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From Decline to Revival: Policies to Unlock Human Capital and Productivity

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From Decline to Revival: Policies to Unlock Human Capital and Productivity

Abstract

The productivity slowdown in many OECD countries over the last decades coincided with a significant deceleration in human capital growth. We show that nearly one-sixth of this productivity slowdown can be attributed to a decline in human capital growth, mainly driven by the decline in the quality of human capital, as measured by PISA scores. An analytical framework used to understand this decline considers education policies, the until recently largely unregulated use of digital devices in classrooms and the impact of the COVID-19 pandemic. The results highlight the negative effects of smartphone and social media usage on student performance and suggest that responsible internet use programs and education policy reforms could mitigate these effects. The paper also shows that public policies can help countries deploy more efficiently their human capital to enhance productivity. Without policy intervention, continued declines in PISA scores could reduce long-term MFP growth by nearly 3%. Combining education reforms with structural reforms could mitigate these effects and boost long-term MFP by about 1.5%. Therefore, efficient deployment and reallocation of human capital are crucial for sustaining productivity growth.

JEL-Codes: E240, I200, I250, I260, I280.

Keywords: productivity slowdown, human capital, PISA scores, digital device, public policies, OECD.

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1. Introduction

The question of why productivity growth slowed from the early-to-mid 2000s continues to interest policymakers. A range of structural explanations have been advanced, including slowing innovation (Brynjolfsson et al. 2021), stalling technological diffusion and “winner-take-all” dynamics (Andrews, Criscuolo and Gal, 2016), declining reallocation (Decker et al. 2020), rising market power (De Loecker et al. 2020); reversal of deregulation (Syverson, 2011), mismeasurement (Syverson, 2017), weak investment (Ollivaud, Guillemette and Turner, 2018) and slowing global integration (Goldin et al., 2024). But the role of human capital accumulation in the post-2005 productivity slowdown has received less attention, with the literature typically more concerned with the longer-term plateauing in the average years of schooling (Goldin et al. 2024; Moss et al. 2020).²

Against this backdrop, this paper shows that almost one-sixth of the productivity slowdown in OECD countries since the mid-2000s can potentially be accounted for by the slowdown in human capital accumulation. The productivity slowdown coincided with a notable slowdown in the growth of the human capital stock, driven by deteriorating quality, as measured by the sharp decline in PISA test scores. Indeed, the generation of young workers – who have performed more poorly on standardised testing since 2003 – have entered the workforce and are now placing downward pressure on the human capital stock. And if future generations of students continue to perform poorly in PISA tests, the decline in the human capital stock will persist, ultimately dragging down productivity even further. This places high priority on accounting for the forces behind the decline in PISA scores and assessing the scope for education policy reforms to mitigate this damage.

To make progress on these questions, the paper proposes an analytical framework combining education policies, the widespread – and until very recently largely unregulated – use of digital devices in classrooms and the COVID-19 pandemic to understand the decline in PISA scores. Drawing on cross-country regressions, and consistent with a range of other studies, we identify a negative COVID-19 effect on student performance: students who had access to daily online classes during school closures scored an estimated 30 points higher on the 2022 PISA test than those without remote education. But this does not explain why PISA scores declined across many OECD countries in the decade before the pandemic.

The pre-pandemic deterioration in PISA performance can be potentially understood in terms of a common technological factor: the rapid diffusion of smartphone technology and related social media platforms from the late 2000s.³ Contemporary accounts argue that this trend dramatically transformed the lives of children and teenagers around the world, and in some cases, for the worse. Indeed, a number of OECD countries experienced a pronounced rise in the incidence of teenage anxiety and depression in the early 2010s, which has been linked to the corrosive effects of social media usage, especially for girls (Haidt 2024; Khattar and La Cava 2024). Haidt (2024) identifies four foundational concerns stemming from the unrestricted use of smartphone technology, spanning social deprivation, sleep deprivation, attention fragmentation and addiction.⁴ By investigating the potential for such technological forces to also undermine

² Notably, Moss et al. (2020) identifies a structural break in educational attainment trends in the United States. While educational attainment at the age of 30 increased significantly from approximately 7 years in 1876 to 13 years in 1946, the subsequent period from 1946 to 1986 saw a much more modest increase of only 1.5 years.

³ The iPhone was released in 2007 while the first commercial Android touchscreen phones launched in 2008. Key social media platforms had their genesis around this period, including Facebook (publicly launched in 2006), Twitter (founded 2006), Tumblr (2007), WhatsApp (2009), Instagram (2010), Snapchat (2010) and Pinterest (2010).

⁴ *Social deprivation*: a smartphone is an “experience blocker”, taking up hours a day that would otherwise be spent in physical play or in-person conversations with friends and family. *Sleep deprivation*: too many teenagers stay on their

educational achievement, we join three literatures spanning the productivity slowdown; PISA score drivers; and the social welfare consequences of digital device use.

It is plausible that the rising – and until recently largely unregulated – use of digital devices in schools contributed to the decline in OECD PISA scores over the past 15 years. Micro-econometric evidence suggests that in 2018, students involved in regular online activity scored between 1.5 and 3 PISA points lower than the control group. In 2022, one additional hour spent on unstructured digital device use while in school carried a penalty of 6 PISA points. Yet policies can play a role in mitigating such headwinds: students in schools with responsible internet use programmes scored 5 PISA point higher in 2022, up from 2 points in 2018, compared to those without such programmes. While these results reflect correlations – as opposed to causal relationships – they bring into closer focus recent policy measures to restrict smartphone use in the classroom in some OECD countries.

There remains significant scope for education policy reforms to boost test scores. Micro-econometric estimates show that policies such as early childhood education, teacher quality, homework assistance and school policies about responsible internet use play an important role in explaining student-level variation in PISA scores. The stance of these policies varies significantly across countries: teacher quality is a major issue in the Netherlands, Belgium, and Estonia, while it is less of a concern in Lithuania, Denmark and Iceland. Nearly all students in the United Kingdom and Ireland received instructions about responsible internet use, while less than half were educated on this matter in Chile, Costa Rica and Latvia. In the average OECD country, education policy reforms could potentially yield 10 additional PISA points – a figure which rises to 15 points in Costa Rica, the Czech Republic, Estonia, Italy, Latvia and Poland.

Finally, simulations from the OECD Quantitative Assessment of Structural Reforms (QASR framework suggests that if the downward trend in PISA scores continues to persist, then MFP could be 3% lower in the long run. Scenario analysis reveals that education policy reform package – which yields the aforementioned 10-point boost to PISA scores – could partially offset these headwinds, but these benefits would unfold over extended timeframes, given that the growth returns to education reforms can take decades to materialise.

Headwinds to productivity growth from deteriorating human capital highlight the need for OECD economies to efficiently deploy the existing stock of human capital. Empirical evidence suggests that the positive link between human capital and MFP is stronger in the Nordics and the United States than in Eastern and Southern Europe and other emerging OECD countries. These patterns are symptomatic of differences in the efficiency of human capital allocation, which in turn are related to the extent to which structural policies support reallocation and adaptability in labour markets. Indeed, structural reforms in these areas – when combined with education policy reforms – could fully counterbalance the negative effects of the COVID-19 pandemic and the persistent decline in PISA test scores on productivity. A key implication is that policymakers should not only focus on growing the stock of workforce talent, but on allocating existing talents more efficiently.

The next section highlights the role of declining PISA test scores in the productivity slowdown – via the human capital accumulation channel. To better understand the decline in PISA scores, Section 3 posits an analytical framework combining education policies, the widespread – and until recently largely unregulated – use of digital devices in classrooms and the pandemic. It then empirically evaluates the relative importance of these channels and the scope for educational policy reforms to boost PISA scores. Section 4 quantifies the extent to which our analytical framework can account for the average decline in PISA scores observed across OECD countries since 2009. Section 5 investigates the cross-country differences in the efficiency of human capital allocation. Section 6 simulates the implications of ongoing changes in

smartphones late at night when they need rest. *Attention fragmentation*: alerts and messages continually drag teenagers away from the present moment and tasks requiring concentration. *Addiction*: apps and social media are deliberately designed to hack vulnerabilities in teenagers' psychologies, leading to an inability to enjoy anything else.

PISA test scores for the future of human capital and productivity, and the scope for policy reforms to mitigate these headwinds.

2. Productivity and human capital accumulation: some stylised facts

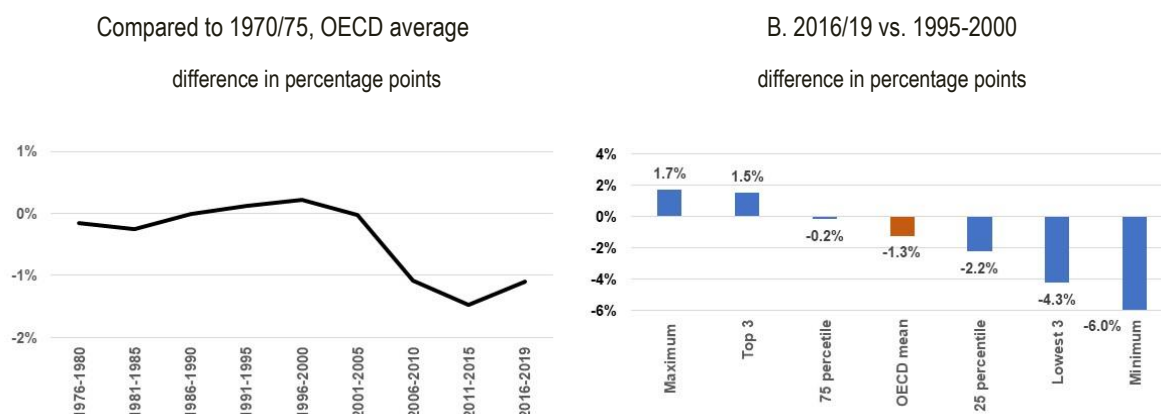
2.1. *Productivity growth has slowed across the OECD*

Over the past 20 years, potential output growth has declined significantly, driven by a sharp slowdown in productivity growth (Ollivaud et al 2016).⁵ Leading studies identify a downward structural break in productivity growth in many OECD countries in the early-to-mid 2000s (OECD, 2015). And the scale of the slowdown is material. Compared to the early 1970s, average annual MFP growth was approximately 1 percentage point lower on average across the OECD by the late 2000s (Figure 1, Panel A) and it has never recovered. The productivity slowdown is even more pronounced when assessed against the second half of the 1990s, when productivity growth was spurred by the rapid diffusion of information and communication technologies (ICT). Between the late 1990s and the second half of the 2010s, MFP growth slowed by 1.3 percentage points on average across the OECD, with most countries experiencing a slowdown (Figure 1, Panel B)

From 1995 to 2023, MFP growth has sharply declined in both small and large advanced OECD countries. In Australia, Austria, Belgium, Canada, France, Spain and the United Kingdom, MFP growth has nearly stalled, while Greece, Italy, Luxembourg and Mexico experienced negative growth over an extended period. Although the United States experienced a noticeable decline, productivity growth partially recovered in the latter half of the 2010s. Similarly, several emerging OECD countries grappled with significant productivity growth slowdowns, yet many of them rebounded from the trough around 2010, although they never fully regained their previous growth rates. Costa Rica and Israel stand out as the sole two countries that saw a steady rise in productivity growth from 1995 to 2023. For a detailed visual, refer to Figure A1 in Appendix A, while longer term country-specific developments are summarised in Figure A2).

The productivity slowdown is likely to reflect a range of factors. Some accounts focus on teething problems associated with the transition to an ideas-based economy, where there is greater need for complementary investments (Autor et al., 2020; Bloom et al., 2020; Syverson, 2017). Other accounts stress the rise of market power (De Loecker et al. 2020), a reversal in deregulation (Syverson, 2011) and other adjustment frictions that stymie the forces of competition and economic dynamism (Andrews, Criscuolo and Gal, 2016; Decker et al., 2020). Others argue that weak investment (Ollivaud, Guillemette and Turner, 2016; Goldin et al., 2024), a slowdown in innovation and technological adaption (Brynjolfsson et al. 2021), mismeasurement (Syverson, 2017) or a slowdown in global trade (Goldin et al., 2024) are to blame. But much less research has focused on the role of human capital accumulation, which as we discuss in the next section has slowed materially over time.

⁵ Multi-factor productivity (MFP) and productivity are used interchangeably in this paper.

Figure 1. Productivity slowdown in the OECD

Note: Panel A: figures are derived from a regression model where productivity growth is regressed on period dummies, as indicated in the chart. The coefficient estimates shown in Panel A reveal how much slower productivity growth was compared to the reference period of 1970/75.

Panel B: Figures summarise country-specific data, comparing average productivity growth between 2016/19 and the reference period of 1970/75. Years 2020, 2021 and 2022 are omitted, due to their significant impact from the COVID-19 pandemic.

Both panels include 20 OECD countries for which data was available from 1970 to 2019.

2.2. The rate of human capital accumulation has slowed over time

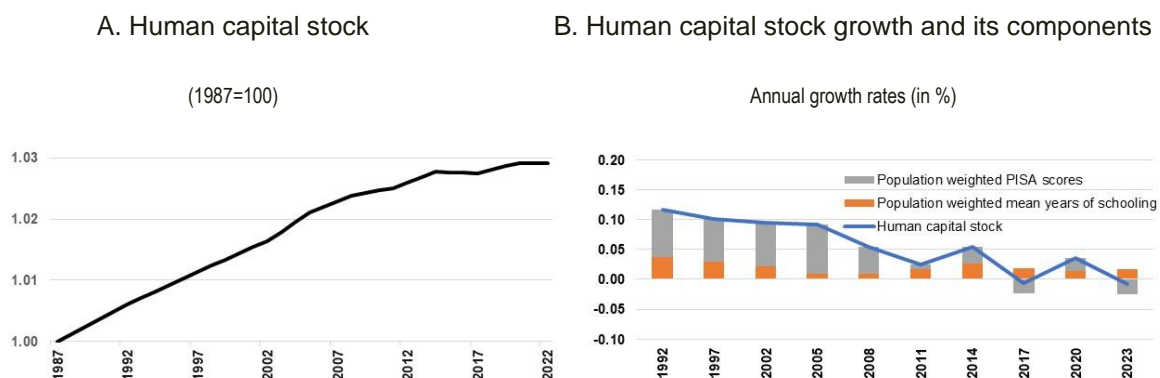
This paper uses the OECD's measure of human capital stock, developed in 2022, to fill the empirical gap in the productivity literature surrounding time varying, cross-country measures of education quality and quantity. As explained in Box 1, this measure of human capital stock is estimated by combining the cohort-weighted average of historical PISA scores (which reflect the quality of education) for the working age population with the corresponding mean years of schooling (which represent the quantity of education). The human capital stock improves if new cohorts exhibit higher education levels and older cohorts that exit possess lower than average education levels. But when incoming young cohorts have poorer education levels, a headwind to human capital accumulation emerges – a scenario that has now materialised in many countries.

Over time, growth in the human capital stock has declined. We estimate that the human capital stock expanded at an average rate of 0.11% between 1987 and 2005, but then slowed to 0.05% between 2005 and 2016 and remained flat after 2017 (Figure 2, Panel A). The slowdown in human capital accumulation largely reflects changes in the quality of human capital (Figure 2, Panel B), which, as discussed below, reflects a significant decline in PISA scores.^{6,7} Meanwhile, the quantity of human capital has made a more limited contribution to the slowdown.

⁶ PISA scores reflect standardised test results across mathematics, science and reading for 15-year-old students.

⁷ There are some differences about the speed and timing of the decline in the contribution of the quality of human capital growth (see Figure C1 in Appendix B).

Figure 2. Human capital stock in the OECD, 1987-2022



Note: Includes only countries for which the human capital series start in 1987: Australia, Chile, Germany, Finland, France, Hungary, Italy, Japan, United Kingdom, Netherlands, New Zealand, Sweden, United States. Panel B shows the arithmetic average of these countries. PISA scores and mean years of schooling are cohort weighted averages such as they enter the measure of human capital stock.

Box 1. A novel measure of human capital stock combining education quality and quantity

The measure of human capital used in this study is the one developed in Égert et al. (2024). The measure leverages data on mean years of schooling and quality of education data from two prominent OECD assessments: the Programme for International Student Assessment (PISA) that tests mathematics, science and reading for the 15-year-old and the Programme for the International Assessment of Adult Competencies (PIAAC) that tests numeracy, problem solving and literacy for adult workers. The new measure is a cohort-weighted average of historical PISA scores (which reflect the quality of education) for the working age population and the corresponding mean years of schooling (which represent the quantity of education).

The motivation behind this new measure lies in the limitation of using PIAAC alone. While PIAAC provides valuable adult test scores to calculate a cohort weighted stock measure of human capital, its country coverage is limited, and it lacks the necessary time series depth (one observation in time per country as of mid-2024) for cross-country time series regression analysis.

To address this, PIAAC adult test scores are matched with mean years of schooling and PISA student test scores of the corresponding cohort who took the student tests as 15-year-olds. PIAAC test scores are then regressed on matched PISA test scores and mean years of schooling. Coefficient estimates are used to calculate PIAAC scores i) for country/cohort for which PIAAC is not available, and ii) for past years for which PIAAC was not available.

This approach offers two key advantages. First, it expands the data coverage to a broader set of countries and extends over many more years than PIAAC alone. Second, unlike previous literature that imposed fixed weights for quality and quantity components,¹ this method directly estimates the relative importance of education quality and quantity in the human capital measure.

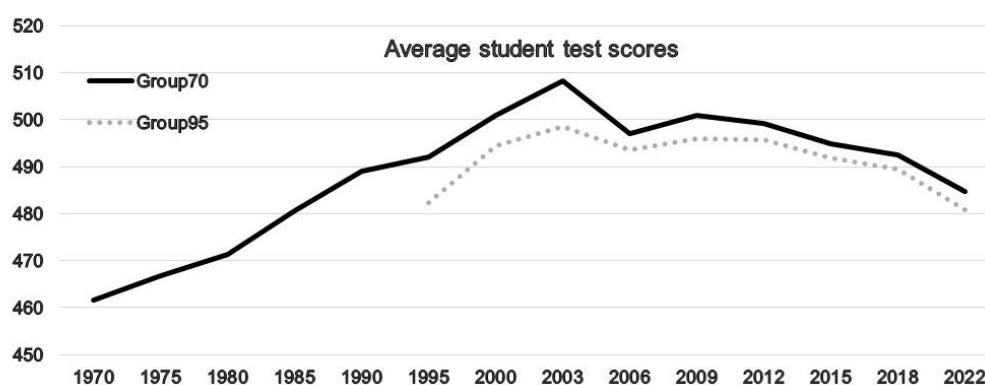
Source: Égert et al. (2024)

¹ Recent research conducted at the World Bank led to the development of a measure of human capital, referred to as Learning-Adjusted Years of Schooling (LAYS), that combines the quantity and quality of education (Filmer et al., 2020). The basic variant of this measure is obtained as cohort-specific mean years of schooling multiplied by relative cohort-specific student test scores (TIMSS and PISA scores) where a country's cohort's test score is compared to a high performer country (Singapore or an average of top 5 countries). Consequently, the elasticities on quantity and quality are imposed by construction to be equal rather than estimated, representing an important difference

between the OECD and World Bank measures. For countries for which both LAYS, and the OECD's new measure of human capital are available, the cross-country correlation between the two measures is around 0.9 (no time series is available for LAYS).

The slowdown in human capital growth primarily arises from declining student test scores. On average across OECD countries, there was a consistent improvement in student test performance from 1970 to 2003 (Figure 3). But following a period of volatility, PISA test scores exhibited a sustained decline after 2009 – a pattern that was exacerbated by the COVID-19 pandemic.

Figure 3. Student test results in the OECD, 1970/1995-2022



Note: Group70 includes countries starting in 1970 (AUS, CHL, DEU, FIN, FRA, GBR, HUN, ISR, ITA, JPN, NLD, NZL, SWE and USA). Group95 includes all OECD countries except BEL, COL, CRI, EST, POL, TUR. The data series are based on PISA data extended with two vintages of the World Bank Global Data Set on Education Quality (Altinok et al., 2018).

In most OECD countries, the rising trend in student achievement halted between 2003 and 2009. From 2009 to 2018, PISA scores declined in most OECD countries, particularly Finland, Greece, Iceland, the Netherlands, New Zealand and Slovakia, while modest gains were recorded in Ireland, Israel, Japan and Türkiye (Figure 4, Panel A). Outside of Korea and Japan, the pandemic compounded this downward trend, with particularly sharp declines in student performance of over 20 PISA points observed in Norway, the Netherlands and Poland after 2018 (Figure 4, Panel B). Analysis of the different subject areas reveals a broad-based deterioration in mathematics test scores across OECD countries after 2018.⁸ Smaller declines in reading scores were observed, while science students in approximately half of the countries did not perform worse in 2022 than in 2018 (Figure 4, Panel C).⁹

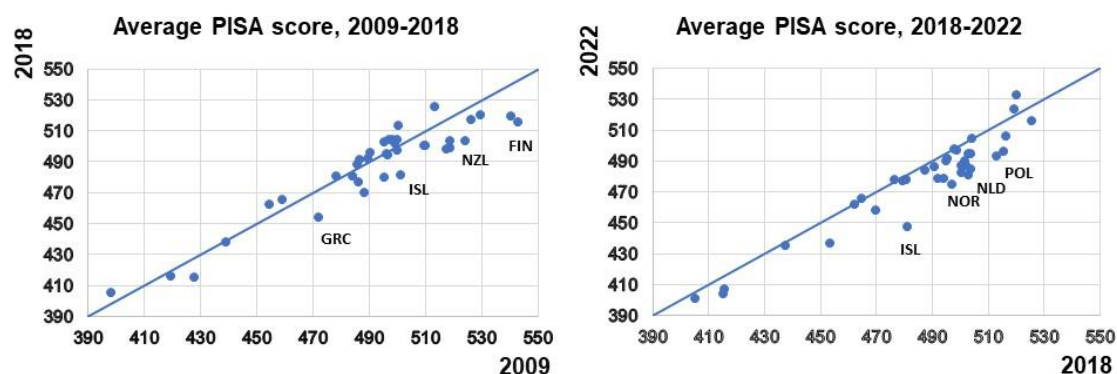
⁸ Drops in PISA scores affect the whole distribution of the student population. Exploring the inequality aspects of the worsening PISA scores is an avenue for future research.

⁹ The relatively stable results in science can be explained by a number of factors, including: i) the engaging nature of hands-on experiments; ii) the stability of the science curriculum; iii) adaptable assessment methods to the online environment; and iv) increased student interest and motivation due to the pandemic's focus on health and scientific developments (OECD, 2022a).

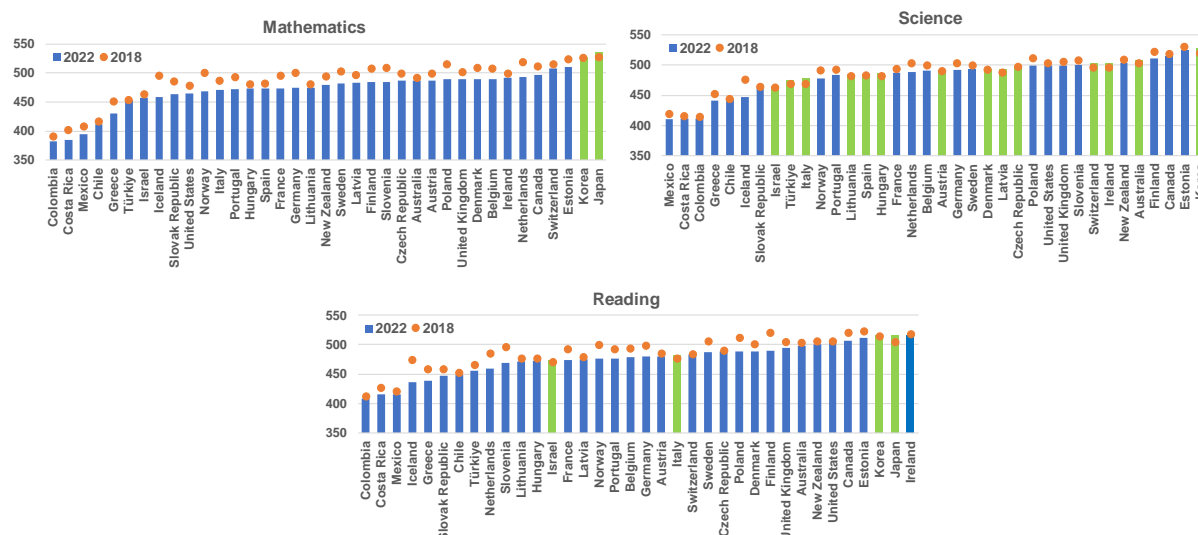
Figure 4. Change in PISA scores over time and across OECD countries

A. Changes from 2009 to 2018

B. Changes from 2018 to 2022



C. Changes from 2018 to 2022, different subject areas for individual OECD countries



Note: Panel A and B: Average PISA test scores in 2009 (2018) plotted against those in 2018 (2022). Panel C: Green bars denote countries where test scores did not fall between 2018 and 2022.

While the human capital stock changes gradually over time, the medium-term outlook for human capital and productivity is significantly impacted by the decline in PISA scores. Indeed, younger individuals – that performed relatively worse on PISA from 2009 – have now entered the workforce. This has placed downward pressure on the human capital stock and ultimately productivity – a trend that will persist if future generations of students continue to perform poorly on PISA. For these reasons, Section 3 investigates the forces behind the decline in PISA scores and the scope for education policy reforms to arrest this decline.

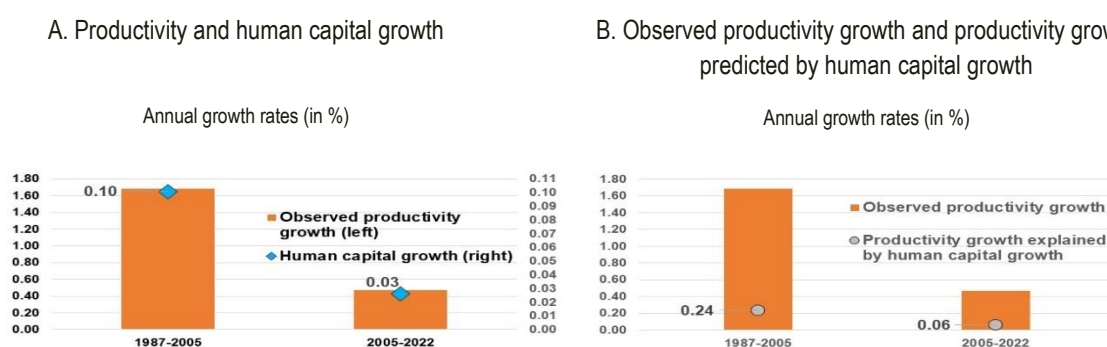
But first, we operationalise the OECD QASR framework to provide fresh evidence on the link between human capital and the productivity slowdown.¹⁰

2.3. The productivity slowdown coincided with a human capital deceleration

The slowdowns in productivity growth and human capital accumulation were synchronized. Crucially, the slowdown in human capital accumulation emerges in the mid-2000s – around the time that leading studies identify a downward structural break in productivity growth in many OECD countries (OECD, 2015). Indeed, plotting human capital and productivity growth side by side demonstrates forcefully that weaker human capital growth went hand in hand with weaker productivity growth (Figure 5, Panel A). Between 1987 and 2006, OECD MFP growth averaged just under 1.69% per annum, while the human capital stock expanded at an annual rate of 0.11%. In the post-2006 period, these figures had declined to 0.47% and 0.03% respectively.

How important was the deceleration in human capital accumulation for the productivity slowdown? To establish a counterfactual scenario, we start from an updated version of the MFP equation in the OECD QASR framework, which links: (log) human capital to (log) MFP, controlling for other drivers such as innovation and trade openness (Égert et al. 2024). The coefficient estimate (slightly above 2, see Table A1) is then applied to the human capital growth rates above. The actual slowdown in human capital accumulation implies that the contribution of human capital to annual MFP growth declined to 0.06 percentage points between 2005 and 2022 (Figure 5, Panel B). But had human capital accumulation not slowed after 2006, and instead maintained its 1987 to 2005 average growth rate (with a contribution to productivity growth of 0.24 percentage points), we estimate that human capital would have contributed 0.18 percentage points more to annual MFP growth between 2005 and 2022. Comparing the difference between these two scenarios (0.18 percentage points) to the aggregate MFP slowdown implies that the deceleration in human capital accumulation accounts for 16% or almost one-sixth of the aggregate MFP slowdown (see Table B1 in Appendix B).

Figure 5. Human capital accumulation and the productivity slowdown in the OECD, 1987-2022



Note: Countries shown are those for which human capital series are available from 1987 onwards.

The contribution of the deceleration of human capital stock growth to the productivity growth slowdown differs across OECD countries (Figure 6). It potentially accounts for 40 percent of the productivity slowdown in Italy and Sweden, where the human capital deceleration was particularly sharp (Figure B1 and Table

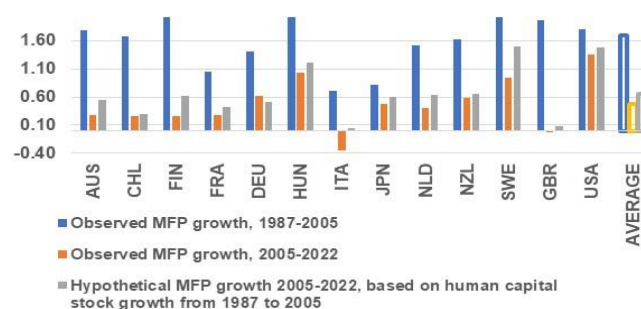
¹⁰ QASR links human capital to country-level MFP in a reduced-form equation including other policies such as product market regulation, innovation intensity and trade openness. This equation is estimated in a cross-country time series panel regression framework. See Appendix C for more details on QASR and the estimated link between the stock of human capital and productivity.

B1 in Appendix B). By contrast, human capital accumulation slowed less in Chile, the United Kingdom and Hungary, and was thus less of a factor in the productivity slowdown. And in Germany, human capital growth accelerated slightly over time – though from a very low level – and hence counteracted somewhat the productivity slowdown.

To be sure, if human capital accumulation had not slowed after 2006, MFP growth would have still slowed materially, consistent with a range of other headwinds to productivity growth. But under this scenario, annual MFP growth across the OECD could have been more than one-third higher (~0.65%) than the mediocre growth (of 0.47%) that was observed. Indeed, if human capital accumulation had not slowed, annual MFP growth in Australia and Finland could be nearly double and it could have saved Italy and the United Kingdom from negative MFP growth (Figure 6, Panel A). These headwinds to productivity growth from deteriorating human capital highlight the need for OECD economies to efficiently deploy the existing stock of human capital, which we explore in the Section 5.

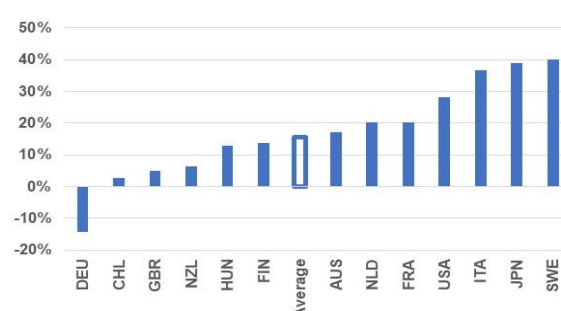
Figure 6. Human capital and the productivity slowdown – country-specific estimates

A. Observed productivity average annual growth from 1987 to 2005 and from 2005 to 2022, and productivity growth predicted by human capital growth from 1987 to 2005



B: Proportion of the productivity growth slowdown explained by human capital slowdown

Selected OECD countries, 1987 to 2005 vs. 2005 to 2022



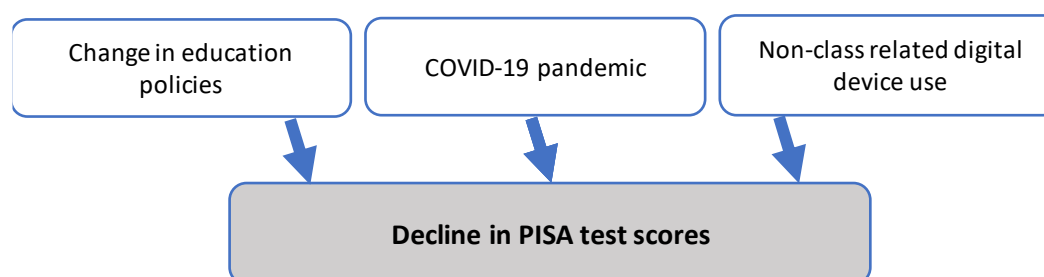
Note: Countries for which the human capital series start in 1987 are: Australia, Chile, Germany, Finland, France, Hungary, Italy, Japan, United Kingdom, Netherlands, New Zealand, Sweden, United States. Panel A compares observed average annual MFP growth to MFP growth that would prevail if human capital growth had remained at its 1987-2005 level.

Source: Human capital series taken from Égert, de La Maisonneuve and Turner (2024).

3. Human capital accumulation and education policies

The previous section has shown that the slowdown in human capital accumulation accounts for a substantial portion of the decline in productivity growth. It also showed that the slowdown is mainly driven by the quality component of human capital, i.e. the plateauing and then decline in student test scores after the mid-2000s. Accordingly, this place high priority on better understanding the forces behind this decline and the scope for education policy reforms to mitigate this damage. This section explores the links between PISA outcomes and policies. Section 3.1 posits an analytical framework that stresses three potential forces behind declining educational performance: *i*) changes in education policies; *ii*) students' increasing – and until recently largely unregulated – use of smartphones and the internet; and *iii*) pandemic-induced teaching disruptions (Figure 7). Using regression analysis based on individual PISA test scores across a wide range of OECD countries, Section 3.2. estimates the relative importance of these channels, while Section 3.3 explores the scope for educational policy reforms to boost PISA scores.

Figure 7. Why did PISA scores decline? A framework for analysis



3.1. Main channels affecting PISA test scores

3.1.1. How can education policies support education outcomes?

Education policies significantly impact student outcomes. While access to early childhood education and higher quality teachers yield positive benefits, other factors – such as school autonomy and accountability, early tracking and ability grouping, and class size – are more contentious. This section reviews some of these fundamental policies.

By fostering essential cognitive and non-cognitive skills, quality early childhood education (from birth to age five) can have profound implications for later education outcomes, particularly amongst disadvantaged children (Heckman et. al., 2013; Braga et al., 2013; Attanasio, 2015; OECD, 2022b). Investing in early childhood education is particularly cost effective due the critical brain development during this period (Cunha et al., 2006). Despite challenges in scaling up pre-school experiments to the national level, empirical evidence from OECD countries shows that increased access to high-quality early childhood education is associated with improved educational and health outcomes, higher earnings and reduced crime rates.

Better teachers can improve long-term education outcomes (OECD, 2022c) by motivating students to learn and study and helping them acquire essential skills (Braga et al., 2013). School-level studies consistently highlight teaching quality as a crucial factor influencing student performances (OECD, 2005). While measuring teacher quality is challenging, it often stems from a combination of solid subject knowledge, effective teaching methods and positive classroom management. Policies aimed at improving teacher

quality should consider offering competitive salaries and recognising teachers' status in schools and society. While the former may be costly, the latter can be difficult to achieve in practice (OECD, 2022c).

Greater school autonomy, especially when coupled with increased school accountability, is associated with better student performances. Schools that possess greater autonomy over the selection of teachers exhibit modestly higher PISA test scores (OECD, 2018b), especially when schools are accountable for their students' achievements as this sharpens their incentives to improve their teaching quality and standards (Smidova, 2019). The use of external exit exams at the upper secondary level can aid accountability by allowing for easier comparison and competition among schools and are positively associated with PISA test scores (Égert, de La Maisonneuve and Turner, 2024).

Early tracking and ability grouping tend to reduce student performance. In countries where tracking occurs at an early stage, under-achieving students from disadvantaged families are often directed into specific vocational tracks. While this path may provide immediate job-specific skills, it risks not equipping students with the general skills necessary for lifelong learning. From this perspective, delaying tracking until a later age may mitigate the negative impact of family background on educational attainment. Empirical evidence at the country level yields mixed results (Smidova, 2019). A milder form of tracking involves sorting students by ability within different subjects within schools, which correlate with lower student test scores (Schneeweis and Winter-Ebmer, 2007).

3.1.2. *Digital device and smartphone use in schools: a curse or a blessing?*

Digital devices in the classroom were once hailed as revolutionary for the teaching profession. The use of digital devices can potentially: *i)* improve student engagement and learning through educational games and immersive learning experiences like virtual reality technologies; *ii)* allow for personalized learning and expand educational resources through digital libraries and online platforms; *iii)* make administration easier; and *iv)* equip students with new digital skills for future jobs, while also enhancing collaboration and providing quick access to information. Indeed, the pandemic truly accelerated the integration of technology in the classroom, particularly through online teaching (Johnes, 2024). But to fully benefit from successful digital technology adoption and integration, teachers need to master the new technology and should receive sufficient support and professional development (Taylor et al., 2021).

Over the past 15 years, an increasing proportion of children in OECD countries (and elsewhere) have started using smartphones extensively. Recent data suggests that more than 90 percent of children aged 14 own a smartphone in the United Kingdom and United States (Rideout et al., 2022; Skopeliti, 2024). The recent EU Kids Online survey shows that children's internet usage has doubled from 2010 to 2017-19. Smartphones have become the primary device for going online. Children are reported to use smartphones daily or almost constantly, primarily related to social media, short online videos (YouTube, TikTok) and video games (Smahel et al., 2020; Kopecky et al, 2021). These activities are often driven by boredom, stress reduction and social connections (Gimena et al., 2023).

Crucially, children often use smartphones while at school (Merod, 2023), sparking a rich debate about the downsides of digital devices. Recent research supports the view that smartphones used in class can negatively impact academic performance, not only in primary and secondary schools but also in tertiary education (UNESCO, 2023). Due to their portability and diverse entertainment functions, smartphones entail a more ready source of distraction, potentially disrupting the learning environment. Indeed, unstructured non-class related cell phone use – such as notifications, social media checks, web browsing and gaming – can weaken focus, hinder comprehension and impede retention (Smale et al., 2021; UNESCO, 2023). As a result, students may miss important instructions or fail to fully engage in class. More generally, an overreliance on technology can diminish critical thinking skills, as students become dependent on quick answers from search engines rather than developing problem-solving abilities. It can also lead to a loss of basic skills like handwriting and arithmetic.

Smartphone use can have indirect negative effects on educational performances through mental health disorders. Teenagers, in particular, are susceptible to developing smartphone addiction, leading to increased rates of anxiety and mental health disorders – all of which can contribute to weaker academic achievements (Yadav et al., 2021). Some attribute the rise in mental health issues among teenagers to the emergence of social media and a decline in unstructured discovery play (Haidt, 2024). Excessive phone and internet use exposes individuals to cyberbullying and other inappropriate behaviours and explicit content. Girls tend to spend more time on social media and hence may be more prone to anxiety and mental health challenges (Khattar and La Cava, 2024). Spending too much time on the internet can also lead to physical health problems, notably poor posture and eye strain, as well as obesity to the extent that it crowds-out physical activity.¹¹ For these reasons, Haidt (2024) recommends banning smartphones for those under 14 years and banning access to social media for those under 16 years.

Restrictions on smartphone use in the classroom have been implemented in many OECD countries. New York City implemented a district-wide cell phone ban in schools in 2005. In Ontario, Canada, a complete ban on cell phones in classrooms was implemented in 2019. OECD countries have very recently put in place some form of restrictions on or are planning to restrict smartphones in schools. Examples include Australia, England, France, Greece, Hungary, Israel, the Netherlands, New Zealand, Spain and Sweden (Table 1). However, complete bans on cell phones have been notoriously difficult to enforce, as students might find ways to circumvent the ban (Hatfield, 2024).

¹¹ The increasing prevalence of obesity in many OECD countries (OECD, 2024), academic pressure and the COVID-19 pandemic could also explain the rise in anxiety and mental health problems among teenagers (Foulkes, 2024).

Table 1. Restrictions applying to smartphone use in schools in OECD countries

Country	Year	Type of restriction
United States	2005	New York banned smartphones from the classroom.
Spain	2014	Currently bans apply in 9 regions.
France	2018	French students aged 15 or younger (<i>écoles primaires</i> and <i>collèges</i>) are required to switch off their smartphones while at school. Smartphone can be used strictly for pedagogical purposes. Since September 2024, pupils are banned from having their smartphones in class, in a policy experiment covering 200 lower secondary schools (<i>collèges</i>). This policy may soon be extended to all students.
Canada	2019	Complete ban on cell phones in Ontario.
Sweden	2023	In 2023, the Swedish government proposed a law to ban smartphones in elementary schools. It also aims to promote the use of physical books and screen time reduction.
Australia	2024	Several Australian States have banned phones from school, although there is no national ban. The government announced plans to set a minimum age limit, likely between 14 and 16 years, for social media use.
Czech Republic	2024	Smartphones banned in selected school.
England	2024	The Department of Education issued new guidance allowing headmasters to decide how to restrict smartphone use in school. Bans can take the form of no smartphone policies, collecting phones upon arrival or locking phones during classes.
Finland	2024	Plans to restrict smartphones during lessons.
Greece	2024	Students are allowed to have their smartphone and other digital devices in school but they need to switch them off while in school.
Hungary	2024	As of September 2024, Hungary banned smartphones and other internet-enabled digital devices from primary and secondary schools. Digital devices are collected in school upon arrival.
Italy	2024	As of Fall 2024, the use of smartphones is banned in classrooms in primary and low secondary schools. This tightens guidelines introduced in 2007, according to which phones could be used in the classroom only when authorised by the teacher.
Netherlands	2024	The government issued guidelines for school aimed at banning smartphones, tablets and smart watches from schools.
Norway	2024	A national recommendation says that mobile phones should be taken out of classrooms in both primary, secondary and upper secondary schools. 96 per cent of primary schools have now introduced restrictions on mobile phone use.
Portugal	2024	Smartphones prohibited in selected schools.

Source: Dezső (2024) and information collected from internet sources.

3.1.3. Student performances deteriorated during the COVID-19 pandemic

Starting in March 2020, most countries made the decision to close schools as a measure to curb the spread of the virus. On average, OECD countries experienced full school closures lasting 13 weeks, with an additional 24 weeks of partial closures, between March 2020 and October 2021. This cumulative closure period is roughly equivalent to a full school year. But the duration of closures varied significantly across countries: schools in Switzerland and Iceland were closed for less than 10 weeks, while Korea, Chile and Colombia endured nearly one and a half years of school closures.

In most OECD countries, education continued through online platforms, email and photocopies during school closures.¹² The effectiveness of these measures varied according to households IT resources, internet access, teacher experience in remote teaching and parental support. In many OECD countries, less than half of rural households had access to internet with sufficient speed during the closure period. Even when connectivity was not an issue, some students did not receive an adequate number of instructional hours: at the onset of the pandemic in the United Kingdom, 71% of children in State schools

¹² Radio and TV educational programmes were also utilised in some countries, including Latvia, Türkiye and the United Kingdom.

received no daily online classes (Green, 2020). And in Germany, only 6% of students had daily online lessons and over half had them less than once a week (Woessmann et al., 2020).

During the pandemic, school closures had significant negative effects on student learning. Research across OECD countries found that student test scores declined, with learning losses ranging from 0.1 to 0.3 of a standard deviation. (de La Maisonneuve, Égert and Turner, 2022). Disadvantaged students, those not speaking the language of instruction at home, pre-primary students, and those learning fundamental skills (like reading and writing) were particularly impacted. Interestingly, some studies suggest that online learning could enhance outcomes by allowing curriculum review and more efficient teaching methods.

3.2 The link between PISA scores and education policies, digital device usage and the COVID-19 pandemic

3.2.1. Empirical methodology

We build on an established literature (see Égert et al. 2024) which uses regression analysis to study the link between average PISA scores and education policies. PISA provides standardised test results in mathematics, science and reading, administered to 15-year-old students across OECD countries (and in several non-OECD countries as well). It also includes information on: i) student characteristics such as sex, age, family background and the language spoken at home; and ii) school level policies – such as ability grouping within and across classes, selective school entry, teacher quality assessments by principals, teacher qualifications and school autonomy and accountability – as well as student-level policy variables such as access to early childhood education. The 2018 and 2022 PISA datasets also capture information on school policies related to digital device use. The 2022 PISA survey inquired about how students and schools addressed the COVID-19 pandemic.

Regression analysis is conducted using separate cross-sections of PISA data (spanning 2009, 2012, 2015, 2018 and 2022), as different versions of PISA datasets cannot be combined into a proper panel dataset (for instance, students aged 15 in 2015 are already 18 years old in 2018). Later PISA editions provide more detailed information on certain policies and cover aspects not included in earlier versions. For instance, PISA 2009 captures whether a student participated in early childhood education and the duration (less than one year or more than one year). In contrast, starting from 2015, subsequent editions provide precise age information regarding students' early childhood education initiation. Balancing the need for consistent specifications across years with the desire for more comprehensive policy coverage, this paper employs simpler regression models spanning 2009 to 2022. Additionally, COVID-19 and digital device effects are estimated for 2022 (and 2018) including a more extended policy coverage.

For each PISA vintage from 2009 to 2022, the following baseline equation is estimated:

$$PISA_{c,s,is} = f(\sum_{i=1}^k CHAR_{i,c,s,is}, ECE_{c,s,is}, \sum_{j=1}^l SP_{j,c,s,is}) \quad (1)$$

where: c , s and is stand for country, school and individual students. PISA is the average of PISA results for math, science and reading. CHAR is a set of student characteristics, including the student's age, sex, socioeconomic background and whether the language spoken at home is different from the language of instruction in school. ECE captures whether the students spent more than one year in Early Childhood Education. SP comprises school-level policies such as ability grouping within and across classes and selective entry at school. Regressions include country fixed effects to control for unobserved country-level factors. As is the case with most cross-country econometric exercises, we caution against applying a causal interpretation to the coefficients, which instead reflect robust correlations.

Additional regressions with more policy variables are estimated for later years, as more recent PISA datasets offer data on more policies. For 2015, teacher quality and homework assistance in school are

added. For 2018 and 2022, variables concerning internet and digital device use at school (DDU) and school policy regarding responsible internet (PRIS) use are also considered:

$$PISA_{c,s,is} = f(\sum_{i=1}^k CHAR_{i,c,s,is}, ECE_{c,s,is}, \sum_{j=1}^l SP_{j,c,s,is}, DDU_{c,s,is}, PRIS_{c,s}) \quad (2)$$

Finally, the 2022 PISA dataset includes questions on how students and schools dealt with the COVID-19 pandemic. Two additional variables are added to regression (2), which capture whether students received online teaching (OT) and the difficulty individual schools faced to maintain teaching (DIFF_OT):

$$PISA_{c,s,is} = f(\sum_{i=1}^k CHAR_{i,c,s,is}, ECE_{c,s,is}, \sum_{j=1}^l SP_{j,c,s,is}, DDU_{c,s,is}, PRIS_{c,s}, OT_{c,s,is}, DIFF_OT_{c,s}) \quad (3)$$

3.2.2. Empirical results

The baseline estimates, consistent with the literature, are summarised in Table 2. Spending more than one year in early childhood education is associated with a roughly 6-point increase in average PISA test scores. While ability grouping within classes is not correlated with educational outcomes, grouping students by ability across classes (within the same school) is associated with lower average PISA scores, although this finding varies across years. Finally, students attending schools with a selection process upon entry tend to achieve higher PISA scores (Table 2).¹³

Table 2. Drivers of PISA test scores – baseline regressions, 2009-2022

PISA=f(student & school-level policies, controls, country fixed effects)

Dependent variable: PISA score (average of math, science and reading)				
	(1)	(2)	(3)	(4)
	2009	2015	2018	2022
Policies				
ECE participation, one year or more	6.459**	6.723**	6.023**	6.473**
Ability grouping, across classes	-1.124	-10.460**	-1.618	-14.492**
Ability grouping, within class	-1.303	-3.160	0.921	2.086
Selective entry to school	9.836**	5.807**	4.405**	7.452**
Student characteristics				
Socioeconomic background	31.990**	28.859**	30.581**	32.031**
Foreign language spoken at home	-14.520**	-21.888**	-19.287**	-22.815**
Girls dummy	3.616**	1.805**	4.334**	1.941**
R-squared	0.299	0.268	0.256	0.272
No. of observations	2.8e+05	2.3e+05	2.6e+05	2.5e+05
No. of countries	37	38	38	36
Country fixed effects	YES	YES	YES	YES

Note: Regressions contain country fixed effects. * and ** indicate statistical significance at the 10% and 5 % levels. Student observations are weighted with their sampling probabilities. Missing data (under 5% for most variables) have been treated by imputing plausible values. In practice, when a value is missing, it is replaced either by the weighted (student final weights) school average or the weighted country average when the school average is missing. Standard errors in the regressions are computed using balanced repeated replicate (BRR) weights following the PISA data analysis manual. Results for 2012 are not reported as they are very similar to the 2009 and 2015 results.

Regression estimates suggest that students from more affluent socioeconomic backgrounds perform better while students who speak a language at home other than the language of instruction at school tend to score lower. On average, girls have a small advantage over boys, driven by their superior performance in reading, which more than compensates for their underperformance in maths and science relative to boys (see Table D1 in Appendix D).

Table 3 examines those policies that are available in the PISA dataset from 2015. Better teachers and homework assistance in schools appear to support student achievements. Headmasters' assessment of

¹³ See Tables D1 to D4 in Appendix D for detailed estimation results.

lower teacher quality is correlated with substantially lower PISA scores. In contrast, PISA test scores tend to be higher in schools that provide homework help to students.

Table 3. Drivers of PISA test scores – additional policies, 2015-2022

PISA=f(student & school-level policies, controls, country fixed effects)

Dependent variable: PISA score (average of math, science and reading)			
	(1)	(2)	(3)
	2015	2018	2022
Poor teacher quality - somewhat & very bad	-12.645**	-11.380**	-12.350**
Room for homework in school	4.514**	9.834**	10.993**
R-squared	0.286	0.278	0.297
No. of observations	2.0e+05	2.2e+05	1.9e+05
No. of countries	38	38	36
Policies included:			
ECE participation, ability grouping in school, selective school entry			
Control variables included:			
Socioeconomic background, girls dummy, foreign language spoken at home			
Country fixed effects	YES	YES	YES

Note: See table 2. Regressions include variables used in Table 2. Full results are reported in Table D2 in Appendix D.

Table 4 analyses the role of digital device use and school policies related to internet use, which are available from 2018. The questions on digital device use differed between the two years but the results consistently indicate that time spent using digital devices is associated with lower test scores, whereas school policies aimed at educating student about responsible internet use tend to correlate with better scores:

- In 2018, students who engaged in online chatting (at home or at school) regularly score 1.5 points lower compared to their counterparts who did not chat online. The penalty from regular involvement in online discussion forums is even larger, associated with a loss of around 3 PISA points compared to students who were not involved.
- The 2022 question specifically asked students about the hours spent on digital devices for non-class purposes while at school. Any additional hours spent on such devices were associated with a loss of 6 PISA points.
- Students enrolled in schools that implemented education programmes about responsible internet use outperformed students in schools without such policies by approximately 5 PISA points in 2022, up from 2 points four years earlier.

Table 4. Drivers of PISA test scores – digital device use, 2018-2022

PISA=f(student & school-level policies, controls, country fixed effects)

Dependent variable: PISA score (average of math, science and reading)		
	2018 (1)	2022 (2)
School policy for responsible internet use (=0 no, =1 yes)	2.323*	4.798**
Digital use - chat online (=1 no, =5 regularly)	-0.331**	
Digital use - online discussion forums (=1 no, =5 regularly)	-0.647**	
Digital use for leisure - in school (hours per day)		-6.065**
R-squared	0.295	0.348
No. of observations	2.2e+05	1.8e+05
No. of countries	38	35
Policies included:		
ECE participation, ability grouping in school, selective school entry, teacher quality, school homework assistance		
Control variables included:		
Socioeconomic background, girls dummy, foreign language spoken at home		
Country fixed effects	YES	YES

Note: See Table 2. Regressions include variables used in Tables 2 and 3. Full results are reported in Table D3 in Appendix D.

Table 5 examines the role of COVID-19-related school closures, utilising 2022 PISA data which surveys students and schools about their coping strategies during lockdown. Students benefiting from daily online classes during COVID-19-related school closures significantly outperformed those who did not receive remote education. Although the sample size for this module is considerably smaller than other parts of the PISA survey, students who participated in daily remote classes scored an estimated 30 points higher than students who were not involved in regular remote learning. At the school level, students enrolled in schools that struggled to provide online classes faced challenges in the PISA tests. The difference in performance between students in the best and worst performing schools in terms of their capacity to deliver remote instructions is a staggering 30 points (Table 5).

Table 5. Drivers of PISA test scores – COVID-19 effects, 2022

Dependent variable: PISA score (average of math, science and reading)	
	(1)
COVID-19 - school level	
COVID - problems with schools' capacity to provide remote instructions (from -3 to +3, higher values more problems)	-5.225**
COVID-19 - student level	
Students receiving real time online learning on a daily basis	29.140**
R-squared	0.374
No. of observations	1.4e+04
No. of countries	31
Policies included:	
ECE participation, ability grouping in school, selective school entry, teacher quality, school homework assistance, school policy for responsible internet use, digital device use for leisure (in school, hours per day)	
Control variables included:	
Socioeconomic background, girls dummy, foreign language spoken at home	
Country fixed effects	YES

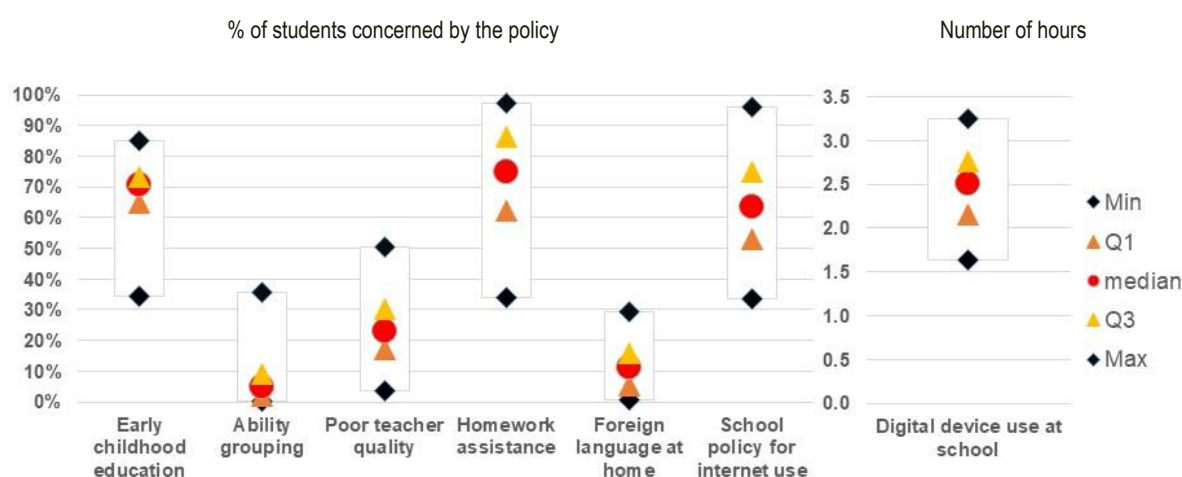
Note: See Table 2. Regressions include variables used in Tables 2, 3 and 4. Full results are reported in Table D4 of Appendix D.

3.3. The economic significance of the estimated effects for education policy reforms

Utilising coefficient estimates and cross-country variation in education policies, this section calculates the potential improvements in PISA scores resulting from the adoption of policies of the top three performing countries. These improvements are computed for both individual OECD countries and the OECD average.

Education policies vary substantially across OECD countries, which creates scope for future policy reforms to boost educational performance in some countries (Figure 8). For instance, in Türkiye, only slightly more than 30% of students who passed the PISA test in 2022 had spent more than one year in pre-primary education. In contrast, countries like Mexico, Spain, Ireland, the Netherlands and France had a rate of 80 percent (Figure 9).¹⁴ Similarly, there are substantial differences across countries with respect to ability grouping, teacher quality, homework assistance at school and school policies related to responsible internet use. The prevalence of foreign language spoken at home also varies widely, ranging from zero to 30 percent. Digital device use in schools was twice as high in Central and Eastern European countries compared to Japan and Ireland. Nearly all students in the United Kingdom and Ireland received instructions about responsible internet use, while less than half were educated on this matter in Chile, Costa Rica and Latvia (Figure 9).

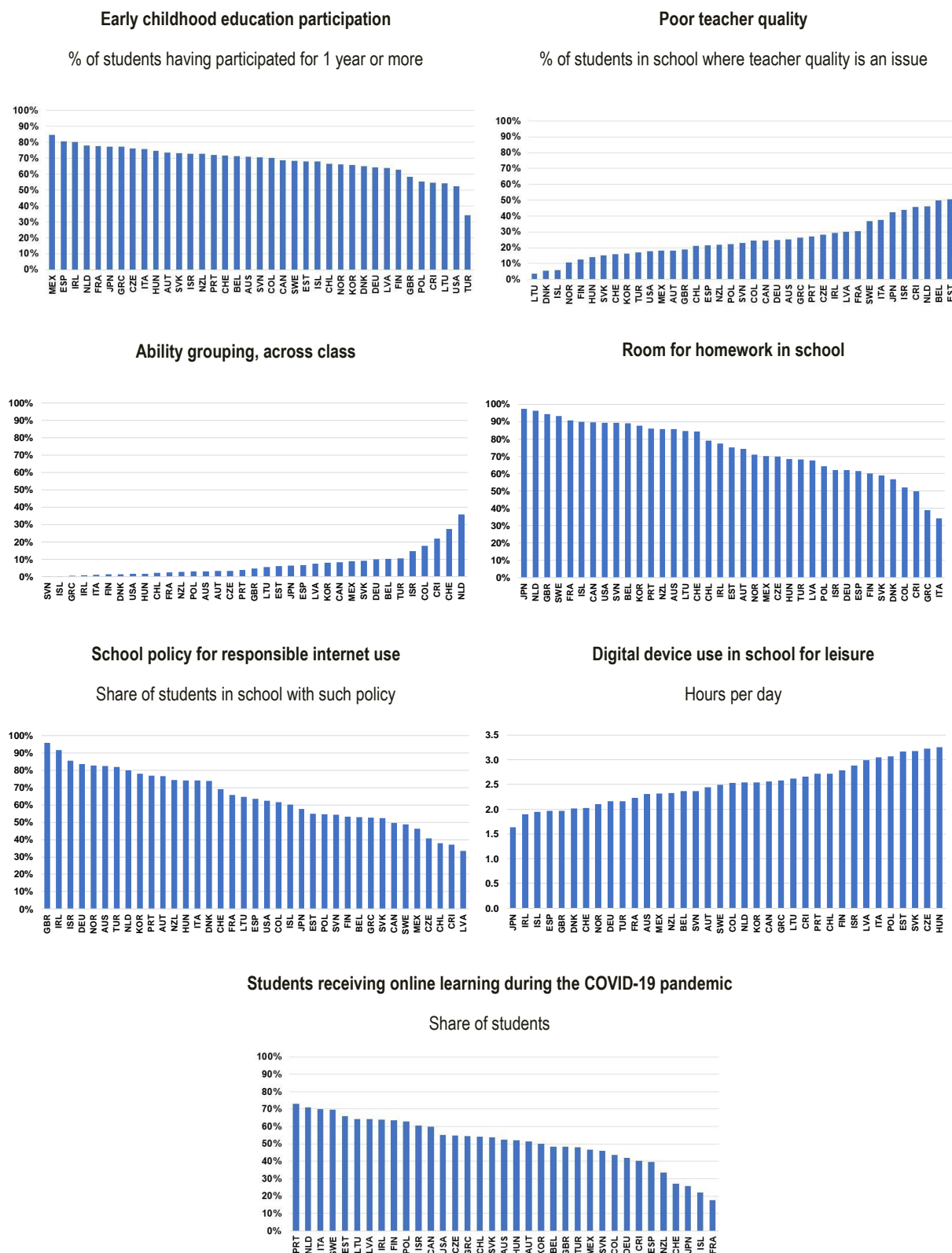
Figure 8. Education policies vary across OECD countries, 2022



Note: Figures shown are calculated using PISA 2022. Ability grouping refers to grouping students across classes within schools. Foreign language spoken at home is not a policy *per se*, but it is interesting to show how it correlates with student performance.

¹⁴ Early childhood education participation for children aged between 0 and 6 in 2022 progressed considerably since 2008-2013.

Figure 9. Education policies vary across OECD countries, 2022

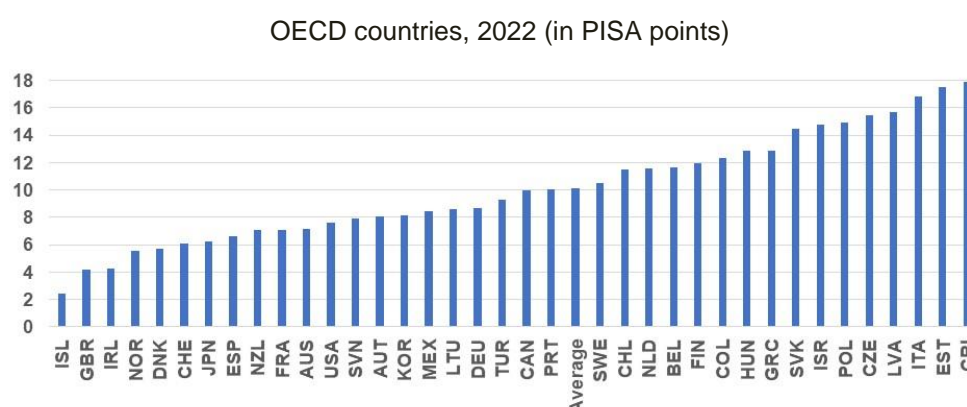


Source: PISA 2022.

Exploiting the reform potential in an average OECD country could result in a more than 10-point increase in PISA scores (Figure 10). The most significant gains are linked to reducing non-class-related digital device use in schools, enhancing teacher quality, and providing better homework support at school. Additionally, promoting early childhood education and emphasising responsible internet use policies would contribute to a one-point-improvement in PISA test results. Reducing ability grouping within schools would yield only marginal benefits.

There exist significant variations in country specific policy effects. Countries close to the policy frontier would experience smaller benefits. For instance, Denmark and Norway would gain 6 PISA points and the United Kingdom and Ireland would gain 4 points. Conversely, potential gains are significantly larger in Costa Rica, the Czech Republic, Estonia, Italy, Latvia and Poland, totalling more than 15 points. Key potential policy reforms in these nations concern enhancing teacher quality and managing non-class-related digital device use in schools. Türkiye has the largest potential gain (3 PISA points) by raising pre-school participation. Additionally, aligning ability grouping with top performance would particularly benefit the Netherlands (by almost 2 points). Finally, promoting policies related to responsible internet use would raise PISA scores the most (2 points) in Costa Rica and Latvia (Table E1 in Appendix E).

Figure 10. The scope for education policy reforms to lift PISA performance



Note: Based on Table E1 in Appendix E.

4. Accounting for the decline in PISA test scores since 2009

Armed with the regression coefficients from Section 3.2, this section quantifies the extent to which our analytical framework can account for the average decline in PISA scores observed across OECD countries since 2009, based on pandemic effects and the observed changes in structural education policies and digital device usage. Since our approach is necessarily crude and involves a number of assumptions (see Box 2), the resulting estimates – summarised in Table 6 – are best viewed as “ballpark”.

Box 2. Assumption underlying the accounting framework

The effects of various policies are calculated using changes in policy variables multiplied by the respective coefficient estimates averaged over several years (regressions for 2009, 2018 and 2022), reflecting OECD averages. This exercise makes three key assumptions:

First, the estimated coefficients are assumed to be common across countries, which may restrict our ability to account for country specific movements.

Second, we assume that the estimated relationship is stable over time by using the average of the coefficient estimates from consecutive cross-sectional regressions.

Third, econometric results are correlations and cannot identify causal relationships because of the purely cross-sectional nature of the PISA datasets.

Additional assumptions are employed for specific policies:

Teacher quality: the change in teacher quality is calculated between 2015 and 2022 (and not 2009 and 2022), as this variable is not available in the 2009 and 2012 PISA datasets.

Digital device use: the calculations assume that daily non-class related digital device use in schools increased by 1 hour from 2009 to 2018 and by 0.5 hours from 2018 to 2022, against the background of an OECD average of 2.3 hours per day in 2022. The 0.5- and 1-hour changes are rescaled to country-specific averages. For instance, a country with an average of 3.5 hours will have a change of $1 * (3.5/2.3)$ hours and $0.5 * (3.5/2.3)$ hour.

School policy for responsible internet use: this variable is reported in the 2018 and 2022 PISA datasets. The calculations assume that only half of the schools which had such policies in 2018 had also one back in 2009.

COVID-19 effects: the calculations assume that those who received online lessons represent the non-COVID counterfactual. The negative COVID-19 effect applies to those who did not receive online lessons.

Table B2-1 Changes in the policy variables, OECD average

	Change	
	2009-2018	2018-2022
<i>Policies and student characteristics</i>		
ECE participation, 1y or more, % of students	4.1%	-4.1%
Foreign language spoken at home, % of student	3.2%	3.0%
Ability grouping, across classes, % of students	-0.3%	-1.2%
Poor teacher quality (first observation 2015, not 2009), % of students concerned	-4.7%	9.9%
Room for homework in school, % of students	2.9%	-0.2%
<i>Digital device and internet use</i>		
School policy for responsible internet use, % of students	29%	6%
Digital device use in school, number of hours	1.00	0.50
<i>COVID-19 effects</i>		
% of students receiving real time online learning on a daily basis	--	51%

Between 2009 to 2022, PISA scores declined by 14.1 points, and back-of-the-envelope calculations suggest our framework can account for 12.8 points of this decline. The implied changes for two subperiods around the COVID-19 pandemic – 2009 to 2018 and 2018 to 2022 – are 4.5 and 8.3 PISA points, respectively. These figures contrast with the observed decreases of 5.1 and 9 points during the same time frames (Table 6).

The decline in PISA test scores since 2009 can be attributed primarily to two factors: digital device use and the COVID-19 pandemic. Non-class related digital device use in schools accounts for an almost 8-point decline in PISA scores, which reflects a 5-point decline over 2009-2018 and almost a 3-point decline from 2018 to 2022 (Table 6). At the same time, school policies, designed to inculcate students with the principles of a responsible use of internet partially counteract the trend: these policies reduced the negative effects of digital device use by 1 PISA point between 2009 and 2022. Finally, the COVID-19 effect accounts for an almost 4-point decrease in overall PISA scores after 2018.

Result suggests that the combined effect of education policies was relatively small in absolute terms and pales in comparison to the impact of digital device use and the COVID-19 pandemic. Initially, these policies had a positive effect from 2009 to 2018. However, they contributed 2 points to the overall PISA score decline from 2018 to 2022. Four specific policies were considered: early childhood education participation, ability grouping across classes, teacher quality (post 2015) and assistance with homework at school:¹⁵

- Declining teacher quality during 2018-2022 had a minor negative effect, likely due to challenges faced by teachers during remote education.
- Ability grouping and homework assistance made small positive contributions.
- Early childhood education had a net zero effect, despite its positive effect from 2009 to 2018. This shift may be linked to the temporary decrease in early childhood education participation in the aftermath of the 2007/08 economic and financial crisis, during which students aged 15 in 2022 attended pre-primary schools.
- Foreign language spoken at home,¹⁶ - though not an education policy variable – consistently detracted 1 point from the overall PISA score from 2009 to 2022, reflecting the difficulty of adjusting the schooling system to cope with the influx of migrants since 2010 into (many European) OECD countries.

¹⁵ Some variables used in the regressions are discarded, including: i.) school autonomy, because of a change in definition between 2018 and 2022, ii.) selectivity at school entry, because it is not possible to scale it up to 100%, and iii.) country-level external exit exams because of data problems.

¹⁶ In the PISA survey, this variable is referred to as the language spoken at home different from the language of instruction at school.

Table 6. The decomposition of drivers of declining PISA test scores, OECD average

	Implied changes in PISA points (Average of math, science and reading)		
	2009-2018	2018-2022	2009-2022
OBSERVED CHANGE IN PISA SCORES	-5.09	-8.98	-14.07
Total changes in PISA points implied by calculations	-4.53	-8.26	-12.79
<i>Policies and student characteristics</i>	0.49	-1.90	-1.41
ECE participation, 1y or more	0.25	-0.26	0.00
Foreign language spoken at home	-0.55	-0.50	-1.05
Ability grouping, across classes	0.02	0.06	0.07
Poor teacher quality, 2015 onwards	0.57	-1.19	-0.62
Room for homework in school	0.21	-0.01	0.19
<i>Digital device and Internet use</i>	-5.02	-2.82	-7.84
School policy for responsible internet use	1.04	0.22	1.26
Non-class related digital device use in school	-6.07	-3.03	-9.10
<i>COVID-19 effects</i>	0.00	-3.55	-3.55
Students receiving real time online learning on a daily basis	--	-3.55	-3.55

Note: Calculations based on assumptions set out in Box 2.

Decomposing the three channels contributing to the decline in PISA scores provides a satisfactory explanation for the observed losses in PISA results across many individual OECD countries. For instance, the three channels can explain more than half of the observed decline in PISA scores in countries such as Australia, Belgium, Canada, France, Germany, Hungary, Korea, Mexico, Portugal, the Slovak Republic and Slovenia.¹⁷

However, this decomposition fails to account for overall moderate PISA improvements from 2009 to 2022 in countries like Colombia, Czech Republic, Estonia, Ireland, Israel, Japan and Türkiye. These improvements appear to be influenced by factors beyond the channels considered, dominated by negative digital device use and COVID-19 effects (Table E2 in Appendix E), or may reflect country-specific differences in coefficient responses. We leave this question for future research.

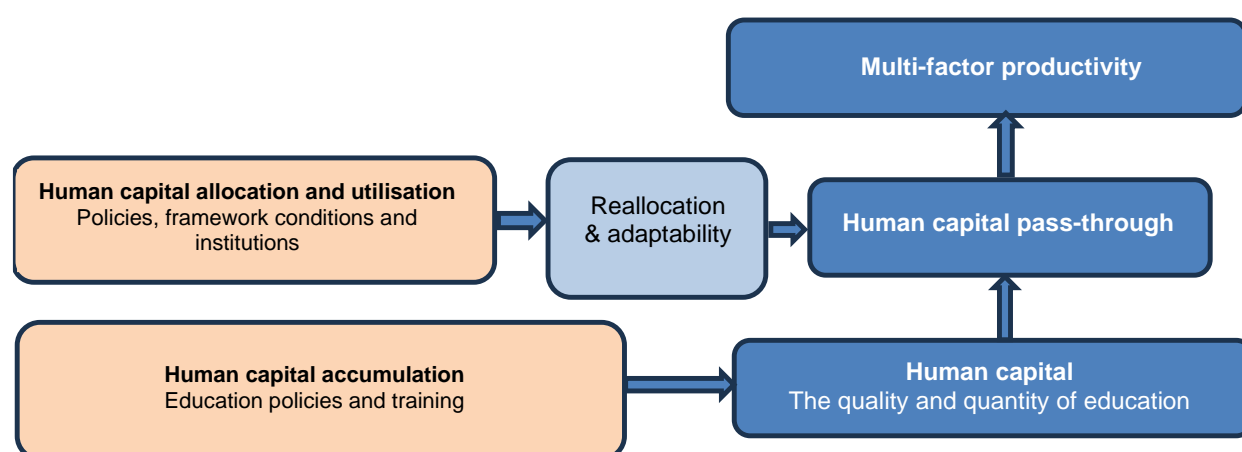
5. Human capital allocation and productivity growth

Policymakers should be concerned with allocating the existing stock of human capital more efficiently. Given that the growth benefits of human capital-augmenting policies (e.g. education reforms) can take a long time to materialise, it is crucial to put the existing stock of human capital to its best use. Doing so will also improve the ‘bang-for-the-buck’ – or productivity benefits – of education reforms. Figure 11 below shows the two stages through which human capital influences multi-factor productivity in the QASR framework. First, human capital accumulation has a direct relationship with multi-factor productivity outcomes as more human capital can boost productivity. Second, the strength of this relationship hinges on how well any given stock of human capital is allocated and utilised. To the extent that the benefits of some human capital-augmenting policies can take a long time to be realised, policies that improve the allocation of human capital in the near term can potentially enhance the ‘bang-for-the-buck’ (i.e., productivity impact) of education policies. Similarly, rapid technological changes may work to render the existing stock of human capital redundant – even in countries with high education attainment – highlighting

¹⁷ On the other hand, the contribution of these channels explains only a smaller portion of the observed PISA losses in Costa Rica, Finland, Iceland, the Netherlands, New Zealand, Norway and Switzerland. In some cases, the estimated decline exceeds the actual one (e.g., Austria, Chile, Denmark, Italy, Latvia, Lithuania, Poland, Spain, Sweden, United Kingdom and the United States).

the importance of policies that support retraining and labour market adaptability. As discussed below, structural policies can play an important role in shaping labour market reallocation and adaptability.

Figure 11. Productivity, human capital accumulation and human capital utilisation & allocation

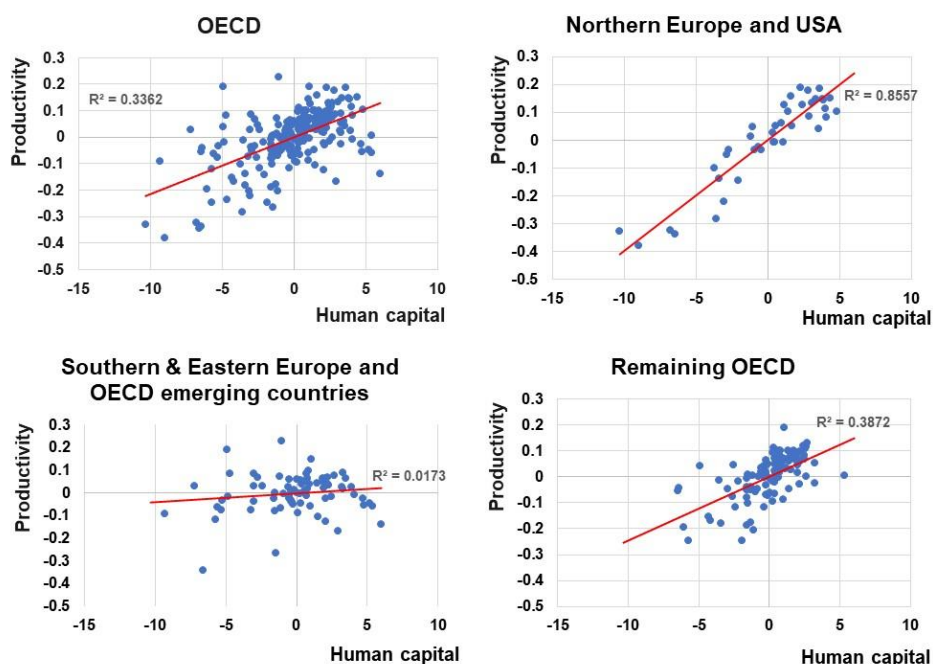


The strength of the relationship between human capital and productivity varies across countries, suggesting that some countries are more efficient at allocating human talent than others.¹⁸ Figure 12 shows that the link between human capital and productivity is much stronger in the Nordic countries and the United States than in Southern and Eastern Europe and other emerging economies (e.g. Chile, Mexico and Türkiye). At first glance, these patterns are symptomatic of differences in the efficiency of human capital allocation, given that the share of workers with skill mismatch is on average one-third higher in Southern and Eastern European countries than in Nordic countries and the United States (Figure 13).

More formally, we test the hypothesis that a greater skill mismatch might weaken the relationship between human capital and productivity. The baseline OECD QASR MFP equation is augmented with an interaction term between human capital and skill mismatch. The results indicate that there is a robust negative link between skill mismatch and productivity (see column 1; Table 7), suggesting that the pass-through of human capital to productivity is stronger in countries where the skill mismatch is lower.

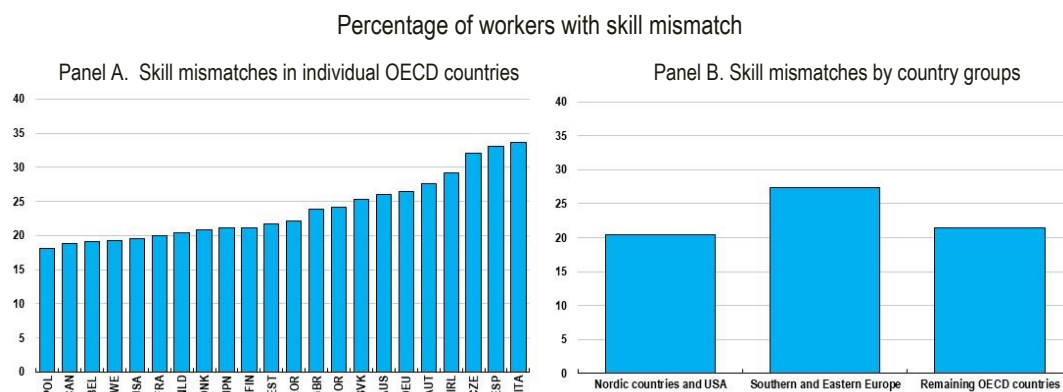
¹⁸ Existing empirical evidence demonstrates a robust connection between human capital and productivity on average across OECD countries (Égert, de La Maisonneuve and Turner, 2024). This finding assumes that the relationship is a homogenous one.

Figure 12. Human capital - productivity link varies across the OECD



Note: Human capital and productivity growth are demeaned at the country level to facilitate the comparison of changes in human capital and productivity across countries. Northern Europe and USA include Denmark, Finland, Norway, Sweden and the United States. Southern & Eastern Europe and OECD emerging countries include Greece, Italy, Portugal and Spain, Chechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia, and Chile, Colombia, Costa Rica, Israel, Mexico and Turkey. Remaining OECD include countries not included in the previous country groups.

Figure 13. Skill mismatches in OECD countries



Note: Figures show the percentage of workers who are either over or under-skilled and the simulated gains to allocative efficiency from reducing skill mismatch in each country to the best practice level of mismatch. The figures are based on OECD calculations using OECD, Survey of Adult Skills (2012)

Source: Adalet McGowan and Andrews (2015).

The pass-through of human capital to productivity may vary across countries due to differences in the extent to which framework policies:

- **Support job reallocation** and labour market fluidity, to enable workers to move to better matched roles. Reallocation-friendly structural policies – including pro-competition product

market regulations (PMR), insolvency regimes that do not impede business restructuring and employment protection legislation (EPL) that does not excessively raise the cost of labour adjustment – can spur productivity-enhancing labour reallocation and lower skill mismatch (OECD 2015; Andrews and Cingano, 2014; Adalet McGowan and Andrews, 2017).

- **Enhance adaptability** to reduce the likelihood that the existing human capital stock becomes obsolete in the face of technological and labour demand shifts, particularly ALMPs and retraining programmes. Recent evidence suggests that ALMP programs can also support productivity improvements within firms (Lombardi et al 2018).

New empirical evidence confirms that the productivity payoffs of human capital accumulation are shaped by policy frameworks that support reallocation and adaptability. This hypothesis is tested by augmenting the QASR MFP equation to include interactions between human capital and relevant policies. Estimation results show that passthrough of human capital to MFP is stronger in countries with pro-competitive product market regulations, less stringent EPL, and where insolvency regimes help firm restructuring and exit. The link between human capital and MFP is also higher in countries that devote a higher share of public resources to Active Labour Market Policy (ALMP) spending and where there is greater participation of (both low- and high-skill) workers in training (Table 7). Results also show that a decrease in the gender gap, measured by the difference between the prime-age female and male employment rates, boosts return on human capital.

Table 7. Human capital interacted with framework policies in the QASR Productivity regressions, 1985-2022

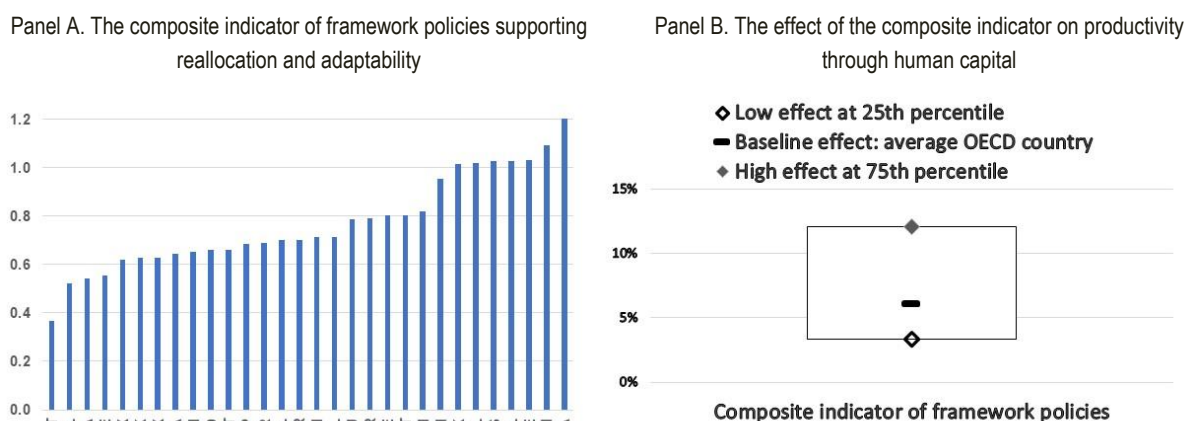
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	-5.0698**	4.305*	-8.397**	-2.585	-4.96	-4.58*	-4.038	-4.28**	-14.131**	-1.700
Trade openness (adjusted for country size)	0.001*	0.002**	0.001**	0.001**	0.0002	0.001*	0.001**	0.002**	0.001**	0.001**
Output gap	0.0086**	0.01**	0.012**	0.013**	0.0083**	0.006**	0.006**	0.011**	0.009**	0.013**
Logged human capital stock	2.8162**	1.136**	3.401**	2.372**	2.7963**	2.745**	2.653**	2.662**	4.412**	2.220*
Innovation intensity	0.0303**	0.044**	0.059**	0.061**	0.0692**	0.024**	0.01	0.035**	0.044**	0.071**
ETCR	-0.0397**	-0.034**	-0.046**	-0.038**	-0.044**	-0.047**	-0.05**	-0.041**	-0.043**	-0.044**
INTERACTIONS - Human capital with framework policies										
Skill mismatches	-0.8405**									
Product market regulation (PMR), administrative burden to start-ups	-11.198**									
Employment protection legislation (regular contracts)	-5.639**									
Insolvency regime	-13.266**									
ALMP - total of active measures, % of GDP	8.2838**									
Share of low-skill workers participating in training	0.524**									
Share of high-skill workers participating in training	0.494**									
Composite indicator (PMR, EPL and insolvency)	16.186**									
Composite indicator (PMR, EPL, insolvency and ALMP % GDP)	22.036**									
Employment gap (prime-age female employment rate - prime-age male employment rate)	0.133**									
Adjusted R-squared	0.967	0.978	0.971	0.964	0.983	0.974	0.973	0.98	0.986	0.963
No. observations	511	603	603	603	514	419	419	603	514	603
Number of countries	27	33	33	33	28	21	21	33	28	33

Note: * and ** indicate statistical significance at the 10% and 5% levels. Regressions include country fixed effects but no year fixed effects. The composite indicators are calculated as i.) the average of PMR, EPL, insolvency regime; ii.) the average of PMR, EPL, insolvency regime and ALMP spending. PMR, EPL and insolvency regime are inverted so that higher numbers indicate better/less restrictive policies. ALMP spending is calculated as a share of GDP, scaled between 0 and 1.

In order to analyse the potential for structural reforms to offset the productivity consequences of weaker human capital accumulation in Section 6, a composite indicator that combines PMR, EPL, insolvency and

ALMP spending is constructed.¹⁹ This composite indicator – which is increasing when policy better supports reallocation and adaptability – is presented in Figure 14, Panel A.²⁰ Regression analysis shows that the **link between human capital and MFP is stronger in countries where policy frameworks support reallocation and adaptability** and the economic magnitude of this effect is material (Figure 14, Panel B).

Figure 14. Human capital pass-through to productivity, conditional on policies enhancing reallocation and adaptability



Note: Panel A: composite indicator is calculated as the average of PMR, EPL, insolvency regime and ALMP spending. PMR, EPL and insolvency regime are inverted so that higher numbers indicate better/less restrictive policies. ALMP spending on training is calculated as ALMP spending on active labour market measures as a share of GDP, scaled between 0 and 1. Composite indicator not available for Colombia, Costa Rica, Lithuania and Türkiye due to unavailability of one or more of the underlying indicators.

Panel B: Based on regression analysis reported in Table 7. The baseline effect corresponds to the effect of an increase of one standard deviation in the cross-section in 2022 (2%) in the human capital stock on MFP at the OECD average of the composite indicator. The upper effect is calculated for the 75th percentile of the composite indicator (leading countries) whereas the lower effect is computed for the 25th percentile of the indicator (laggard countries).

6. The future of human capital and productivity

We use simulations based on the OECD QASR framework to study two sets of scenarios: i) the implications of ongoing changes in PISA test scores for the future of human capital accumulation and productivity (Section 6.1); and ii) the potential for education policy reforms and structural reforms targeted at improving human capital allocation to counterbalance these headwinds (Section 6.2).

6.1 Baseline scenarios

The first set of scenarios use assumptions based on past events, holding policy settings constant:

¹⁹ The composite indicator includes the PMR, EPL and the insolvency indicators. The training variables reduce the country coverage by one third. In order to maximise the number of countries in the sample, spending on ALMP is used in the composite indicator instead of the training indicators.

²⁰ We also do this to address limitations related to the fact that the PMR, EPL, the insolvency and the training variables are individually added to the baseline QASR productivity regression, interacting with human capital. As a result: i) the estimated policy effects cannot be simply added up; and ii) it is not possible to include all these variables in the regressions at the same time as their intercorrelation poses challenges.

Scenario 1: The effect of the 2009-2018 decline in PISA scores (“2009-18 counterfactual: decline through 2009-2018”): this scenario illustrates the impact of the 2009-2018 decline in PISA test scores on both human capital and productivity. PISA scores are assumed to remain constant from 2018.

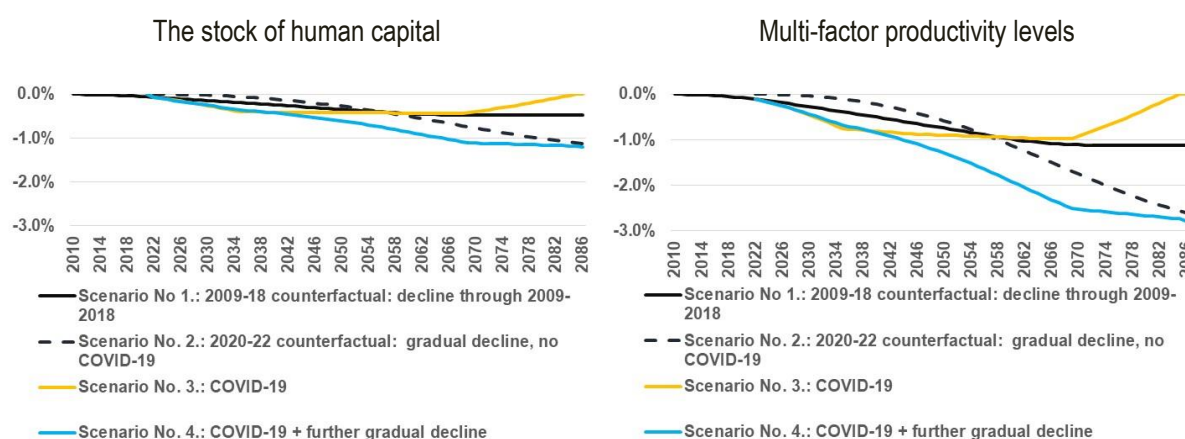
Scenario 2: No COVID-19 counterfactual scenario (“2020-22 counterfactual: further gradual decline, no COVID-19”): this scenario assumes no impact from COVID-19. However, it assumes that the gradual decline in PISA scores from 2009-2018 will continue in the future, at an annual rate of about 0.12%.

Scenario 3: Post-COVID-19 scenario (“COVID-19”): this scenario accounts for the long-term consequences of COVID-19, assuming that the generations aged between 3 and 16 in 2022 will be affected by the COVID-19-related decline in PISA scores and mean years of schooling. Subsequent cohorts’ PISA scores remain at the level of 2018 scores. The COVID-19 effect will peak around 2040, once the cohort aged 3 in 2020 will enter the labour force.

Scenario 4: A combination of scenarios No. 2 and No. 3 (“COVID-19 + further gradual decline”): this scenario considers the effect of COVID-19 and adds the gradual decline effect for future cohorts not affected by COVID-19. This is the most pessimistic scenario.

Figure 15 shows the results. First, the decline observed from 2009 to 2018 in PISA scores (scenario 1) will have a moderate but lasting impact on both human capital stock and productivity, with respective declines of approximately 0.5% and 1% in the long run. Second, a gradual decline starting in 2022 and following through multiple cohorts (scenario 2) will have a larger compound effect on human capital and productivity, more than doubling the negative effect implied by Scenario 1. Third, the COVID-19 effect (scenario 3) entails a sharp decline in both human capital and productivity over the next few decades. But these impacts are transitory – since only selected cohorts are affected – with a gradual return to the pre-COVID-19 counterfactual scenario expected only after 2080.²¹ Finally, COVID-19 effects combined with a gradual decline in PISA scores (scenario 4) implies declines in the human capital stock and productivity of roughly 1% and almost 3% in the long run. Scenario 4 is used as the starting point for the examination of the policy reforms below.

Figure 15. Projected future human capital and productivity without policy action



²¹ This prolonged effect primarily results from cohort effects – those impacted by the pandemic, including individuals entering, staying in, and exiting the labour force in the coming decades.

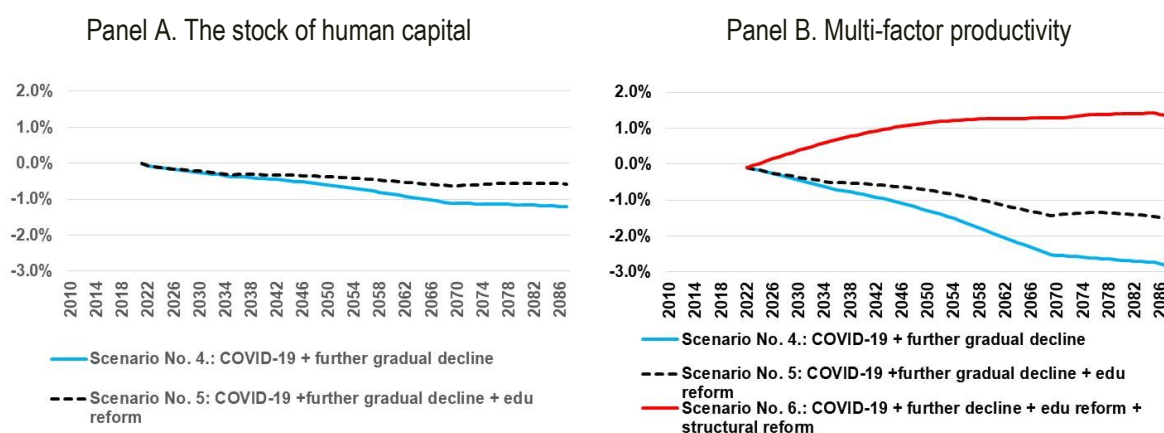
6.2 Policy reform scenarios

- The simulations in Figure 16 combine scenario 4 with the projected human capital and productivity effects of policy reforms with a view to understand the scope for policy reforms to lean against the headwinds implied to human capital and productivity of the most pessimistic scenario:
- Scenario 5: A combination of scenario 4 with education policy reforms (“COVID-19 + further gradual decline + edu reform”): juxtaposing the negative COVID-19 effect and gradual decline with an education policy reform package that is assumed to boost PISA scores by 10 points in 2026 (see Section 3.3 and Table E1 in Appendix E), this scenario analyses the extent to which education policy reforms can provide a countervailing force to the headwinds implied by the most pessimistic scenario.
- Scenario 6: scenario 5 plus a structural reform package that improves the allocation of the existing human capital (“COVID-19 + further decline + edu reform + structural reform”): assumes structural reforms boost the labour market reallocation and adaptability composite indicator from the 25th percentile to the OECD mean (see Figure 14, Panel B). Results for this scenario are only available for productivity, not human capital, since these reforms operate to boost the productivity returns of human capital at any given (unchanged) level of human capital stock.

Education policy reforms equivalent to a 10-point increase in PISA scores by 2026 will boost human capital and productivity to a considerable degree. The human capital stock and productivity are raised by around 0.6% and 1.5%, respectively in the long run (see Figure E1 in Appendix E). However, Scenario 5 shows that the impact of education policy reforms is insufficient to offset the joint headwinds of COVID-19 and the gradual secular decline in PISA test scores as embodied in Scenario 4.

Policy reforms to allocate the stock of human capital more efficiently can mitigate the productivity headwinds arising from the slowdown in human capital accumulation (scenario 6). By implementing reforms that are equivalent to move the composite structural reform indicator (including PMR, EPL, insolvency regimes and ALMP spending on training) from the 25th percentile to the OECD mean, policymakers can effectively counterbalance negative future developments right from the onset. The direct effect of these reforms is estimated to boost productivity by nearly 3% in the long run (see Figure E1 in Appendix E), more than fully offsetting the decline in human capital stock. When combined with education policy reforms, these reforms will yield a net positive effect of raising productivity by 1% in the medium term and peak at around 1.5% in the longer term.

Figure 16. Projected future human capital and productivity with policy action



Concluding remarks

This paper combined microeconomic and country-level data to explore the forces shaping the human capital accumulation process and its impacts on aggregate productivity. The paper demonstrated that the productivity slowdown, which emerged in many OECD countries before the 2007/2008 Economic and Financial Crisis, coincided with a marked deceleration in the rate of human capital accumulation.

The paper showed several key stylized facts. First, across the OECD, the human capital stock expanded at an average rate of 0.11% between 1987 and 2005, but then slowed to 0.05% between 2005 and 2016 and remained flat after 2017. Second, this slowdown in human capital accumulation is primarily due to a deceleration in the quality component of human capital, driven by a noticeable fall in student (PISA) test scores over the past 15 years. Finally, counterfactual estimates using the OECD Quantification of Structural Reforms (QASR) framework suggest that weaker human capital accumulation may account for almost one sixth (or 16%) of the slowdown in annual multifactor productivity (MFP) growth, which declined by around 1.2 percentage point on average across the OECD since the mid-2000s till 2022.

Given the policy challenges posed by stagnating human capital, the paper explored two questions. *First, why did PISA scores decline and how much scope is there for education policy reforms to counter these headwinds?* On average across the OECD, PISA scores declined by 15 points between 2009 and 2022, with less than half of that decline occurring before the pandemic. An analytical framework combining education policies, the widespread – and until recently largely unregulated – use of digital devices in classrooms (and outside) and the COVID-19 pandemic is useful for understanding this decline in PISA scores. Education policy reforms – including expanding early childhood education, measures to improve teacher quality, providing homework support, and regulating unstructured internet and digital device use in schools – could boost PISA scores by an estimated 10 points in the average OECD country.

The second question the paper addresses is how can countries deploy a given human capital stock more efficiently, to generate higher productivity growth? Cross-country differences in the efficiency of human capital allocation emerge, with the positive link between human capital and MFP stronger in the Nordics and the US compared to Eastern and Southern Europe and other emerging OECD countries. Countries with framework policies that support reallocation and adaptability in labour markets tend to allocate human capital more efficiently, as suggested by a stronger pass-through of human capital to aggregate MFP.

Simulations showed that if the downward trend in PISA scores were to persist, then long-run MFP growth could be almost 3% lower as a result. While an ambitious education policy reform package (as outlined above) would materially boost human capital accumulation and thus MFP, these benefits would take a long time to materialise and only offset one half of these headwinds. But combining education policy reforms with structural reforms to enhance labour market reallocation and adaptability could turn these headwinds into tailwinds and boost long-run MFP by about 1.5%. Overall, policymakers should focus not only on growing the stock of workforce talent, but also on allocating existing talent more efficiently.

Future research is necessary to enhance our understanding of the changes in human capital and productivity, along with their driving forces. First, the upcoming PIAAC data offers a valuable opportunity to examine how policies, particularly adult training, shape the quality of human capital beyond the formal education system. It will also explore whether managerial quality, as measured by PIAAC results of managers, affects firms' productivity through, among others, a better allocation of skills. Second, future research needs to investigate the distributional aspects of declining PISA scores. Notable, it could address whether this decline is specific to particular socioeconomic groups, to low- or high-performing students.

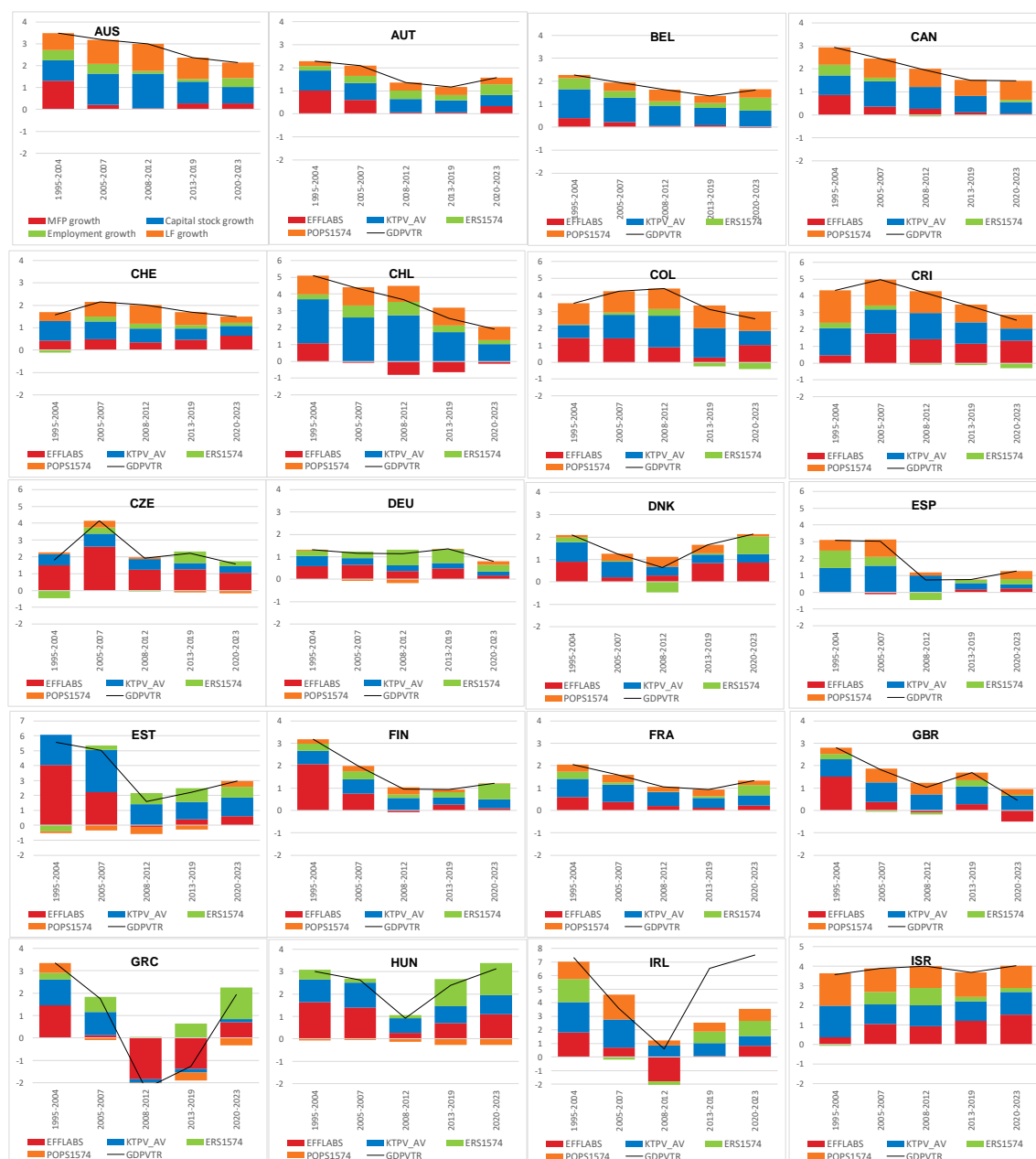
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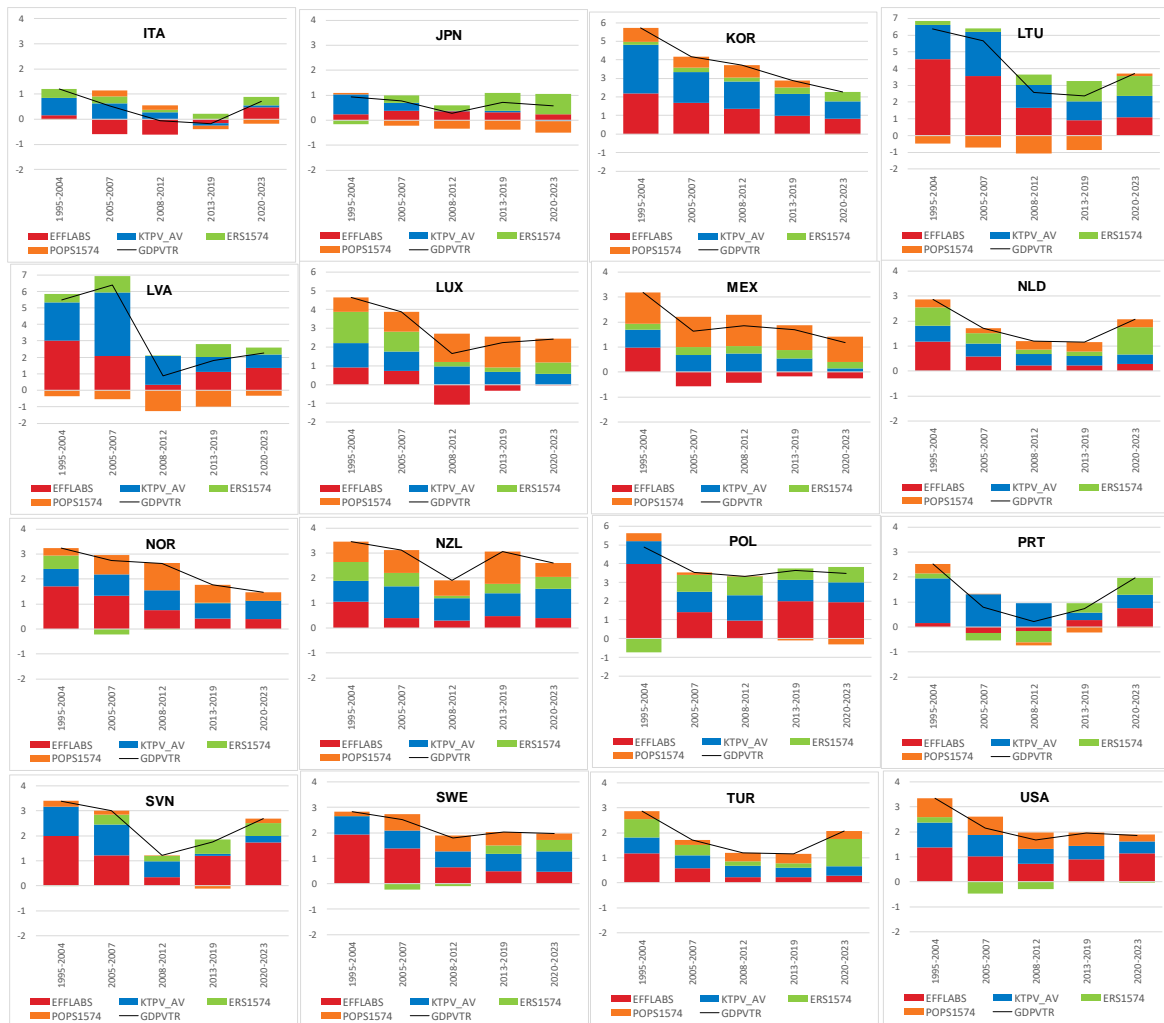
Appendix A. Productivity growth

Figure A1. Potential growth decomposition



Note: GDPVTR = trend growth, contributions to growth from EFFLABS = trend multifactor productivity, KTPV_AV = capital stock, ERS1574 = trend employment rate, POPS1574 = trend population growth

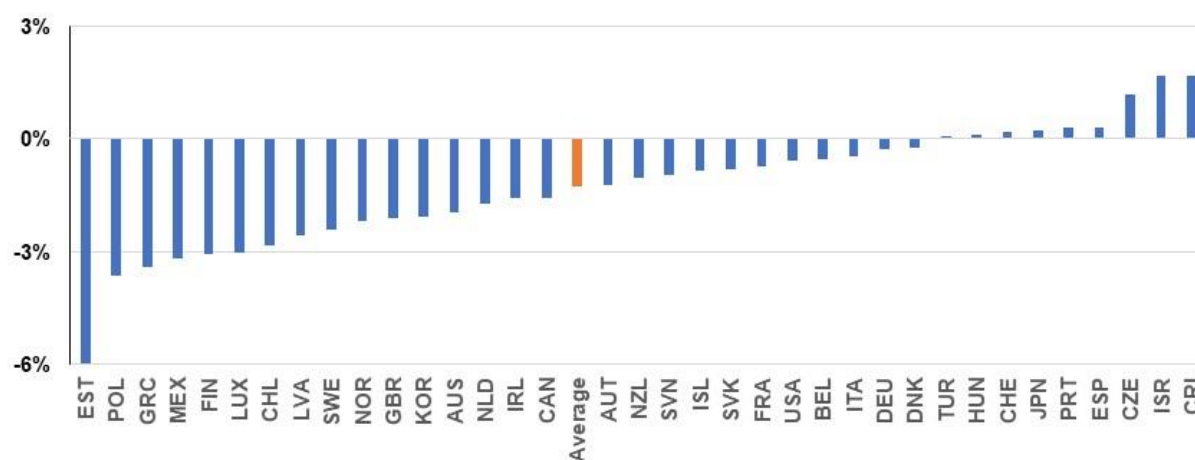
Figure A1 (cont'd).



Note: GDPVTR = trend growth, contributions to growth from EFFLABS = trend multifactor productivity, KTPV_AV = capital stock, ERS1574 = trend employment rate, POPS1574 = trend population growth

Figure A2. Productivity slowdown in the OECD, 2016/19 vs. 1995-2000

percentage points



Note: Figures summarise country-specific data, comparing average productivity growth between 2016/19 and the reference period of 1970/75. Years 2020, 2021 and 2022 are omitted, due to their significant impact from the COVID-19 pandemic. There are 20 OECD countries for which data was available from 1970 to 2019.

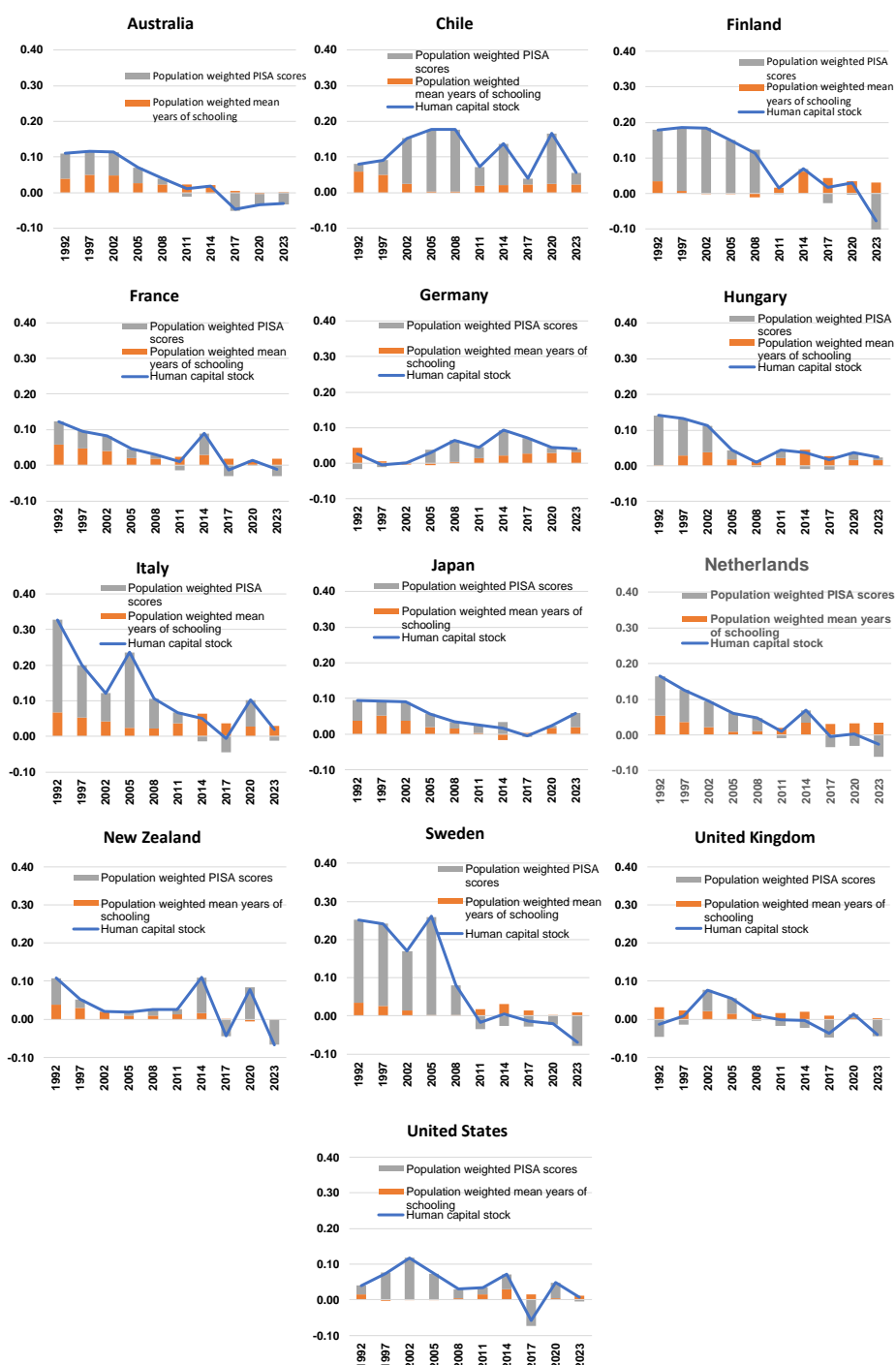
Table A1. Updated QASR Productivity regressions, 1985-2022

	(1)
Constant	-1.378
ETCR	-0.041**
Trade openness, adjusted for country size	0.001**
Private R&D spending by industry (% GDP)	0.079**
Stock of human capital	2.162**
Output gap	0.013**
Error correction term	-0.026*
Adjusted R-squared	0.961
No. observations	603
No. countries	33
Country fixed effects	YES
Year fixed effects	NO

Note: * and ** indicate statistical significance at the 10% and 5% levels. Regressions include country fixed effects but no year fixed effects.
Source: Authors' calculations.

Appendix B. Human capital growth

Figure B1. Human capital growth and its components, OECD, 1987-2023



Note: See Figure 2.

Table B1. Productivity and human capital growth, OECD, 1987-2022

	AUS	CHL	FIN	FRA	DEU	HUN	ITA	JPN	NLD	NZL	SWE	GBR	USA	AVERAGE
MFP growth (p.p)														
(A) 1987-2005	1.78	1.68	2.78	1.04	1.40	2.50	0.71	0.82	1.51	1.61	2.33	1.96	1.80	1.69
(B) 2005-2022	0.29	0.25	0.27	0.27	0.62	1.02	-0.35	0.47	0.40	0.59	0.93	-0.02	1.35	0.47
Human capital growth (p.p)														
(C) 1987-2005	0.10	0.12	0.17	0.09	0.01	0.11	0.22	0.08	0.11	0.05	0.23	0.03	0.08	0.11
(D) 2005-2022	-0.01	0.11	0.03	0.02	0.06	0.03	0.06	0.03	0.02	0.02	-0.01	-0.01	0.02	0.03
MFP growth predicted by human capital growth from 1987 to 2005 (p.p)														
(C) x 2.36	0.24	0.29	0.41	0.20	0.03	0.25	0.52	0.20	0.26	0.12	0.54	0.07	0.18	0.26
MFP slowdown														
(E) = (A) - (B)	1.50	1.43	2.51	0.77	0.78	1.47	1.06	0.35	1.11	1.02	1.40	1.99	0.45	1.22
Human capital slowdown (p.p)														
(F) = (C) - (D)	0.11	0.02	0.15	0.07	-0.05	0.08	0.16	0.06	0.09	0.03	0.24	0.04	0.05	0.08
MFP slowdown explained by human capital slowdown (p.p)														
(G) = (F) x 2.36	0.26	0.04	0.34	0.16	-0.11	0.19	0.39	0.14	0.22	0.07	0.56	0.10	0.13	0.19
Contribution of human capital slowdown to productivity slowdown (%)														
(E) / (G)	17	3	14	20	-14	13	37	39	20	6	40	5	28	16

Appendix C. The link between human capital and productivity in the QASR framework

1. **Human capital shows a strong link to productivity, both in levels and growth rates.** Human capital is widely viewed as a key driver of multifactor productivity. While large cross-sectional datasets covering countries at various stages of economic development clearly demonstrate the connection between quantity-based measures of human capital on the one hand and per capita income and productivity on the other, this link remains less evident for more homogeneous groups of countries and when examining changes in human capital and productivity rather than their absolute levels. Analysing these variables for OECD countries reveals a strong positive relationship between a new measure of human capital, recently developed at the OECD (Box 1 in the main text), accounting for both the quality and quantity of education, and multifactor productivity (as shown in Panel A in Figure C1). Regression analysis further indicates that a one percent improvement in the stock of human capital is associated with a more than two percent rise in multifactor productivity in an average OECD country in the long run (see Égert et al., 2024 and column 1 in Table A1 in Appendix A).
2. **The impact of human capital on productivity is positive but takes a long time to materialise.** The OECD Quantification of Structural Reforms (QASR) framework provides empirical evidence for this. QASR links human capital to country-level multi-factor productivity in a reduced-form equation including other policies such as product market regulation, innovation intensity and trade openness. This equation is estimated in a cross-country time series panel regression framework (see Box C1).
3. **OECD research adds two nuances compared to previous literature.** First, the productivity gains stemming from human capital improvements is significantly higher in estimation frameworks that account for quality (proxied by PISA and PIAAC test scores) in addition to the quantity of human capital (as determined by years of schooling) (Box C1). Second, the long-term impact of enhancing human capital on multifactor productivity, while comparable to the effects of standardised improvements of other reforms (such as product market deregulation), materialises with very long delays for two reasons. If sustained improvements in education quality occur across successive student cohorts, it takes nearly 50 years for these improvements to fully manifest in the working age population. Furthermore, due to the nature of the modelling approach and the estimated slow adjustment to the long-run equilibrium, there is an additional lag before these enhancements are fully reflected in multifactor productivity (Panel B in Figure C2).²²

Box C1. The OECD Quantification of Structural Reforms (QASR) framework

The OECD Quantification Assessment of Structural Reforms (QASR) framework aims to evaluate the impact of structural policies on economic outcomes. It relies on three reduced-form equations that link productivity, investment, and employment to a range of regulations and institutions.

Specifically, the productivity block connects multifactor productivity to several factors: product market regulation (PMR), trade openness (exports and imports as a percentage of GDP, adjusted for country size), innovation intensity (measured by business spending on R&D as a percentage of GDP), and human capital (Figure C.1).

The capital stock, measured as a share of GDP, is connected to product market regulation, employment protection legislation (EPL) and elements of the user cost of capital.

²² This suggests that policies promoting upskilling and lifelong learning among the existing workforce can directly influence adult test scores. However, the literature suggests that returns on adult education tend to be lower compared to investments in education for younger children.

Employment, decomposed into demographic groups and sex (young workers, prime-age male workers, prime-age female workers and older workers), is connected to a host of labour market policies and institutions, product market regulation and a number of control variables including the cycle, the cyclically adjusted government balance and the level of education of the labour force. Figure C1 shows how education reforms effect economic outcomes through the QASR framework.

Figure C1 Human capital and the QASR framework

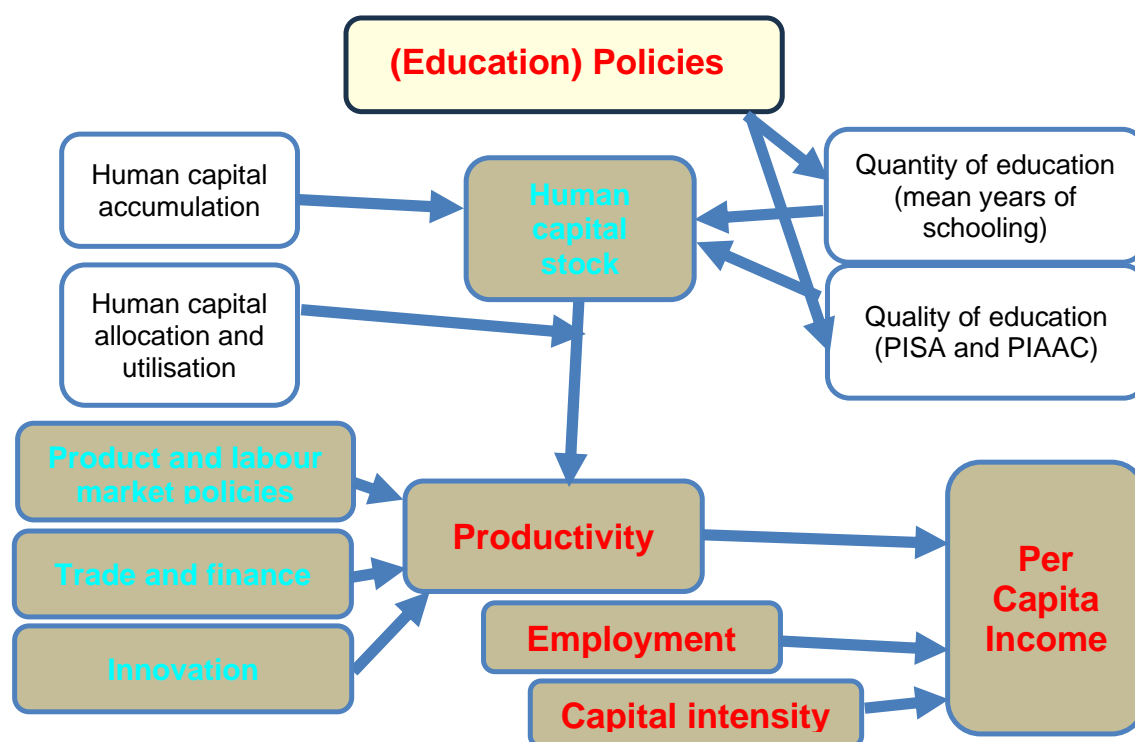
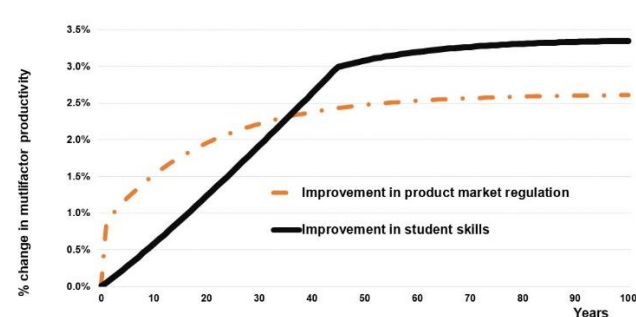


Figure C2. Human capital and productivity across countries

A. Link between human capital and productivity



B. Transmission lag from human capital to productivity



Source : Égert, de La Maisonneuve and Turner (2024)

Note: Panel A shows average MFP and human capital stock for 53 OECD and non-OECD countries (averages over 1987 to 2020 depending on data availability).

Appendix D. Detailed estimations results

Table D1. Subject-specific results, 2009-2022

PISA=f(student & school-level policies, controls, country fixed effects)

PISA (student & school level policies, controls, country fixed effects)									
Dependent variable: PISA score (math, science and reading)									
PISA score	Math (1)	2009 Science (2)	Reading (3)	Math (4)	2018 Science (5)	Reading (6)	Math (7)	2022 Science (8)	Reading (9)
Policies									
ECE participation, one year or more	7.572**	5.484**	6.320**	8.647**	4.090**	5.330**	8.986**	4.909**	5.524**
Ability grouping , across classes	-0.874	-2.563	0.065	-2.355	-0.746	-1.754	-14.158**	-14.978**	-14.339**
Ability grouping, within class	-4.621*	0.569	0.142	0.222	-0.033	2.573	0.947	2.236	3.076
Selective entry to school	9.358**	9.795**	10.356**	4.162**	4.374**	4.679**	7.462**	7.726**	7.167**
School accountability	10.719**	9.138**	8.318**	5.664**	5.903**	5.610**	-3.268**	-4.943**	-5.706**
Student characteristics									
Socioeconomic background	32.174**	31.791**	32.004**	30.363**	29.660**	31.719**	31.486**	32.452**	32.154**
Foreign language spoken at home	-9.705**	-18.864**	-14.990**	-12.231**	-24.274**	-21.355**	-16.767**	-26.542**	-25.137**
Girls dummy	-15.635**	-4.977**	31.461**	-8.836**	-1.372**	23.208**	-10.968**	-3.903**	20.694**
R-squared	0.310	0.289	0.270	0.272	0.235	0.220	0.294	0.251	0.227
No. of observations	2.8e+05	2.8e+05	2.8e+05	2.6e+05	2.6e+05	2.6e+05	2.5e+05	2.5e+05	2.5e+05
No. of countries	37	37	37	38	38	38	36	36	36

Note: see Table 2.

Table D2. Full results, 2015-2022

PISA=f(student & school-level policies, controls, country fixed effects)

Dependent variable: PISA score (average of math, science and reading)						
	2015		2018		2022	
	(1)	(2)	(3)	(4)	(5)	(6)
Policies						
Starting age of ECE, 1y	-11.408**	-3.482**	-11.781**	-11.346**	-0.510	-0.942
Starting age of ECE, 2y	7.530**	11.651**	6.741**	2.384**	11.761**	1.677
Starting age of ECE, 3y	15.412**	17.573**	16.529**	9.633**	18.960**	5.402**
Starting age of ECE, 4y	11.864**	9.619**	13.324**	4.556**	15.457**	1.901
Starting age of ECE, 5y	-0.532	-5.535**	1.347*	-8.573**	4.127**	-7.730**
Ability grouping, across classes	-10.445**	-9.387**	-2.867	-2.173	-14.299**	-16.268**
Ability grouping, within class	-3.310*	-14.677**	0.023	-13.222**	3.448**	-12.415**
Selective entry to school	5.750**	5.820**	4.473**	6.233**	6.791**	9.560**
School accountability	6.746**	-3.643**	5.799**	1.236	-3.231**	-1.631
Poor teacher quality - somewhat & very ba	-12.645**	-7.099**	-11.380**	-5.440**	-12.350**	-7.444**
Room for homework in school	4.514**	20.544**	9.834**	20.031**	10.993**	22.902**
Student characteristics						
Socioeconomic background	27.601**	33.349**	29.363**	35.364**	30.673**	37.187**
Foreign language spoken at home	-21.280**	-18.851**	-21.344**	-16.509**	-23.579**	-16.958**
Girls dummy	2.699**	2.801**	5.057**	5.130**	4.597**	4.556**
R-squared	0.286	0.227	0.278	0.233	0.297	0.164
No. of observations	2.0e+05	1.9e+05	2.2e+05	2.1e+05	1.9e+05	7.7e+04
No. of countries	38	36	38	36	36	35

Note: see Table 2.

Table D3. Full results, 2018-2022

PISA=f(student & school-level policies, controls, country fixed effects)		
Dependent variable: PISA score (average of math, science and reading)		
	2018	2022
	(1)	(2)
Policies		
Starting age of ECE, 1y	-12.737**	11.370**
Starting age of ECE, 2y	4.952**	18.970**
Starting age of ECE, 3y	14.604**	23.036**
Starting age of ECE, 4y	11.491**	17.152**
Starting age of ECE, 5y	0.018	8.939**
Ability grouping , across classes	-3.115	-15.139**
Ability grouping, within class	0.607	2.663
Selective entry to school	4.276**	9.797**
School accountability	5.188**	-2.171**
Poor teacher quality -somewhat & very bad	-10.733**	-11.148**
Room for homework in school	9.058**	7.579**
Digital device use & policy		
School policy for responsible internet use(=0 no, =1 yes)	2.323*	4.798**
Digital use - chat online (=1 no, =5 regularly)	-0.331**	
Digital use - online discussion forums (=1 no, =5 regularly)	-0.647**	
Digital use for leisure - in school (hours per day)		-6.065**
Student characteristics		
Socioeconomic background	28.506**	28.814**
Foreign language spoken at home	-19.526**	-24.274**
Girls dummy	3.531**	1.145**
R-squared	0.295	0.348
No. of observations	2.2e+05	1.8e+05
No. of countries	38	35

Note: see Table 2.

Table D4. Full results, 2022

PISA=f(student & school-level policies, controls, country fixed effects)	
Dependent variable: PISA score (average of math, science and reading)	
	2022 (1)
Policies	
Starting age of ECE, 1y	-0.348
Starting age of ECE, 2y	13.871**
Starting age of ECE, 3y	16.265**
Starting age of ECE, 4y	8.840**
Starting age of ECE, 5y	1.519
Ability grouping , across classes	-10.635**
Ability grouping, within class	3.906
Selective entry to school	10.649**
School accountability	2.524*
Poor teacher quality - somewhat & very bad	-13.607**
Room for homework in school	4.427**
Digital device use & policy	
School policy for responsible internet use(=0 no, =1 yes)	7.373**
Digital use for leisure - in school (hours per day)	-5.925**
COVID-19 - policies	
COVID-19: problems with schools' capacity to provide remote instructions (from -3 to +3, higher values more problems) // school level	-5.225**
Students receiving real time online learning on a daily basis // student level	29.140**
Student characteristics	
Socioeconomic background	24.858**
Foreign language spoken at home	-14.475**
Girls dummy	-7.030**
R-squared	0.374
No. of observations	1.4e+04
No. of countries	31

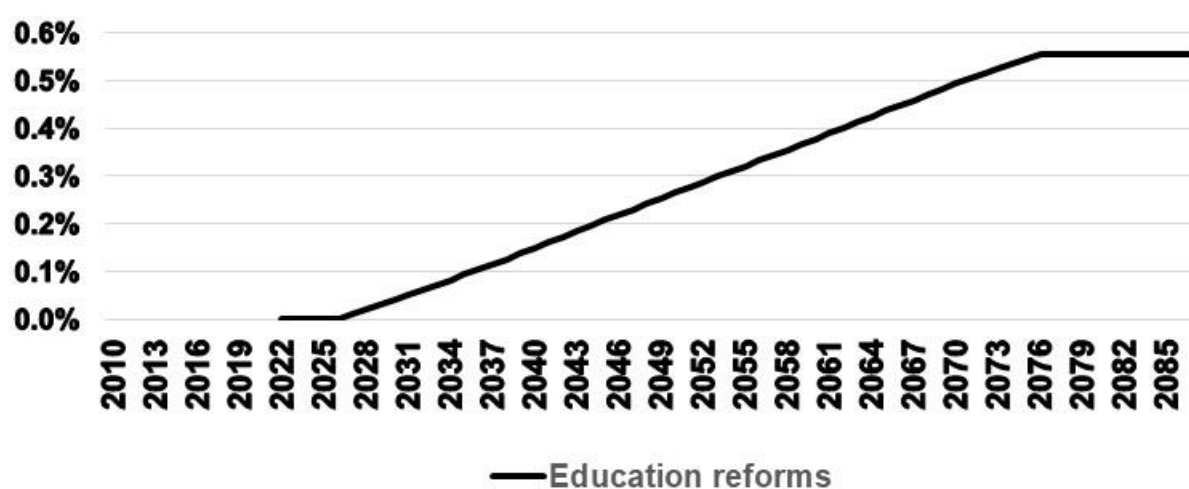
Note: see Table 2.

Appendix E. Reform scenarios and the decomposition of drivers of PISA decline, country-specific results

Figure E1. Macroeconomic effects of education and structural reforms

Effects embedded in the scenario analysis in Section 5.

A. Human capital effect of education reforms (% change in human capital stock)



B. Multi-productivity effects of education and structural reforms (% change)

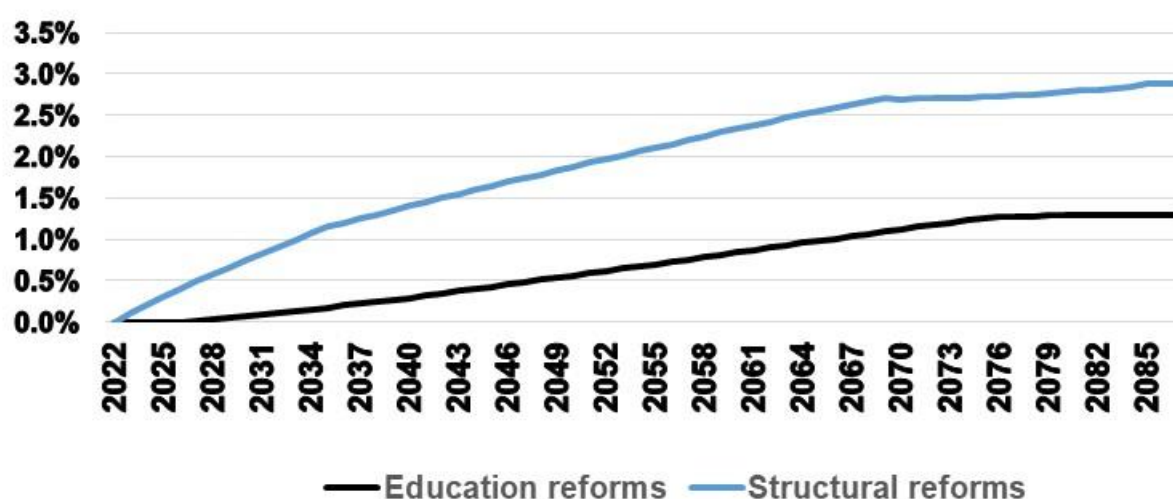


Table E1. The impact of potential country-specific education policy reforms on PISA scores

	ECEC participation, 1y or more	Ability grouping, across class	Poor teacher quality	Room for homework in school	School policy for responsible internet use	Digital device use in school	Total impact
AUS	0.7	0.1	2.4	0.7	0.3	2.9	7.2
AUT	0.5	0.1	1.6	1.6	0.5	3.7	8.0
BEL	0.7	0.5	5.4	0.5	1.4	3.3	11.7
CAN	0.8	0.4	2.3	0.5	1.5	4.5	9.9
CHE	0.6	1.3	1.3	0.8	0.8	1.2	6.1
CHL	1.0	0.1	1.9	1.2	1.9	5.4	11.5
COL	0.7	0.8	2.3	3.2	1.0	4.3	12.4
CRI	1.7	1.0	4.9	3.3	1.9	5.0	17.9
CZE	0.4	0.1	2.8	1.9	1.8	8.5	15.5
DEU	1.1	0.5	2.4	2.4	0.3	2.0	8.7
DNK	1.1	0.0	.	2.8	0.6	1.2	5.7
ESP	.	0.3	2.0	2.5	1.0	0.9	6.6
EST	0.9	0.3	5.5	1.5	1.3	8.1	17.5
FIN	1.2	0.0	0.9	2.6	1.3	5.8	11.9
FRA	0.3	0.1	3.0	0.4	0.9	2.4	7.1
GBR	1.5	0.2	1.7	.	.	0.9	4.2
GRC	0.3	.	2.6	4.1	1.4	4.5	12.9
HUN	0.5	0.1	1.1	2.0	0.6	8.6	12.8
IRL	.	0.0	2.9	1.3	.	.	4.3
ISL	0.9	.	.	0.4	1.1	.	2.4
ISR	0.6	0.7	4.7	2.4	.	6.4	14.8
ITA	0.4	0.0	3.9	4.4	0.6	7.4	16.8
JPN	0.3	0.3	4.5	.	1.2	.	6.2
KOR	1.0	0.4	1.3	0.6	0.5	4.3	8.1
LTU	1.7	0.3	.	0.8	0.9	4.8	8.6
LVA	1.1	0.3	3.0	2.0	2.1	7.1	15.6
MEX	.	0.4	1.6	1.9	1.6	3.0	8.4
NLD	0.2	1.7	4.9	.	0.4	4.3	11.6
NOR	1.0	0.1	0.7	1.8	0.3	1.7	5.6
NZL	0.6	0.1	2.0	0.7	0.6	3.0	7.1
POL	1.7	0.1	2.1	2.3	1.3	7.5	15.0
PRT	0.6	0.2	2.6	0.7	0.5	5.4	10.1
SVK	0.5	0.4	1.2	2.7	1.4	8.2	14.4
SVN	0.7	.	2.2	0.5	1.3	3.3	7.9
SWE	0.8	0.1	3.8	0.2	1.5	4.1	10.5
TUR	3.0	0.5	1.4	2.0	0.3	2.0	9.3
USA	1.8	0.1	1.5	0.5	1.0	2.7	7.6
Average	0.9	0.3	2.6	1.7	1.0	4.4	10.9

Note: Cells with a missing data are the policies for which the country is among the best 3 performers. Numbers calculated using coefficients estimates and the difference in policies compared to the top 3 performing countries.

Table E2. Country-specific PISA effects of education policies, digital device use and Covid-19

	Observed change in PISA scores	Overall implied changes in PISA scores (1) = (2) + (3) + (4)	Policies (2)	Digital device and Internet use (3)	Covid-19 effects (4)
	2009-2022	2009-2022	2009-2022	2009-2022	2018-2022
Australia	-21.9	-11.0	-0.6	-6.9	-3.5
Austria	-0.4	-14.1	-3.1	-7.4	-3.5
Belgium	-23.1	-14.9	-3.4	-7.7	-3.7
Canada	-20.4	-12.8	-1.5	-8.4	-2.9
Chile	-4.4	-10.4	1.9	-9.0	-3.4
Colombia	2.6	-9.2	2.7	-7.8	-4.1
Costa Rica	-23.7	-12.8	0.4	-8.8	-4.4
Czech Republic	0.6	-16.4	-2.0	-11.1	-3.3
Denmark	-9.1	-12.9	-3.8	-5.6	-3.5
Estonia	2.4	-16.1	-3.0	-10.7	-2.5
Finland	-47.5	-13.5	-1.6	-9.2	-2.7
France	-18.1	-9.4	-2.4	-7.0	0.0
Germany	-27.9	-14.5	-4.0	-6.2	-4.2
Greece	-35.8	-11.8	-0.4	-8.1	-3.3
Hungary	-18.3	-14.2	-0.5	-10.1	-3.5
Iceland	-54.3	-6.6	-0.5	-6.1	0.0
Ireland	7.4	-8.6	-1.1	-4.9	-2.6
Israel	6.0	-11.3	0.4	-8.8	-2.9
Italy	-8.4	-13.5	-1.9	-9.4	-2.2
Japan	3.1	-5.7	-0.8	-4.9	0.0
Korea	-16.9	-12.7	-1.3	-7.7	-3.6
Latvia	-2.2	-14.9	-1.7	-10.6	-2.6
Lithuania	-0.9	-8.6	1.9	-7.8	-2.6
Mexico	-12.8	-9.1	2.3	-7.5	-3.9
Netherlands	-38.4	-12.7	-3.0	-7.6	-2.1
New Zealand	-29.7	-13.8	-1.8	-7.2	-4.8
Norway	-25.0	-11.3	-1.3	-6.4	-3.5
Poland	-8.1	-16.8	-3.4	-10.7	-2.7
Portugal	-11.2	-9.6	0.6	-8.3	-2.0
Slovak Republic	-30.5	-16.0	-1.8	-10.8	-3.4
Slovenia	-13.8	-13.8	-2.1	-7.8	-3.9
Spain	-6.8	-10.8	-0.5	-5.9	-4.4
Sweden	-8.6	-12.2	-1.8	-8.2	-2.2
Switzerland	-19.6	-7.6	-1.5	-6.1	0.0
Türkiye	7.3	-5.7	4.1	-6.0	-3.8
United Kingdom	-5.7	-11.1	-1.8	-5.5	-3.8
United States	-6.4	-12.4	-2.1	-7.0	-3.3

Note: See Table 6 in the main text. Negative COVID-19 effects are set to zero for countries with total school closures lasting less than three months (France, Iceland, Japan, and Switzerland). Country-specific number of digital device use is rescaled using the country average hours.