firm (*i*) x year (*t*) level, where *HS* and *LS* stands for the share of high and low-skilled workforce in the total workforce, and which includes a set of controls (demographics: gender and age composition; the share of part-time workers; variables in *X* capturing the occupation structure and relative worker / manager wages) and detailed industry x year fixed effects and firm size categories:

$$\log\left(\frac{VA}{L}\right)_{cit} = \beta_1^c HS_{cit} + \beta_2^c LS_{cijt} + \beta_3^c \left(HS_{cit}\right)^2 + \beta_4^c HS_{cit} * LS_{cit} + f(DemographicStructure_{cit}) + \vartheta_1^c parttime_{cit}^{Female} + \vartheta_2^c parttime_{cit}^{Male} + X_{cit}\boldsymbol{\beta^c} + \sum_{c=2}^{3} \theta_c firmsize_{cit} + \delta_{jt}^c + \varepsilon_{ijt},$$

These are simplified variants of the more general form described in Annex A, in that this table focuses on the overall skill level (not separately of managers and non-managers) where more details on the definition of the variables are provided.

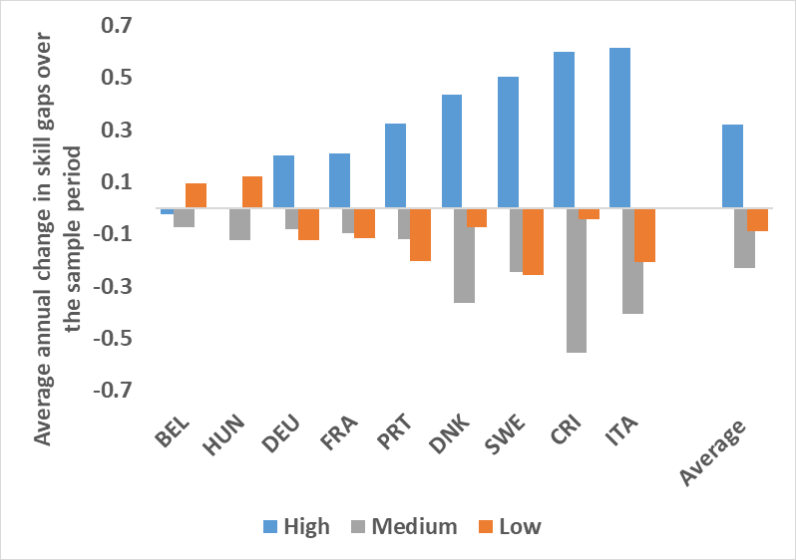
(1) Education based skill groups instead of occupation and PIAAC based, and using a more limited set of controls; (2) Not available in Costa Rica and Sweden.

Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

[7] The interaction term of *High x high* in the 3rd row of Table 2 and *High x low* in the 4th row are both mostly negative and often significant, implying that the omitted category (*High x medium*) is positively related to productivity.

Figure 7. Firms at the frontier are using more and more high skills, with declines in both medium and low skill use

Average annual changes over the sample period in the differential shares of low, medium and high skill shares between the most productive firms and medium performers by country



Note: Figure shows annualized change in low, medium and high skill gaps at the productivity frontier, i.e. the difference in the respective skill group share at frontier versus median firms, over the sample period by country. Results are based on average firm-level share for each skill group by productivity group x STAN A38 industry x year x country cell. Annualized changes in skill gaps are computed as difference between share of high skilled employees averaged across industries by country x year between the first and last sample year, divided by the number of years observed. For DEU, shares have been averaged across first and last three years of the sample period to improve reliability of results in light of its smaller sample size. Baseline skill measure is based on 2-digit ISCO08 occupations ranked by cognitive test scores from PIAAC; where occupational data in sufficient detail is not available, educational attainment is used More details on the construction of skill groups can be found in Box 3 and in Annex A. Frontier and median firms refer to 90th and 40-60th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

31. The high-skill intensity of firms at the productivity frontier increased further over time. Figure 7 shows that the high skill gap – the difference in shares of high skilled workers at the most productive firms relative to medium performers – increased in most countries over the period covered by this analysis. On average across countries, the high skill gap rose by about 0.3 percentage points per year, while the share of medium and low skilled employees declined by about 0.2 and 0.1 percentage points, respectively. This reflects a divergence in the skill structure across firms, and it is compatible with the notion that more advanced technologies used by firms at the frontier are especially complementary to high skilled labour, even more so over time. Indeed, complementarities with high skilled labour are likely to be increasing due to the digital transformation over the past two decades (e.g. Autor (2014[19])). Nevertheless, the fact that – even at the productivity frontier – most of the workforce is made up of less than high-skilled employees suggests that efforts also need to focus on the supply and quality of medium and low skills.

32. The finding that firms at the productivity frontier have become more concentrated in using high skills is compatible with the increased sorting of employees observed in several countries (Card, Heining and Kline, 2013[32]; Håkanson, Lindqvist and Vlachos, 2015[33]; Helpman et al., 2017[34]; Song et al., 2019[35]).[8] It should, however, be noted that the skill measures used in this analysis do not allow identifying

[8] The complementary LinkEED project of the OECD (Criscuolo, Hijzen and Schwellnus, 2020[99]) also investigates sorting, using similar datasets as the current paper.

individual differences in ability *within* occupation- or education-based skill groups. While Figure 7 shows that in most countries firms at the productivity frontier shifted towards an occupational mix that relies more on high and less on low and medium skills, it does not show whether the most productive firms increasingly hired the most able employees within their respective skill group. Moreover, the task content within occupations may have also become more skill-intensive over time (Spitz-Oener, 2006[23]). Our results may thus be seen as a lower bound for the increasing concentration of high-skilled employees at the productivity frontier. Indeed, firms at the frontier – besides becoming more concentrated in high skilled tasks – may additionally pull ahead by being able to attract the best *within* their respective profession and rely on job positions that use more advanced tasks than what is typical for a given occupation.

33. Apart from digitalisation, the rising concentration in high skills at the productivity frontier could also be driven by intensified off-shoring and domestic outsourcing activities. That is, top performing firms may exhibit high productivity in conjunction with shifts towards more high-skill intensive occupations as they focus on their most profitable, core tasks, while relegating less profitable tasks to outside firms at home or abroad (Goldschmidt and Schmieder, 2017[45]; Goos, Manning and Salomons, 2014[21]; Grossman and Rossi-Hansberg, 2008[46]; Firpo, Fortin and Lemieux, 2011[47]; Autor and Dorn, 2013[48]; OECD, 2021[49]). To the extent that the concentration in high skills reflects changes in firm boundaries, rather than the use of more advanced technology or more efficient firm organisation, this may overstate productivity gaps to the frontier and the potential to catch-up by adjusting the firm's skill structure. Future work building on this project will focus on how firms that rise near or to the frontier change their skill mix, e.g. whether productivity growth is associated with downsizing certain occupations with low skill levels while simultaneously increasing spending on intermediate input use - which would be suggestive of outsourcing - or with hiring higher skilled labour.

2.3. More productive firms stand out in their use of specific skills

34. High performance rests on the use of general as well as specific skills. General, basic skills, e.g. measured using educational attainment or cognitive scores by detailed occupation, are transferable across a broad range of tasks and allow employees to perform better in all jobs. Besides general skills, however, firms also need employees who are skilled at performing specific cognitive and non-cognitive tasks.

35. Figure 8 highlights the differential use along the productivity distribution of (i) general basic skills (as measured by educational attainment) and two specific skills – (ii) management and communication and (iii) ICT. For each of these three dimensions, the Figure shows deviations in the overall skill structure (encompassing High, Medium and Low skill levels) from the most productive firms.[9] Interestingly, while firms at the productivity frontier differ systematically in the use of both general and specific skills, they differ much more in their use of specific skills based on their actual tasks compared to general skills based on educational attainment.[10]

[9] To compare the use of specific and general skills in a compact way, we use a "deviation from the frontier" measure for the skill composition as the sum of squared deviations from all three skill levels, in the spirit of an Euclidean distance measure:

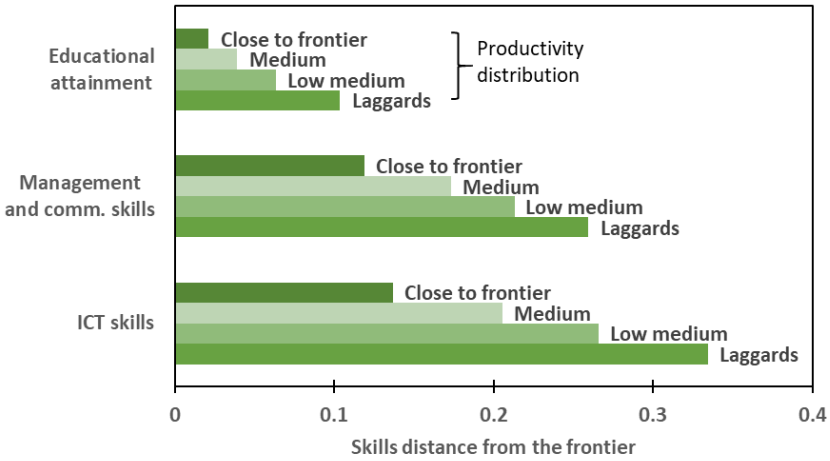
$$Distance_{cipt}^{Skills} = \sqrt{\left(\Delta HiSkill_{cipt}\right)^2 + \left(\Delta MeSkill_{cipt}\right)^2 + \left(\Delta LoSkill_{cipt}\right)^2}$$

where $\Delta HiSkill_{cipt} = HiSkill_{ciFt} - HiSkill_{cipt}$, that is the difference between the share of high skilled at the frontier *F* and in the productivity group *p* below the frontier (analogously for medium and low skills); and Hi, Me, Lo stand for high, medium and low, respectively. Note that for the frontier group, $Distance_{ciFt}^{Skills} = 0$ by definition.

[10] Specific skills are measured using the frequency with which particular tasks are performed by detailed occupations. See more details in Box 3.

Figure 8. The role of different types of skills along the productivity distribution

Deviations in the skill structure to the productivity frontier for different skill types by productivity groups



Note: The figure shows deviations in the skill structure from the productivity frontier for general and specific cognitive and non-cognitive skills along the productivity distribution. Deviations in the skill structure are based on the Euclidean distance for all skill groups of the respective skill type. General skills are based on educational attainment. Specific cognitive and non-cognitive skills are based on rankings of detailed occupations of the frequency with which respective tasks are performed, using PIAAC. Results are based on average firm-level share for each skill group by productivity group x STAN A38 industry x year x country cell. Occupational measures are based on 2-digit ISCO08 occupations. More details on the construction of skill groups can be found in Box 3 and in Annex A. Firms at the frontier x close to the frontier x medium x low medium x laggards refer to 100-90th x 60-90th x 40-60th x 10-40th x10-0th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

36. These large and systematic differences in the use of specific skills along the productivity distribution suggest that having access to employees who are highly skilled at particular tasks, notably ICT and management and communication, is crucial for achieving high performance. More than general skills, which may reflect mostly competences acquired through the educational system, these task-specific skills are often acquired and developed through learning-by-doing and training throughout the career. As a consequence, the larger observed gaps across firms in terms of specific skills might be more rapidly reduced than those of basic, general skills. To provide firms with better access to these specific skills, policies should therefore focus on incentivising and facilitating training by firms and encourage an attitude of lifelong learning by employees, on top of providing good foundational skill through improving the educational system.

3. The role of management

37. Managers are of paramount importance to a firm's performance. How productive a firm is depends importantly on its entire workforce, i.e. the composition and interaction of *all* of its employees. However, the crucial role attributed to managers within the firm's organisation implies that managers can have a disproportionate effect on productivity: by "deciding what to do" and then "getting the organisation to do it" – including selecting and making efficient use of workforce skills through high performance work practices (HPWP) incentivising and monitoring workers – managers can be the enablers or the bottlenecks to the firm's success (Gibbons and Henderson, 2012[50]; OECD, 2019[51]). This key position warrants paying particular attention to managers.

38. The fact that management matters for productivity is well established.[11] Hiring particular managers as CEOs, the behaviour and character traits of managers, have all been found to relate to firm productivity (Adams, Almeida and Ferreira, 2005[52]; Bertrand and Schoar, 2003[53]; Kaplan, Klebanov and Sorensen, 2012[54]; Bandiera et al., 2017[55]; Bianchi and Giorcelli, 2021[56]). Moreover, management quality and management training has been shown to have a distinct, causal role for firm performance (Giorcelli, 2019[57]). Firms using advanced management practices have been shown to be more productive in a broad range of countries (Bloom and Van Reenen, 2007[11]; Bloom et al., 2014[58]; Bloom et al., 2018[59]; Bloom, Sadun and Van Reenen, 2016[60]). Management practices have been related to the adoption and efficient use of new technologies (Bloom et al., 2013[30]; Pellegrino and Zingales, 2017[61]; Andrews, Nicoletti and von Rueden, 2020[7]; Giorcelli, 2019[57]). Efficiency gains from scaling up have been found to be bound up with adjustments in management structure (Caliendo, Monte and Rossi-Hansberg, 2015[62]; Caliendo et al., 2020[31]). Moreover, management yields control over many other aspects that affect firm efficiency, e.g. worker turnover, worker satisfaction, and conflict resolution (Lazear and Shaw, 2007[63]; Adhvaryu, Molina and Nyshadham, 2019[64]; Krekel, Ward and De Neve, 2019[65]).

39. This Section provides additional evidence on how differences in management characteristics relate to the differences in firm productivity observed within industries for the universe of business sector firms across countries. In particular, we focus on how the number and the skills of managers differ *in top productivity firms*. Given the crucial role of management, firms that devote more resources to formal management may indeed be more successful (Caliendo and Rossi-Hansberg, 2012[66]). In addition, firms with a more skill-intensive managerial staff are likely to be better at improving productivity (Bender et al., 2018[67]). Understanding how firms at the productivity frontier are different from less productive ones in terms of management is crucial to design targeted policies aimed at enabling and incentivizing less productive firms to catch up to the frontier.

3.1. Management structure

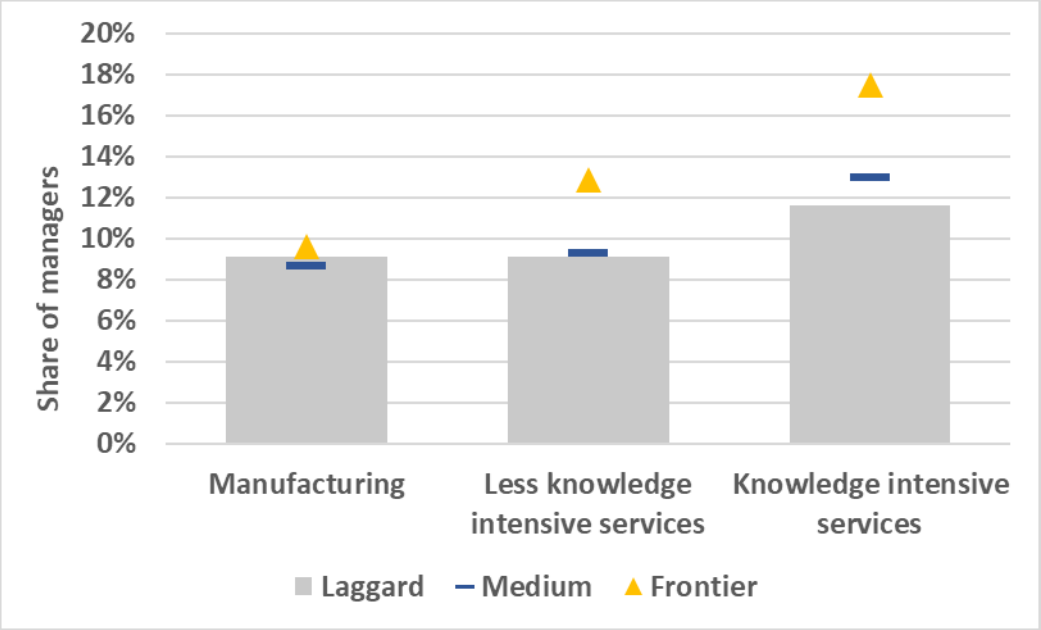
40. The capability of firms to identify and successfully adopt measures that raise firm productivity likely depends on human resources that are devoted to managerial functions. One simple way to capture the extent of such resources is to look at the share of the firm's workforce dedicated to formal management. Figure 9 compares the manager-share – the share of employees who primarily engage in managerial tasks – between firms at the frontier and firms at the median productivity segment – the "typical" firm – as well as laggards by sector.[12] Firms at the frontier are indeed different from less productive firms in that they employ a significantly larger share of managers: on average across countries, between 9-18% of employees at firms are classified as managers, and in all sectors the highest manager-shares are observed in top performing firms.

[11] For a detailed discussion of the channels through which management – and workforce diversity in terms of age, gender and cultural background – can affect productivity, including an additional discussion of existing evidence, see also OECD (2019), "The Human Side of Productivity: Setting the Scene".

[12] The share of managerial workers is identified using detailed occupational information of the firm's employees (see Annex A); the analysis in this Section is therefore restricted to countries for which sufficiently detailed information on occupations was available.

Figure 9. More productive firms devote more human resources to management

Firm-level share of managers along the productivity distribution by sector



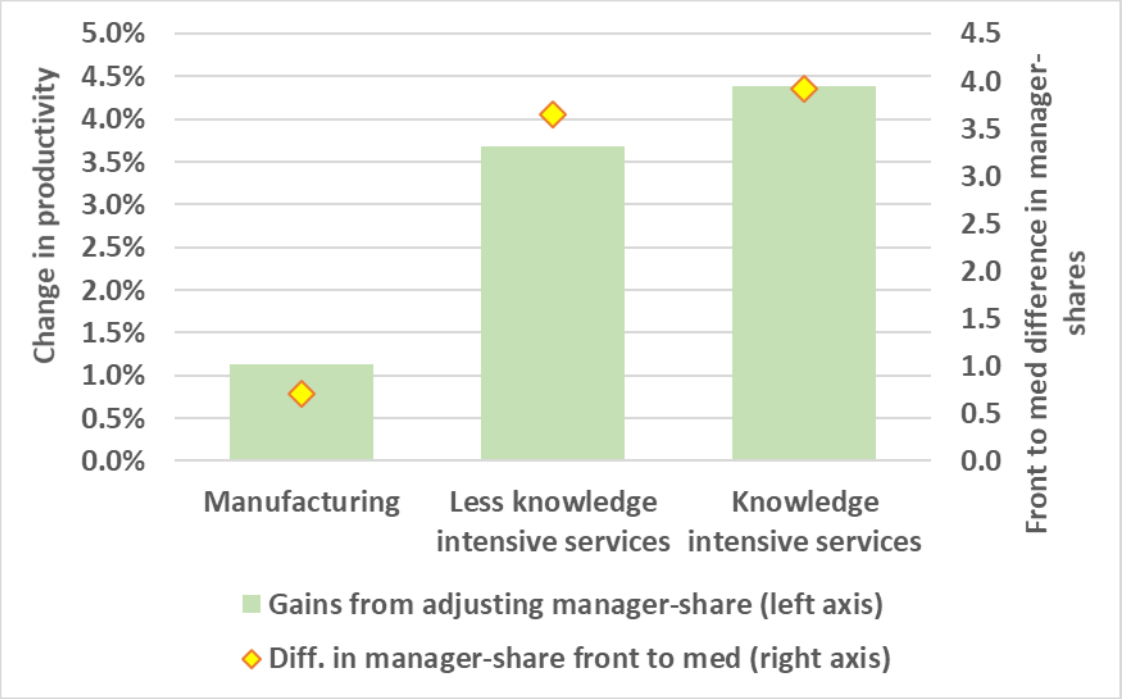
Note: The figure shows the share of employees identified as managers across the productivity distribution by sector. Manager shares are computed at the firm-level based on 2-digit ISCO 08 occupations separately in each country, and averaged across country x STAN A38 industry x year cells by productivity group and sector. Productivity groups refer to frontier (top decile), medium (40-60th percentile), and laggard firms (bottom decile) of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

41. Important differences apply across sectors. Compared to manufacturing, firms in market services – especially in knowledge intensive services such as ICT and professional services – tend to devote more of their employees to management. The gap in manager-shares between firms at and below the productivity frontier is also most pronounced in both segments of services, where the most productive firms devote about 4 percentage points more of their workforce to managing the firm than medium firms do; this compares to a relatively small gap of less than 1 percentage point in manufacturing. Firms in services on average thus exhibit higher manager-shares and larger discrepancies in manager-shares between the most productive firms and the rest. This may reflect the fact that production processes are relatively less standardized in services than in manufacturing, so that non-standard decision making, i.e. managerial input, is more often encountered as a bottleneck to efficient production (Oldenski, 2012[68]).

42. These sectoral differences translate into different magnitudes regarding the link between productivity and the manager-share: our *ceteris paribus* calculations suggest that in services a typical firm below the productivity frontier could gain the most from having a similar manager-share as observed at the frontier (Figure 10). The associated productivity benefits are around 3.5-4.5%, whereas firms in manufacturing would reap somewhat lower gains of about 1%.

Figure 10. Estimated productivity gains associated with imitating the managerial structure of firms at the frontier

Implied productivity increase associated with adjusting the manager-share of medium performers to those found at top performers, average across countries

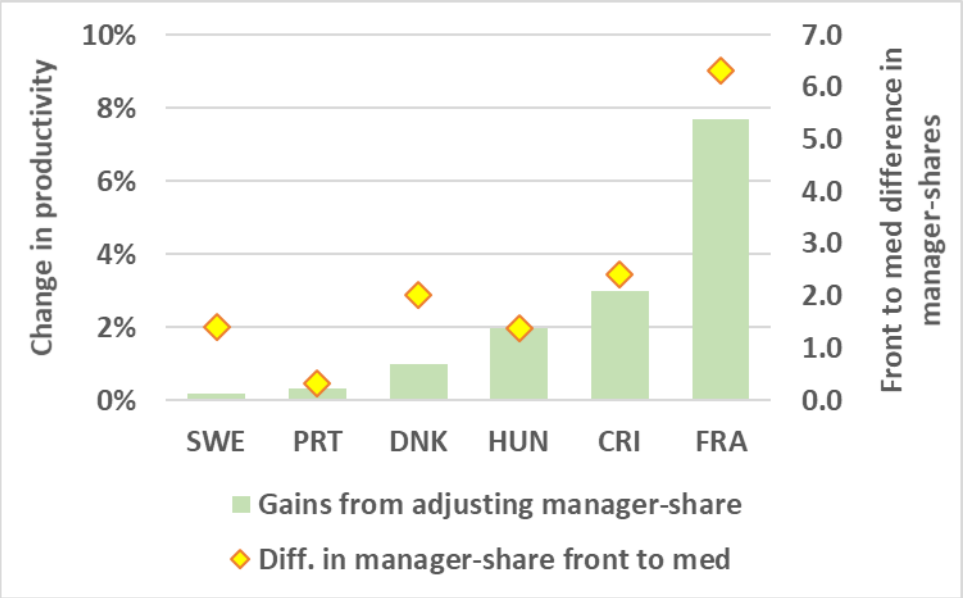


Note: The left axis shows the percentage change in productivity associated with adjusting manager-share of a typical medium firm to match the share of a typical frontier firm. Percentage change in productivity is approximated by difference in log productivity. Right axis shows percentage point difference in manager-share between frontier and medium firms. Results are based on coefficient of manager-share and log productivity estimated from baseline regression at the firm-level separately for each country and sector multiplied by difference in manager-share between typical frontier and medium firm. Baseline regression described in Annex A and Box 1. Results are first computed by country-sector and then averaged across countries by sector. Manager shares are based on 2-digit ISCO 08 occupations. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.

Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

Figure 11. Productivity gains associated with catching up to the manager-share at frontier firms by country

Change in productivity associated with adjusting manager-share for medium performers



Note: The right axis shows the percentage change in productivity associated with adjusting manager-share of a typical medium firm to match the share of a typical frontier firm. Percentage change in productivity is approximated by difference in log productivity. Left axis shows percentage point difference in manager-share between frontier and medium firms. Results are based on coefficient of manager-share and log productivity estimated from baseline regression at the firm-level separately for each country multiplied by difference in manager-share between typical frontier and medium firm. Baseline regression described in Annex A and Box 1. Manager shares are based on 2-digit ISCO 08 occupations. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

43. Figure 11 shows that these productivity gains hide a substantial variation across countries, from just above 0% to almost 8%.[13] These differences either reflect small gaps in the share of managers between medium and frontier firms are relatively small (e.g. in Portugal or Hungary compared to Costa Rica and France) or a weak estimated *link* between the share of managers (e.g. in Sweden and Denmark). Here medium firms exhibit similar gaps to Hungary and Costa Rica but associated gains are much smaller. This could be related to the tendency of Scandinavian countries to adopt organisational modes with flatter hierarchies, thus devoting fewer employees to formal management (Holmberg and Akerblom, 2006[69]).

44. In sum, the high performance of firms at the productivity frontier partly reflects the fact that those firms allocate more of their labour resources to formal management – though cross-country differences suggest that allocating more employees to managerial tasks is but one way among several to achieve good management. Overall, however, management at firms near the top of the productivity distribution may be better able to identify economic opportunities, stay abreast of technological developments, and implement complementary organizational changes more efficiently. To catch up, firms below the frontier would therefore likely benefit from re-organizing and spending more of their resources on the task of managing the firm. Policies facilitating this catch up should enhance the supply of managerial skills and raise awareness of the issue by offering advice to firms whose managerial staff is under resourced.

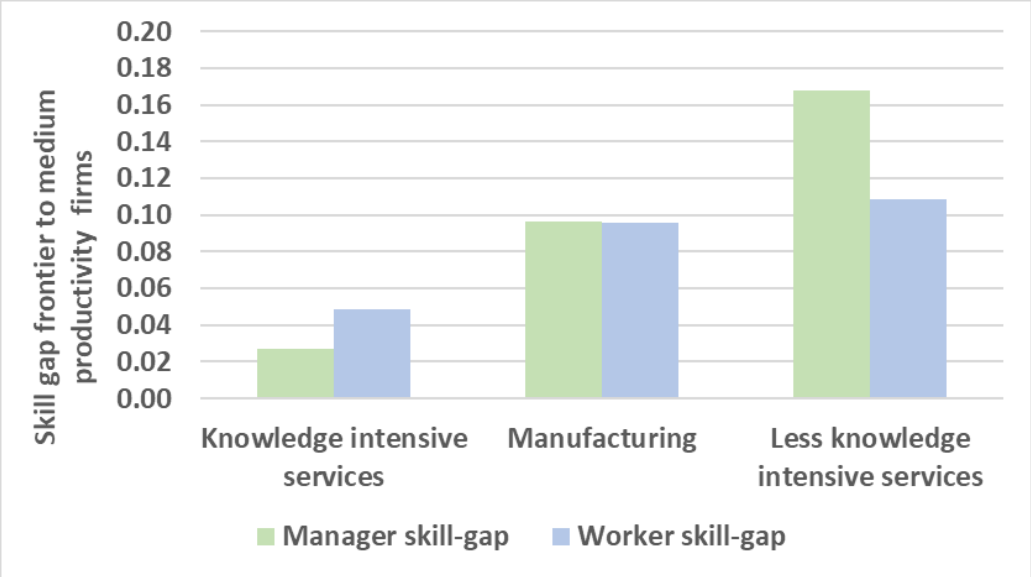
[13] Due to data limitations, some countries have been omitted from this analysis. The analysis uses detailed occupational data at the firm-level to identify managers. Belgium, Germany, Italy and Japan are not included as firm-level information on occupations was not available or not at the required level of detail.

3.2. Management quality

45. How much does a firm benefit from its management in terms of productivity likely depends also on the skills of its managers, in addition to the share of workforce devoted to managerial roles. For a given share of managers, management quality may be higher – and its impact on productivity more positive – the more highly skilled the firm's managers are (Bender et al., 2018[67]). Figure 12 shows that frontier firms are different from other firms in that they employ a more highly skilled workforce of both workers *and* managers.[14] The figure shows differences between frontier and medium firms in the shares of high skilled employees among managers and workers respectively – i.e. manager and worker skill gaps –, averaged across countries by sector: in all sectors, the most productive firms exhibit a more high-skill intensive skill composition of managers and workers. For workers, these skill gaps range from 5 to 11 percentage points across sectors. For managers, sectoral differences are much more pronounced, ranging from 2.5 to 16 percentage points.

Figure 12. Skill gap between top and medium productivity firms for managers and workers across sectors

Percentage point difference in the share of high skilled managers and workers between frontier and medium firms



Note: This figure shows the percentage point difference in share of high skilled workers or managers between frontier and medium productivity firms by sector. High-skill shares are computed at the firm-level and averaged across country x STAN A38 industry x year cells by productivity group and sector. High skilled workers x managers correspond to employees employed in top quartile occupation of within-country occupational wage distribution. More details on the construction of skill groups can be found in Box 3 and in Annex A. Managers and workers are identified based on occupations. Occupational classifications used are 2-digit ISCO 08. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

46. Skill gaps for managers therefore differ widely across sectors – more so among managers than among workers. The managerial skill gap is particularly large in less knowledge intensive services (wholesale, retail, transport, hotels and restaurants, etc.), and comparatively small in knowledge intensive

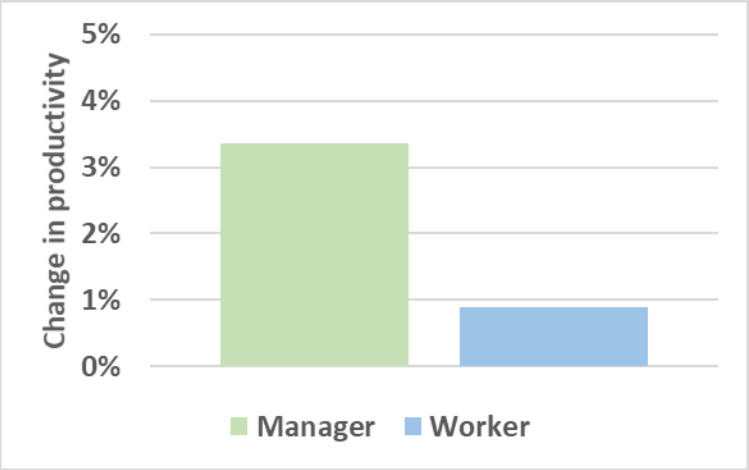
[14] To address the overlap between occupation-based manager classifications and our baseline occupation-based skill groups measure, in this chapter – focusing on the separate roles of managers and workers – skill groups have been identified using information on the relative *wages* of occupations within a country. This approach yields managerial occupations being classified among different skill groups mostly as either medium skilled - e.g. specialized service managers – or high skilled – e.g. top managers.

services. Importantly, however, a small managerial skill gap does not indicate that skills do not matter for managers in this sector. While managerial skill gaps are smallest in knowledge intensive services, frontier firms in this sector exhibit the highest *share* of high skilled managers (on average across countries). The relatively small managerial skill gap in knowledge intensive services thus shows that the typical firm in the sector *already* exhibits comparatively high shares of skilled managers. The largest discrepancy between frontier and non-frontier firms – and thus the largest potential for catch-up – exists in less knowledge intensive services, where the share of high skilled managers is indeed lowest across sectors.

47. Section 2 discussed productivity gains associated with adjusting the firm's overall skill structure, but what are the potential productivity gains associated with upskilling managers relative to upgrading worker skills, holding other factors unchanged? To illustrate this issue, Figure 13 shows that, according to our estimates, upskilling managers could yield gains in firm productivity three times larger than upskilling workers: for a typical medium performer firm, gains associated with upskilling a fixed proportion of the workforce (1%) - either among managers or workers - corresponds to about 3% and 1%, respectively. This three-fold difference in associated productivity gains likely reflects the distinguished role that managers can play in affecting the productivity performance of firms. The disproportionate contribution of the managerial skill structure for firm performance likely reflects the crucial role of managers within the firm's organization, who can act as a lever to raise the workforce's efficiency, e.g. through high performance work practices (HPWP, see OECD (2019[51])). For instance, more high skilled managers in German manufacturing firms have been found to be more likely to use advanced management practices, which in turn are related to better firm performance through monitoring, goal setting and selecting and incentivizing the entire workforce (Bender et al., 2018[67]).

Figure 13. Productivity gains associated with upskilling managers versus workers

Productivity gains for medium productivity firm associated with upskilling 1% of the workforce, either managers or workers

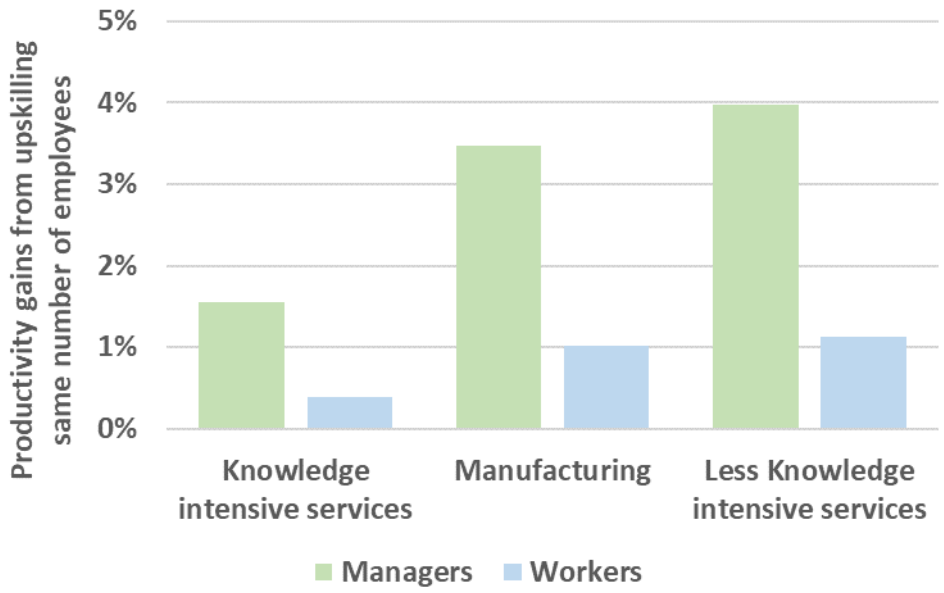


Note: The Figure shows the percentage change in productivity for the medium productivity firm associated with replacing medium skilled managers (workers) with high skilled managers (workers) corresponding to 1% of the firm's workforce. Percentage change in productivity is approximated by difference in log productivity. Results are based on coefficients of skill-shares among managers and workers on log productivity, estimated from baseline regression at the firm-level separately for each country, multiplied by change in shares corresponding to 1% of average firm-level employment in the respective country. Baseline regression described in Annex A and Box 1. More details on the construction of skill groups can be found in Box 3 and in Annex A. Results are first computed by country and then averaged across countries. High skilled workers x managers correspond to employees employed in top quartile occupation of within-country occupational wage distribution. Managers and workers are identified based on occupations. Occupational classifications used are 2-digit ISCO 08. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

48. Figure 14 repeats the same exercise by sector, showing that the prevalent impact of upskilling managers for productivity holds across the economy. In all sectors, manager skills are associated with disproportional productivity gains. Some differences apply with regard to the absolute productivity gains, however: the largest gains associated with upskilling managers could be reaped in less knowledge intensive services. This sector exhibits the largest manager skill gap between the productivity frontier and below (Figure 12) and also represents a large part of the economy comprising a multitude of labour-intensive firms employing many low skilled workers. Smaller but still sizeable gains could be obtained in manufacturing, and to a lesser extent in knowledge intensive services.

Figure 14. Productivity gains associated with upskilling managers versus workers by sector

Productivity gains for medium productivity firm associated with upskilling managers or workers corresponding to 1% of the firm's employment from medium to high skilled by sector



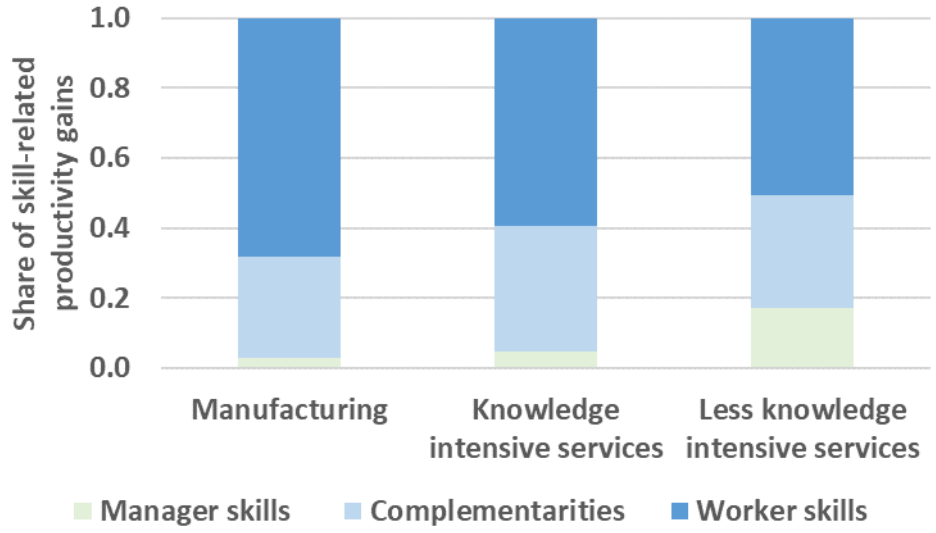
Note: The figure shows the percentage change in productivity for medium productivity firm associated with replacing medium skilled managers (workers) with high skilled managers (workers) corresponding to 1% of the firm's workforce by sector. Percentage change in productivity is approximated by difference in log productivity. Results are based on coefficients of skill-shares among managers and workers on log productivity, estimated from baseline regression at the firm-level separately for each country and sector, multiplied by change in shares corresponding to 1% of average firm-level employment in the respective country-sector. Baseline regression described in Annex A and Box 1. More details on the construction of skill groups can be found in Box 3 and in Annex A. Results are first computed by country-sector and then averaged across countries by sector. High skilled workers x managers correspond to employees employed in top quartile occupation of within-country occupational wage distribution. Managers and workers are identified based on occupations. Occupational classifications used are 2-digit ISCO 08. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

49. The disproportional impact of manager skills on productivity does not imply that less importance should be given to worker skills, for at least two reasons. First, given the much larger share of non-managerial workers in the typical firm, most skill-related productivity gains are associated with workers Figure 15). Second, our analysis identifies substantial manager-worker skill complementarities. In particular, Figure 15 shows how much of the productivity gains – that a typical medium firm could obtain from matching the skill structure at the frontier – can be directly attributed to managers, workers, or manager-worker skill complementarities. In all sectors, the bulk of productivity gains, between 50-60%,

arises directly from upskilling workers, reflecting their large employment share. Upskilling managers makes a disproportional contribution but is comparatively small in absolute terms when looked at in isolation, ranging from about 3% in manufacturing and knowledge intensive services to about 18% in less knowledge intensive services. Moreover, between 30-40% of skill-related productivity gains can be attributed to the complementarities that arise from combining better skilled managers with better skilled workers.

Figure 15. Manager and worker skills are crucial to reap productivity gains from upskilling

Share of total productivity gains from adjusting skill composition of medium to frontier firm accruing to managers and workers by sector



Note: Figure shows contribution to total productivity gains from adjusting skill composition of managers and workers for medium firm to match skill composition of frontier firm by sector. Results are based on coefficients of skill-shares among managers and workers on log productivity, estimated from baseline regression at the firm-level separately for each country and sector, multiplied by difference in shares between typical frontier and medium firm in the respective country-sector. Baseline regression described in Annex A and Box 1. More details on the construction of skill groups can be found in Box 3 and in Annex A. Results are first computed by country-sector and then averaged across countries by sector. Skill groups for workers x managers based on within-country occupational wage distribution. Managers and workers are identified based on occupations. Occupational classifications used are 2-digit ISCO 08. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

50. Overall, the managerial skill structure can make a disproportionate contribution to firm performance. This likely reflects the crucial role of managers within the firm's organization. For instance, more high skilled managers in German manufacturing firms have been found to be more likely to use advanced management practices, which in turn are related to better firm performance through monitoring, goal setting and selecting and incentivizing the entire workforce (Bender et al., 2018[67]). The ability of high skilled managers to implement productivity-enhancing management practices may be important to adjust to the new working environment in the wake of COVID-19. While intensive teleworking was often necessitated during the pandemic, many managers and workers wish to continue regular teleworking permanently. (Criscuolo, 2021[70]) and (OECD, 2020[71]) discuss how more widespread telework can affect firm performance and what role managers can play in enabling efficient teleworking.

51. To reap the full potential of skill-related productivity gains from upgrading managerial quality, policies should aim to facilitate the upskilling of managers in combination with adjusting the skill structure of workers. In addition to increasing the skill supply of mostly younger workers who are entering the labour

market through the education system, increasing the skill supply of the existing workforce through higher uptake and improved quality of adult learning and training will be key. Providing incentives and supporting access to high quality training is also an important lever for the dissemination of high-performance work practices, which form a crucial part of managerial skills (OECD, 2019[72]). Policies may also need to go beyond improving the supply of able managers and address the incentives of people selecting these managers, that is, the firm's owners. For instance, as discussed in Box 4, which focuses on family firms in Italy, differences in management quality may be related to different ownership structures.

Box 4. How does ownership relate to management and productivity? New evidence from Italian firms

An important factor influencing differences in management quality across firms is ownership: who owns the firm clearly plays a key role in choosing the firm's management. Given the key role played by management for productivity, this generates a link between ownership and firm performance. Family ownership in particular has been shown to be often associated with weaker firm performance (Bloom and Van Reenen, 2007[11]; Pellegrino and Zingales, 2017[61]; Bandiera et al., 2015[73]; Bandiera et al., 2018[74]).

Work conducted in the context of the Human Side of Productivity project scrutinized the link between family ownership, management and firm performance in Italy, drawing on a representative sample of about 31.000 limited liability firms in manufacturing and services (excluding financial and public services) observed in 2010 and 2015 from Rilevazione Imprese e Lavoro (RIL), a firm-level survey, complemented with balance sheet data (Andretta, Brunetti and Rosso, 2021[75]).

Results of this work confirm that ownership is strongly linked to firm performance in Italy. Family-owned firms are about 30% less productive in terms of TFP or labour productivity compared to other forms of ownership; in contrast, foreign-owned firms are about 50-60% more productive than domestically-owned firms. The study shows that this negative link of productivity with family ownership is partly mediated through management: family ownership is associated with lower management quality, consistent with the notion that family firms choose managers from a narrower pool, who are thus less likely to have high managerial abilities. For instance, family-owned firms are shown to be more likely to choose managers who are related to the owners, and less likely to be college educated, and firm's with college educated managers are in turn shown to be more likely to engage in process or product innovation.

While the management of family firms tends to achieve lower productivity, this may also reflect owners of family firms deliberately choosing managers who are better aligned with their preferences. For instance, owners of family firms may attach more importance to their relationship with the local community or their reputation, thus exhibiting longer investment horizons and allowing them to achieve relatively more stable employment (Sraer and Thesmar, 2007[76]; Bassanini et al., 2011[77]; Bennedsen et al., 2019[78]; Amore, Pelucco and V, 2021[79]). This in turn may contribute to better resilience. For instance, in Italy family firms have shown better financial performance than non-family firms in the wake of the COVID-19 crisis, possibly reflecting their closer relationships to their workforce and community that may have helped to stem the crisis and retain access to finance (Amore, Quarato and Pelucco, 2020[80]).

Source: Andretta, C. I. Brunetti and A. Rosso (2021): "Productivity and Human Capital: The Italian case", OECD Productivity Working Paper Series, No. 25.

4. The role of diversity: gender, age and cultural background

52. This Section focuses on the role of *gender, cultural* and *age diversity* for firm productivity. A more diverse managerial workforce may be better at managing because its diversity allows for a better informed and more encompassing perspective – hence for better decision making (Parrotta, Pozzoli and Pytlikova, 2012[81]). Firms capable of bringing together managers from diverse backgrounds may be particularly well positioned to exploit business opportunities and improve productivity: combining employees with different backgrounds permits a broader perspective and can enhance decision making (Woolley et al., 2010[82]); drawing from a broad range of demographic groups when filling vacancies allows firms to choose among a broader pool of candidates (Bennett et al., 2020[83]).

53. Cultural diversity – captured by the mix of people with different countries of origin or nationality – can be particularly important in a global economy, where close ties to foreign suppliers, customers and other stakeholders are key to success (Lazear, 1999[18]). In addition, the increasingly global nature of the production and consumption of goods, often spanning several continents, is bound to bring together people from a diverse set of countries and cultural backgrounds. Whether firms can realize the potential this global economy holds for productivity – e.g. through the participation in global value chains (GVCs) and cross-border knowledge flows – likely depends on the extent to which they can `feel at home' in such an environment, e.g. be connected to global knowledge flows, access information in foreign countries, anticipate preferences, or understand different ways of doing business. A more culturally diverse managerial workforce may help firms to operate with relative ease in such an environment (Lazear, 1999[18]; Ottaviano, Peri and Wright, 2018[84]).

54. Also, opening up access to managerial jobs for hitherto underrepresented demographic groups, for instance women and people with foreign cultural background, drastically broadens the pool of scarce talent from which firms can choose (Hsieh et al., 2019[85]; Bennett et al., 2020[83]). The link between age diversity and productivity has been the topic of recent OECD work that looked at a range of ageing related issues more broadly (OECD, 2020[86]).[15] It finds important complementarities between employees of different age groups. This is compatible with the notion that more age diverse firms directly benefit from the experience of older employees – and in particular of older managers –, are better able to raise the productivity of younger employees by transmitting knowledge, and are less susceptible to disruptions that may result, for instance, from larger cohorts of employees retiring simultaneously or the higher mobility of young employees.

55. Aside from managers, the benefits of diversity may also behold for other workers who likewise engage in decision making as well as contacts with stakeholders and teamwork (Lazear, 1999[18]; Prat, 2002[87]; Pletzer et al., 2015[88]; Post and Byron, 2015[89]). However, to the extent that these tasks are relatively less prevalent among workers, and the potential of higher communication costs relatively more important, the link of productivity with worker diversity is expected to be weaker than with managerial diversity (Alesina and Ferrara, 2002[90]; Marx, Pons and Suri, 2021[91]).[16]

[15] In (OECD, 2020[86]), the analysis on the age-profile of the workforce and its links to firm-level productivity were conducted in cooperation with the Human Side of Productivity project, which the authors of the current report gratefully acknowledge.

[16] Not distinguishing between manager and worker diversity might be one reason behind the often mixed or inconclusive results on the link between diversity and performance in the existing literature (Parrotta, Pozzoli and Pytlikova, 2012[81]; Trax, Brunow and Suedekum, 2015[129]; Calder-Wang, Gompers and Huang, 2021[97]; Marx, Pons and Suri, 2021[91]).

4.1. Gender diversity

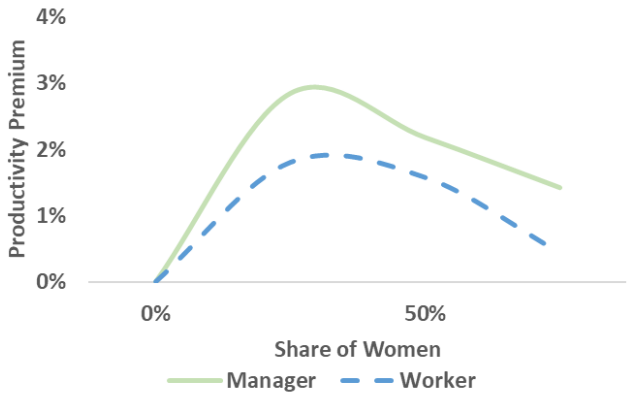
56. Firms that employ a more gender diverse managerial workforce are more productive (Figure 16). In particular, the figure depicts productivity premia associated with employing higher women shares among managers or workers respectively, after controlling for a range of other workforce and firm characteristics. The figure depicts an inverted U-shape relationship between the share of women and productivity, peaking at about 40% with associated productivity premia of about 3% for managers and 2% for workers.

57. Although gender diversity appears to be associated with higher performance, strong headwinds for women in the labour market, regarding in particular their career progression, suggest that the full potential of diversity for productivity might be even stronger. That is, removing headwinds may allow for larger productivity gains associated with gender diversity, and higher women shares being associated with productivity gains, than depicted in Figure 16. For instance, many women experience career breaks – that are often experienced by during and after pregnancy – take a lasting toll on their subsequent employment experience relative to their male peers, especially when parental leaves are uneven across genders. This may in turn restrict the number of women in managerial positions for which experience is crucial. In the future, diversity may be even more beneficial for productivity as the playing field with respect to parenthood becomes more level and the corresponding losses in experience and human capital are lessened. Recent OECD work examining the deep drivers of the gender wage gap suggests a key role for policies to further raise the gains from gender diversity while reducing economic inequalities (Ciminelli, Schwellnus and Stadler, 2021[92]).

58. While Figure 16 likely understates the productivity gains from gender diversity, the estimated premia already suggest that many firms stand to gain from becoming more gender diverse. More than half of firms in the sample exhibited women shares among managers of less than 20%, well below the current implied peak. A similar finding emerged for workers, although to a lesser extent: more than a quarter of firms had less than 20% of women.

Figure 16. Productivity gains associated with employing a diverse workforce: Gender diversity

Productivity gains associated with employing a higher share of women among managers and workers on average across countries

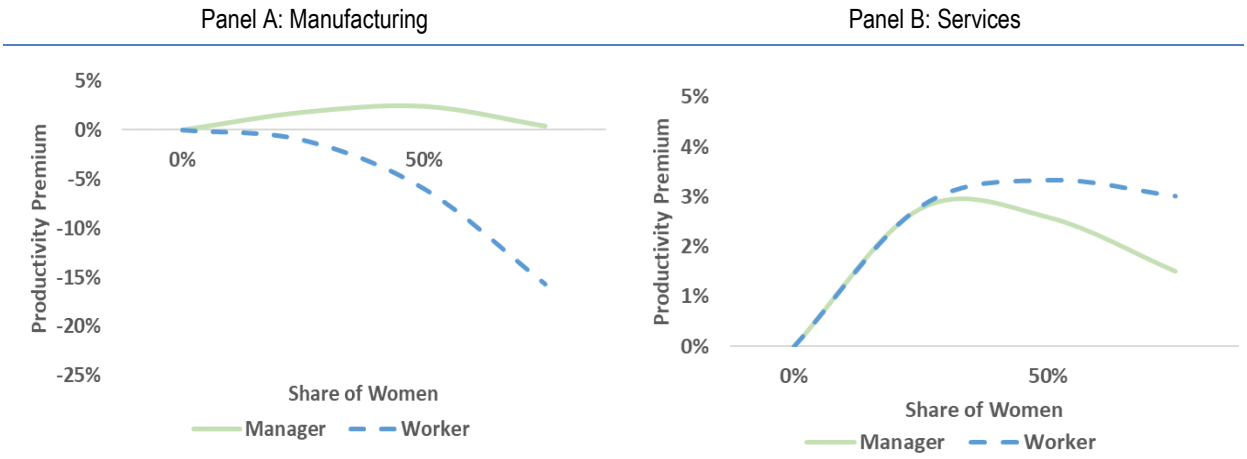


Note: Figure shows productivity premium associated with employing a higher share of women among managers or workers respectively. Results shown are smoothed dummy estimates for women share bins (in 20 percentage point categories) compared to the baseline category of having a women share of 0-20% in the respective group by sector. Productivity premium is approximated by difference in log productivity. Results are based on baseline firm-level regression estimated separately for each country. Baseline regression described in Annex A and Box 1. Estimates shown are averaged across countries ; estimates insignificant at the 10% confidence level are replaced with 0 when computing the average. Managers are identified based on 2-digit ISCO 08 occupations. Productivity is measured as log of value added per worker. On average across countries, most firms are located in categories 0-40% and less than 25% of firms located in categories 60-100%, are so identification of categories above 60% is based on relatively few observations and thus more uncertain.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

59. Gender diversity among managers and workers is associated with higher productivity on average across countries for the entire economy, but important differences apply across sectors, as shown in Figure 17. Gender diversity of managers is associated with higher productivity in each sector, with an associated productivity premia of around 2.5%, and typically larger premia in services. For workers, results are more nuanced. Gender diversity in manufacturing is associated with lower productivity, while similar or even larger gains as for managers are observed in services. Rather than signalling that firms in manufacturing cannot benefit from gender diversity, this may reflect a relatively higher prevalence of obstacles to efficient cooperation, e.g. a male-dominated work culture (Ali, Kulik and Metz, 2011[93]). The finding that gender diversity in services among workers appears to be just as important as among managers may reflect that social interactions and non-routine decision making – for which diversity may be particularly helpful – are comparatively more common for non-managerial employees in these sectors (Oldenski, 2012[68]).

Figure 17. Gender diversity and productivity by sector

Productivity gains associated with employing a higher share of women among managers and workers on average across countries by sector



Note: The figure shows the productivity premium associated with employing a higher share of women among managers or workers respectively by sector. Results shown are smoothed dummy estimates for women share bins (in 20 percentage point categories) compared to the baseline category of having a women share of 0-20% in the respective group by sector. Productivity premium is approximated by difference in log productivity. Results are based on baseline firm-level regression estimated separately for each country and sector. Baseline regression described in Annex A and Box 1. Estimates shown are averaged across countries by sector (service sector averaged between knowledge and less knowledge intensive services); estimates insignificant at the 10% confidence level are replaced with 0 when computing the average. Managers are identified based on 2-digit ISCO 08 occupations. Productivity is measured as log of value added per worker. On average across countries, most firms are located in categories 0-40% and less than 25% of firms located in categories 60-100%, are so identification of categories above 60% is based on relatively few observations and thus more uncertain.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

60. An inverted U-shape relationship between the share of women in management and firm level productivity was also found in a recent OECD study, relying on a different set of countries and an alternative cross-country data source based on financial accounts of large corporations matched with information on their senior management (Box 5). The study also showed that diversity is more tightly linked with positive productivity performance in large firms and public policies seems to play a particular role for the gender diversity of such firms through the introduction of gender quotas.

Box 5. Gender diversity in senior management: cross-country evidence from financial accounts

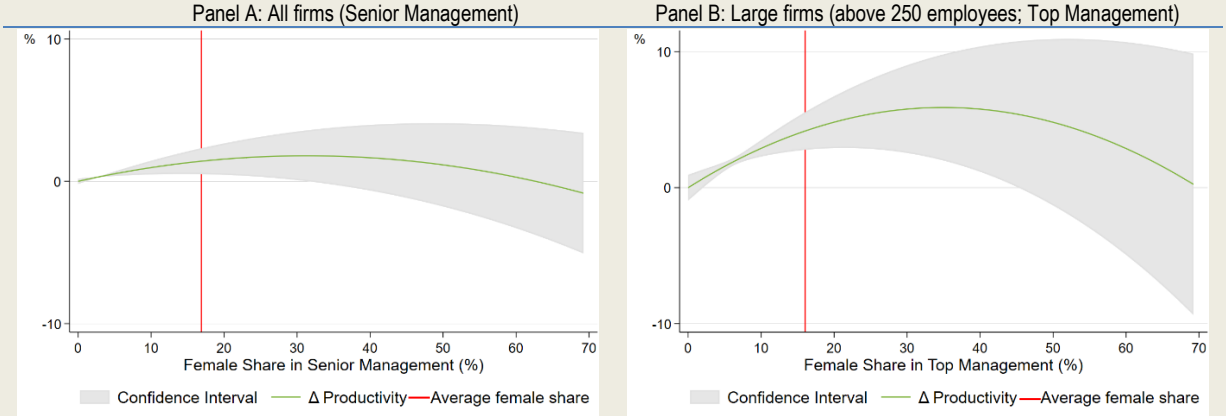
Firms with more gender diverse management are more productive

Relying on a cross-country commercial dataset of financial accounts (Orbis) and covering a somewhat different set of countries (Belgium, Germany, Denmark, France, Great Britain, Ireland, Italy, Portugal, and Sweden), (Criscuolo et al., forthcoming[94]) also analyses the link between gender diversity and firm characteristics, notably productivity and wages. This approach allows for a more refined definition of management across all countries, also extending the analysis of the diversity-productivity nexus to more sophisticated productivity measures such as variants of multi-factor productivity (MFP). It also allows for a more robust measurement of the link with productivity thanks to the possibility of a single pooled regression that includes firms from all countries. The study focuses specifically on *senior management,* defined as managers who are responsible for at least about 20 employees on average (captured with the ratio of top managers to the total workforce below 5%). For large firms with at least 250 employees, the study can capture *top managers,* responsible on average for about 120 employees.

The results confirm the inverted U-shape relation between gender diversity and productivity, and show that it is especially pronounced for top management (i.e. senior management in large firms) (Figure 18). The peak values of productivity gains – around 2-3%, in Panel A – associated with a 30-50% female share are similar to the results relying on the linked employer employee datasets in the Human Side of Productivity study, even though the two analyses use different sources, definitions and regression specifications. For top managers in large firms, more diversity is associated with an even larger productivity premium (up to 6%, on Panel B). Also, given that the mean female share (around 18%) is below the top of the inverted U relationship, for most firms increased diversity in management means increasing the share of women. Given that there are very few firms with high female shares in top management, the estimates become more imprecise for values higher than 50% (confidence intervals widen and include zero).

Figure 18. Gender diversity in senior management and productivity

Productivity premium as a function of female share in senior management



Note: This graph reports the graphical estimates a quadratic regression on the female share within top management, controlling for detailed industry and country fixed effects and firm age and with cluster robust standard errors at the country-industry level. The values on the vertical axes show the predicted productivity differences of firms (in %) by having higher shares of women in their top management relative to the case when there are no women in top management (0 on the horizontal axis). The vertical lines show the average value of the female share in top management in the sample. Productivity refers to labour productivity on value added, but results are very similar when using production function based MFP estimates (Wooldridge, 2009[95]). The sample covers 9 OECD countries for years 2017 and 2018.

What can public policy do? The role of gender quotas

The work also sheds light on gender quotas for management boards – legally referring to executive or supervisory bodies –, a key potential policy lever to increase gender diversity. In most cases, they apply only for large businesses, based on various minimum thresholds (employment or sales). Figure 19 is suggestive of the effectiveness of such measures in achieving more diverse gender representation in top management: in countries that impose gender quotas, the share of women in the senior management of large firms (with at least 250 employees, that is, firms for which gender quotas are generally binding) is 19.3%, which is more than 3 percentage point more than in countries where such quotas do not exist. There are no such differences among smaller firms across countries with or without quotas.

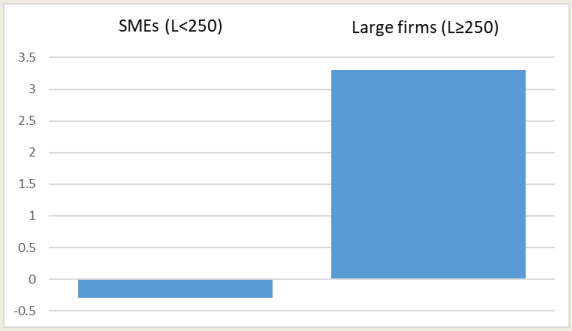
Figure 19. More women in top management when gender quotas are imposed

The share of women in senior management by firm size and by country group

Average share of women in Senior Management (%), 2017-2018

	No Quota	Quota
Large firms (L≥250)	15.9	19.3
SMEs (L<250)	17.8	17.6

Differences in Female Share in Senior Management between countries that have and those that do not have gender quotas in management (% points), 2017-2018



Note: Calculations based on Orbis Financials (2019 Vintage) the Orbis Management Boards & Directors Data and OECD Corporate Governance Factbook (2021). Countries in the sample with gender quotas: Belgium, Germany, France, Italy, Portugal. The sample covers 9 OECD countries for years 2017 and 2018.
Source: Management composition module matched with Orbis by Bureau van Dijk x Moody's as described in Criscuolo, C., P. Gal, C. Koegels, C. Schwellnus (2021b) "Gender composition in top management", forthcoming.

4.2. Cultural diversity

61. Firms that are more culturally diverse, as measured by the share of employees with a foreign cultural background – based on country of origin or nationality – were also found to be more productive. Figure 20 depicts the productivity premia from employing a larger share of managers or workers with a foreign cultural background – holding other factors constant – compared to firms exhibiting the lowest share (<5%). Large productivity gains are associated with employing a culturally diverse managerial workforce: firms that employ 5-10% of managers with a foreign cultural background are about 7% more productive than firms which employ very few or no managers (<5%) with a foreign cultural background. Following again an inverted-U pattern, firms employing very high shares of foreign managers are less productive than those who employ intermediate levels. Productivity gains from cultural diversity reflect a trade-off between gaining a more comprehensive perspective for better decision making and facing higher communication costs. Very high shares of employees with foreign cultural background may diminish productivity as communication costs outweigh information gains. Cultural diversity appears to be relatively

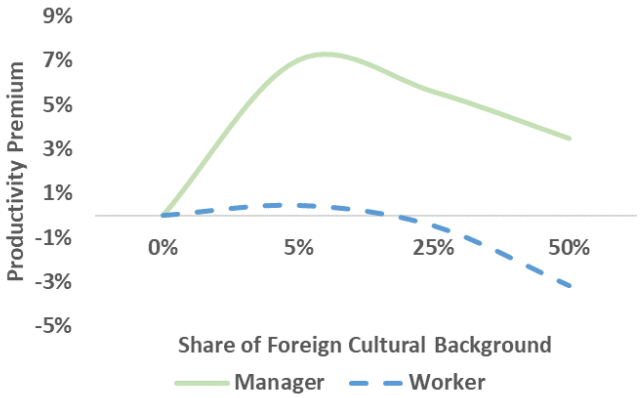
less important among workers – in line with cultural diversity facilitating decision making and information gathering which are more salient tasks for managers. Employing 5-10% of workers with a foreign background is still associated with positive albeit very small productivity gains of about 0.5%; employing higher shares is associated with lower productivity.

62. As with gender diversity, most firms are at the left (lower) segment of the inverted U-shape relationship with productivity: more than three-quarters of firms employ fewer than 5% of managers with a foreign cultural background; and around half of firms employ less than 5% of foreign workers (on average across countries). Thus for most businesses, a more diverse workforce and especially a more diverse managerial staff is likely to be beneficial for productivity performance.

63. The productivity gains associated with higher shares of managers with a foreign cultural background may also reflect the positive effects of being more globally integrated, e.g. as exporters or as subsidiaries of multi-national enterprises. This integration may well be a cause *and* a consequence of employing a more diverse managerial workforce: a more culturally diverse workforce may allow to better integrate into the global economy, but firms already participating in GVCs may also be more likely to hire employees from diverse backgrounds. In either case, it suggests that firms capable of harnessing the potential of globalization find it beneficial to hire employees from a range of different cultural backgrounds.

Figure 20. Productivity gains associated with employing a diverse workforce: Cultural diversity

Productivity gains associated with employing a higher share of employees with foreign cultural background among managers and workers on average across countries



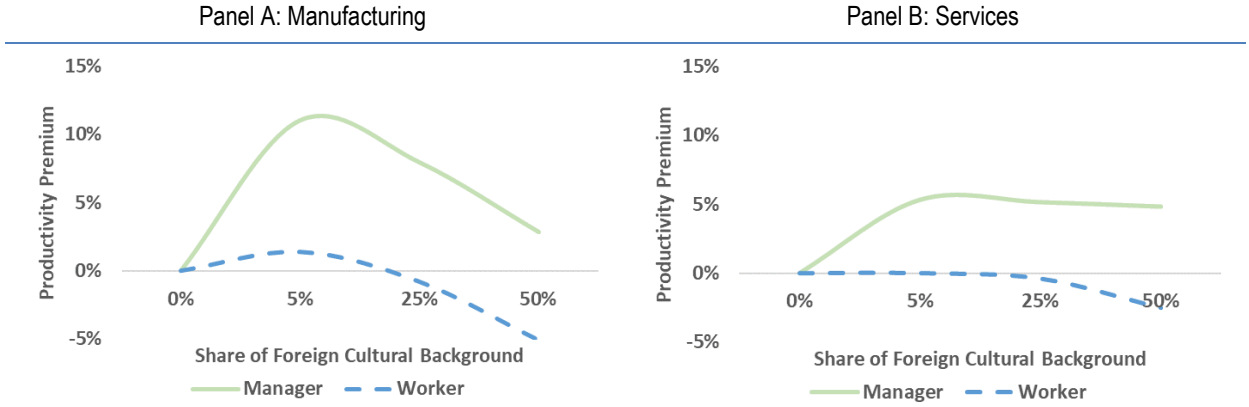
Note: The figure shows the change in firm-level productivity associated with employing a higher share of managers or workers with foreign cultural background respectively compared to the baseline category of having a share of of 0-5% with foreign cultural background in the respective group. Percentage change in productivity is approximated by difference in log productivity. Results are based on coefficients of foreign cultural background share categories among managers and workers on log productivity, estimated from baseline regression at the firm-level separately for each country. Baseline regression described in Annex A and Box 1. Estimates shown are averaged across countries ; estimates insignificant at the 10% confidence level are included with 0 when computing the average. Managers are identified based on 2-digit ISCO 08 occupations. Productivity is measured as log of value added per worker. On average across countries, about 90% of firms are located in the 0-25% region, so the estimates for categories above 25% are based on relatively few observations and thus more uncertain.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

64. Figure 21 depicts the link between cultural diversity and productivity by sector. Cultural diversity among managers is particularly important in manufacturing, with firms employing 5-10% of managers with foreign cultural background being about 11% more productive than firms employing almost none (<5%); these high productivity gains may partly reflect that more culturally diverse firms may be more likely to be exporters. Consistent with this, productivity gains are smaller – but still sizeable around 5% – in services, which are typically more domestic-oriented. Cultural diversity among workers appears to be less important.

While in manufacturing workers' cultural diversity is associated with a small productivity premium of about 1.5%, there is no such association in services.

Figure 21. Cultural diversity and productivity by sector

Productivity gains associated with employing a higher share of employees with foreign cultural background among managers and workers on average across countries by sector



Note: The figure shows change in firm-level productivity associated with employing a higher share of managers or workers with foreign cultural background respectively compared to the baseline category of having a share of of 0-5% with foreign cultural background in the respective group by sector. Percentage change in productivity is approximated by differences in log productivity. Results are based on coefficients of foreign cultural background share categories among managers and workers on log productivity, estimated from baseline regression at the firm-level separately for each country and sector. Baseline regression described in Annex A and Box 1. Estimates shown are averaged across countries by sector; estimates insignificant at the 10% confidence level are replaced with 0 when computing the average. Managers are identified based on 2-digit ISCO 08 occupations. Productivity is measured as log of value added per worker. On average across countries, about 90% of firms are in the 0-25% region, so the estimates for categories above 25% are based on relatively few observations and thus more uncertain.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

4.3. Age diversity

65. Employees' age diversity also affects firm performance as suggested by recent OECD work exploring how the age composition of its employees relates to firm productivity. The study also documents important complementarities between managers and workers of different age groups (OECD, 2020[86]).[17]

66. Results point to especially strong productivity gains from employing older managers: it shows that the average age of managers is higher in more productive firms. In addition, the age gap between the CEO and the median employee increases in parallel with firm productivity: at top performing firms, the CEO is older relative to the rest of the workforce. This may testify to the crucial role of experience for managers – the ability to manage well builds on a broad set of skills, which may take many years to refine.

67. Firms also benefit from combining employees of different age groups among the entire workforce: younger employees are more productive when a larger share of older employees is present, and vice versa. Also, wages of incumbent employees increase after hiring additional, older employees. Employing a mix of employees of different ages may raise productivity because it allows to better leverage the knowledge of more experienced workers, and to improve the skills of younger workers through learning-by-doing. Hiring a mix of employees with different ages can also protect the firm from disruptive worker

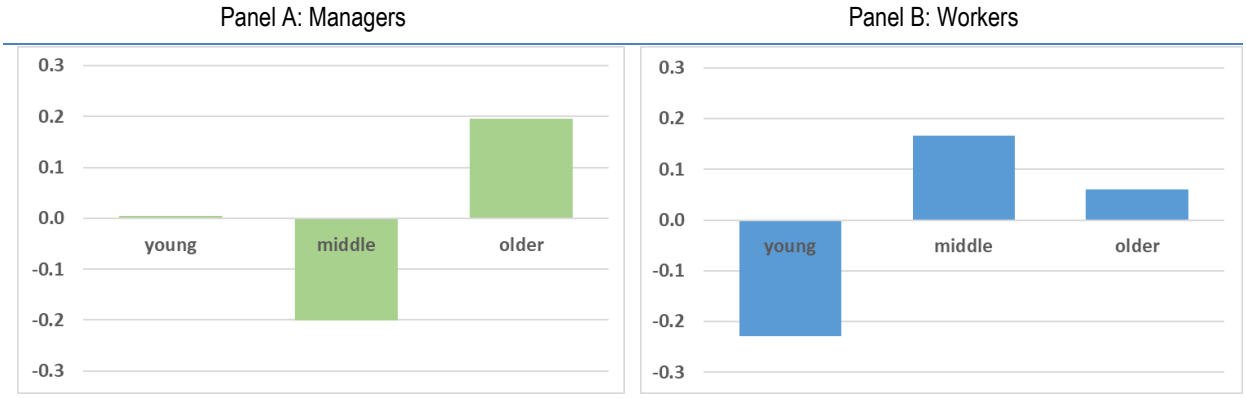
[17] The link between age diversity and productivity has been explored in more detail in (OECD, 2020[86]) in cooperation with the Human Side of Productivity project, which the authors of the current report gratefully acknowledge.

transitions, e.g. if large cohorts of employees would enter retirement at once, or due to the relatively high turnover of younger employees.

68. The finding that age diversity can benefit firm productivity is of particular importance in light of demographic changes observed across countries. With an ageing population, firms experience the forces of demographic change as a pressure to shift towards an older workforce composition – either directly, due to changes in the composition of the active labour force, or indirectly, through increases in the retirement age. Figure 22 confirms that this shift need not harm productivity. In particular, the figure shows that, compared to medium or low-performers, the most productive firms increased their use of older employees – especially managers – most strongly. Over the sample period, on average across countries, top productivity firms increased their share of older managers by about 0.2 percentage points more per year than medium performers. Among workers, top productivity firms increased their share of older workers by about 0.15 percentage points more than medium performers. Thus relying on older employees more intensively, in particular in managerial roles, has been compatible with top firm performance.

Figure 22. Workforce ageing has been more pronounced in firms at the productivity frontier

How much faster or slower did age group shares change at top productivity firms compared to medium performers?



Note: The figure shows the difference in the annualized rate of change in percentage points of age groups between firms at the productivity frontier and medium performers across countries by sector. Age groups refer to young (<30), middle aged (30-49) and older (50+) managers or workers respectively. Annualized rates of change are computed separately for each country-sector as total percentage point change in age group shares divided by number of sample years, and then averaged across countries by sector . Managers are identified based on 2-digit ISCO 08 occupations. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD GFP calculations based on cross-country micro-aggregated linked employer-employee data.

69. In sum, employing a more diverse workforce is associated with sizeable productivity gains – with the positive link between diversity and productivity being much stronger for managers than for the non-managerial workforce. Many firms may forfeit these productivity gains associated with diversity because they are unaware of the potential benefits of a more diverse workforce. Thus policies raising awareness may benefit especially firms below the frontier. In some cases, carefully devised quotas – for instance for female managers – may allow to accelerate the move towards a more diverse workforce across the economy. However, to realize the potential productivity gains from diversity, it seems essential that firms not simply employ more people with different characteristics and backgrounds, but also provide an inclusive work culture in which diverse people feel comfortable to interact and share their insights; enforced diversity, without the necessary inclusiveness prerequisites, could even harm the performance of teams (Creary et al., 2019[96]; Calder-Wang, Gompers and Huang, 2021[97]).

70. Some firms, however, may also be aware but unable to hire a more diverse workforce. Policies aimed at improving the acquisition of skills and especially managerial experience of employees with diverse backgrounds may increase supply, as may policies aimed at facilitating hiring employees with scarce talents from abroad (special visa possibilities or beneficial tax status). Ultimately, activating the potential of hitherto underrepresented demographic groups and supporting labour mobility across countries would allow to drastically broaden the market for talent open to firms.

5. Adding it all up : illustrating the size of the productivity gains

71. Differences in the Human Side of firms account for over one third of gaps between the best and the median productivity performers in the countries covered by this study (Figure 23). In other words, upgrading the Human Side to that of the best performers would close a significant part of such gaps, contributing to lifting aggregate productivity and living standards in our economies, as well as helping to reduce earnings inequality that largely depends on differences in average productivity across firms (Cavalcanti and Tavares, 2016[98]; Criscuolo, Hijzen and Schwellnus, 2020[99]). Using an original dataset combining information about firms and their workers, previous chapters have detailed the individual contributions of skills, management and diversity to the closing of the gaps via upgrading the Human Side. Figure 23 summarises these findings by cumulating the predicted contributions from upgrading all these characteristics. A few lessons emerge from the analysis.

72. First, management is paramount for firm performance. The number, quality and diversity of managers accounts for 16% of productivity gaps. Median performers could boost their productivity significantly by aligning the characteristics of their managerial staff to those of top performers along these three dimensions.

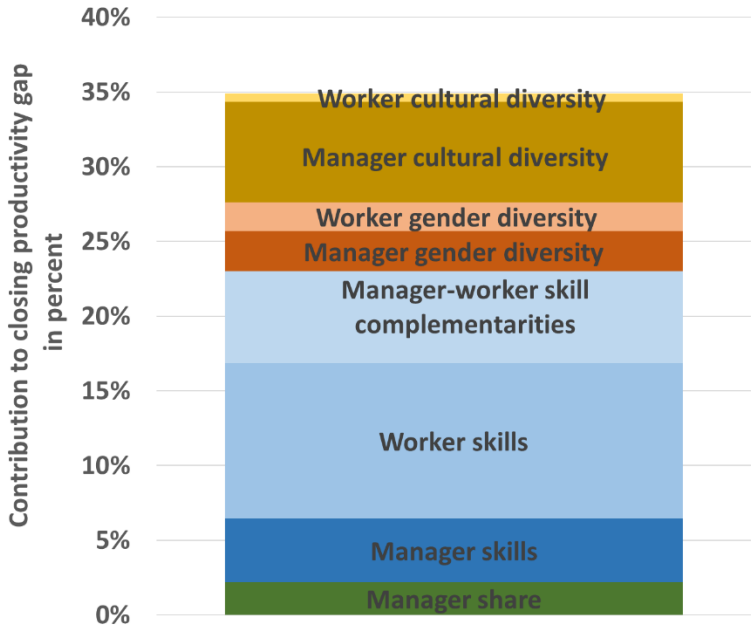
73. Second, adjusting the composition of workers is equally crucial, especially considering the important complementarities between manager and worker skills. Additionally matching the composition of workers to those observed in firms at the frontier is associated with further reductions in the productivity gap by 19%, of which over 6% can be gained from upskilling managers and workers simultaneously.

74. Third, increasing diversity -- especially on the managerial side -- not only contributes to inclusiveness of our economies but also enhances overall efficiency by helping to significantly close productivity gaps. Since closing such gaps also helps reduce inequalities, diversity offers a triple dividend in terms of productivity, integration and equity. But our results also suggest that diversity also involves a trade-off: better decision-making thanks to a more encompassing and better informed perspective stands against a potentially more difficult communication among diverse employees.

75. These general implications of our analysis must be tempered by the consideration that, in practice, changes in the Human Side of firms go together with additional complementary investments in new technologies and business processes and organisation. To the extent that changes in the Human Side are often a precondition for such investments and are harder to achieve then purchasing new equipment, focusing on such changes and designing policies to support them is a priority.

Figure 23. How much can management and diversity contribute to closing productivity gaps?

Estimated productivity gains from simultaneously upgrading all aspects of the *Human Side*, expressed as a percentage of the total productivity gap between median and top performers



Note: The figure shows the productivity gains for medium firm from adjusting components of the Human Side as percentage of productivity gap between top and medium performer. Adjustments for manager-share and skill structure correspond to medium firm adopting values at frontier; for gender and cultural diversity measures, adjustments correspond to non-diverse firm adjusting to diversity levels with the highest estimated productivity levels (gender diversity: 20-40%; cultural diversity: 5-10% of the workforce with foreign cultural background). For manager-share and skill structure adjustments correspond to catching adopting; gender & cultural diversity. Counterfactuals are based on baseline regression described in Annex A and Box 1. More details on the construction of skill groups can be found in Box 3 and in Annex A. Results are first computed by country and then averaged across countries. Manager- and skill classifications based on 2-digit ISCO 08 occupational classifications. Frontier and medium firms refer to 10th decile and 40-60th percentile of the productivity distribution within country x STAN A38 industry x year cells. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

6. A broad-based policy approach to support productivity catch-up through the *Human Side*

76. As shown in previous Sections, differences in the workforce composition can explain about *one third* of productivity differences between typical firms and the productivity frontier. Supporting and incentivizing firms below the frontier to adopt best practices concerning their *Human Side* thus holds the potential to promote catch-up, reduce productivity gaps and boost aggregate productivity; it can additionally reduce economic inequalities that are related to compositional differences between firms, e.g. wage inequality and gender wage gaps.

77. The sweeping trends of digitalisation and globalisation during the past decades have likely been giving even more leverage to the firm's Human Side to affect firm performance. Shortfalls in workforce composition may be increasingly costly. However, existing economic disparities may affect lagging firms' ability to attract suitable workers, rendering catch-up more difficult.

78. Indeed, comprehensive changes to the workforce should be accompanied by further adaptations. For instance, investments in human capital often go together with investments in tangible or other intangible capital and changes in firm organisation. While successful catch-up builds on all these

adjustments, many firms find difficult to finance investments, especially in intangibles, and being able to attract and retain the right talent may prove to be a critical hurdle due, *inter alia*, to skill shortages and market rigidities. Moreover, private incentives to upgrade the workforce may be insufficient, for instance due to the inability to appropriate all returns from investment in training.

79. Therefore, while getting access to the "right" mix of employees is a crucial stepping stone for initiating catch-up and spurring productivity growth, public policies aimed at facilitating and, in some cases, even supporting changes in the Human Side, especially of laggards, are crucial. To stimulate workforce changes, revert polarisation of business performance and achieve broad-based growth in the future, this Section discusses the rationale and the scope for such Human Side oriented policies.

80. A broad-based policy approach is needed to enable and support the comprehensive changes to the firm's workforce needed for productivity catch-up. The broad range of relevant workforce characteristics and the comprehensive nature of adjustments suggest combining cross-cutting policies – facilitating general adjustments – with more targeted policies focusing on specific characteristics of the firm's workforce. Such a policy mix should support catch-up through pursuing three policy objectives: (1) increase the ***supply*** of employees with the needed characteristics, (2) facilitate the ***upgrading*** and restructuring of the existing workforce, and (3) improve the ***matching*** between the existing supply of employees with the firms' demands – a ***SUM*** of various approaches.

81. Addressing these goals with a combination of cross-cutting and targeted policies would maximize the policy impact by bringing to bear important complementarities. For instance, increasing the ***supply*** of general skills through educational policies would make future training more effective. Inducing firms to ***upgrade*** their workforce would raise the demand for skills and activate efforts to invest in skills and up-skill existing employees, including by raising the returns from such investments and upskilling. Cross-cutting policies improving the ***matching*** of skills to jobs would allow to use existing skills more efficiently and, by raising returns on human capital, provide more incentives for employees to acquire skills. Approaching these policy goals simultaneously is also essential to curb productivity divergence and achieve more broad based growth. Improving supply without promoting upgrading and allowing for better matching may disproportionately benefit high productivity firms who are better able to attract talent. Conversely, promoting upgrading and improving matching without increasing skill supply fails to provide firms with the means for a more broad-based catch-up and might not ensure sustained productivity improvements for the longer run. Again, it is in this sense that, to achieve the full potential of productivity gains through the Human Side, the SUM of policies is needed. Table 3 summarizes the policies that could form part of such a comprehensive policy mix, which are discussed in more detail below.

Table 3. Policies supporting catch-up through the Human Side

	Manager share	Manager & worker skills	Manager & worker gender diversity	Manager & worker cultural diversity
Supply	• Management training	• General and vocational education system • Training & lifelong learning	• Social benefit and tax system • Supportive infrastructure & child-care • Address gender inequalities in education	• Immigration policies
Upgrade	• Information campaigns	• Employment protection, social benefit system & active labour market policies	• Management quotas	
Matching	• Product market regulation • Geographical mobility and flexibility through housing, telework and transport • Data-driven career guidance			

Source: GFP.

6.1. Policies increasing labour supply

6.1.1. Improving the quality of the educational system to increase the supply and quality of general skills

82. Fostering the ability and habit to learn enables people to better acquire skills throughout their life. It enables people to attain generally higher levels of educational degrees and increases the supply of general skills. Focusing on improving the capacity to learn early on has a particularly large impact because it acts as a lever for improving learning outcomes for all subsequent stages of education and training.

83. Policies improving the capacity to learn include removing financial and other barriers to participation in early childhood education and care, which can help improve cognitive and non-cognitive skills before entering compulsory schooling and has been shown to improve later education outcomes. Substantial scope exists across OECD countries to improve teaching quality; PISA shows that major differences exist in student performance, equivalent to several years of schooling, towards the end of lower secondary. Teaching quality could be improved by selecting and retaining high ability teachers, incentivising career development and training and encouraging collaboration and exchange among teachers. To reduce early school leaving, systems could be put in place to detect and provide targeted support to low-performing students and schools. High ability teachers may be attracted with financial and career incentives to where there are particular needs, e.g. schools in poor areas. Spending on educational institutions could be raised, which, on average across the OECD, increased less than GDP in recent years; budgetary pressures resulting from the COVID-19 pandemic should not lead to decreases in educational spending. If anything, the COVID-19 pandemic and the resulting lockdown of schools and use of distance learning have made existing educational gaps even more evident and the need for increased investment more pressing. In addition, existing funds may be used more efficiently by improving the governance of the education system, e.g. by better aligning accountability and the capacity to allocate funds and by fostering collaboration between stakeholders (OECD, 2019[72]; OECD, 2020[100]).

6.1.2. Diversify and improve vocational education to increase the supply of a broad range of skills

84. Providing high quality vocational education diversifies educational pathways to match individual needs and equips people with a broad range of relevant skills. It enables future skill acquisition by providing an effective way to integrate young people into the labour market and by opening access to tertiary education, thus offering an additional lever to increase supply of specific and general skills.

85. Substantial scope exists for improving the quality of vocational education by adapting programmes to better combine school- and work-based learning: across the OECD, only one third of students in vocational education are enrolled in programmes combining school- and work-based learning, even though countries with strongly integrated programmes exhibit better labour market outcomes among adults with vocational education. Enabling students to move between programmes and promoting pathways into tertiary education increases incentives for completing vocational education. Drop-out rates for vocational education tend to be comparatively high but are lowest in programmes offering pathways to further education. Many programmes already offer this option – on average across OECD countries 7 out of 10 vocational students have direct access to tertiary education after completion – but few students make use of the opportunity. Take-up could be increased by making information more easily accessible or by removing financial and other barriers (OECD, 2020[100]).

6.1.3. Improving the uptake, relevance and quality of training and lifelong learning to facilitate upskilling

86. Participating in training is a crucial component of lifelong learning, allowing people to acquire and develop skills throughout their lifes and to adapt to changing skill demands, while allowing firms to upgrade their workforce by up-skilling current employees. Improving the uptake, relevance and quality of training would go a long way to improve skill through acquisition and adaptation and facilitate workforce upgrading for firms.

87. To improve training uptake, policies could raise awareness about the benefits and available opportunities for training, e.g. through information campaigns targeted at employers and employees and by providing easy access to comprehensive and user-friendly information. Improving the recognition and accreditation of training courses would enhance the visibility of training and make qualifications more easily transferable, thus increasing incentives for participation. To reduce financial barriers, training costs should be spread across stakeholders benefitting from training, including employers and communities. For Portugal, training grants provided as part of the European Social Fund have been shown to have led to a substantial increase in training expenditure and hours with large and persistent positive impacts on various firm-level outcomes, including productivity and employment (Martins, 2021[101]). Training uptake is particularly low among the low-skilled, who are most in need of up-skilling. The provision of training is relatively low at SMEs, for whom administrative costs or costs of replacing workers during training tend to be higher. Targeted financial support would provide incentives to improve training provision and participation among these groups.

88. To improve the relevance and quality of training, policies should increase coordination among stakeholders, e.g. by fostering partnerships between training institutions, employer and employee associations, to better match training supply with skill demand. Policies should promote monitoring for continuous quality assurance, while allowing for innovation and identifying successful approaches with potential for scale-up. Lastly, policies should leverage digital technologies for training provision, e.g. to reach critical mass to make courses viable or promote “nano courses” teaching the use of specific tools (OECD, 2019[51]). The COVID-19 pandemic might have been a catalyser for the development and uptake for such digital learning and training provision.

6.1.4. Giving particular focus on management training to increase supply of managerial skills

89. Management training increases the supply of managerial skills and helps to disseminate best practices. Devoting particular attention to management training is justified in light of the pivotal role management has for firm performance and, if high uptake and quality can be achieved, promises large gains.

90. To increase uptake, policies should raise awareness about the benefits of management training for firm performance, e.g. through information campaigns and developing diagnostic tools to help firms identify training needs. Providing financial support to incentivize participation, e.g. in terms of tax breaks, can be justified by the large positive impact on productivity that can be expected from improving management quality. Past management training programmes have been shown to have raised firm productivity by 30-50% over a 10 year period (Giorcelli, 2019[57]; Bianchi and Giorcelli, 2021[56]). The wider dissemination of managerial best practices creates positive knowledge spill-overs, e.g. through worker flows or through the supply chain, offering an additional rationale for subsidising management training (Bianchi and Giorcelli, 2021[56]).

91. To increase the supply and quality of management training, policies could establish partnerships between employer associations and training institutions with the aim of fostering management quality. The supply of management training could be raised by devoting more funds to management schools or by increasing the provision of management skills development programmes at educational institutions.

6.1.5. Activating unused potential by addressing gender inequalities to increase women's participation in the labour force participation

92. Tapping into hitherto unused potential by increasing the labour market participation, skill acquisition and allocation of talent of women promises large gains. Activating women offers a lever which, compared to reforms in the educational system, could potentially realise improvements in skill supply fast and at comparatively low cost.

93. To better integrate women into the labour market, policies could remove financial, fiscal and other barriers preventing women from working or stifling their careers. Policy makers may consider adapting their tax systems to reduce potential disincentives for women to work, e.g. by revising tax breaks for single earner households.[18] Motherhood often acts as a break on women's careers. To mitigate the impact on women's careers, parental leave should allow women to return to their previous position. The length of parental leaves should be carefully designed to avoid loss of skills or encourage employer discrimination when hiring or promoting. To this end, parental leave systems could be adapted to share responsibilities more equally among women and men. While many OECD countries offer parental leave to fathers, uptake is low. Providing additional incentives, e.g. "bonus months", could induce more fathers to take parental leave. To better accommodate work and caretaker responsibilities, which disproportionately fall on women, the supply and quality of childcare could be improved. Investments in childcare facilities may be required. Targeted financial support could be offered to improve affordability (OECD, 2017[102]; OECD, 2020[103]).

94. To fully utilise the potential of women in the labour market, policies need to address structural inequalities. Gender-specific differences in exposure and expectations can affect performance and career choices throughout people's lifetime. Some women may be deterred from choosing careers in particular subjects or key positions associated with high productivity, e.g. in STEM or management, for which they exhibit high ability. For instance, exposure to female inventors has been shown to increase the probability of women becoming inventors in the US (Bell et al., 2019[104]). Addressing societal expectations and increasing exposure with a view to activate women to acquire scarce skills, e.g. through mentoring

[18] See more in Harding, Perez-Navarro and Simon (2020[131]).

programmes, business counselling, support in building entrepreneurial networks or information campaigns, may go a long way to increase women's skill supply. Promoting gender equality in public life, e.g. through quotas for management or affirmative action to move more women into public leadership, could additionally tackle stereotypes (OECD, 2017[102]).

6.1.6. Increasing skill supply of employees with foreign cultural background and diverse talent through immigration policies

95. Enabling and facilitating immigration by providing incentives, reducing barriers and providing information, improves access to the global skill supply. It increases the pool of candidates, especially of people with scarce skills, that firms can draw on and allows firms to employ a more culturally diverse workforce.

96. Policies can seek to encourage international labour mobility and attract employees from abroad by providing limited financial incentives, e.g. income tax breaks for a fix time period after taking on employment as done in the Netherlands (OECD, 2021[105]) or in Italy.[19] Targeting incentives at employees with specific skills, e.g. STEM or managerial talent, provides a way to address particular skill gaps in the home country. Policies can encourage immigration also by reducing barriers, e.g. simplifying visa procedures, providing quick visas for specific occupations, providing assistance to settling down, finding housing and child care, facilitating access to the domestic health insurance and pension system, etc. Policies can also help simply by providing information: public campaigns can inform potential candidates about job opportunities as well as about potential incentives and advertise simplified procedures and support for settling down. To reduce mental barriers to immigration and support the establishment of networks, policies could further promote student and work exchange programmes to provide people with at least some degree of experience of living abroad.

6.2. Policies facilitating workforce upgrading

6.2.1. Reviewing the policy mix regulating hiring, dismissals and worker security

97. Reviewing employment protection legislation and related labour market policies to identify any potential to allow firms to better adapt to economic and technological changes while providing workers with job security may yield more flexibility for firms to adjust their workforce.

98. Policies addressing the trade-off between workforce adaptability of firms and workers' need for job security could be reviewed with a view to "protect workers rather than jobs". Dismissal regulations have been shown to reduce labour reallocation and unemployment duration. Revising strict dismissal regulations in combination with active labour market policies and unemployment benefits may offer ways to provide security for workers while giving firms more flexibility to adjust. Denmark, for instance, facilitates labour market reallocation while prodiving support and secure income to workers by combining low restrictions on hiring and firing with high unemployment benefits and strong activation policies ("flexicurity") (OECD, 2016[106]). The policy mix may also be reviewed to reduce labour market duality. Regulatory gaps between regular and temporary employment increase the use of temporary work, which disproportionately affects young workers, and has been associated with lower productivity, e.g. because workers have fewer incentives to acquire firm-specific human capital. Addressing labour market duality holds the potential to reduce overly strict dismissal regulations while improving inclusiveness (OECD, 2020[107]).

[19] In addition to tax breaks for inpatriate foreign workers, Decree no. 34/2019, the so-called 'Decreto Crescita', offered tax incentives for member of their diaspora to come back to Italy, thus allowing the country to benefit from the exposure to foreign culture, knowledge and networks of its emigrants through a "brain-return".

6.2.2. Considering carefully designed management quotas to encourage firms becoming more diverse

99. Considering carefully designed management quotas could induce firms to employ a more gender and culturally diverse management. Given the pivotal role of managers, a more diverse management could lead to important knock-on effects promoting workforce diversity more generally. Besides prompting firms to benefit from potential productivity gains associated with management and workforce diversity, such quotas stand to activate hitherto underrepresented groups and reduce labour market inequalities.

100. Policies promoting quotas on gender or cultural diversity with a view to boost productivity should be designed to carefully balance the need to spur changes in management and workforce diversity with the need for complementary adjustments, e.g. creating an inclusive company culture, that may be required to make diversity beneficial for productivity (Calder-Wang, Gompers and Huang, 2021[97]). Relevant policy dimensions concern the level of quotas and their enforcement, e.g. via law, voluntary targets or disclosure requirements about the gender make-up of the firm's management (OECD, 2020[103]). The level of quotas could be raised gradually to allow firms to adapt while providing incentives to attract, support and promote underrepresented employees early on in their career. Agreeing on quotas in dialogue with social partners, e.g. employer and employee representatives, may allow to better accommodate worker and business needs and achieve wider support.

6.2.3. Creating awareness for the need to and benefits of restructuring the workforce and management through information campaigns

101. Information campaigns promoting knowledge about best practices regarding workforce and management structure could be an effective addition in the Human Side policy toolbox. Such policies should be considered complementary to providing firms with the means to upgrade, e.g. management and other training opportunities. Many firms may refrain from utilising these opportunities due to lack of awareness. Ignorance about good management practices has been cited as an important reason for their limited diffusion (Bloom and Van Reenen, 2010[108]). Relatedly, family owned firms are less likely to use good management practices and suffer from weaker firm performance, arguably due to choosing managers from a more narrow pool (Bloom and Van Reenen, 2010[108]; Andretta, Brunetti and Rosso, 2021[109]). To the extent that the link between family ownership and firm performance reflects lack of knowledge about good management practices, targeted information campaigns could raise performance among these firms.

6.3. Policies improving job matching

6.3.1. Revising the regulatory framework to promote competition and encourage a more efficient use of labour resources

102. Making markets more competitive through product market reforms, e.g. by reducing barriers to entry and trade or reducing regulatory complexity, would help speed up and make reallocation more productivity enhancing. Besides freeing up talent bound up in firms with limited potential for growth, spurring innovation and making it easier to challenge leaders, such reforms stand to reduce managerial slack and – through raising returns on skills – provide additional incentives for skill acquisition finally they might allow smaller and younger player to attract and retain talent in a more levelled playing field.

103. The productivity enhancing benefits of product market reforms are well established. Pro-competitive reforms have been shown to boost productivity, investment in capital and employment (e.g. Nicoletti and Scarpetta (2003[110]) and Gal and Hijzen (2016[111])) Well-designed product markets and bankruptcy laws are associated with lower skill mismatch across countries (Adalet McGowan and Andrews, 2015[112]). They may also help to counteract the polarisation of the business environment. In fact, in sectors

where pro-competitive reforms were least extensive productivity gaps increased the most (Andrews, Criscuolo and Gal, 2016[4]).

104. Substantial scope remains for improving competition in OECD countries, despite important achievements in recent years. In particular, the majority of OECD countries could further improve competition by reducing barriers to entry in retail trade and professional services, cutting red tape for new firms, improving the governance of state owned enterprises and in addressing lobbying (Vitale et al., 2020[113]) and adapting anti-trust policies to the digital transformation. Digitalisation, especially boosted by additional investments during the pandemic, creates particular challenges for market dynamism to the extent that large platform-based digital services benefit from strong network effects and make entry more difficult. Accordingly, the competition policy's toolkit should be updated to be more forward looking to prevent too much concentration on product and labour markets alike, to ensure the ability of less dominant firms to attract and retain skills (OECD, 2021[114]).

6.3.2. Promote geographical mobility and flexibility of employees by improving housing, transport and by leveraging flexible working arrangements

105. Higher mobility brings firms and people closer together. It improves job matching between firms and employees and encourages labour market participation. Besides providing firms with better access to skills, improved job matching can raise returns to skills and thus wages and can reduce regional economic inequalities. Large scope exists for promoting mobility through better housing and transport and promoting the widespread use of telework (Causa and Pichelmann, 2020[115]).

106. To improve housing conditions, policies should encourage investments to raise supply and to reduce house prices and rents especially in urban areas. House prices and rents have been rising disproportionately in recent years and are making up an increasingly large share of household spending. Affordability has been particularly affected in job-rich urban areas. This restricts people's ability to move to areas with the best job prospects and, conversely, firms' ability to attract suitable candidates. In fact, countries with housing policies more conducive to residential mobility exhibit lower skill mismatch, suggesting it is easier for employees and firms to match well (Adalet McGowan and Andrews, 2015[112]). Increasing public investment in housing – which on average across OECD countries has been shrinking from 0.17% of GDP in 2001 to 0.06% in 2018 – could increase the supply of affordable housing in job-rich areas. Land-policy reforms could remove obstacles to investment and improve governmental decision making –. by removing overly tight building height restrictions, minimum lot size requirements, or addressing coordination failures between often several authorities involved in planning and decision-making. To incentivize construction and mobility, taxation could shift from housing transaction taxes to annual taxes on immovable property, with current land prices rather than the value of structures serving as tax base. Additional policy areas could concern revising landlord-tenant regulations, tax benefits for mortgages and compensatory measures to reduce costs for meeting stringent environmental standards (OECD, 2021[116]).

107. Policies promoting the widespread use of telework should encourage and enable its voluntary use and improve gains from telework for productivity and well-being, while assuring that welfare gains from telework are widely shared. Policies could promote investments to enhance the capability and resilience of the communication infrastructure and bridge the digital divide between urban and rural areas. Policies could promote training to provide managers and workers with the skills to telework more efficiently, e.g. as done in Italy; particular attention may need to be given to train and up-skill low skilled workers, who tend to benefit less from telework than the high skilled workers (OECD, 2021[49]). The creation of co-working spaces across the country could create suitable working spaces while facilitating knowledge transfer. Bilateral tax agreements or adaptations to the social and pension systems could facilitate cross-border working. Regulations may need to be revised in dialogue with social partners to mitigate side effects such as hidden overtime or to prevent national labour standards being undermined (OECD, 2020[71]). More

widespread telework would substantially reduce commuting times, thus allowing firms to hire employees living further away. Voluntary telework may also improve efficiency in itself, e.g. by increasing employees' ability to focus on demanding cognitive tasks and, indirectly, by contributing to their well-being. In fact, most employees and managers wish to continue teleworking more frequently in light of recent, mostly positive, experiences during COVID-19, and most managers wish to do so because they expect better firm performance (Criscuolo, 2021[70]).

108. Improving transport could complement policies on housing and telework to increase mobility and flexibility further. Re-evaluating transport needs and promoting infrastructure investments, e.g. in high-speed rail, in light of the more widespread use of telework could substantially widen commuting zones. When doing so, policy makers should follow best practices addressing the deep uncertainty involved in long-term strategic transport planning (ITF, 2021[117]). Besides further enlarging the pool of candidates firms can draw on, it could further relieve pressure on densely populated areas and help addressing the supply-demand mismatch in housing.

6.3.3. Improving the collection and provision of information for career guidance to reduce mismatch

109. Providing easy access to high quality and timely information about the labour market outcomes of different career paths enables people to make more informed career decisions that are better aligned with labour market needs.

110. The high prevalence of field-of-study mismatch and qualification mismatch suggests scope for reducing mismatch by providing more information on labour market outcomes associated with different career choices throughout people's life. Policies could promote career guidance systems by collecting and making easily available systematic information on employment rates and wage distributions associated with different career paths (OECD, 2019[51]).

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Annex A. Data and methodology

1. This Annex provides details on the dataset and methodology underlying the results discussed in this report. First, it describes the dataset construction and what information it contains. Second, it describes the methodology used to conduct the analysis.

Building a dataset on firms and their employees across countries

Distributed microdata approach

2. The main analysis of the Human Side of Productivity is based on a cross-country micro-aggregated dataset with detailed information on firms and their employees. In order to build this novel dataset, the OECD adopted a *distributed microdata (DMD)* approach. This approach builds on a network of country partners brought together under the auspices of the OECD Global Forum on Productivity.

3. *Data access* for each country was achieved through country partners who had direct access to the confidential micro-data such as social security records or tax records of individuals and x or companies. Together with these partners, the OECD liaised on the basic data structure and properties (metadata), specified the required data preparation steps to carry out on their side and shared a common set of program codes. These codes, first, implemented additional data preparation and harmonisation and, second, conducted analyses, which in turn produced a set of micro-aggregated results – detailed summary statistics and regression results – satisfying the country-specific confidentiality requirements. After country partners ran these codes on the micro-data, they sent results and log-files to the OECD for further analysis in a centralised manner. For a few countries, data access was simplified, and the OECD had in-house access to the micro-data and proceeded with the data preparation and implementation of the analysis in line with the instructions agreed with country partners.

4. This micro-distributed data approach allows for a substantial degree of *harmonization* across countries. First, data preparation was harmonised through liaison with country partners about basic data preparation and through further data preparation via a common set of codes. In particular, this allowed to harmonise the coverage of firms and employees included in the analysis and the definition of variables, including the conversion of occupational and educational variables to common, international classifications (ISCO and ISCED, respectively). Second, data analysis was harmonised as it was based on a common set of codes that was produced by the OECD and shared with country partners, which assured that results were produced in a comparable fashion across countries. Throughout this process, the OECD team could draw on extensive experience with previous projects using DMD analysis, notably from the OECD MultiProd and DynEmp projects.

Description of the dataset

5. This approach allowed to construct a micro-aggregated dataset drawing on detailed information on firms and their employees for 10 countries (Belgium, Costa Rica, Denmark, France, Germany, Hungary, Italy, Japan, Portugal, Sweden), generally covering the full population of salaried workers and full population of firms in the business sector with at least 10 employees and spanning a period from 2000 until 2018. Exceptions for data coverage are Japan, which covers firms with at least 50 employees, and

Germany, which is based on a representative sample of establishments, covering about 15.500 annually.[20] Table A1 summarizes the information contained in the each country dataset, including the period covered and coverage of key variables.

Table A.1. Data coverage by country

Coverage of period and key variables in the underlying country-specific linked employer-employee datasets

	Period	Output		Labour input		2-digit ISCO 08 occupations	ISCED 2011 educational attainment	Foreign cultural background	Part-time	Capital intensity
		Gross output	Value added	Number of employees	Hours worked					
BEL	2000-2018	X	X	X	X	-	X	X	X	-
CRI	2006-2017	X	X	X	-	X	X	X	-	-
DEU	2000-2016	X	X	X	-	X	X	X	X	-
DNK	2008-2017	X	X	X	X	X	X	X	X	-
FRA	2002-2015	X	X	X	X	X	-	X	X	Tangible & intangible
HUN	2009-2018	X	X	X	X	X	-	-	X	Tangible & intangible
ITA	2015-2018	-	X	X	-	-	X	X	X	-
JPN	2000-2013	X	X	X	X	-	X	-	X	-
PRT	2002-2017	X	X	X	X	X	X	X	X	Tangible & intangible
SWE	2001-2018	X	X	X	-	X	X	X	-	Composite measure

Note: The table summarizes the key information contained in the country-specific linked employer-employee dataset underlying the cross-country analysis. Period coverage refers to the datasets prepared by country partners, which are at the employee x firm x year level. The sample population for each dataset generally refers to the full population of firms with at least 10 employees in the non-farm, non-financial business sector and the full population of salaried employees at these firms. Exceptions are Japan, for which firms with at least 50 employees are covered, and Germany, where the data correspond to a representative establishment sample covering about 15.500 establishments per year.

6. The basic dataset prepared by country partners contained information at the employee x firm x year level, with repeated identifiers for firms across years. If applicable, country partners and OECD liaised to convert country-specific occupational and educational classifications to 2-digit ISCO 08 and ISCED 11 codes.

7. Using the common codes prepared and shared by the OECD, basic data cleaning was implemented to restrict the dataset to observations on employees aged between 15 and 85 years old and excluding observations on firms with less than 10 employees and firms in STAN A38 industries agriculture, fishing and forestry (STAN A38 code 1); financial and insurance activities (STAN A38 code 64); public sector, education and other services (STAN A38 codes 84 to 96). Observations with missing information

[20] The following datasets were used for each country: linked employer-employee data from CBSS and NBB for Belgium; CRLEED and REVEC for Costa Rica; FIRE, IDAN, IDAP, UDDA, BFL, BEF, and RAS for Denmark; DADS (cross-section) and FICUS-FARE for France; LIAB for Germany; linked annual CIT and employers' monthly employee level social security and payroll tax filings for Hungary; ASIA occupazione and RACLI for Italy; Basic Survey on Wage Structure and Basic Survey of Japanese Business Structure and Activities for Japan; QdP and SCIE for Portugal; LISA and FEK for Sweden.

on key employee and firm variables were dropped (for firms: gross output, employment, industry; for employees: age, gender, wage, occupation [if applicable]). After constructing key variables at the employee-level, the dataset was collapsed to the firm x year level. Note that productivity measures and wages were computed in logs, effectively dropping observations on firms with negative value added.

8. To minimise measurement error or noise, outlier-filtering was implemented by computing annual productivity growth rates and dropping the entire firm if in any year it exhibited growth rates in the topxbottom percentile of the growth rate distribution within STAN A38 industries for any productivity measure, or if in every year no growth rate could be computed.[21] Afterwards, continuous variables were replaced with 3-year backward-looking moving averages. Note that this effectively removed firms with less than 3 consecutive periods (i.e. very short lived firms).

9. After outlier-filtering, firms were grouped into deciles of the annual productivity distribution within STAN A38 industries. Groupings were blanked if less than 10 moving-average firm-level observations were available within STAN A38 x year cells. Table A2 reports basic summary statistics on employment and wages by productivity group for each country. It reveals that employment and wages both rise as we move higher up the productivity distribution.

Table A.2. Key firm characteristics along the productivity distribution

	Productivity group	BEL	CRI	DEU	DNK	FRA	HUN	ITA	JPN	PRT	SWE
Normalised mean log productivity*	Laggard	-1.0	-0.9	-0.9	-0.7	-0.8	-1.1	-0.8	-0.7	-0.8	-0.6
	Frontier	1.0	1.5	1.1	0.8	0.9	1.3	1.1	0.7	1.2	0.8
Mean employment	Laggard	214.9	44.1	69.2	40.4	67.8	46.2	33.6	948.9	45.3	39.3
	Medium	101.5	72.2	216.6	58.6	97.9	103.3	56.0	1202.6	71.4	71.9
	Frontier	344.5	259.5	349.9	114.1	244.3	174.5	135.3	2050.4	150.7	159.9

Note: The table provides summary statistics on firm-level employment and wages by productivity group. Results show the average or mean log productivity and the level of employment, originally computed at the productivity group x STAN A38 industry x year level for each country and then averaged to the productivity group by country. Frontier, median and laggard firms refer to 90th, 40-60th and 10th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
* Mean log productivity normalised by computing difference between log productivity with median firms.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

Definition of key measures

10. The preparation of the dataset yielded the following key measures at the firm × year level separately in each country's national database:

- **Productivity:** The baseline measure for productivity is constructed as value added per employee (headcount, to maximise comparability across countries); alternative measures computed for the analysis included the logarithms of value added or gross output per employee and hour worked (or full-time equivalent, if available) respectively (always in logs).
- **Productivity group:** For each productivity measure, firms were assigned to productivity groups based on productivity deciles of the annual productivity distribution within STAN A38

[21] This step, besides minimising the risk of reporting errors, also removes firms that underwent genuine but radical changes due to, for instance, mergers or split-ups; or had extraordinary revenues.

industries as follows: frontier (10th decile), close to frontier (7-9th decile), medium (5-6th decile), low medium (2-4th decile), laggard (1st decile).

- **Capital intensity:** Capital intensity was computed as the stock of (tangiblexintangible) capital per employee (in logs). Capital intensity measures were constructed separately for tangible and intangible capital. If information on capital was available but not separately for tangible and intangible capital, a measure for capital intensity was constructed without distinguishing tangible and intangible capital.
- **Skill shares:** Several skill shares were computed – among all employees and among various employee sub-groups, e.g. managers and non-managers, men and women, etc. – by identifying the respective employees at the employee x year level and collapsing to the firm-level:
- PIAAC based measures: For each measure, groupings were computed as follows: first, using results based on PIAAC results, average scores were computed for 2-digit ISCO 08 occupations. Second, using these average scores, occupations were ranked (where available, rankings were based on country-specific average scores; otherwise, scores averaged across available countries were used). Occupations in the bottom (top) quartile were grouped as low (high) skilled in the respective measure; occupations in the middling quartiles were grouped as medium skilled.
    - Cognitive skills: 2-digit ISCO 08 occupations were ranked based on the occupation-specific average of the PIAAC test scores averaged across numeracy, literacy and problem solving in technology-rich environments. For robustness, rankings were produced excluding test scores on problem solving, which left the rankings largely unchanged.
    - Management and communication skills: 2-digit ISCO 08 occupations were ranked based on indicators for managing and communication skill requirements, which have been derived from several PIAAC items using factor analysis in Grundke et al. (2017[42]). Helpful support and advice from the authors is gratefully acknowledged.
    - ICT skills: 2-digit ISCO 08 occupations were ranked based on an ICT composite variable which, following Nedelkoska and Quintini (2018[43]), reflects several PIAAC items on the use of ICT at the job and in everyday life. Helpful support and advice from the authors is gratefully acknowledged.
- Education based measures: ISCED 2011 educational attainment levels were assigned to low (levels 0 to 2; less than primary, primary and lower secondary), medium (levels 3 to 4; upper secondary and post-secondary non-tertiary), and high skill (levels 5 to 8; tertiary) groups.
- Wage based measures: Occupations were ranked based on their average wage over the sample period. Average occupation-specific wages were computed by first averaging wages by year and then averaging across years. Rankings use employment weights. Occupations in the bottom (top) quartile were assigned to low (high) skilled; occupations in the middling quartiles were assigned to medium skilled. If available, 2-digit ISCO 08 occupations were used; otherwise country-specific occupational classifications were used. If country-specific classifications were too broad to group employees into quartiles based on their occupation, as was the case for Italy, rankings were based on STAN A38 industry x occupations.
- **Manager share:** Manager shares at the firm-level were computed by identifying employees as managers at the employee-level and collapsing to the firm-level. Employees were first identified as managers based on their 2-digit ISCO 08 occupation (codes 11-14). Then, the average of manager shares were computed by firm-size class x STAN A38 industry, serving as a “benchmark” value for that group of firms. Next, for firm-years for which no manager was identified based on occupations, managers were identified based on the annual wage

distribution *within* firms, grouping the highest earning employees as managers, to match the respective benchmark manager share in the group where the firm belongs to. Finally, at firms that were too small to identify a manager using benchmark shares (e.g. for a firm with 12 employees and a benchmark manager share of 8%), the top earning employee was identified as single manager.

- **Foreign cultural background share:** Shares of employees with foreign cultural background were computed by identifying the cultural background of employees, based on information about either their nationality or country-of-birth, and then collapsing to the firm-level. Shares were computed among all employees and among managerial and non-managerial employees separately. Two different classifications were computed: first, a binary category of "foreign" and "non-foreign" cultural background, by grouping all employees as "foreign" whose nationality or country-of-birth did not correspond to the respective domestic country.[22]

Analysing the Human Side of Productivity: linking skills, diversity and firm organisation to firm productivity

11. The data preparation described above resulted in an intermediate firm-level dataset for each country, to be used in the subsequent analyses. Two sets of analyses were implemented through the codes shared by the OECD: first, a set of micro-aggregated summary statistics, satisfying country-specific confidentiality requirements, was derived. Second, a set of regressions was estimated using firm-level data, for all and different subsets of the data, for which point estimates, confidence intervals and other relevant information were retrieved. Country partners sent both sets of results for their country, if possible along with log-files for the data preparation and analyses, to the OECD to assemble a dataset of cross-country micro-aggregated results for further analysis.

Detailed summary statistics

12. Descriptive results for all firm-level measures were produced for each country by collapsing the firm × year level longitudinal data to the productivity group × STAN A38 industry × year level. Measures computed while collapsing included averages (e.g. shares for different employee groups, productivity, employment, wages), the median for selected variables (e.g. for employment, wages), and the sum of the number of observations on firms and workers.

13. Country-specific confidentiality requirements (minimum number of firms x employees; the maximum revenue share accounted for by a single firm) in each productivity group × STAN A38 industry × year cell were automatically applied by the code. Cells not satisfying confidentiality requirements were blanked. This could result in loss of information for descriptive statistics, which, however, would not affect information used for firm-level regressions, especially when datasets were small (e.g. as for Germany).

Regression analysis

14. The analysis estimated various regression specifications for each country at the firm-level. Regressions were estimated for several measures of key variables (e.g. productivity or skill measures) and for different subsets of observations (e.g. among all observations, separately by sector and by time period)

[22] A more detailed grouping was also created, following Mensah and Chen (2014[132]), to assign employees based on their nationality or country-of-birth into 10 distinct categories (domestic; Anglo-Saxon; German; Nordic; Eastern European; Latin European; Middle-Eastern; African; Latin-American; Confucian; South-East Asian). However, the results based on this grouping would need further analysis to arrive at clear conclusions.

and for different employee-groups (e.g. shares referring all employees, or differentiating between managerial and non-managerial employees).

15. The most general and extensive regression specification – which underlies results in Sections 2-5 and the main counterfactuals – is as follows:

$$prod_{ijt} = \beta_0 + \sum_{g \in M,W} \Big(\beta_1^g young_{ijt}^g + \beta_2^g old_{ijt}^g + \beta_3^g \left(young_{ijt}^g \times old_{ijt}^g \right) + \sum_{c=2}^{5} \gamma_c^g women_{cijt}^g + \sum_{c=2}^{5} \omega_c^g culture_{cijt}^g + \beta_4^g low_{ijt}^g + \beta_5^g high_{ijt}^g + \beta_6^g \left(low_{ijt}^g \times high_{ijt}^g \right) + \beta_7^g (high_{ijt}^g)^2 \Big) + \beta_8 \left(high_{ijt}^M \times high_{ijt}^W \right) + \vartheta_1 managershare_{ijt} + \vartheta_2 wagestructure_{ijt} + \vartheta_3 taskvariety_{ijt} + \vartheta_4 parttime_{ijt}^{Female} + \vartheta_4 parttime_{ijt}^{Male} + \sum_{c=2}^{3} \theta_c firmsize_{cijt} + \delta_{jt} + \varepsilon_{ijt} \quad (2)$$

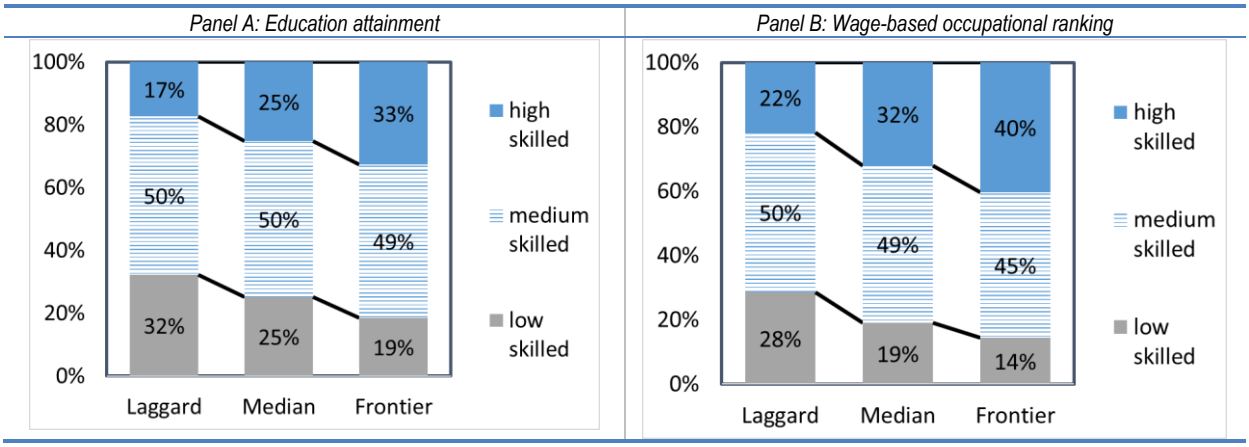
where $Prod_{ijt}$ is the log of value added per employee of firm i in industry j in year t; $young^g$, old^g refer to firm i's share of young (15-30 years) and old employees (50-85 years) among employee group $g \in M,W$, with M denoting managers and W workers. Variables $women_c^g$ and $culture_c^g$ denote dummies for the firm's share of women – or employees with foreign cultural background – falling into the share bin c, for managers and workers separately (share bins correspond to quintiles for $women$ and shares 0-0.05, 0.05-0.1, 0.1-0.25, 0.25-0.5, 0.5-1 for $culture$). The omitted category in either case refers to the lowest share. Variables low^g, $high^g$ refer to the firm's share of low and high skilled employees, based on the respective skill measure, for managers and workers separately (in more simplified versions there is no differentiation between these two groups). The variable $managershare$ denote's the firm's share of managers among its entire workforce.

16. The regression includes several additional variables controlling for firm characteristics. The variable $wagestructure$ measures the firm's wage structure defined as the ratio of the average of the log wage of managers versus non-managers. The variable $taskvariety$ measures the firm's degree of task specialisation measured as 1 minus the Herfindahl-Hirschman index over detailed occupations (at ISCO 08 2-digit level or the most detailed available). The variable $parttime$ measures the firm's share of employees working less than full-time among the firm's entire workforce separately for men and women (when available). The variable $firmsize_c$ denotes dummies for the firm's employment size (10-49; 50-249; 250+ employees; omitted category 10-49).

17. The regression controls for detailed STAN A38 industry × year fixed effects, denoted δ_{jt}. The error term is denoted ε_{ijt} . Standard errors were clustered at the firm-level. All variables that are part of interaction terms were de-meaned before entering the multiplication.

Annex B. Additional results

Figure B.1. The link between productivity and skills: alternative skill measures



Note Figure shows workforce skill composition along the productivity distribution. Workforce composition shown as firm-level shares of low, medium and high skilled employees. Firm-level shares are computed as average firm-level skill group shares by productivity group x STAN A38 industry x year x country; results shown are averaged by productivity group across STAN A38 industries x years x countries. In Panel A, education attainment based skills relate to primary and lower secondary ("low"), upper secondary and vocational ("medium") and tertiary ("high"), following ISCED categories. In Panel B, wage-based occupational ranking based skills ranks occupations by observed average wages and divides them into the top and bottom 25% segment for high and low skilled, respectively, and the rest as medium. More details on the construction of skill groups can be found in Box 2 and in Annex. Frontier, median and laggard firms refer to 90th, 40-60th and 10th percentile of the productivity distribution by country x STAN A38 industry x year. Productivity is measured as log of value added per worker.
Source: OECD calculations based on cross-country micro-aggregated linked employer-employee data.

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