Adult Skills and Productivity: New Evidence from PIAAC 2023

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Abstract

The 2023 Programme for the International Assessment of Adult Competencies (PIAAC) reveals large cross-country differences in adult skill levels that carry important implications for productivity. Cross-country analysis shows a positive relationship between labour productivity and the average level of adult skills at the industry level. This reflect partly a positive link between adult skills and R&D intensity – which is estimated to account for one-quarter of cross-country differences in industry productivity. But the ways in which skilled workers are allocated to different job roles and firms also matters. Higher productivity is observed in industries with lower labour market mismatches and where high-skilled workers are employed in larger and more dynamic firms. Differences in these patterns of allocation can account for at least 12 per cent of the productivity gaps between countries. These findings highlight the importance of policies aimed at enhancing adult skills and structural reforms to improve labour market adaptability and reallocation.

Human capital is widely recognized as a key determinant of cross-country differences in living standards – primarily through its impact on productivity (Hall and Jones, 1999; Jones, 2016; Hanushek 2017) – and is thus a structural policy priority for many countries (OECD, 2018). Recent OECD research found that nearly one-sixth of the productivity slowdown in advanced OECD countries could be accounted for by the slowdown in the pace of human capital accumulation (Andrews *et al.*, 2024). It also suggested that OECD countries differed in their capacity to allocate human capital efficiently, although the aggregate nature of the exercise prevented deeper analysis of this phenomenon. Thus, the release in December 2024 of the

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latest Programme for the International Assessment of Adult Competencies (PIAAC) is particularly timely, as it provides a fresh opportunity to examine the channels linking the level of adult skills and their allocation across job roles and firm types to productivity.

A large body of literature, including OECD research, has investigated the skills-productivity nexus via the role of skills shortages and mismatch, managerial quality and organizational structure, and skill composition on firm-level productivity performance. For example, Adalet McGowan and Andrews (2017) used PIAAC to illustrate the relevance of skill mismatch for labour productivity via the allocative efficiency channel but focused less on how the level of skills shaped industry productivity. Other studies find that skill shortages and mismatch reduce firm productivity by increasing hiring costs, compelling firms to employ less productive workers, or limiting their ability to invest in innovation (Fox and Smeets, 2011; Ilmakunnas *et al.*, 2004; Marcolin and Quintini, 2023; OECD, 2024b). Across OECD economies, skill mismatch remains a significant issue, particularly in fast-changing high-tech and science-driven industries, where firms struggle to align skill supply with market demand (Andretta *et al.*, 2021; Bijnens and Dhyne, 2021; Criscuolo *et al.*, 2021). Well-managed firms are found to better utilise their workforce and invest in continuous training (Caroli and Van Reenen, 2001; Bender *et al.*, 2018).

Against this background, the contribution of this article is to study how the level and allocation of adult skills relate to labour productivity performance, including an assessment of the relative magnitude of these two channels. In doing so, this article leverages a novel cross-country, sector-level dataset derived from the newly published PIAAC data and examines how adult skills are intertwined with productivity through two key channels: i) the direct level of skills (PIAAC score) effect on labour productivity in non-farm business sectors; and ii) the allocation of skills to different job roles and types of firms. This latter channel reflects the capacity of economies to more efficiently allocate their existing stock of skills at any point in time – by minimizing labour market mismatches – as well as to redeploy scarce high-skilled labour over time to underwrite the expansion of dynamic firms. A further layer of analysis explores how skills shape labour productivity performance via the R&D channel. Regression analysis combined with closing-the-gap (between country-level skills and global best practice) simulations are employed to illustrate the economic significance of these channels.

The article is organized as follows. The first section highlights key insights from the 2023 PIAAC data. Section 2 introduces an analytical framework to examine the transmission channels using sector-level datasets. Section 3 then empirically evaluates the significance of these channels using cross-country sector-level regressions and conducts simulation exercises to demonstrate the economic relevance of the results. Section 4 provides a brief policy discussion in light of the empirical findings.

The Programme for the International Assessment of Adult Competencies (PIAAC)

The Programme for the International Assessment of Adult Competencies (PIAAC), also known as the Survey of Adult Skills is an OECD initiative to evaluate and analyze adult skills across various OECD countries. This comprehensive survey assesses key information-processing skills such as literacy, numeracy, and adaptative problem-solving in technology-rich environments for adults aged between 16 and 65. These skills are considered essential for individuals to effectively participate in society and for fostering economic growth. The first cycle of PIAAC was conducted over three rounds between 2011 and 2018 and involved 31 OECD and 6 non-OECD countries. The second cycle began in 2022, with participation from 29 OECD and 2 non-OECD countries. The results from the first round of this second cycle, published in December 2024, provide updated insights into the evolving skills landscape of the adult population.[2]

In 2023, PIAAC scores – whether measured by literacy, numeracy or adaptative problem-solving – varied significantly across countries, reflecting stark disparities in adult skill levels across countries (Chart 1). Based on a simple average of the three PIAAC components, the top performers include Finland, Japan and Sweden, whereas Chile, Poland and Portugal have the lowest PIAAC scores (Chart 1, Panel A). And the scale of these differences is material: average PIAAC scores in the top three performing countries are around 10 per cent higher than the OECD average and 25 per cent higher than in the bottom three performing countries.

An analysis of literacy, numeracy, and problem-solving rankings across countries reveal a degree of consistency among the top performers, suggesting well-rounded and balanced skill levels (Chart 1, Panels B to D)[3]. Yet, some countries exhibited heterogeneous performance across the domains, highlighting the nuanced challenges countries face in achieving balanced adult skills. For example, Austria performed relatively well in numeracy and problem solving but lagged in literacy. Latvia was doing much better at numeracy than at literacy and problem solving. Ireland exceeded the OECD average in literacy but fell behind in numeracy and problem solving. New Zealand and the United States also displayed strong literacy skills but lagged in numeracy and, to a lesser extent, in problem solving.

Adult Skills and Productivity: The Analytical Framework

As discussed in this section, a nuanced understanding of the latest PIAAC results requires an analysis of granular – sector-level – data to pin down the key mechanisms linking adult skills and productivity, including via the innovation and reallocation channels.

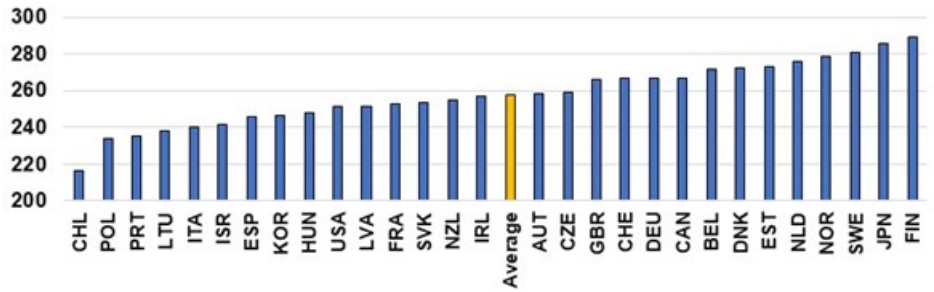
Skills and Productivity: Towards a Better Understanding of the Chan-

2 See Box 1 in Andrews *et al.* (2025) for more details on the construction of the PIAAC scores.

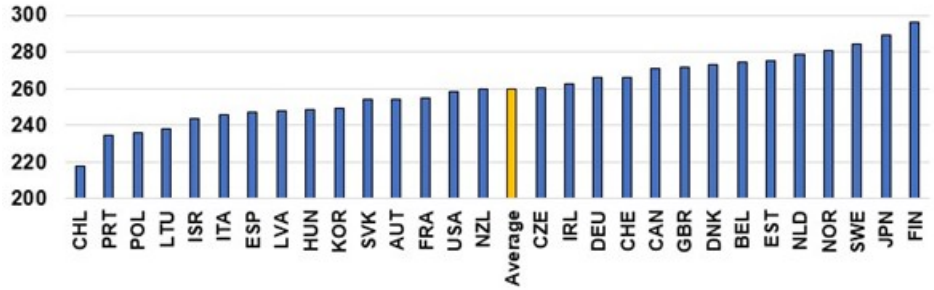
3 Finland, Japan, Sweden, Norway and the Netherlands are the top five performers across all three areas.

Chart 1: PIAAC Scores in 2023 in OECD Countries, in points

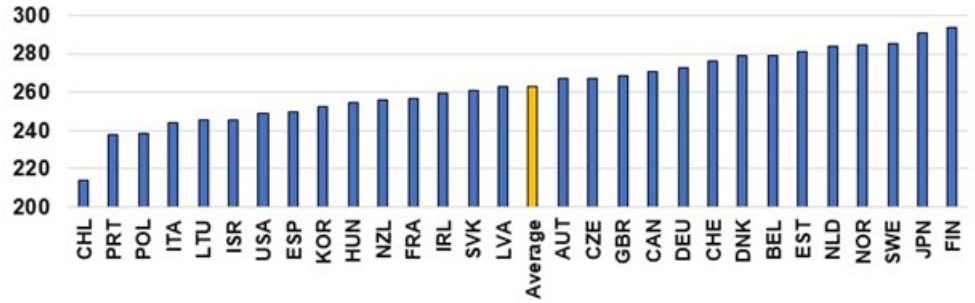
Panel A. Average PIAAC Scores



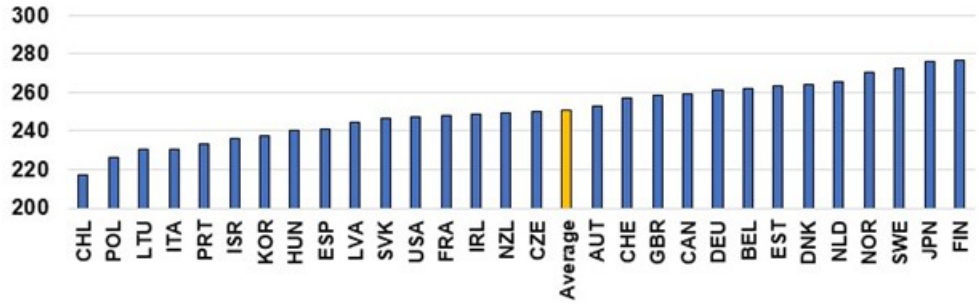
Panel B. PIAAC Literacy Scores



Panel C. PIAAC Numeracy Scores



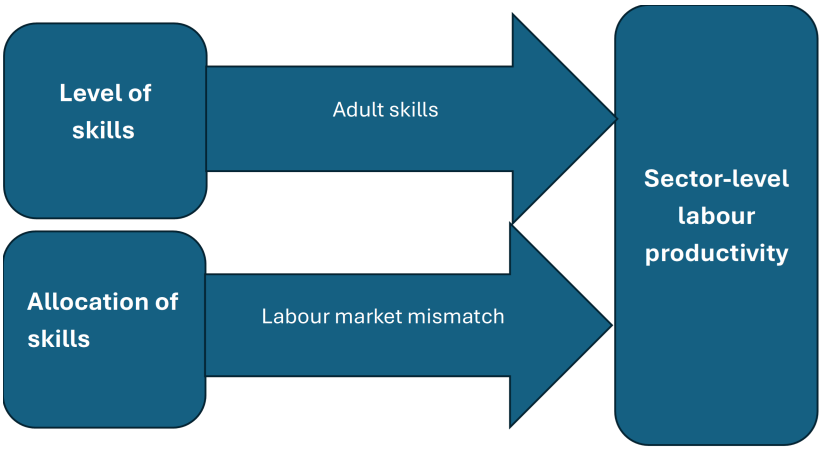
Panel D. PIAAC Problem Solving Scores



Note: Average PIAAC scores displayed in Panel A are the simple averages of the PIAAC scores on literacy, numeracy and problem solving. In this chart and in the rest of the article, Belgium (BEL) refers to the Flemish Region and the United Kingdom (GBR) refers to England. The PIAAC scores are for all adults aged 16-65 including the 20 per cent of adults who are not in the labour force.

Source: Authors' calculations.

Figure 1: PIAAC-implied Country-level Productivity Gains in the OECD



Source: Authors' calculations.

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A key observation is that within any given sector, a higher average level of adult skills will directly support aggregate productivity performance (Figure 1). A greater proportion of highly skilled workers – relative to lower-skilled workers – will enable both the broader diffusion of new and existing ideas and the generation of new ideas, via investments in R&D.

But adult skills will also impact productivity via indirect channels through the allocation of skills across job roles and firm types. Since the stock of adult skills is relatively fixed in the short to medium term, the extent to which skilled workers are allocated efficiently across firms will also matter for sector-level productivity (Figure 1). Earlier OECD research found that higher rates of skill mismatch within industries go hand in hand with lower labour productivity due to inefficient resource allocation (Adalet McGowan and Andrews, 2017). From the perspective of a single firm, hiring an over-skilled worker may be beneficial for productivity.[4] But over-skilling in any given firm could be harmful for aggregate productivity if there exist more productive firms that could better utilize these skills but find it difficult to expand due to a lack of suitable labour.[5] Indeed, frictions to the matching process are likely to be particularly costly to aggregate growth in R&D intensive sectors, to the extent that it impedes innovation and the scope for produc-

4 This assumes there are no adverse effects on job satisfaction and the higher wages do not more than offset any associated productivity gains. The definition of overskilled is A PIAAC score, as a proxy for technical skills, above that required for the job or a level of educational attainment greater than that required for the job based on minimum education requirements for occupations.

5 Mismatches arise from reallocation being hindered by labour market rigidities relating to insufficient short-term wage adjustments, stringent labour market regulations (including dismissal regulations and anticompetitive non-poaching clauses) and the absence of geographical mobility across regions.

6 Labour market mismatch collectively dampens innovation prospects via a few channels: i) mismatched researchers may struggle with efficiency, hinder creativity, and slow scientific breakthroughs; ii) high turnover disrupts projects and erodes institutional knowledge; iii) firms incur higher training costs, and skill mismatches create frictions that delay R&D and increase errors; and iv) skilled researchers may end up in less innovative

tivity spillovers to other sectors (Acemoglu *et al.* 2018; Adalet McGowan and Andrews, 2017; Lehr, 2024; Moretti, 2021).[6]

In an economy where firms are relatively homogenous, the potential gains to aggregate productivity from a better allocation of mismatched workers would be relatively small. In practice, however, the degree of firm heterogeneity is striking:

- First, highly productive firms co-exist with low productivity firms: even within narrowly defined industries in the United States. Firms at the 90th per centile of the total factor productivity (TFP) distribution are twice as productive as firms at the 10th per centile (Syverson, 2004).
- Second, the same is true with respect to the firm size distribution, with many small firms co-existing with a smaller number of very large firms, which are typically more productive (Bartelsman *et al.*, 2013).
- Finally, firms vary greatly in their growth potential: many firms do not grow at all, a small cadre of young firms tend to disproportionately drive net job creation, while small and old firms tend to destroy jobs on net (Haltiwanger *et al.* 2013; Criscuolo *et al.* 2014).

This widespread firm heterogeneity implies that aggregate productivity will also depend upon how skilled workers – which are currently in short supply (OECD, 2024a) – are allocated across firms and matched to various job roles. At any point in time, aggregate productivity is an increasing function of static allocative efficiency, which measures the extent to which scarce resources are allocated to their highest valued use in the form of higher quality (i.e. more productive) firms (Haltiwanger, 2011; Andrews and Hansell, 2021). Dynamic allocative efficiency captures the extent to which resources are moving towards higher quality firms over time. Achieving static allocative efficiency in one period requires sufficient dynamic allocative efficiency in preceding periods, and differences in this process is now a leading explanation for why some countries are more productive than others (Bartelsman *et al.*, 2013; Hsieh and Klenow, 2009).

Skills and Productivity: The Estimation Framework

To analyze and identify the effects of the level and the allocation of skills on productivity, this article exploits a novel cross-country sector-level database created by merging sector-level labour productivity data from the OECD National Accounts database with a range of skills indicators drawn from the 2023 PIAAC dataset. This dataset encompasses twelve one-digit industries across 25 OECD countries (listed in Chart 2).

The analysis focuses exclusively on non-farm business sectors, excluding non-market-based sectors and sectors such as agriculture, public administration, arts, health, education and mining, mainly because of problems associated with the measurement of labour productivity in these

firms, while geographical mismatches and lack of clustering further impede innovation.

sectors. The dataset is purely cross sectional and focuses on 2023 (and nearby years). Appendix A in Andrews *et al.* (2025) provides data definitions, sources and selected descriptive statistics.

Chart 2 provides a snapshot in the cross-county variation in the level of adult skills across key industries in the non-farm business sector. On average, adult skills are higher in intangible-intensive sectors such as finance and insurance and professions, scientists and technicians than elsewhere. For example, the average level of adult skills in finance and insurance is 15 per cent higher than in administrative and support services. Nevertheless, there remains significant cross-country variation in the level of adult skills within any given industry, which we exploit for identification purposes in this article.

The different channels through which adult skills shape sector-level productivity outcomes are examined through a series of regressions. Two broad channels emerge:

- A direct channel relating labour productivity to the level of skills, reflecting the generation of new ideas (via R&D) and the diffusion of leading technologies. Raising the floor of basic skills, i.e. reducing the share of workers with low literacy and numeracy, facilitates technological diffusion and, in turn, boosts productivity growth.
- An indirect channel linking labour productivity to the allocation of skills to different jobs (i.e. labour market mismatch) and firms (according to their size and growth potential).[7]

In the baseline regression, the log of sectoral labour productivity (LABPROD, equation 1) or R&D intensity (R&D expenditure as a share of value added) (equation 2) is regressed on the log of average PIAAC scores, the mean of literacy, numeracy, and problem-solving scores, in corresponding industries (the level of skills effect):

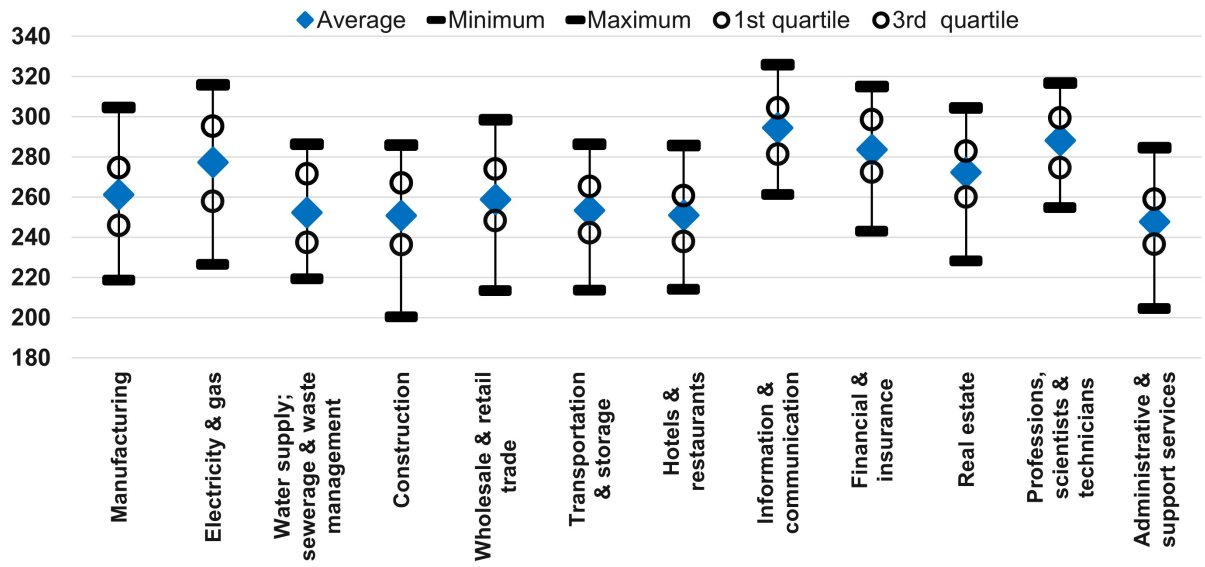
$$\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) + CFE_c + SFE_s + \varepsilon_{c,s} \quad (1)$$

$$R\&D_{c,s} = \theta \cdot \log(PIAAC_{c,s}) + CFE_c + SFE_s + \varepsilon_{c,s}. \quad (2)$$

where c and s denote countries and sectors, and CFE and SFE are country and sector fixed effects. Country fixed effects absorb country-specific factors, such as economic structure, policy and institutions. Sector fixed effects capture technological and market characteristics common across countries. By controlling for these unobserved factors, the model uses within-country and within-sector variation to isolate the impact of adult skills on productivity, mitigating endogeneity and omitted-variable bias. Fixed effects also limit reverse causality, when it operates through unobserved factors, if productive sectors systematically attract skilled workers due

7 Additional channels, not considered here explicitly, as they are largely captured by our fixed-effects structure, include ICT intensity (connected to the R&D channel), the capital-labour complementarity and age and gender composition. Managerial quality is an additional channel. Yet, in the 2023 PIAAC dataset, there are various definitions of managers and data availability differs across definitions, countries and sectors, which leads us to exclude this channel from the empirical analysis.

Chart 2: PIAAC Scores in Non-farm Business Sectors across OECD Countries, 2023



Note: Individual-level PIAAC scores are aggregated to the sectoral level and cover workers aged 16 to 65 using representative weights.

Source: Authors' calculations based on PIAAC 2023.

to inherent advantages such as advanced technologies, innovation and better managerial practices (which supply dynamic work environments and professional development opportunities).

However, fixed effects may not fully eliminate reverse causality if sector-specific factors differ across countries. If highly productive sectors invest more in training or attract skilled workers differently, the coefficient α on the $\log(PIAAC)$ in equation (1) may be upwardly biased. To reduce this risk, three additional strategies are applied:[8] *i)* controlling for the allocation of skilled workers across firms of differing growth potential and size; *ii)* adding controls for sectoral R&D intensity (equation (3)), managerial skill, and training participation; and *iii)* including capital per worker and, as a robustness check, using total factor productivity (TFP) as the dependent variable, though this results in a non-trivial reduction in sample size. R&D intensity (R&D) can be added to equation (1) to capture the effect of R&D on labour productivity:

$$\begin{aligned}\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) \\ + \beta \cdot R\&D_{c,s} \\ + CFE_c + SFE_s \\ + \varepsilon_{c,s}.\end{aligned} \tag{3}$$

To proxy the allocation of skills, equation (1) is augmented with two allocative terms: the degree of qualification and field-of-study mismatch (*labour market mismatch*) and the extent to which skilled workers are allocated to high-growth firms

8 Alternatively, an instrumental variables strategy could be employed but identifying valid instruments in a cross-country, cross-sector context for adult skills is particularly challenging.

(*skills allocation to firms*):

$$\begin{aligned}\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) \\ + \ \delta \cdot mismatch_{c,s} \\ + \ \gamma \cdot skills\ allocation\ to\ firms_{c,s} \\ + \ CFE_c \ + \ SFE_s \ + \ \varepsilon_{c,s}.\end{aligned} \tag{4}$$

In this article, workers are deemed mismatched if they are misaligned in terms of both their specialization (field-of-study mismatch) and their qualification (qualification mismatch).

Qualification (vertical) mismatch compares workers' highest qualification (level of education) to the qualification required for their job. Field of study (horizontal) mismatch compares workers' field of study (area of education) with the area of their current job (for more details, see Andrews *et al.* 2025). Research shows that labour market mismatch is particularly costly for individual workers but also at the aggregate level if field-of-study mismatch is associated with qualification mismatch (Montt, 2015, 2017).

Our mismatch indicator, combining qualification and field-of-study misalignment, has some potential shortcomings. First, education-based proxies may conceal large variation in actual skills: some workers may lack the competencies their jobs nominally require, while others may exceed task demands without the "correct" credential or major. Second, the indicator is static and does not account for work experience and learning (e.g. on-the-job training, informal upskilling, or micro-credentials), which can close gaps irrespective of initial education. Finally, the measure omits soft skills as well as firm- and sector-specific human capital.

In this article, the allocation of skills to firms captures: i) a snapshot of the state of allocation and is calculated as the difference in the average skills (i.e. PIAAC score) of workers in large and small firms (in terms of employment); and ii) the dynamic allocation across growing and declining firms by comparing the average skills (i.e. PIAAC score) of workers in growing firms (in terms of employment) and the average skills of workers sunk in declining firms.[9]

As an extension to the baseline results, R&D is regressed on adult skills (PIAAC) and an R&D-specific mismatch metric that combines qualification and field-of-study mismatches among engineers and scientists, who are primarily responsible for R&D activities.[10] Some caution is warranted when interpreting these results, given the significant reduction in sample size. The regression is specified as follows:

$$\begin{aligned}R\&D_{c,s} = \theta \cdot \log(PIAAC_{c,s}) \\ + \ \vartheta \cdot R\&D\_specific\ mismatch_{c,s} \\ + \ CFE_c \ + \ SFE_s \ + \ \varepsilon_{c,s}.\end{aligned} \tag{5}$$

9 Some caution is needed regarding the variables using firm characteristics as PIAAC data on firms do not provide a representative sample at the firm level within a sector. Additionally, individuals are selected without ensuring they reflect the entire workforce of their respective firms.

10 This corresponds to STEM (Science, Technology, Engineering and Mathematics).

Table 1: Cross-country Sector-level Estimates of Adult Skills (PIAAC) Effects on Productivity

	Panel A: log(labour productivity)					**Panel B:** R&D expenditures as a share of value added			
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	−1.081	0.690	−1.586	−0.307	3.668	−1.582**	−1.386**	−1.623**	−1.508**
Level of skills effect									
log(average PIAAC)	2.300**				1.374**	0.291**			
log(literacy)		1.982**					0.256**		
log(numeracy)			2.377**					0.298**	
log(problem solving)				2.176**					0.278**
R&D intensity					2.922**				
R^2	0.883	0.881	0.884	0.881	0.889	0.764	0.758	0.773	0.755
No. observations	293	293	293	293	293	199	199	199	199
No. countries	25	25	25	25	25	18	18	18	18
Country fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: * and ** denote statistical significance at the 10% and 5% levels, respectively, based on robust standard errors. Average PIAAC scores are the simple average of the PIAAC scores on literacy, numeracy, and problem solving.
Countries in labour productivity specifications: Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom.
Countries in R&D specifications: Austria, Czech Republic, Estonia, Finland, France, Germany, Hungary, Italy, Japan, Latvia, Lithuania, Netherlands, Norway, Portugal, Slovakia, Spain, Sweden, United Kingdom.

Source: Authors' calculations.

Productivity, Adult Skills and Reallocation at the Sector Level

The Level of PIAAC Scores and Sector-level Productivity

Baseline Results

Graphical inspection of the data suggests a positive cross-country relationship, at the industry level, between average PIAAC scores and both sectoral labour productivity and R&D intensity (see Andrews *et al.*, 2025). Regression analysis formally confirms these patterns.

Regression analysis suggests that a 1 per cent increase in average PIAAC scores is associated with more than a 2 per cent gain in labour productivity (Column 1, Panel A of Table 1). To explore whether different skills have a different impact, the regression was re-run with literacy, numeracy and problem-solving scores included individually (Table 1, Columns 2 to 4). The elasticity on numeracy (2.4) exceeds those on literacy (1.9) and problem solving (2.2), but these differences are not substantial.

Turning to Column 5, controlling for R&D intensity in the labour productivity regression indicates that a sizeable part of the level of skills effect can be explained by R&D: the coefficient on average PIAAC scores drops from 2.33 (Table 1, Column 1) to 1.37 (Table 1, Column 5). One interpretation is that around 60 per cent of the direct effect of skills on productivity is general – that is, related to the adoption of existing knowledge – while 40 per

cent emanates from R&D activities that are typically devoted to the generation of new knowledge. Accordingly, Panel B of Table 1 explores the link between R&D intensity and adult skills, confirming a robust positive association between R&D expenditure as a share of value added and average PIAAC scores. Similarly to the labour productivity regressions in Panel A, numeracy yields the highest coefficient estimate in the R&D regression, while literacy has the lowest, but again these differences should not be overstated.

Before proceeding, we test the robustness of the baseline results. Each test is based on fewer observations due to limited data for additional variables. First, regressions adding intangibles show that including managerial skills barely affects the PIAAC coefficient, while including adult training slightly reduces it. Second, the coefficient on adult skills remains positive and significant after controlling for capital per worker and when using total factor productivity (TFP) instead of labour productivity, despite the smaller sample (Table B1 in Appendix B, Andrews *et al.*, 2025).

Economic Significance

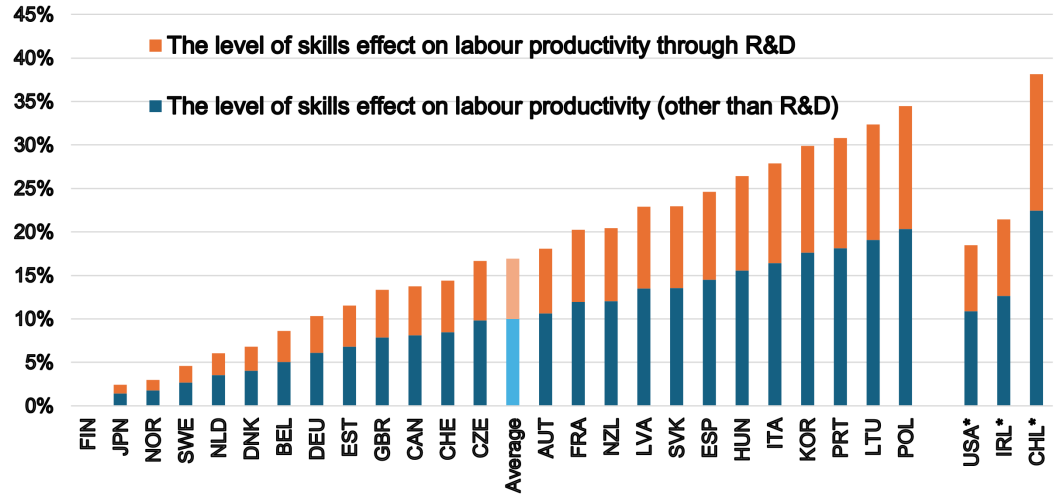
How large are the aggregate labour productivity gains from closing the sector-level adult skills gap to the top-performing countries? To answer this question, back-of-the-envelope calculations are conducted.[11] They suggest that closing the PIAAC gap would boost productivity by 17 per cent on average across OECD countries (Chart 3). However, this effect amounts to more than 30 per cent in laggard countries such as Portugal, Lithuania or Poland. Purely for illustrative purposes, Chart 3 also includes implied productivity gains for three countries which are included in PIAAC but lack adequate industry-level productivity data. These estimates should be treated with caution.

The total PIAAC effect in Chart 3 can be decomposed into two main channels: i.) the effect of the general level of skills that affects labour productivity in a broad sense, and ii.) the effect through R&D. For the average OECD country, closing the PIAAC gap with the top performers could boost labour productivity by 17 per cent, of which 10 per centage points would be accounted for by the general skill effect and 7 per centage points would reflect the R&D channel.

Thus far, the analysis shows that raising the average level of adult skills could yield material productivity gains across OECD countries. Given the large and persistent cross-country productivity differences, it is natural to ask how much of these gaps stem from adult skill disparities. To explore this, we extend the simulation exercise by comparing the implied productivity gains from raising each country's skill level to the average of the three best performers

11 First, the difference between a country-sector's PIAAC score and the mean of the average PIAAC scores of the top 3 performing OECD countries in the corresponding sector is calculated. The average performance of the top three countries is used instead of that of the single top performer, primarily to reduce the influence of any outlier country. Second, the estimated coefficient linking PIAAC to productivity (Table 1, Column 1) is applied to translate the PIAAC gap into productivity gains. Third, sector-specific weights (in terms of value added) are used to aggregate the sectoral results to the country level.

Chart 3: Country-level Labour Productivity Gains Resulting from Closing the Sector Skills Gap, 2023



Note: The total labour productivity gains arising from closing the sector-level PIAAC gaps are calculated as follows: i.) sector-level PIAAC gaps are determined relative to the 3 best performing sectors, ii.) sector-level productivity gains are calculated by multiplying the sector-level PIAAC gap by the estimated coefficient linking sector-level labour productivity to PIAAC, and iii.) sector-level productivity gains are aggregated to the country level using sectoral value added weights. The general level of skills effect (blue part) accounts for around 60 per cent of the total productivity gains. This 60 per cent is obtained as the difference between the coefficient estimate on PIAAC without and with controlling for R&D (2.300 vs. 1.374). The rest, in orange, indicates productivity gains through the R&D channel. Countries marked with an asterisk (*) lack sectoral productivity data. For these countries, sector-level productivity gains can be estimated by multiplying the sector-level PIAAC gap by the coefficient that links sector-level labour productivity to PIAAC in in-sample countries.

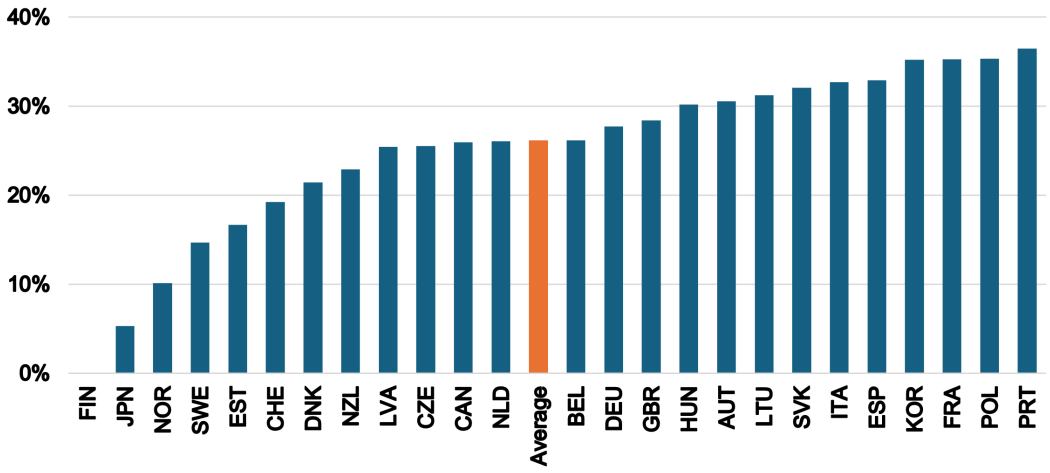
Source: Authors' calculations.

(Chart 3) with observed sector-level productivity gaps. On average, differences in adult skills can potentially account for one-quarter of cross-country productivity variation (Chart 4), and up to one-third in some Southern and Eastern European countries. These estimates leave plenty of scope for other factors to explain the productivity gap – including the efficient allocation of skills – which is explored below.

The results presented in Table 1 show the average positive relationship between labour productivity and PIAAC scores at the sector level. However, this average relationship masks significant differences across group of countries in the extent to which adult skills translate into productivity gains. Specifically, the pass-through of adult skills to productivity is considerably stronger in Nordic countries compared to other OECD economies (Table D1 in Appendix D in Andrews *et al.* (2025)). This disparity may reflect the greater efficiency of Nordic economies in allocating human capital, possibly supported by structural policy frameworks that facilitate reallocation and adaptability (Andrews *et al.*, 2024). This observed heterogeneity across countries motivates a deep dive into the link between human capital allocation and productivity in the next section.

The Allocation of Skills and Productivity Performance

Chart 4: Country-Level Productivity Gap Explained by Sector-Level PIAAC Differences, 2023



Note: Country-level productivity gap explained by sector-level PIAAC differences, compared to top 3 PIAAC performing countries. The bar for each country is a weighted (by value added share) average of the PIAAC contribution of each sector to overall productivity. The overall average is a simple average of the contributions in each country. PIAAC scores used for the calculations are the simple averages of the PIAAC scores on literacy, numeracy and problem solving.

Source: Authors' calculations.

While labour productivity is clearly connected to the average level of adult skills, so far we have been silent on how those skilled workers are allocated across firms and jobs within a given sector. To address this question, we emphasize two interrelated concepts: how efficiently skills are allocated at any point in time (i.e. static allocative efficiency) and whether skills are being allocated to better/more productive firms over time (i.e. dynamic allocative efficiency). While PIAAC does not contain data on firm productivity, it does contain information on the size of firms (measured by headcount) as well as the growth status of firms (i.e. headcount is growing, static or declining), from which we can draw inferences about firm performance. Moreover, PIAAC contains various measures of labour market mismatch, which previous OECD research has shown to have a close theoretical and empirical link with static allocative efficiency (Adalet McGowan and Andrews, 2017).

Labour Market Mismatch

Labour market mismatch arises when workers are employed in jobs that are either too demanding or not challenging enough. Qualification and field-of-study mismatches are prevalent in OECD countries. On average, nearly 35 per cent of workers in the OECD are employed in jobs that require a lower or higher qualification than their highest level of qualification. Similarly, over 35 per cent of workers holds jobs that do not align with their field of study. These mismatches differ across countries. For instance, Korea has the highest level of field of study mismatch but performs much better in terms of qualification mismatch. Conversely, Switzer-

land excels in minimizing qualification mismatch but faces challenges in terms of field of study mismatch.

Labour market mismatch is potentially most acute when measured by the combination of qualification and field of study mismatch – that is, when workers are mismatched both in terms of qualification and field of study. According to this metric, more than 10 per cent of workers on average across the OECD experience mismatch. The incidence of mismatch tends to be higher in industries such as transport, hospitality and administrative services and lower than average in ICT, finance and professional services.

Allocation of Skills Across Firms

The way in which skills are allocated to firms of various size is also connected to the concept of static allocative efficiency. There is evidence that larger firms are often more productive than smaller firms and can better deploy skilled workers and that better-skilled workers can perform jobs more productively in larger firms (Haltiwanger, 2011). In this regard, the new 2023 PIAAC data confirms that average worker skills are higher in larger firms on average across the OECD (Chart 5, Panel A), but the strength of this connection varies significantly across countries (Chart 5, Panel B).

The dynamic allocation of skills across firms can be measured through the skills of workers employed in growing, static and declining firms in terms of employment (Chart 6, Panel A). Improving allocative efficiency over time implies that growing firms would attract and employ more skilled workers while declining firms would be left with workers with lower skills. On average across the OECD, skills are moving in the right direction over time: growing firms employ more skilled workers than declining firms, by a margin of 4 per cent on average across OECD countries (Chart 6, Panel B). However, this is not always the case: in New Zealand and Italy, declining firms employ workers with better skills than growing and static firms (Figure 8 and Appendix E in Andrews *et al.* (2025)).

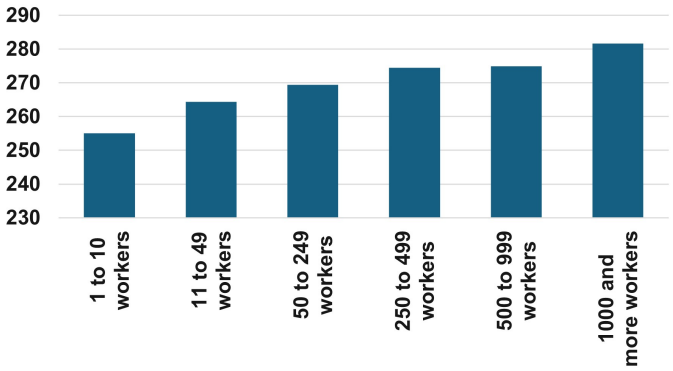
Labour Market Mismatch, Skills Allocation Across Firms and Productivity

Preliminary eyeball econometrics, based on binscatter charts, explained in Chart 7, suggest a negative relationship between overall labour market mismatch and labour productivity (Chart 7).

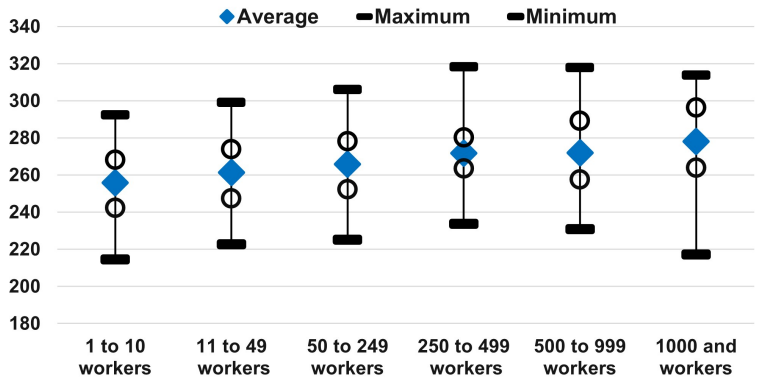
More formally, the cross-country sector-level estimation results indicate that the share of mismatched workers tends to be negatively related to sector-level productivity, particularly when field-of-study and qualification mismatches are combined (Table 2, Columns 2 to 6). Similar results are obtained for the R&D-specific labour market mismatch, which focuses on mismatch amongst engineers and scientists (see Box 3 in Andrews *et al.*, 2025). Put differently, countries and industries that achieve a more efficient matching of workers in terms of qualification and specialization are found to exhibit higher labour productivity. Interestingly, the coefficient on average PIAAC declines somewhat with the inclusion of mismatch, consistent with the negative cross-country relationship between the two variables (Figure A3 in Ap-

Chart 5: Adult Skills by Firm Size, OECD Average:

Panel A. PIAAC Scores in Points by Firm Size



Panel B. The Distribution of PIAAC Scores by Firm Size

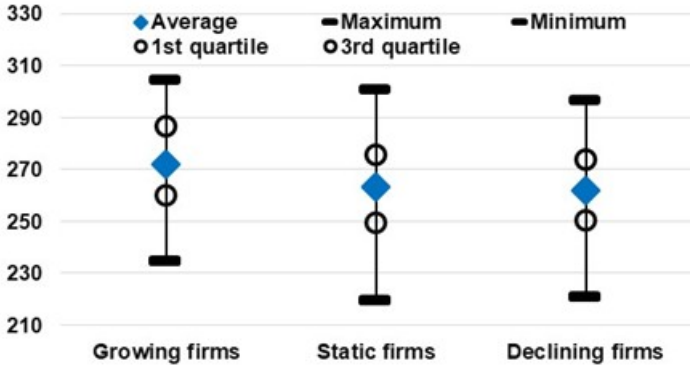


Note: PIAAC scores displayed are the simple averages of the PIAAC scores on literacy, numeracy and problem solving.

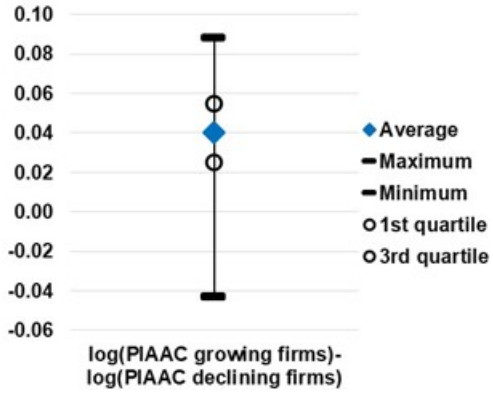
Source: Authors' calculations.

Chart 6: PIAAC Scores of Workers in Growing, Static and Declining Firms

Panel A. PIAAC scores by types of firms



Panel B. The Difference in PIAAC Scores between Growing and Declining Firms



Note: PIAAC scores displayed are the simple averages of the PIAAC scores on literacy, numeracy and problem solving. Firms are growing, declining or static in terms of headcount. Static firms refer to firms that "stayed more or less the same" in terms of headcount.

Source: Authors' calculations.

pendix A in Andrews *et al.* (2025)).

The allocation of skilled workers across firms of different sizes also plays a significant role (Table 2, Columns 3 and 4). First, productivity is higher in industries where larger firms employ a greater proportion of more skilled workers compared to smaller firms. Consistent with this is the finding, that more skilled workers in smaller firms tends to act as a drag on sectoral productivity. On the dynamic side, allocating higher-skilled workers to expanding firms at the expense of declining firms is associated with higher productivity (Table 2, Columns 5 and 6). The inverse holds true: productivity is lower when higher-skilled workers remain trapped in declining firms. Finally, additional analysis suggests that the link between labour productivity and the allocation of skills to dynamic firms remains intact after controlling for the role of financial frictions and insolvency regimes (see Box 4 in Andrews *et al.* 2025).

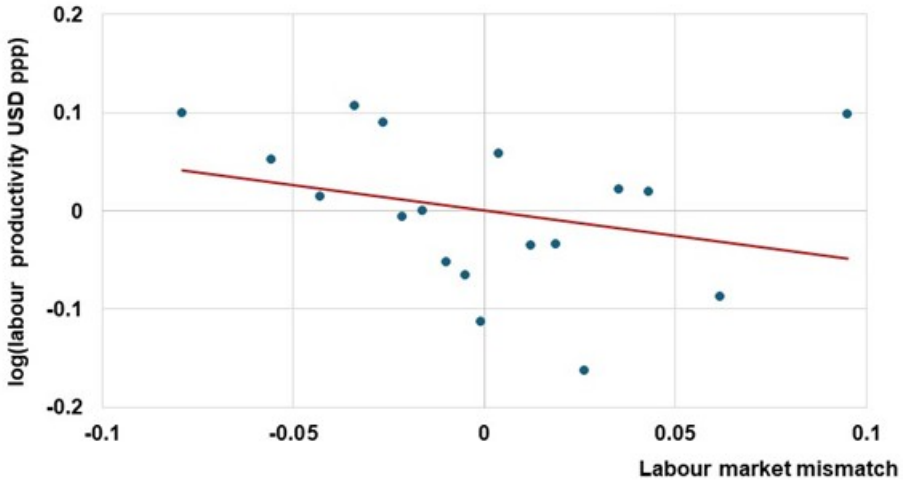
Economic Magnitudes

How large are the aggregate labour productivity gains from closing the sector-level labour market mismatch gap to the best-performing sectors/countries? This exercise is similar in spirit to the one conducted for the gaps in adult skill levels.[12] These simulations suggest that closing the mismatch gap would be associated with a productivity boost of almost 5 per cent on average across OECD countries (Chart 8). This is in the same ballpark as estimated by Adalet McGowan and Andrews (2017).

A useful comparison is between the potential productivity gains from closing adult skill gaps (Chart 3) and mismatch gaps (Chart 8). Countries such as Finland and Norway combine high skill levels with low mismatch, yielding limited poten-

12 The calculations involve deriving the sectoral mismatch gaps relative to the best 3 performing OECD countries, followed by the calculation of the sectoral productivity gains (calculated as the mismatch gap multiplied by the coefficient estimate on mismatch (Column 2 in Table 2)). Finally, the sectoral productivity gains are aggregated to the country level by using sectoral value-added.

Chart 7: Labour Productivity and Labour Market Mismatch



Note: The figure uses the STATA binscatter command: it shows logged average labour productivity for each of the 18 bins of labour market mismatches, purged of country- and sector fixed effects. Labour market mismatch is measured as the combination of qualification and field-of-study mismatch.

Source: Authors' calculations.

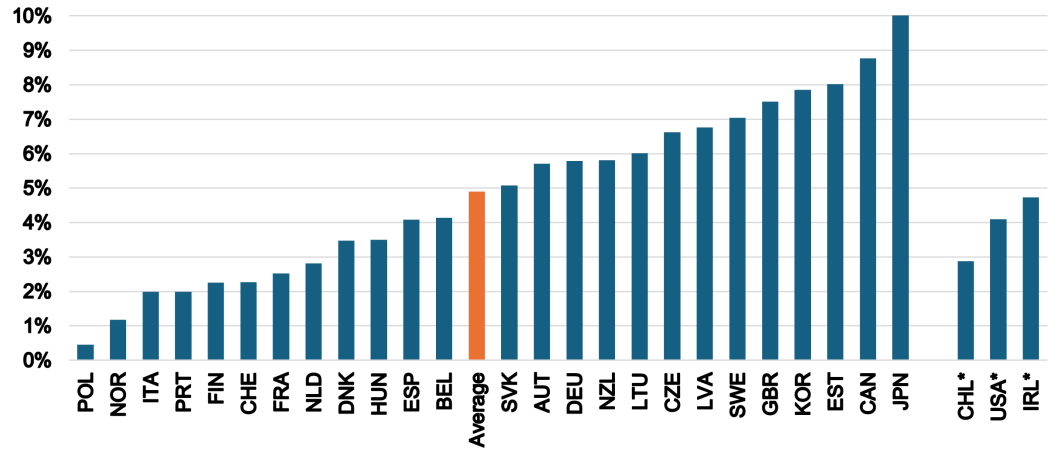
Table 2: Labour Productivity and the Allocation of Skills

	log(**labour productivity**)					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
PIAAC = average of literacy, numeracy and problem solving						
Constant	−0.508	1.035	1.489	0.099	0.161	−0.767
Adult skills effects						
log(PIAAC)	2.303**	2.044**	3.689**	2.054**	2.928**	2.219**
Allocation of skills effects						
Labour market mismatch						
Labour market mismatch (qualification and field-of-study)		−1.031**	−0.984**	−0.994**	−1.060**	−1.012**
log(PIAAC small firms)			−1.733*			
log(PIAAC large) − log(PIAAC small)				0.663*		
Allocation of skills across firms						
log(PIAAC declining firms)					−0.861**	
log(PIAAC growing) − log(PIAAC declining)						0.579**
R^2	0.880	0.885	0.887	0.886	0.887	0.887
No. observations	278	278	278	277	273	272
No. countries	25	25	25	25	25	25
Country fixed effects	YES	YES	YES	YES	YES	YES
Sector fixed effects	YES	YES	YES	YES	YES	YES

Note: * and ** denote statistical significance at the 10% and 5% levels, respectively, based on robust standard errors. Average PIAAC scores used in the regressions are the simple average of the PIAAC scores on literacy, numeracy, and problem solving.

Source: Authors' calculations.

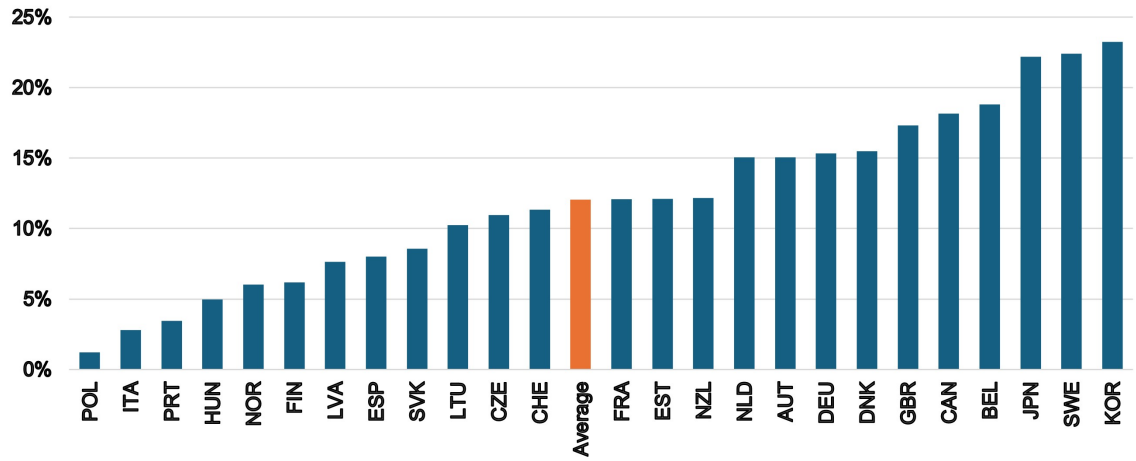
Chart 8: Country-Level Labour Productivity Gains Implied by Closing Sector-Level Labour Market Mismatches



Note: Country-level productivity gains implied by closing sector-level labour market mismatches are calculated as follows. First, the mismatch gap is determined vis-à-vis the top 3 least mismatched countries/sectors. Second, the coefficient estimate of -1.031 from Table 2 is used to calculate the implied sectoral productivity gains. Finally, sectoral value-added weights are employed to obtain country-level implied productivity gains. Countries marked with an asterisk (*) lack sectoral productivity data. For these countries, sector-level productivity gains can be calculated by multiplying the sector-level labour market mismatch gap by the estimated coefficient linking sector-level labour productivity to mismatch in in-sample countries.

Source: Authors' calculations.

Chart 9: Country-Level Productivity Gap Explained by Sector-Level Labour Market Mismatch Disparities



Note: The calculations are done as follows. First, we calculate the difference in labour market mismatch of all countries in a specific sector relative to the average of the top 3 countries with the least mismatch. Coefficient estimates from column 1 of Table 2 are used to derive the implied labour productivity gap, which is then compared to the observed productivity gap. Sectoral value-added shares are used to calculate the contribution of mismatches to the country level productivity gap. Labour market mismatch is used to proxy static allocative efficiency and the estimates are potentially conservative estimates as they do not include dynamic allocative efficiency effects.

Source: Authors' calculations.

tial gains from either channel. In contrast, Korea shows both low skills and high mismatch, implying large gains from improving both the level and allocation of skills. These patterns align with the negative correlation between adult skills and labour market mismatch across OECD industries (Chart A3 in Andrews *et al.*, 2025), though the relationship is far from perfect. Some countries that would benefit most from reducing mismatch are not those with the largest skill shortfalls. For example, Poland and Portugal exhibit low mismatch and potential productivity gains of only about 1 per cent, while Japan, with substantial mismatches, could gain up to 9 per cent, despite minimal returns from higher skill levels (Chart 3).

What proportion of the cross-country labour productivity gaps can be explained by the allocation of skills? The implied productivity gains in Chart 8 are compared with the observed overall productivity gap. For the average OECD country, differences in labour market mismatch explain around 12 per cent of cross-country productivity gaps relative to best practice (Chart 9). This is a conservative estimate because dynamic allocative efficiency effects will eventually feed into static allocative efficiency. In some countries (e.g. New Zealand, Italy, Canada), skilled workers are not strongly concentrated in expanding firms, limiting productivity growth. If these countries could match the allocation pattern observed in the average OECD economy, labour productivity could be 3 per cent higher. Similarly, moving from the bottom quartile to the OECD average in skill allocation (Chart 6, Panel B) would yield productivity gains of roughly 1 per cent. While the aggregate benefits of better skill allocation appear substantial, a more systematic quantification of dynamic allocative effects is left for future research.

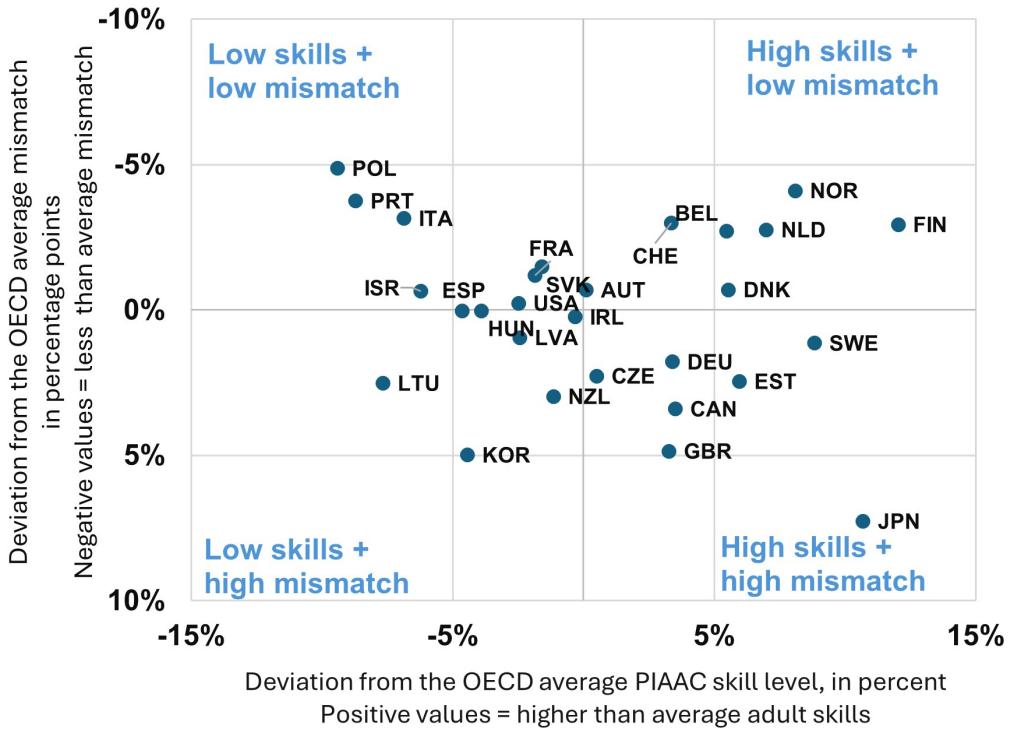
Overall, for an average OECD country, the general and R&D-specific level of skills channel accounts for almost 25 per cent of these gaps, while the allocation of skills, captured through the general labour market mismatch, explains more than 12 per cent. Collectively, differences in the level and allocation of adult skills can explain roughly 40 per cent of productivity gaps across OECD countries.

Policy Discussion

The results illustrate the importance of adult skills for productivity and raise two key policy questions for future research. First, given the strong link between sectoral productivity and worker skills, what can policy do to raise workforce skill levels? Second, how can countries better allocate existing skills, since productivity tends to be higher where labour market mismatch is lower and skilled workers are employed in more productive firms?

Before addressing these policy questions, Chart 10 summarizes country performance on two dimensions, adult skills and labour market mismatch, to sharpen the focus on productivity-enhancing reforms. The top-right quadrant includes countries such as Finland, Norway, and the Netherlands with above-average adult skills and below-average labour market mismatch and thus serve as role models. In the bottom-right quadrant, Japan and, to a lesser extent, the United Kingdom perform well on skills but face high mismatch, indicating scope to

Chart 10: OECD Countries in Terms of Adult Skills and Labour Market Mismatch



Note: The calculations are done as follows. First, we calculate the difference in labour market mismatch of all countries in a specific sector relative to the average of the top 3 countries with the least mismatch. Coefficient estimates from column 1 of Table 2 are used to derive the implied labour productivity gap, which is then compared to the observed productivity gap. Sectoral value-added shares are used to calculate the contribution of mismatches to the country level productivity gap. Labour market mismatch is used to proxy static allocative efficiency and the estimates are potentially conservative estimates as they do not include dynamic allocative efficiency effects.

Source: Authors' calculations.

improve labour market matching. Human-capital and skill-building policies remain priorities for countries on the left-hand side, especially Korea and Lithuania, which face the dual challenge of below-average skills and above-average mismatch.

The first policy question is relevant for countries needing to boost adult skills. Work-related training is crucial for improving adult skills, as it enhances adaptability and productivity and is strongly correlated with higher PIAAC scores. Yet in many OECD countries, participation in training programs remains low (OECD, 2020), especially amongst less-educated workers who stand to benefit most. This underscores the importance for early education policies that build strong foundational skills. OECD research emphasizes that participation in high-quality early-childhood education, high-quality teachers, school support for homework and regulated use of digital devices all improve student outcomes (Andrews *et al.*, 2024). These foundations make future workers more adaptable to changing job demands and technologies.

OECD research also emphasizes flexibility in adult learning, allowing individuals to choose when, where, how, and what to learn, is essential for increasing participa-

tion and inclusiveness, especially amid disruptions from digitalization and the green transition (OECD, 2023). Many OECD countries support training in green and AI-related fields, but availability varies and low-skilled workers are less likely to access such opportunities, highlighting the need for stronger incentives and outreach (OECD, 2024c).

The second policy question, improving the allocation of skills, is particularly important for countries with large labour market mismatches. Although the effect is smaller than that of improving average skills, this channel may yield quicker gains. Evidence suggests that financial frictions and rigid insolvency regimes hinder restructuring and penalize entrepreneurship, constraining productivity in dynamic sectors. Future research should explore how policies can better support the efficient reallocation of skills (see Box 4 in Andrews *et al.*, 2025).

On this front, it is significant that the share of workers in growing firms is positively associated with policy frameworks that support reallocation, measured by a composite indicator covering product market regulations, employment protection, insolvency regimes, and ALMP spending (Andrews *et al.*, 2025). Barriers such as occupational licensing, non-compete clauses, and housing constraints may also impede mobility. Overall, structural reforms that promote labour market fluidity and firm dynamism remain essential to ensure efficient skill matching, especially at a time when headwinds to human capital accumulation have never been stronger (Andrews *et al.*, 2024).

Conclusion

This article exploited the 2023 Programme for the International Assessment of Adult Competencies (PIAAC), which reveals large cross-country differences in adult skill levels. Average PIAAC scores in the top three performing countries are around 10 per cent higher than the OECD average and 25 per cent higher than in the bottom three performing countries.

Cross-country sector-level analysis suggests that the latest PIAAC outcomes have important implications for aggregate productivity in three ways. First, there is a robust positive correlation between the level of labour productivity and the average level of adult skills in the non-farm business sectors. Assuming a causal relationship, cross-country sector-level analysis implies that i.) closing the sector-level gap in PIAAC outcomes of the average OECD country to the top three performing countries could lift the average OECD labour productivity level by 17 per cent; ii.) This level of skills effect can potentially account for on average one-quarter (and up to one-third) of cross-country sector-level labour productivity gaps; and iii.) There is a positive relationship between R&D intensity and adult skills and over one-third of the impact of adult skills on labour productivity can be accounted for by the R&D channel (which supplies the generation of new ideas). This leaves plenty of scope for adult skills to impact productivity via other channels, such as the adoption of existing technologies.

Second, the mismatch of workers in terms of qualification and field of study and the effective allocation of skilled work-

ers to different job roles and firm types varies across countries, with important implications for productivity. Labour productivity is higher in sectors where labour market mismatch is lower and where high-skilled workers are more likely to be allocated to larger – as opposed to smaller – firms. Productivity is also higher when high skilled workers are deployed to growing firms, while it tends to be lower when they are trapped in declining firms.

Finally, assuming a causal relationship, closing the labour market mismatch gap of the average OECD country to the best performing countries can potentially account for more than one-tenth of the cross-country sector-level productivity gaps to best-performing countries.

These findings suggest that high priority should be assigned to understanding the scope for policies – including adult training programmes – to raise the average level of adult skills. However, significantly improving adult skills through raising the foundational skills of younger generations is a process that spans across generations. While the aggregate productivity impact of the allocative channel is more modest, it may be more leverageable by policy in the near term, highlighting the role of structural reforms to support labour market reallocation and adaptability.

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