Background paper

The Human Side of Productivity: Setting the Scene

By the OECD GFP team

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The Human Side of Productivity: Setting the Scene

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Preliminary

Conference background paper for the 4th Annual Conference of the OECD Global Forum on Productivity

Abstract

This paper sets the scene for the new project of the OECD Global Forum on Productivity: the *Human Side of Productivity*. It motivates how opening up the "black box" of the firm – to take account of the people therein (owners, managers and workers) – can advance our understanding of weak aggregate productivity growth and the large productivity differences across firms. It discusses the key channels and mechanisms through which the human side characteristics of firms matter, highlighting also existing relevant empirical evidence. It then outlines a measurement framework for providing a new set of stylised facts across countries on the role of skills and diversity for firms at different segments of the productivity distribution, by accessing detailed confidential linked employer-employee databases (distributed microdata analysis). Preliminary results from two pilot countries – Portugal and Denmark – are presented to highlight the potential for extensions to other countries. Finally, the broad range of potential policies are discussed, highlighting how they can change incentives, capabilities and the dynamism of people in and across firms and through that, productivity outcomes.

"Yes, excessive automation at Tesla was a mistake. [...] Humans are underrated."

Elon Musk, 13 April 2019

1. Introduction

1. Improving productivity growth is the ultimate source of economic growth and rising living standards over the long run. Alas, aggregate productivity growth has been slowing in most OECD economies in recent decades, starting well before the global financial crisis (OECD, 2015[1]; OECD, 2019[2]).[2] This sluggish performance seems at odds with the emergence of information and communication technologies and the yet more recent wave of digital technologies, which are expected to deliver important efficiency gains. This "productivity puzzle" has led to an intense debate about the nature of these innovations and their productivity impacts (Brynjolfsson and McAfee, 2012[3]). In addition,

[1] The paper has been prepared by members of the OECD Global Forum Secretariat. They would like to thank Priscilla Fialho (Portuguese data), Søren Gaard, Katrine Bagge Thorball, Christina Charis Godtfredsen, Dorte Høeg Koch and Magnus Skafte-Larsen (Danish data) for providing access to the matched employer-employee dataset from their countries and running the Stata codes. The authors also thank Sarah Michelson (OECD Economics Department) for excellent editorial assistance.

[2] Recently released labour productivity developments are more positive in a few countries (US, UK) but it is too early to tell whether the long-standing decline in productivity growth is about to reverse.

an ageing society and the plateauing of educational attainment levels act as further obstacles to income per capita growth by limiting the contribution of labour and human capital to economic growth (Gordon, 2015[4]). To counteract these and other headwinds (such as environmental degradation and rising inequality, see Braconier, Nicoletti and Westmore (2015[5])), it is all the more important to find effective public policy solutions to revive productivity in a sustainable way.

2. It has proven useful to take a granular, firm-level approach to shed some light on the productivity puzzle. This line of research uncovered large and persistent differences in the productivity performance across businesses, even within narrowly defined sectors (Bartelsman and Doms, 2000[6]; Syverson, 2011[7]). It has shown that the extent to which the more productive firms capture a larger share of resources – higher allocative efficiency – matters greatly for aggregate productivity (Bartelsman, Haltiwanger and Scarpetta, 2013[8]), but that it has deteriorated in certain countries, notably in Southern Europe (Gopinath et al., 2017[9]). There is also evidence about a growing dispersion in productivity across leading and lagging firms, within several individual countries (Berlingieri et al., 2017[10]) as well as globally (Andrews, Criscuolo and Gal, 2016[11]).3 These findings indicate that the widespread diffusion of the latest technologies and business practices is not a given – even though the best performing segment of firms manages to benefit from them. This provides an important clue as to why digital technologies are everywhere except in the (aggregate) productivity statistics – to paraphrase the famous quote by Robert Solow from 1987.4

3. Taking into account the large heterogeneity across firms is also crucial to design more targeted, more country-specific policy responses to the productivity challenge. Policy reforms and structural changes – such as digitalisation and globalisation – can have different effects on firms depending on where they are in the productivity distribution (Gal et al., 2019[12]). Firms at the top ("frontier") tend to advance through genuine innovations while for firms at the bottom ("laggards") it is more about the successful adoption of existing technologies and business practices (Berlingieri et al., 2018[13]). In other words, firms have different abilities to achieve productivity benefits, and policies can have diverse effects depending on the nature of the productivity challenge that a country is facing.

4. But what drives these differences in the abilities of firms? The "Human Side of Productivity" project of the Global Forum on Productivity aims to answer this question by opening up the 'black box' of the firm and by considering the key people within them: workers, managers and owners. The project seeks to provide a new set of stylised facts on the skill composition and the diversity (along gender, age and possibly cultural background) of the most productive firms, comparing it with medium performers and the least productive segment of firms. To better understand the changing role of skills, it is indeed crucial to build the evidence base about how intensively the most productive firms use workers with different skill levels compared to medium performers and laggards; how this varies by sectors with different technologies; and how this changes over time. For instance, it is not yet clear whether the most productive firms rely on a larger and larger share of high skilled workers (increased sorting) or rather an appropriate combination of various skills (increased complementarities between skills). Documenting how these

[3] These diverging trends are observed on average across sectors and countries but they are not uniform across them.

[4] "You can see the computer age everywhere but in the productivity statistics." (Solow, 1987[100])

patterns vary across countries with different institutional and policy settings will also provide a link to the role public policies can play in shaping productivity outcomes.

5. In the context of the intense debate on the rising adaptability required of workers, risk of automation for future jobs and more general concerns about inclusiveness, the human side of firms is more important than ever (OECD, 2018[14]). The combination of historically high employment rates in many OECD countries, rising skill shortages reported by companies but low wage growth points to substantial mismatches between the demand and supply of skills. It also raises the question whether the current wave of technological change is primarily a substitute or complement for workers. The answer is likely to depend on the type of tasks the workers are performing (Acemoglu and Restrepo, 2019[15]). With detailed information on the type of occupations that workers have, it is possible to investigate this issue.5 Looking forward, and potentially in other related projects, detailed information on the movement of workers across firms along their career can also be useful to explore wider issues, such as the social costs of the increased dynamism and flexibility that are needed in a rapidly changing technological environment.

6. This conference background paper sets the scene for analysing some of these questions. First, it describes the main channels and mechanisms through which the "human side" of firms plays a role, highlighting the existing empirical evidence (Section 2). It then proposes a measurement framework that allows building comparable cross-country evidence on these issues (Section 3). This involves several modules, notably i) on the role of skills and occupations, ii) on diversity along several diversity dimensions (age, gender, nationality), iii) on management practices and iv) on organisation. Previous analysis considered the firm as a 'black box' largely because of difficulties in accessing more detailed information about firms in a comparable systematic manner across countries. This project attempts to make progress by tackling some of these data limitations, primarily through distributed microdata analysis of linked employer-employee datasets, building on OECD expertise and a network of contacts that was partly built up in the MultiProd and Dynemp projects (see Box 1 and examples (Berlingieri et al., 2017[10]; Criscuolo, Gal and Menon, 2017[16])) as well as recent collaborative OECD projects focusing on these data (OECD, 2019[17]). In addition, national management surveys and information on ownership can be potentially drawn on.

7. Section 2 also features a set of preliminary results from two "pilot" participating countries who kindly provided early access to their linked employer-employee data: Denmark and Portugal. Simple descriptive statistics and regressions obtained from these data confirm that as we move higher in the productivity distribution – from laggards through medium performers to the frontier – firms employ a higher fraction of high skilled workers (both measured by occupations and by educational attainment) and a higher fraction of managers. Over time, the share of skilled worker increased in each segment of the firm distribution, but most strongly at the frontier. Differences across firms regarding demographic diversity (gender and age) are much more weakly related to productivity according to these preliminary results. These initial findings serve as an illustration of the potential use of these combined micro-databases, and will be further enriched in subsequent stages of the project with a more detailed look by sectors and by involving more countries.

[5] The changing task content *within* occupations cannot be tackled with such data. However, this limitation is mitigated to some extent when more detailed occupation categories are used in the analysis for which tasks are more likely to remain stable.

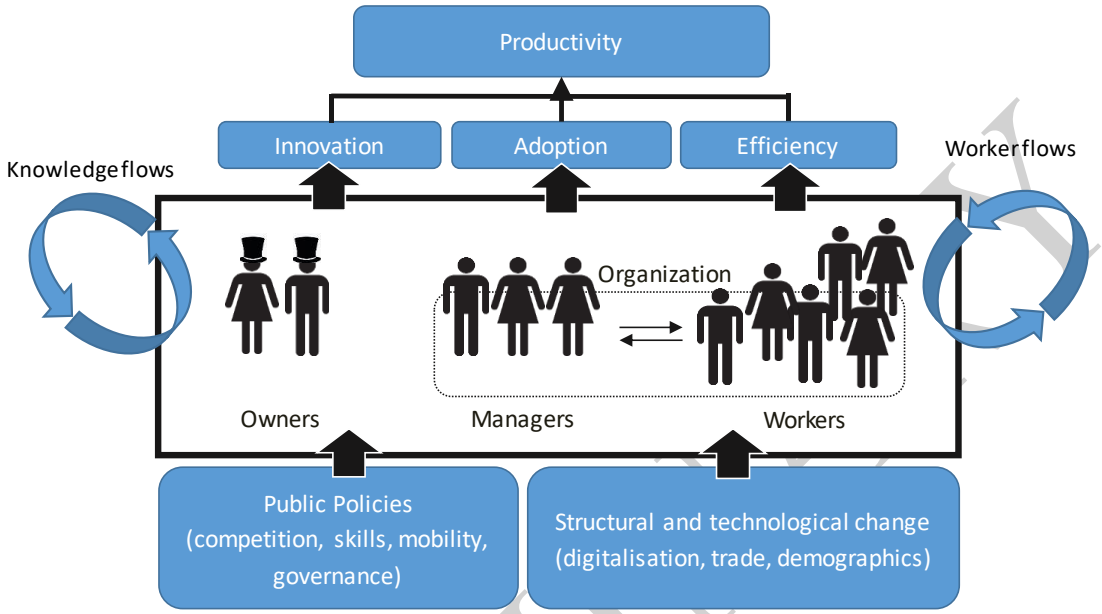
8. Section 3 then provides a mapping between a wide set of public policies and the role of workers, managers and owners in determining firm performance, grouped along three key policy levers: incentives, capabilities and dynamism. The final section outlines the next steps of the analysis.

9. This project extends and supplements previous OECD work on the determinants of aggregate productivity developments, including via the complementarity between digitalisation and skills (Calvino et al., 2018[18]; Gal et al., 2019[12]). It is also related to several existing and ongoing streams of work at the OECD. It is closely related to the LinkEED project which aims to better understand the role of firms in driving wage inequality (OECD, 2019[17]). Our work will also benefit from an ongoing project that collects new indicators on occupational licensing which is likely to be an important lever of labour mobility.

2. Channels and evidence on the Human Side of Productivity

10. Understanding the vast productivity differences across firms requires opening up the `black box' of the firm to examine the firm's internal productivity determinants. Such internal factors can be thought of as determining the ability and willingness of the actors within the firm to implement productivity-enhancing changes via innovation, technology adoption or other efficiency enhancing measures (Figure 1). In contrast, external factors mainly reflect features of the institutional or economic environment, providing the market incentives and the availability of skills that motivate and enable actors within the firm to implement such changes (Andrews, Criscuolo and Gal, 2016[11]; Andrews, Nicoletti and Timiliotis, 2018[19]). Opening up the `black box' is therefore important for understanding the mechanisms leading to productivity differences across firms as well as for understanding how external factors, i.e. policy, technological and structural changes, operate through differences in the human characteristics of firms (Syverson, 2011[7]).

Figure 1. A schematic overview of the human side of the firm's black box.



Source: OECD.

11. To organize the discussion of the literature of firm-internal factors of productivity, Figure 1 provides a schematic overview of these different actors and mechanisms. People inside the firm can be grouped into – potentially overlapping – categories of owners, managers, and workers, who can differ in terms of skills, gender, age, or other characteristics.[6] Reflecting the internal structure of firms, *owners* affect productivity by selecting and controlling managers, and *managers* affect productivity by coordinating the production process as "conductors of an input orchestra" (Syverson, 2011, p. 336[7]), whose outcome in turn depends crucially on its implementation by *workers*. Coordinating the production process provides managers with a key role in the firm's internal setup. Managers select, train, control and incentivize workers and further shape the production process by determining the firm's internal *organization*. In addition, adopting new technologies and business practices also entails managing *knowledge flows* and learning from other firms, as well as the hiring and firing of workers and managers (*worker flows*) (Davis, Faberman and Haltiwanger, 2012[20]). The following subsections discuss the mechanisms and evidence related to each of these internal factors in more detail, also highlighting the complementarities across themselves and with external factors (technology and structural changes).

2.1. Owners

12. Owners affect firm performance by selecting and controlling managers. Principal-agent issues, ignorance, and differences in managerial skills imply that managers may have

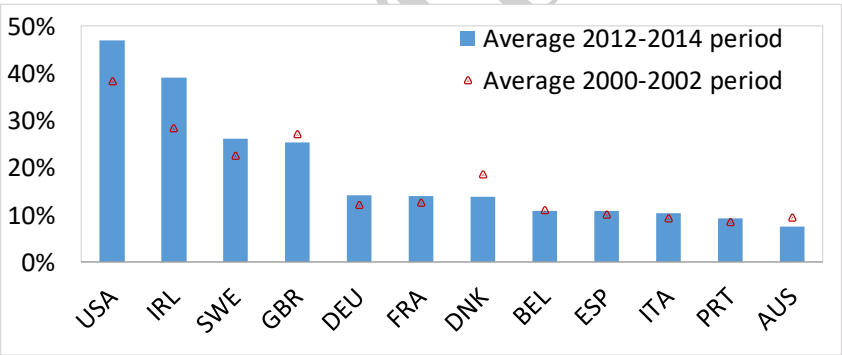
[6] People in the firm can potentially fulfil several roles at once. For instance, mid-managers are workers, from the perspective of the CEO, but are managers, from the perspective of workers further down the hierarchy. Also, most entrepreneurs are at the same time owners and managers, and workers are often also owners, e.g. by holding shares of their company.

only weak incentives to innovate or adopt technologies or to successfully implement them. By choosing highly skilled managers and overseeing their efforts owners can increase firm performance. The extent to which owners possess the incentives and ability to do so, however, depends on the ownership structure of the firm, as owner types generally differ in their of willingness to take risks, investment horizon, and market-specific knowledge (Demmou, Franco and Stefanescu, 2019[21]). For instance, managers at privately held firms owned largely by venture capitalists may be incentivised to make risky investments with high potential pay-offs in the long-run, while managers at firms owned largely by hedge funds may be incentivized to make investments with short-run pay-offs, and managers at publicly traded firms owned by a large number of (passive) index funds may largely escape ownership influence.

13. To exemplify differences in ownership, Figure 2 compares the importance of institutional- and non-institutional owners across countries. Institutional owners include a range of owner types, such as insurance companies, mutual funds, hedge funds and pension funds. Such ownership is relatively high in the US and Ireland, and low in many Continental European countries and Australia. To the extent that increased institutional ownership is associated with more passive investment and common ownership, institutional ownership may generate lower engagement with management and lower competitive pressures, channels examined in recent preliminary OECD work (Demmou, Franco and Stefanescu, 2019[21]).

Figure 2. Differences in institutional ownership across countries

Average shares of firms held by institutional owners between 2000 and 2014.



Note: Institutional ownership is defined for each firm as the percentage share of total firm market capitalization that is held by institutional investors. Results shown have first been averaged across firms within each country and year, and finally, for each country, over the 2000-2002 and the 2012-2014 periods.
Source: Preliminary calculations by (Demmou, Franco and Stefanescu, 2019[21]) based on Thomson Reuters Global Equity Ownership database.

14. Empirical evidence in fact confirms that particular types of ownership are related to better firm performance. For instance, cross-country evidence shows that private equity owned firms are more prone to employ advanced managerial practices (Bloom, Sadun and Van Reenen, 2015[22]); for the US institutional ownership is positively related to innovation through reducing information asymmetries between managers and owners (Aghion, Van Reenen and Zingales, 2013[23]). Family-ownership in combination with primogeniture (the selection of the eldest son as CEO) can decrease management quality and firm performance as managers are chosen from a smaller pool and possess fewer incentives to invest in skills (Bandiera et al., 2018[24]). In fact, the high prevalence of primogeniture in France, UK and Italy has been associated with lower average use of modern managerial practices and

weaker firm performance compared to Germany and the US (Bloom and Van Reenen, 2007[25]; Pellegrino and Zingales, 2017[26]). Conversely, evidence for Spain shows family managed firms can be more responsive to competitive pressures, leading to larger productivity gains in face of rising import competition, as family managers tend to be particularly committed to the survival of the family firm (Chen and Steinwender, 2019[27]). An additional ownership dimension that is empirically important is foreign ownership, particularly in the form of multinational enterprises (MNEs). MNEs can impart management practices used at the headquarter to its domestic affiliates, and therefore constitute an important transmission channel for the propagation of management quality across countries (Criscuolo and Martin, 2009[28]; Bloom, Sadun and Van Reenen, 2012[29]). Finally, entrepreneurs as owner-managers play an important role for business start-ups and radical innovation, and, in addition to avoiding principal-agent issues, have been associated with personality traits reflecting high managerial ability and the ability to operate in high risk environments (Kerr, Kerr and Xu, 2018[30]).

2.2. Managers

15. Managers play a key role for firm-level productivity by organizing the production process at all levels in the firm's hierarchy. On a fundamental level managers organize the production process by "deciding what to do", e.g. CEOs at the top-level deciding strategic aspects, and by "getting the organization to do it", e.g. middle-managers implementing operative aspects of the production process at intermediate levels through the use of managerial practices and hiring and firing of workers (Bloom and Van Reenen, 2007[25]; Gibbons and Henderson, 2012[31]; Braguinsky et al., 2015[32]). Employing highly able managers for top- and middle management therefore matters for firm performance as high managerial ability, potentially reflecting innate talent and accumulated managerial skills, implies that the firm's strategy and production process are more likely to be productivity-enhancing.

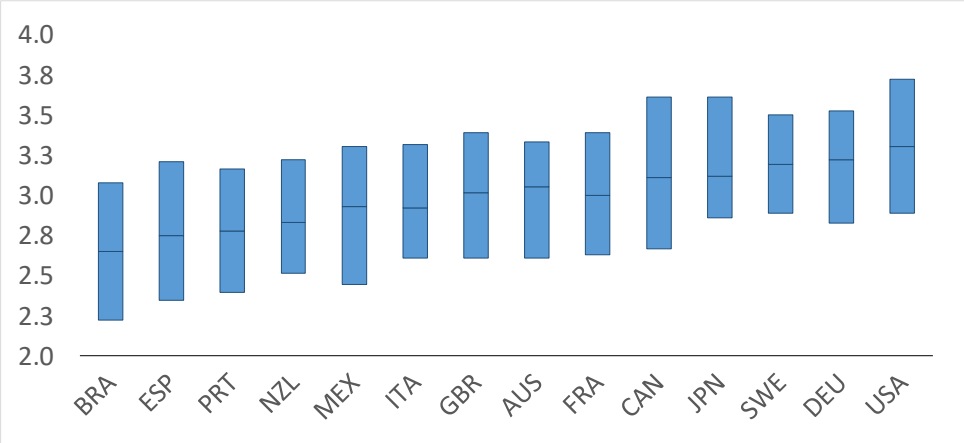
16. The intuitive notion that top-level managers are crucial for the firm's performance has been confirmed by a number of studies of US firms, demonstrating that employing particular CEOs correlates with firm performance (Adams, Almeida and Ferreira, 2005[33]; Bertrand and Schoar, 2003[34]), and that successful CEOs differ systematically in their management behaviour and character traits (Bandiera et al., 2017[35]; Kaplan, Klebanov and Sorensen, 2012[36]).

17. An important lever for managers at the level of middle-management is the use of managerial practices. By setting targets, monitoring and incentivizing workers, managers can raise the productivity for a given workforce. As managerial practices lend themselves to standardization, they have been used extensively to measure the effect of management on firm performance and serve as proxy for management quality more broadly (Bloom et al., 2014[37]; Bloom et al., 2018[38]). The use of "good" managerial practices in fact correlates positively with firm-level productivity across a broad range of countries (Bloom and Van Reenen, 2007[25]; Bloom, Sadun and Van Reenen, 2016[39]).

18. The use of managerial practices thereby varies substantially across firms and even within firms across plants; in addition, there is substantial cross-country variation in the magnitude of such cross-firm differences, as shown by Figure 3. Differences in management quality across countries. As shown there, management quality is generally high in countries like the US and Germany, and low in countries like Brazil and Spain. The dispersion within countries also matters. For instance, Canada and the US both have well managed firms, but compared to the US Canada's average score is dragged down by a

larger tail of relatively badly managed firms. These differences matter for performance. Overall, dispersion in managerial practices can account for up to one third of MFP differences between countries and across firms within countries (Bloom and Van Reenen, 2007[25]; Bloom, Sadun and Van Reenen, 2016[39]).

Figure 3. Differences in management quality across countries



Note: The figure shows the distribution of management scores across countries for randomly sampled medium-sized firms with 50 to 5000 employees in manufacturing from 2004 to 2014. Countries in the figure are ranked by country-level average management scores. The boxes indicate the country's second and third quartile and it's median. Management scores are taken from (Bloom et al., 2014[37]), and comprise average scores of all firms sampled from 2004 to 2014. Management scores reflect the simple average of 18 items of management practices, which have been scored from 1 (worst) to 5 (best) based on detailed survey's with the respective firm's managers. Items surveyed comprise managerial practices on target setting, monitoring and incentivizing. *Source*: OECD calculations based on World Management Survey (Bloom et al., 2014[37]).

19. An additional important lever for managers are human resource and pay policies to build up and retain a highly skilled workforce, e.g. by choosing high wage policies or offering large variable pay components (Lazear and Shaw, 2007[40]). Large and persistent differences in worker churning rates within industries across UK firms in fact suggest wide variation in personnel policies leading to large differences in the firms' ability to hire and retain suitable workers (Burgess, Lane and Stevens, 2002[41]). Reflecting such differences in personnel policies, lower worker turnover rates have been linked to management quality for German firms (Bender et al., 2018[42]), and to enabling worker voice to communicate discontent in Indian firms (Adhvaryu, Molina and Nyshadham, 2019[43]). In addition to hiring workers possessing the required skills, managers can invest in worker training. Human resource and pay policies allowing to retain workers may be complementary to investments in training, as training will be more profitable if workers are expected to have longer tenure at the respective firm (Mortensen, 2003[44]).

20. The quality of management, and its impact on the firm's performance, depend importantly on the human capital of its managers and the use of managerial practices and personnel policies, but is not entirely reducible to either (Bender et al., 2018[42]). Instead, overall management quality ultimately reflects how complementarities between various aspects of the firm's internal setup are exploited: the selection of workforce and technologies, implementing organizational change and so on (Bloom, Sadun and Van Reenen, 2016[39]; Bender et al., 2018[42]). For instance, installing IT equipment can increase labour productivity by substituting tasks previously done by workers. However, as the use of IT equipment disrupts the workflow and affects the remaining tasks done by

workers, e.g. rendering them more specialized, a successful implementation additionally requires changes in the workflow, which in turn require adaptations in skill composition of the workforce (Autor, Levy and Murnane, 2002[45]). In fact, management practices correlate positively with higher ICT adoption rates and higher productivity gains from using ICT capital in Europe and the US (Bloom, Sadun and Van Reenen, 2012[29]; Pellegrino and Zingales, 2017[26]; Andrews, Nicoletti and Timiliotis, 2018[19]). Also, the effect of structural managerial practices on productivity is increasing in the skill level of the workforce (Bender et al., 2018[42]).

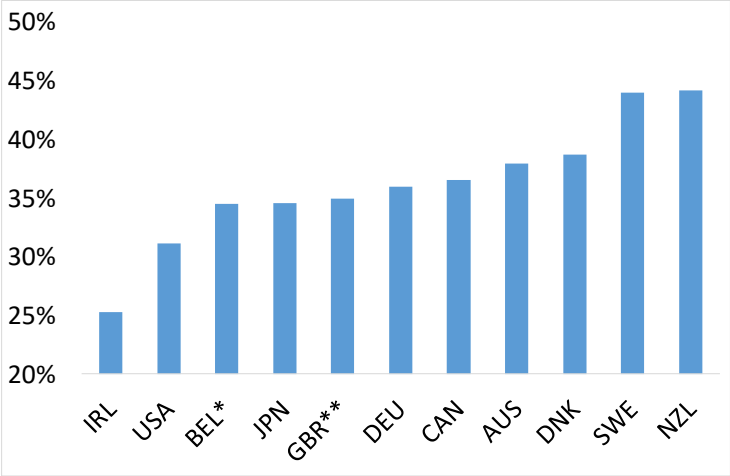
2.3. Workers

21. Workers affect productivity by providing the skills, knowledge and other characteristics needed to implement the production process implied by the firm's technology choice. Moreover, successful technology adoption also requires managers to adjust the composition of the workforce (Acemoglu and Restrepo, 2019[15]; Caselli, 1999[46]). For instance, increased sorting of workers with similar skills across firms may reflect firms adapting their internal organizations to production processes associated with advanced technologies (Caroli and Van Reenen, 2001[47]; Kremer and Maskin, 1996[48]). In fact, sorting increased in many countries, e.g. USA, Germany, Sweden, and Brazil (Card, Heining and Kline, 2013[49]; Håkanson, Lindqvist and Vlachos, 2015[50]; Helpman et al., 2017[51]; Song et al., 2019[52]), while Italy saw no increase in sorting from 1981 to 1997 – possibly reflecting a relatively slow adoption of advanced technologies during this period there (Iranzo, Schivardi and Tosetti, 2008[53]).

22. Relevant aspects of the workforce composition include (a) the skill level of the workforce and (b) the dispersion of skills and other characteristics, e.g. gender, age and nationality, among the workforce. Given skill complementarities of many advanced technologies, the successful implementation of such technologies often requires employing a highly skilled workforce (Acemoglu and Autor, 2011[54]; Acemoglu and Restrepo, 2019[15]; Autor, Levy and Murnane, 2003[55]). Worker characteristics relevant for the use of advanced technologies comprise a range of skills, e.g. cognitive skills such as verbal and technical abilities as well as non-cognitive skills like extroversion and persistence (Håkanson, Lindqvist and Vlachos, 2015[50]). A limiting factor for firm performance may therefore be its ability to hire and retain such workers, which in turn is closely related to the management's personnel policies discussed above. Skill shortages were in fact found to be related to lower productivity gains of digital technologies, implying that the role of personnel policies becomes more important in tighter labour markets (Gal et al., 2019[12]). As demonstrated by Figure 4. Technological literacy across countries, skill scarcity varies substantially across countries. While access of firms to technologically competent workers is relatively high in countries like Sweden and New Zealand, it is relatively low in Ireland and the US, making it more difficult for firms to recruit suitable workers in the latter countries.

Figure 4. Technological literacy across countries

The percentage of high-performing adults in solving technologically demanding problems across countries



Note: The figure shows the percentage of adults high-scoring adults (level 2 or 3) in problem solving in technology-rich environments in the Survey of Adult Skills (PIAAC). *Data for Belgium includes only Flanders. **Data for the United Kingdom excludes Northern Ireland.
Source: OECD calculations from PIAAC database (2015).

23. To the extent workers with different skills complement each other in their use of advanced technologies, such technologies additionally require employing workers with different skills or a given average skill level of the workforce, and the dispersion of skills can affect productivity, as found for Italian firms (Iranzo, Schivardi and Tosetti, 2008[53]). For instance, the use of IT capital may substitute for routine tasks and augment the productivity of high skilled workers, who in turn are complemented by low skilled workers performing the remaining, non-cognitive non-routine tasks, requiring the firm to employ workers with more dispersed skills (Autor, 2014[56]).7 In addition to the skill dispersion of the entire workforce, successful technology implementation can hinge on employing highly able workers with scarce skills in key positions, e.g. managers or innovators (Bell et al., 2017[57]; Rosen, 1981[58]). In fact, better managed firms, measured through managerial practices, employ more skilled workers overall, as shown for German firms. However, the statistical link between management quality and firm performance operates to a large extent through the most skilled workers at the firm: those firms tend to be more productive whose most highly skilled workers, possibly reflecting middle- and top-managers, are especially able (Bender et al., 2018[42]).

24. Additionally, dispersion in terms of age, gender, and cultural background can affect firm performance by facilitating or hampering knowledge transfer and problem solving (Parrotta, Pozzoli and Pytlikova, 2012[59]). Gender diversity of corporate board members received particular attention. Although evidence for a positive link between gender diversity on boards and firm performance is mixed (Pletzer et al., 2015[60]; Post and Byron, 2015[61]), more recent work attempts to qualify these mixed findings by

[7] Amazon provides a fitting example: A large number of smaller retail stores, arguably employing mostly medium skilled workers, has been replaced by a single firm employing highly skilled workers, some of which are literally using rocket-science to predict required inventories, alongside many unskilled warehouse clerks.

highlighting a welcoming board culture – actively encouraging contrasting views – as a necessary condition to benefit from diversity, arguing also for the benefits of more encompassing, i.e. ethnic, social and professional diversity (Creary et al., 2019[62]). While the empirical evidence on the effect of diversity of the general workforce on firm-level productivity is still unclear[8], employment of immigrant workers can positively affect firm performance by facilitating exporting, as shown for UK firms (Ottaviano, Peri and Wright, 2018[63]; Parrotta, Pozzoli and Pytlikova, 2012[59]).

25. Also, trust among workers can affect the firm's organization and ability to grow to efficient scale. Countries with higher social capital, e.g. Sweden, tend to have more decentralized and larger firms compared to countries with lower social capital, e.g. France (Bloom, Sadun and Van Reenen, 2012[64]). The degree of trust could also be linked to the composition of workers, although the evidence on this is scarce (Alesina and Ferrara, 2002[65]; Parrotta, Pozzoli and Pytlikova, 2012[59]).

2.4. Organization

26. For a given workforce composition, firm organization affects productivity by matching workers to tasks and leveraging skill and knowledge differences across workers in a hierarchical structure. As the use of advanced technologies affects the workflow of the production process and the relative costs of acquiring or communicating information, implementing advanced technologies often requires organizational innovations to match technological innovation.

27. The firm's internal organization increases productivity to the extent it makes efficient use of workers with different skills to match the production process. Different technologies imply different production processes, and generally imply different forms of optimal organization. For instance, production processes for which small differences in worker skills can lead to large decreases in output, e.g. the production of luxurious cars where mistakes are very costly, imply horizontal organizations among workers with similar skills (Kremer, 1993[66]). In contrast, production processes relying disproportionately on the performance of a small number of workers imply hierarchies among workers with different skills, e.g. professional consultancies leveraging the ability and experience of partners by employing a large number of relatively inexperienced associates (Rosen, 1981[58]). Highlighting the complementarities with other factors, measures of organization, or of organizational change, correlate positively with higher use of ICT capital and higher productivity for US and UK firms (Bresnahan, Brynjolfsson and Hitt, 2002[67]; Crespi, Criscuolo and Haskel, 2007[68]; Garicano and Heaton, 2010[69]; Hubbard, 2003[70]). More active managers, being more likely to adapt the firm's organization in the face of changes to its production process, have been linked to better firm performance (Adhvaryu, Kala and Nyshadham, 2019[71]).

28. To the extent the optimal organization reflects trade-offs between communication and information costs, employing advanced technologies may require further adaptations in the firm's organization (Garicano and Rossi-Hansberg, 2006[72]). For instance, decreasing the cost of accessing information through the use of Enterprise Resource Planning provides more information to plant managers and therefore facilitates decision

[8] Some case studies find no effect of diversity in terms of age, gender or ethnicity on firm performance (Kurtulus, 2011[95]; Leonard and Levine, 2003[96]) while studies based on regional data provide some indirect evidence for worker diversity leading to higher wages and economic prosperity (Alesina, Harnoss and Rapoport, 2016[97]; Ottaviano and Peri, 2006[98]; Peri and Sparber, 2009[99]).

making at lower levels, implying flatter hierarchies. Decreasing communication costs via the use of Intranets in contrast allows managers to leverage their ability and knowledge over a larger number of workers, thus implying a more hierarchical organization (Bloom et al., 2014[73]).

3. Framework for measurement and analysis

3.1. Measurement framework

29. The key initial question that the descriptive part of the analysis aims to address is how successful, high-productivity firms differ from other firms in terms of their 'human' characteristics – workers, managers and owners. For instance, what is the fraction of high-skilled workers and managers in leading firms compared to medium performer or laggards firms? What is the role of demographic composition, that is, diversity along age, gender and nationality? How do these features vary across countries, over time and across sectors? Finally, how is the movement of workers in- and out of the firm related to its position in the productivity distribution (the dynamic aspect)? Documenting the evidence on these issues in a cross-country comparable manner would be a key contribution to build new stylised facts, a necessary first step to investigate the role that public policies could play in shaping differential outcomes across OECD economies.

30. Extracting this evidence is however challenging, given the difficult measurement issues that are inherent in the richness of the underlying micro (worker and firm) level data.9 To overcome some of these difficulties, we build on the OECD's many years of experience with remotely accessing administrative confidential data through distributed microdata analysis ((Bartelsman, 2004[74]; Bartelsman, Scarpetta and Schivardi, 2003[75]), and more recently (Criscuolo, Gal and Menon, 2015[76]; Berlingieri et al., 2017[10]; OECD, 2019[17]); see also Box 1).

31. As highlighted in Figure 6, we use the distributed microdata approach focusing on frontier and laggard firms (Andrews, Criscuolo and Gal, 2016[11]; Berlingieri et al., 2018[13]), digging deep into the drivers of the large productivity differences across them, which requires relying on information about the human characteristics of firms.

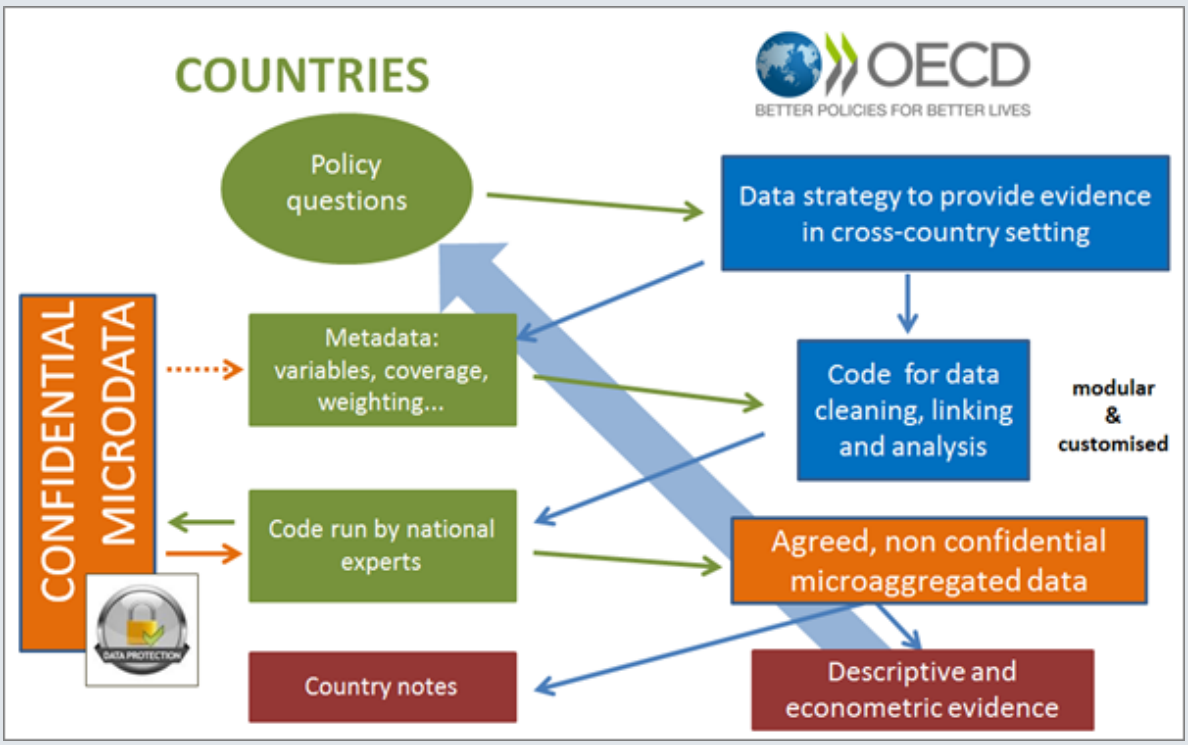
Box 1. What is distributed microdata analysis?

The distributed microdata analysis was pioneered in the early 2000s in a series of cross-country projects on firm demographics and productivity (Bartelsman, 2004[74]; Bartelsman, Scarpetta and Schivardi, 2003[75]), aiming to conduct cross-country analyses using representative national microdata. It involves running a common program code, implementing the same set of operations in a decentralised manner by representatives in national statistical agencies or experts in governments or public institutions, who have access to the national micro-level data. The centrally designed but locally executed program codes generate micro-aggregated data or regression estimation results, which are then sent

[9] There are examples comparing a few countries, for instance the Germany and Netherlands (Bartelsman, Dobbelaere and Peters, 2015[101])

back for comparative cross-country analysis to the OECD (Figure 5. Overview of distributed microdata analysis).

Figure 5. Overview of distributed microdata analysis



Note: Schematic description of the distributed microdata approach for conducting cross-country analysis using representative national microdata.
Source: OECD.

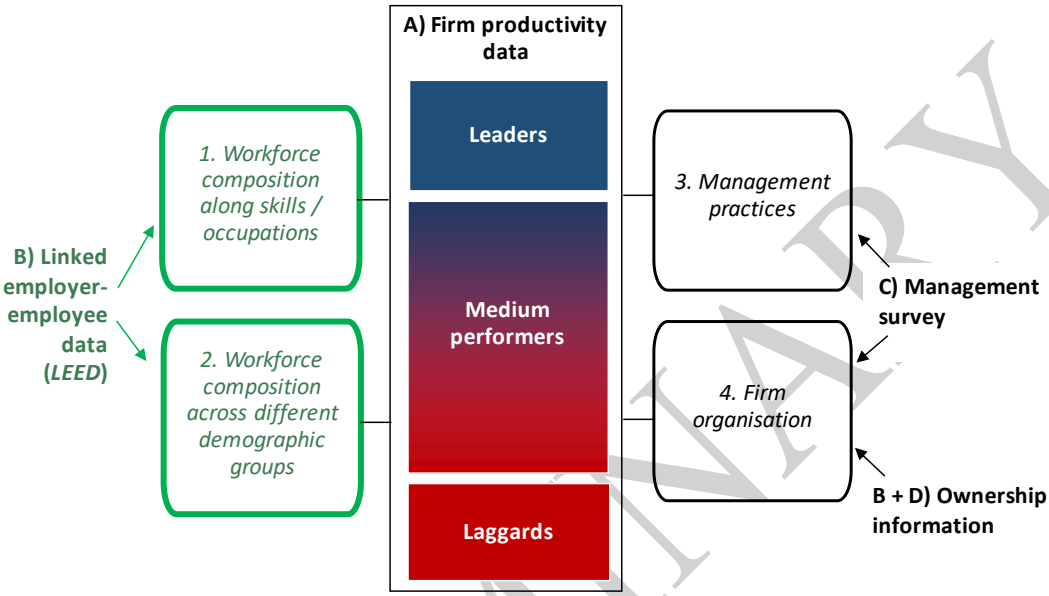
The advantages of this novel data collection methodology are manifold. It puts a lower burden on national statistical agencies and limits running costs for such endeavours. Importantly, it directly uses national micro-level representative databases, while at the same time achieving a high degree of harmonisation and comparability across countries, sectors, and over time. The OECD currently follows this approach in several ongoing projects, including the OECD MultiProd, DynEmp, microBeRD, and LinkEED projects. See the relevant project websites and a few example papers below, including our current project:

- Human Side of Productivity: *The current scene setting paper*
- LinkEED: OECD (2019[17])
- MultiProd: Berlingieri et al. (2014[77]), Berlingieri et al. (2017[10])
- DynEmp: Criscuolo, Gal and Menon (2014[78]), Calvino, Criscuolo and Menon (2016[79])
- microBeRD: OECD (2018[80])

32. We break down the descriptive analysis and measurement into separate 'modules': 1. Workforce composition along skills and occupations; 2. Workforce composition across diverse demographic groups (age, gender, nationality); 3. Management practices; and 4.

Firm organisation. These modules require different data sources, with the common requirement being firm-level productivity (A). Modules 1 and 2 rely on linked employer-employee data (LEED) (B); module 3 would work from management surveys (C) which module 4 could complement with ownership (D) and LEED information (B).

Figure 6. How to measure the role of human factors in firm productivity?



Note: Numbered boxes 1-4 indicate separate modules for measurement. Capital letters A-D indicate data sources.
Source: OECD.

33. In modules 1 and 2, we take as starting point simple descriptive statistics which report the composition of workers along three segments of the within-sector productivity distribution: leaders, laggards and the medium performers in between. Leaders (laggards) are identified based on the highest (lowest) 10 or 20% of firm productivity, using a persistent measure of productivity by taking a moving average. The composition of workers along the productivity distribution is then reported by country, year and detailed industries (STAN A38) which can be grouped into meaningful sectors such as manufacturing, knowledge intensive and less knowledge intensive services.

34. To better isolate the "returns to productivity" of the various human side characteristics, regression analysis is used. The regressions have (the log of) productivity of firms (i) in a given year (t) as the dependent variable and human side characteristics (HS_{it}) as the key explanatory factor. Their coefficient estimate $\beta^{(c)}$ is allowed to vary at least by country (hence the c superscript), and potentially by further dimensions (sector and year). The regressions also control for other firm characteristics such as firm size (captured in X_{it}) and sector-time fixed effects interactions (D_{st}) to control for sector specific general developments:

$$\log(Productivity_{it}) = \beta^{(c)} HS_{it} + \gamma X_{it} + D_{st} + \varepsilon_{it}. \quad (1)$$

35. Productivity is measured in various ways, from the simplest and most easily available labour productivity measure (gross output over number of employees) to more

sophisticated but more data demanding multi-factor productivity measures (Gal, 2013[81]; Berlingieri et al., 2017[10]), also using hours worked whenever possible. Both productivity and the human side characteristics are measured in three-year moving averages to reduce the influence of abrupt year-to-year changes and potential measurement error.[10]

36. An alternative specification that better captures potential non-linearity at the top (or at the bottom) of the distribution is set up as a linear probability model. It estimates the probability of belonging to the leader (or frontier, F), or laggard (L) group, conditional on the human side characteristics of the firm, where I_{it}^{F} is an indicator variable equal to 1 if the firm *i* in year *t* is in the frontier group F and 0 otherwise:[11]

$$I_{it}^{F} = \beta^{(c)} HS_{it} + \gamma X_{it} + D_{st} + \varepsilon_{it}. \quad (2)$$

37. The human side characteristics variable HS_{it} capture the share of a particular type of employee in the firm. A key characteristic is the skill level, which can be measured in more crude or more accurate ways, depending on data availability. In particular, educational attainment levels are a very crude measure but they are more readily available than the alternative, i.e. detailed occupation based skill groups. Using occupation groups requires a mapping between the specific occupation structure breakdown that is available for the country and skill levels. In that, we follow Goos, Manning and Salomons (2014[82]), who allocate occupations into 3 broad groups (high-paying, middling and low-paying) using 2-digit International Standard Occupational Classification (ISCO) categories (see Table A.1 in Annex A).12 For those countries where this ISCO is not available and the mapping to it is imperfect, we will also rely on the wage distribution by occupations, exploiting the fact that wages and skill levels are correlated. A final alternative, which relies only on observed wage levels is based on extracting worker fixed effects from an AKM-type (Abowd, Kramarz and Margolis, 1999[83]) wage regression.13

38. Regarding demographic diversity, we consider age (young – aged 15 to 32 – , old – aged 51 to 85 and the remaining mid-aged group); gender; and – if available – nationality or country of origin.

39. Regressions are then enriched by including several human side characteristics simultaneously to better isolate the individual factors (denoted by *k*) and control for potential correlations between skills, managerial roles, gender and age:

[10] Firm-level standard error clustering is applied to appropriately take account of serial correlation in the moving averaged variables that are included in the regressions.

[11] Compared to logit or probit models, a linear probability model has the advantage of yielding readily interpretable coefficient estimates and can be estimated without further complications in the presence of large dimensional fixed effects and very large numbers of observations.

[12] Beyond these measures, there are further, more sophisticated measures that take into account the task content of occupations (Deming and Kahn, 2018[102]), but they are outside the scope of what is currently available in a cross country setting.

[13] AKM regressions estimate worker and firm fixed effects simultaneously with individual worker wages as the dependent variable, to isolate the worker and firm-specific component of wages. Their proper estimation requires observing some degree of mobility of workers across firms over time.

$$\log(Productivity_{it}) = \sum \beta_k^{(c)} HS_{k,it} + \gamma X_{it} + D_{st} + \varepsilon_{it}. \quad (3)$$

3.2. Illustrative results from two pilot countries: Portugal and Denmark

40. This section presents simple preliminary statistics from Portugal and, due to data constraints, in more limited form from Denmark. They have a purely descriptive nature and do not capture causality between the human side characteristics and productivity at this stage. The figures below show unconditional differences in the human characteristics of firms across the firm distribution – frontier, medium performer and laggard – while the tables report regression results confirming that the differences across firm groups are statistically significant and robust to jointly considering all human characteristics at the same time as well as to controlling for firm size (conditional correlations, following equation 3). Throughout this part, the preferred productivity measure is gross output (or sales) divided by the number of hours worked.14

41. Figure 7 shows the results from Portugal for the employment share of high and low skilled employees (Panel A) and managers (Panel B), for laggards, medium performers and firms at the frontier, using simple averages across all 2-digit sectors and over time.15 The latter group has 32% of high skilled employees, about 10 percentage points more than medium performers – while laggards stand at 15%. This pattern confirms the basic intuition that more productive firms employ a larger share of skilled employees. Interestingly, differences across these three groups in terms of variations in the low-skilled employee share are much smaller and range between 12-17% (of course, with the opposite sign: more productive firms have a smaller fraction of low-skilled employees). This indicates that firm productivity is mostly correlated with the extent to which high- or medium skilled employees are present in the firm – and less so with variations in low-skilled employees. A larger share of managerial roles in the firm is also positively correlated with productivity (Panel B). Importantly, this remains when controlling for additional, potentially related factors (skills and firm-size; see further below) and indicate that more productive firms operate with a larger share of managerial roles.

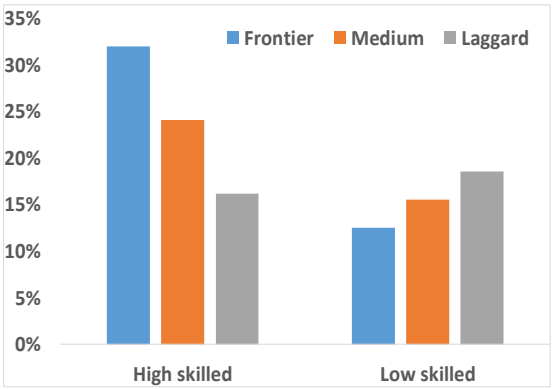
[14] As the tables of the regression results illustrate, there are important differences between the hours and headcount based productivity measures when it comes to the share of young employees, potentially indicating a high prevalence of part-time work in this group of employees.

[15] At a later stage, weighting by employment size could be envisaged, using such uniform (e.g. OECD average) sector weights so that cross-country comparability is not affected by a different sector-composition.

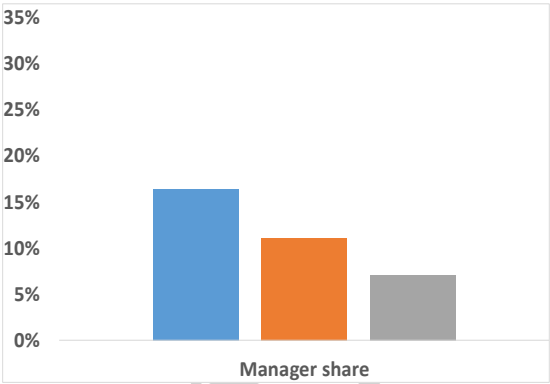
Figure 7. The role of skills and occupations by firm-productivity segments in Portugal

Average across firms and sectors over 1991-2009

Panel A: Share of high and low skilled employees



Panel B: Share of managers among all employees



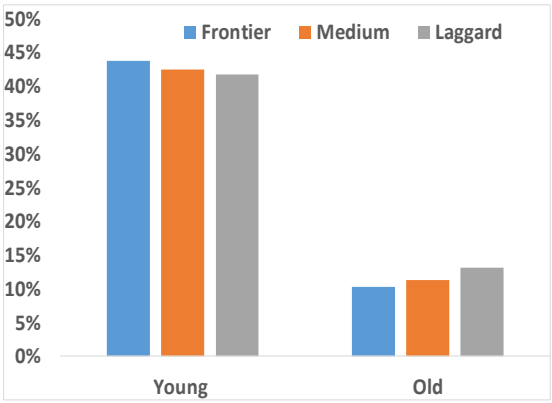
Note: The figure shows workers shares for different occupational and skill groups by frontier, medium and laggard firms. Frontier and laggard firms are defined as the most and least productive decile of the productivity distribution in each year and industry. The productivity measure is based on sales and hours worked. Worker shares are computed as 3-year backward moving average, for frontier, medium and laggard firms, averaged over all years and STAN A38 industries, excluding agriculture, mining and utilities. The classification of workers into low, medium and high skilled groups is based on 2-digit occupational classifications following Goos, Manning and Salomons (2014[84]). Data for Portugal are based on Quadros de Pessoal 1991 to 2009.
Source: OECD calculations based on Portuguese linked employer-employee data.

42. Figure 8 shows initial findings for Portugal in terms of demographic diversity: the share of young and older workers (Panel A) and the share of women (Panel B) at the same three segments of the productivity distribution. The differences across productivity groups are much smaller than in the case of skills or managerial roles and range between 40-45% (young), 10-15% (old) and 32-37% (women). The slightly higher young/old ratio in frontier firms than in other segments of the distribution seems at face value inconsistent with the role of experience, but this should be further investigated by looking at how this may vary across sectors (e.g. knowledge intensive vs other sectors). Regarding the role of gender, differences are even smaller, but again can hide different patterns across sectors. Overall, based on these preliminary findings, the relationship between these demographic factors and firm productivity seems much less strong – also in line with mixed or weak results from the literature – and invites a more granular analysis.

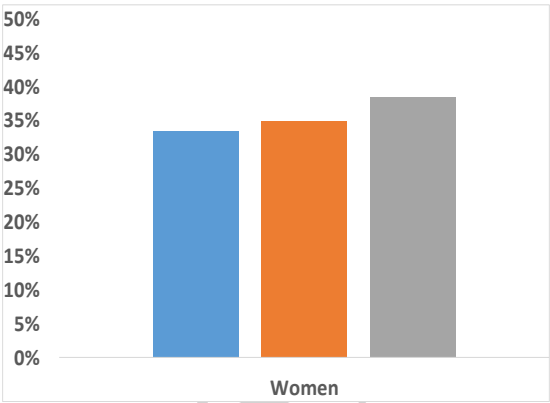
Figure 8. The role of demographic diversity by firm-productivity segments in Portugal

Average across firms and sectors over 1991-2009

Panel A: Share of young and old employees



Panel B: Share of women

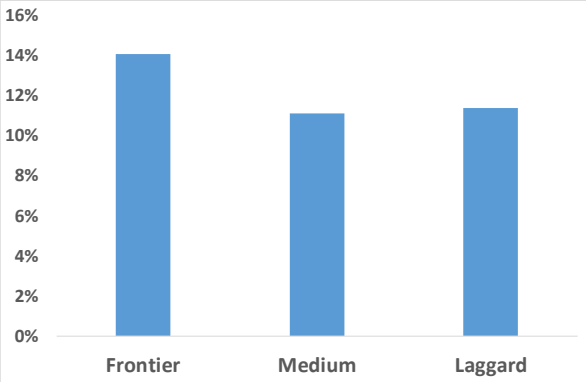


Note: The figure shows workers shares for worker diversity in terms of demographics by frontier, medium and laggard firms. Frontier and laggard firms are defined as the most and least productive decile of the productivity distribution in each year and industry. Productivity measure is based on sales and hours worked. Worker shares are computed as 3-year backward moving average, for frontier, medium and laggard firms, averaged over all years and STAN A38 industries, excluding agriculture, mining and utilities. Young workers are aged 15 to 32, and old workers are aged 51 to 85. Data for Portugal are based on Quadros de Pessoal 1991 to 2009.
Source: OECD calculations based on Portuguese linked employer-employee data.

43. While these previous figures focused on differences across groups, on average over the whole sample period (1990-2009), Figure 9 shows changes over time in terms of the role of skills at different segments of the distribution. It highlights that high-skilled employees are employed at larger proportions at each segment of the distribution – but the increase is larger at the frontier, which is indicative of sorting, in line with most of the international evidence (see Section 2).

Figure 9. Portugal: the rising importance of skills, especially at the frontier

The increase in the share of high skilled workers across the productivity distribution (1990 to 2009)



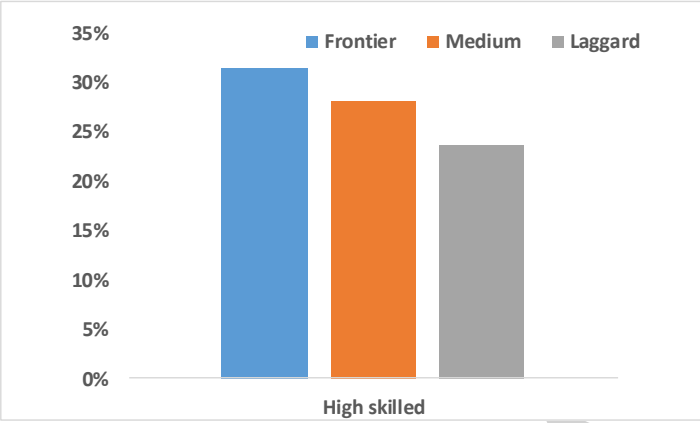
Note: The figure shows the percentage point change in the 3-year backward moving average share of high skilled workers between the 1993-1995 and 2007-2009 for frontier, medium and laggard firms. The classification of workers into high skilled groups is based on 2-digit occupational classification following Goos, Manning and Salomons (2014[84]). Frontier and laggard firms are defined as the most and least productive decile of the productivity distribution in each year and industry. Industries refer to STAN A38 classification, excluding agriculture, mining and utilities. Productivity measure is based on sales and hours worked. Data for Portugal are based on Quadros de Pessoal 1991 to 2009.
Source: OECD calculations based on Portuguese linked employer-employee data.

44. The findings for Denmark at this stage are more limited and preliminary, they do confirm – using an alternative skill measure based on the level of education and for a more recent period of 2009-2016 – that firms at the productivity frontier employ a larger share of skilled workers (Figure 10).

Figure 10. The role of skills in Denmark – a preliminary look

Share of highly educated workers across the productivity distribution

Average across firms and sectors over 2009-2016



Note: The figure shows worker shares for the high skilled education group by frontier, medium and laggard firms. Frontier and laggard firms are defined as the most and least productive decile of the productivity distribution in each year and industry. Productivity measure is based on sales and number of hours worked. Worker shares are computed as 3-year backward moving average, for frontier, medium and laggard firms, averaged over all years and STAN A38 industries, excluding agriculture, mining and utilities. Shares may be biased because in current dataset not all employees at the firm-level are covered. Classification of workers into low, medium and high skilled groups is based on educational groups. Data for Denmark are based on FIRE, RAS, UDDA, BFL and BEF from 2009 to 2016.
Source: OECD calculations based on Danish linked employer-employee data.

45. Table 1 shows preliminary results for the statistical link between the level of firm-productivity and worker shares for different characteristics. They only report the results when all factors are jointly included (equation 3). In particular, they are obtained by regressing the log of labour productivity at the firm-level on worker shares measured as fractions of young workers (aged 15 to 32), old workers (aged 51 to 85), women, managers, as well as low and high skilled workers, controlling for industry-year interacted fixed effects and firm-size group fixed effects. Coefficient estimates indicate the partial correlation between firm-level productivity and worker shares. For instance, a ten percent increase in the share of high skilled workers at the firm in a given firm-size group, year and industry is associated with a nine percent increase in the firm's productivity, holding all other worker shares constant (column 1).

46. Results in Table 1 generally confirm the picture highlighted by the bar-charts (Figure 7-Figure 8) and, more importantly, they are also in line with results obtained from the linear probability model (Table A.2 in Annex A). They show that firms which employ more managers and high skilled workers, or fewer low skilled, old and female workers are on average more productive, although the strength of these relationships across these aspects varies greatly and is larger for high-skill levels and manager status. Interestingly, they clearly indicate an additional and separate effect for high skilled workers and managers, both being the strongest positive correlates of firm-productivity. The relatively large negative coefficients for older and women employees warrants further analysis, in particular by detailed sectors.

47. With the exception of young and low skilled employees, the patterns are robust to using alternative definitions of productivity measures (sales divided by hours worked instead of number of workers). The coefficient of young workers on productivity changes

sign when measuring productivity based on hours worked rather than number of employees, presumably reflecting young workers being more likely to work part-time. Although no sign change occurs for low-skilled employees, the coefficient increases significantly when hours worked are used, indicative of a higher prevalence of low hours worked in this group. Also, the relative role of managerial roles increases and becomes the most important positive correlate with hours-based firm productivity. Overall, these differences highlight the particular importance of using productivity measures based on hours worked when assessing the role of employee characteristics for firm-level productivity.

Table 1. Human characteristics and firm-level productivity

Regression results with the log of firm-level labour productivity as the dependent variable

	(1)	(2)
Productivity definition:	Sales/Number of workers	Sales/Hours worked
Young employees	-0.1931***	0.2077***
	(0.0171)	(0.0180)
Old employees	-0.3112***	-0.4696***
	(0.0302)	(0.0319)
Women	-0.6273***	-0.5263***
	(0.0154)	(0.0159)
Low skilled employees	-0.2509***	-0.0847***
	(0.0191)	(0.0194)
High skilled employees	0.9042***	0.6645***
	(0.0272)	(0.0286)
Managers	0.6362***	0.8315***
	(0.0451)	(0.0458)
Number of observations	299656	299652
R2	0.427	0.392
Industry × year FE	yes	yes
Firm-size group FE	yes	yes

Note: Results for ordinary least squares regression model at the firm-level (equation 1). Dependent variable: Log of labour productivity. Column (1) measures productivity as sales divided by number of employees; column (2) measures productivity as sales divided by total hours worked. All explanatory variables refer to employment shares of worker groups as fractions: Young workers refers workers aged 15 to 32; old workers refers to workers aged 51 to 85 (mid-aged is the omitted, baseline group); low and high skilled workers refers to workers in low and high skilled occupations based on Goos, Manning and Salomons (2014[84]) (while the middle skilled group is the omitted, baseline group). All regressions control for industry times year fixed effects using STAN A38 industries, excluding agriculture, and dummies for firm-size bins. Standard errors clustered at the firm-level in parentheses. Significance levels: * 10%, ** 5%, *** 1%. Results are shown for Portugal, based on Quadros de Pessoal 1991 to 2009.
Source: OECD calculations based on Portuguese linked employer-employee data.

4. Public policies and the human side of productivity

4.1. The range of relevant policies and their main mechanisms

48. This section discusses the wide range of policy areas that can affect productivity through the human dimension of firms. It provides a mapping between the human side of productivity – owners, managers, workers and organisation – and policies, differentiating

along three broad policy levers: incentives, capabilities and dynamism (Table 2).16 The first two of these builds on recent OECD work that looked at the role of structural changes and in particular digital technologies (Andrews, Nicoletti and Timiliotis, 2018[19]) while the latter category is added to emphasise that the movement of workers and managers across firms is a crucial aspect that affects the human side of productivity.

49. Public policies can impact firm productivity by changing the composition of workers, owners and managers. This is a more direct way to think of them and Table 2 focuses mostly on that. But policies and the human side have also a more indirect way of interacting: firms with different compositions and organisations react differently to the same policy reform (e.g. a rise in minimum wages impacts more those firms that have a higher share of low skilled workers). The discussion further below aims to highlight both aspects.

Table 2. The potential role for policies in shaping the human side of productivity

	Human aspects of productivity				
			Workers		
Policy levers	Owners	Managers	Skills	Diversity (age, gender, etc.)	Organisation
Incentives	**Financial and corporate tax system** (financial market regulation; debt bias in corporate taxation; equity markets; public venture capital funds); **corporate governance and antitrust** (antitrust and competition law; antitrust enforcement; cross-border ownership restrictions; trade openness); **tax system** (inheritance tax; within family tax exemptions from capital gains)	**Corporate governance and antitrust** (antitrust and competition law; antitrust enforcement); **tax system** (income taxation); **entry and exit policies** (PMR, insolvency regimes)	**Labour mobility** (ALMPs); **wage setting** (collective bargaining arrangements)	**Tax-benefit system** (pension system; second earner taxation, family support); **Corporate governance** (quotas for female members of corporate boards)	**Corporate governance** (size-dependent regulations)
Capabilities		**Education and training** (management schools)	**Education and training** (schools; apprenticeships; training on the job; lifelong learning)		
Dynamism		**Corporate governance** (FDI restrictions)	**Labour mobility** (occupational licensing; employment protection legislation; non-compete clauses; transport; housing market; ALMPs); **entry and exit policies** (PMR, insolvency regimes)	**Tax-benefit system** (transferability of pensions; childcare policies); **labour mobility** (visa requirements; immigration law)	

Note: PMR denotes product market regulation; ALMP denotes active labour market policies; FDI denotes foreign direct investment.
Source: OECD.

[16] Of course, it is not always clear-cut where a given policy area belongs to – for instance, active labour market policies (ALMPs) can affect both incentives and dynamism.

50. Starting with policies that impact the incentives of firms and the people within, the financial and corporate tax system is an important factor in shaping owners' decisions. For instance, the debt bias in corporate taxation can play a role through selecting what type of financing the firm chooses – more equity or debt – which can directly alter ownership and can make it more dispersed or more concentrated. Tax exemptions from capital gains within families or inheritance taxes can play a role in sustaining family ownership. Managers are affected through corporate governance rules and product market regulations (PMR). In particular, ambitious PMR reforms can help creating a competitive market environment, which incentivises managers to adopt the latest technologies and can thus contribute to productivity improvements further down the productivity distribution (Andrews, Criscuolo and Gal, 2016[11]; Andrews, Nicoletti and Timiliotis, 2018[19]). Incentives for workers include active labour market policies which can potentially improve labour mobility across regions and sectors. Workers' incentives are also affected by firing costs, or through wage setting also incentivized by collective bargaining agreements. Finally, the organisation of firms is also shaped by size-dependent regulations. A key example is stricter employment protection that becomes binding only above a certain firm-size (e.g. 50 employees in France), thus reducing the incentives of firm growth (Garicano, Lelarge and Van Reenen, 2016[85]), which could potentially also encourage the creation of a fractured organisational structure.

51. The capabilities of the human side of firms mostly capture skills – be it managerial skills (the role of business schools), technical skills of workers (IT training) or interpersonal "soft" skills. Education and adult training are the obvious and primary policy areas that can improve these aspects – in tandem with incentives given to firms to carry out on-the-job training of their workers (see the recently introduced Apprenticeship Levy system in the United Kingdom). Being connected to talent is another crucial aspect of improving human capabilities, as the literature on innovators demonstrates. For instance, Bell et al. (2017[57]) have found in the United States that increasing the exposure to innovators at an early age can improve the probability of becoming an innovator later on. Moreover, geographic proximity and concentration of high skilled workers in large cities have been shown to increase the productivity of workers, possibly stemming from a better flow of information and sharing knowledge that is not easily codifiable and shared electronically ("tacit" knowledge) (OECD, 2016[86]). Capabilities are also related to the diversity of the workforce, and here policies on the tax-benefit system and corporate governance can play a role to ensure that firms benefit from the whole range of different and characteristics of diverse worker groups. For instance, a diverse age structure can be important for achieving an efficient organization that matches older, more experienced workers to complex task and frees up younger workers for those tasks requiring less experience (Lembcke and Daniele, 2019[87]).

52. Dynamism captures the healthy flow of workers and managers from one firm to the other, either across geographic areas – including across countries –, sectors or firms within the same sector. This movement of people is a key channel for adjusting to short or long-term economic shocks that call for changing the composition of skills, as well as to transmit knowledge from one firm to the other. Indeed there is evidence from detailed Swedish matched employer-employee data that managers who used to be entrepreneurs have a positive impact on the productivity of the hiring firm (Lappi, 2018[88]). Important policy levers affecting dynamism at the firm-level are exit and entry policies, e.g. product market regulations (in particular barriers to entrepreneurship) and insolvency regimes. More recently, also labour market restrictions attracted attention, especially for their role in limiting flows especially of high skilled workers. Some firms that operate under fierce

competition introduce "non-compete clauses" in their most valued employees' contracts that reduce worker mobility. Building on their findings in the US, Azar, Marinescu and Steinbaum (2019[89]) argue for the need to apply the same antitrust rules to labour as to goods markets to safeguard competition.

53. Geographic mobility is an important aspect of dynamism and here transport and housing infrastructure are the key policy areas. For instance, in France, Charnoz, Lelarge and Trevien (2017[90]) show that the expansion of high speed rail led to important organisational changes, allowing more managers to remain at the headquarters since transport allowed them to overcome long distances more easily. This has also led to an increased profitability of firms. Movement across countries – immigration – has also been shown to be positive for entrepreneurship for the US and for general skill levels (Kerr, 2013[91]; Kerr and Lincoln, 2010[92]). The latter study shows that easing visa requirements can directly contribute to domestic innovation by raising the number of patents filed in the country.

4.2. Framework for policy analysis

54. The empirical analysis of policies depends importantly on the specific mechanisms of the policy, in particular whether it is expected to have larger or smaller impacts on certain groups of firms or workers. Hence at this stage we only briefly outline the basic principles of two broad approaches. The more direct approach is to establish a link between the human side characteristics and policies, and then combine this relationship with the β coefficients obtained from equation 1 or 2. Those regressions will be estimated separately by country, and potentially by sector and year, to increase useful variation, potentially by exploiting differences in the exposure of certain aspects to certain policies (in the spirit of Rajan and Zingales (1998[93])) or exploiting important policy reform episodes. The result will capture the extent to which policy reforms impact productivity through changing the human characteristics of firms.

55. A more indirect approach tests for the presence of interactions between human characteristics and policy reforms in shaping productivity. The basic premise is that suboptimal policy settings can inhibit the matching of workers to managers, thus reducing firm productivity. Moreover, some policies can also hold back the synergies across workers that could stem from diversity (inadequate childcare facilities holding back women participation, for instance). To detect such "worker misallocation" or "worker underutilisation", we utilise the elasticities obtained in the descriptive analysis (the β-s in equations 1 and 2).

5. Next steps

56. The human side of productivity offers rich opportunities to improve our understanding of the determinants of productivity, and of the role policies can play. Data restrictions are the greatest limiting factor in analysing these human factors inside the black box of the firm. Therefore the next step of the project is to refine the measurement framework by assessing data availability across a wide range of GFP member countries. This serves to arrive at a lowest common denominator for measurements of skills, other worker characteristics, and productivity, to harmonize measurements across countries for a comparative analysis following the distributed microdata approach. For this purpose, we invite interested countries by responding to our meta-data questionnaire. This questionnaire collects information on available datasets and variables to implement the analyses discussed above.

57. To obtain more information on firms, e.g. ownership information and board composition, datasets obtained from the distributed microdata approach can be complemented using commercial databases such as Orbis (management board composition) and Zephyr (ownership). Such datasets may also allow to add information from management surveys, such as the World Management Survey.

58. Finally, the next steps will also seek to narrow down the policy analysis to such aspects where policy indicators are available and can be fruitfully exploited in the current context. Moreover, major policy reform episodes will also be considered as a potential area where quantitative analysis, exploiting the human side of firms, can present novel policy insights.

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Annex A.

Table A.1. Three broad skill categories based on occupations and their pay level

Based on 2-digit International Standard Occupational Classification (ISCO)

Occupations ranked by mean European wage	ISCO code
High-paying occupations	
Corporate managers	12
Physical, mathematical and engineering professionals	21
Life science and health professionals	22
Other professionals	24
Managers of small enterprises	13
Physical, mathematical and engineering associate professio	31
Other associate professionals	34
Life science and health associate professionals	32
Middling occupations	
Stationary plant and related operators	81
Metal, machinery and related trade work	72
Drivers and mobile plant operators	83
Office clerks	41
Precision, handicraft, craft printing and related trade workers	73
Extraction and building trades workers	71
Customer service clerks	42
Machine operators and assemblers	82
Other craft and related trade workers	74
Low-paying occupations	
Laborers in mining, construction, manufacturing and transpc	93
Personal and protective service workers	51
Models, salespersons and demonstrators	52
Sales and service elementary occupations	91

Source: Goos, Manning and Salomons (2014[82]), Table 1.

59. Regressions results from the linear probability model (equation 2) show the statistical link in Portugal between a firm's likelihood to belong to the productivity frontier and the worker shares for different characteristics (Table A.2). Results are obtained from estimating equation (2) as a linear probability model, regressing an indicator variable for belonging to the productivity frontier on worker shares measured as fractions of young workers (aged 15 to 32), old workers (aged 51 to 85), women, managers, as well as low and high skilled workers, controlling for industry-year and firm-size group fixed effects. Estimates indicate the change in a firm's likelihood of belonging to the frontier for an increase in the employment share of the respective worker group. For instance, as shown in column (1), a ten percentage point increase in the share of high skilled workers is associated with a two percentage points higher likelihood of belonging to the frontier in a given firm-size group, year and industry, holding all other worker shares constant.

60. Results in Table A.2 overall confirm the link between the human side and productivity depicted in the figures in the main text. In addition to these descriptive figures, results the table below demonstrate the significance of the links and show that these also hold when controlling for other worker shares, although the size of effects is generally small. Column (1) shows that firms more likely to belong to the frontier employ more high skilled workers and managers, and fewer low skilled, young, old and female workers. With the exception of young workers, these patterns are robust to using alternative definitions of the frontier (highest quintile instead of decile) or productivity measures (sales divided by hours worked instead of number of hours workers), as shown in columns (2) and (3). A higher share of young workers is associated with a higher likelihood to belong to the frontier when measuring productivity using hours worked rather than number of employees. This may reflect young workers working relatively often part-time, so productivity is downward biased when measured in terms of number of employees. The positive association with high skilled workers is compatible with advanced technologies being complementary with skills; the positive link with the share of managers is suggestive for organisational differences between frontier firms and the rest.[17] Taken at face value, the negative link for old and female workers may suggest diversity having adverse effects on productivity, e.g. due by hindering communication or undermining trust. It should, however, be emphasized that these results are purely correlational. Further analysis is needed to examine the role of diversity.

[17] Additional analysis, not shown here, provides some evidence that the link between the share of high skilled workers and frontier firms differs in magnitude across sectors, being especially large in ICT intensive sectors.

Table A.2. The human side of the productivity frontier

Linear probability model regression results for the frontier status of firms, explained by the share of different groups of employees

	(1)	(2)	(3)
Frontier definition:	Top productivity decile	Top productivity decile	Top productivity quintile
Productivity definition:	Sales/Number of employees	Sales/Hours worked	Sales/Hours worked
Young employees	-0.0445***	0.0456***	0.0727***
	(0.0056)	(0.0059)	(0.0078)
Old employees	-0.0746***	-0.0675***	-0.1175***
	(0.0102)	(0.0097)	(0.0132)
Women	-0.0701***	-0.0613***	-0.1227***
	(0.0053)	(0.0047)	(0.0064)
Low skilled employees	-0.0283***	-0.0214***	-0.0375***
	(0.0061)	(0.0058)	(0.0080)
High skilled employees	0.2073***	0.1506***	0.2196***
	(0.0100)	(0.0092)	(0.0121)
Managers	0.1845***	0.2297***	0.3405***
	(0.0157)	(0.0150)	(0.0194)
Number of observations	302023	302023	302023
R2	0.045	0.031	0.042
Industry × year FE	yes	yes	yes
Firm-size group FE	yes	yes	yes

Note: Results for linear probability model at the firm-level. Dependent variable: Dummy variable for belonging to productivity frontier. Frontier is defined as top decile (columns 1 and 2) or quintile (column 3) of the firm-level productivity distribution in each year and STAN A38 industry. Column (1) measures productivity as sales divided by number of employees; columns (2) and (3) measure productivity as sales divided by total hours worked. All independent variables refer to employment shares of worker groups as fractions: Young workers refers workers aged 15 to 32; old workers refers to workers aged 51 to 85; low and high skilled workers refers to workers in low and high skilled occupations based on Goos, Manning and Salomons (2014[84]). All regressions control for industry-year fixed effects using STAN A38 industries, excluding agriculture, and dummies for firm-size bins. Standard errors clustered at the firm-level in parentheses. Significance levels: * 10%, ** 5%, *** 1%. Results are shown for Portugal, based on Quadros de Pessoal 1991 to 2009.
Source: OECD calculations based on Portuguese linked employer-employee data.

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