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Fewer Children, Fewer Stars? Top PISA Performers in Europe

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Abstract

Background

PISA results are used in policy related monitoring, however, they are almost always framed around rates and shares, while little attention is given to what these rates and shares mean in absolute terms if applied to entire cohorts. Birth cohorts in Europe have been contracting for two decades, and a stable share of high performers now means fewer high performers. This study asks whether the number of high performers fell and whether this was due to smaller cohorts or to fewer students reaching the top.

Methods

PISA mathematics data from eight cycles (2003–2025) were analysed for 38 European countries (18 post-socialist, 20 other) with three or more comparable cycles. Numbers of high performers were calculated using final student weights for students scoring Level 5 and above. Variance estimates used plausible values, replicate weights, and 2025 score linking errors. Differences were decomposed into cohort coverage and rate components (Kitagawa method) and resident population, alignment and rate components (logarithmic mean Divisia index). Trends were compared across regions using random effects meta regression.

Results

Across the 21 countries with equivalent data across all eight cycles, the number of high performers fell by 50% from about 584,000 to 291,000 (95% CI: 195,000–390,000). By 2018, it was already down 21%. The number fell in 31 of the 38 countries, and fell significantly in 23 countries. 93% of the decline in the panel came from declining proficiency rates, and 6% from changes in resident population size. Cohort contraction was the main component of the count change in 10 of 18 post-socialist countries, compared with 3 of 20 other countries. Proficiency rates declined at a slower rate in post-socialist countries. Tertiary attainment rose in most countries over the same period.

Conclusions

Europe has been producing more credentials while its pool of high performers shrank, and its monitoring frameworks, built on shares, cannot show it. This should be seen as a human-capital loss in its own right, whatever its cause, and one that should be reported as a count, not only a rate.

Introduction

It is arithmetically obvious that, all other things being equal, smaller cohorts will produce fewer individuals that are exceptional in any way we may care about. Although “all other things” are never

equal, the sheer degree of cohort constriction, which has been happening as a result of declining fertility, should prompt us to examine its impact on the decline of absolute numbers of “high performers”. In this paper we look at how the absolute numbers of high-performing 15-year-old students in PISA changed in Europe over the last two decades.

Highly profitable industries and frontier research that feed off innovation require clusters of highly skilled people. With the credential inflation, and the absolute number of graduates even increasing, the positions in those highly productive industries will be filled, but credentials are not the same as ability. Even if the highest-performing members of each cohort went to those highly productive industries, there are other functions all around our society that require exceptional people. We want our doctors to be smart, we want our architects to be creative, we want our governments to be staffed with highly able people. The demand for advanced problem-solving is greater than ever and increasing, but what if the number of young people demonstrating such proficiency is declining? One answer is immigration. However, in headcount terms, one country’s brain gain is another’s brain drain. Within Europe, recruitment redistributes high performers among countries rather than adding to their number, and much of it draws on post-socialist countries whose own cohorts are shrinking fastest.

We argue that a decline in absolute high-performer count, even when driven purely by fewer births, is a human-capital problem in itself. When the rates of high performers fall alongside the cohort size (as we will show has happened across many countries of Europe), the problem becomes much more pronounced.

In Poland, the advanced-proficiency rate was nearly unchanged (10.1% in 2003 and 10.0% in 2025), while the estimated count fell from about 54,000 to 38,000 as the covered cohort shrank (Figure 1A). Take Germany, Europe’s largest economy (Figure 1B). In 2003 (the first PISA cycle on the current mathematics scale) an estimated 143,437 students had advanced proficiency in applying knowledge and reasoning to complex, unfamiliar problems (i.e., scored at Level 5 or above, ≥ 606.99 points), representing 16.2% of the PISA-weighted covered population. By 2025 the corresponding estimates were 56,264 and 7.8%: a decline of 87,173 students or 60.8%. These examples illustrate the question: how much of the decline in the number of high-performing adolescents reflects smaller covered cohorts, and how much reflects a lower share reaching advanced proficiency?

Building on earlier count-based comparisons (Pritchett & Viarengo, 2009), this study examines changes within European countries over successive PISA cycles and partitions those changes into resident-population, population-alignment, and advanced-proficiency-rate components. The most sophisticated multi-dimensional population projections stratify populations by educational attainment (Lutz et al., 2014), and skills-adjusted measures weight attainment by average measured skills (Lutz et al., 2021), but neither tracks the number of high performers. We are not comparing countries by their PISA score, but comparing each country to itself and asking whether the change came from fewer students or from a smaller share of them reaching advanced proficiency.

Education represents a universal good that has intrinsic value beyond just making people more productive. Educational attainment is easy to include as the statistics are readily available. It is no wonder that national and EU-level strategic documents universally include attainment targets. The EU's 2020 and 2030 strategies (Council of the European Union, 2009, 2021) set targets for tertiary attainment (at least 40 percent of 30–34-year-olds and at least 45 percent of 25–34-year-olds, respectively). The same frameworks also set a proficiency benchmark based on PISA results, i.e., the share of low-achieving 15-year-olds (below Level 2) in reading, mathematics and science should fall below 15 percent (Council of the European Union, 2021). Both benchmarks are shares, and neither tracks the upper tail of the proficiency distribution or the absolute number of students it represents.

The Bologna process created pressure toward expanding university credentials throughout Europe (Powell & Solga, 2010). However, a growing body of work challenges the premise that more graduates equals more skilled labor. Hanushek and Woessmann (2008, 2012, 2015) show that cognitive skills measured by international assessments predict economic growth far better than years of schooling. In the growth models reviewed by Hanushek (2016), adding cognitive skills raises adjusted R^2 from 25 to over 70 percent, while the school-attainment coefficient becomes small and statistically insignificant. Updated growth data show a similar pattern (Heller-Sahlgren & Jordahl, 2024), reinforcing the importance of accounting for educational quality (Wößmann, 2003). The quality component of education is estimated to be three to four times more important than the quantity component for explaining cross-country productivity differences (Égert et al., 2024). Lutz and Butz (2014, p. 2) similarly distinguish formal educational attainment from the knowledge and cognitive skills that education develops.

In a sample of fifty countries, a 10 pp. increase in the proportion of high-performing students corresponds to a growth rate increase of 1.3 pp. compared to 0.3 pp. for the same increase in basic literacy (Hanushek & Woessmann, 2011). Pritchett and Viarengo (2009) demonstrated that rates hide order-of-magnitude differences in absolute counts above an advanced mathematics benchmark (PISA test score higher than 625). Aggregate indicators are imperfect proxies as countries with strong averages can underperform at the top (Pitsia et al., 2024). Analyses usually report cognitive performance as mean scores or percentage shares, but these do not show the whole picture. Pritchett and Viarengo (2009) compare the estimates of the absolute number of pupils aged 15 above an advanced PISA mathematics benchmark between Mexico (3,500-6000) and the US (250,000), and argue that this big deficit in upper-tail talent makes it challenging for Mexico to compete in the global knowledge economy.

Does the demand for advanced problem-solving decrease proportionally as new cohorts shrink? Ageing societies need higher productivity, and productivity increasingly depends on innovation. Cross-national evidence (Égert et al., 2024) links the quality of education (measured partly through PISA performance) to later productivity gains, while research across 14 developed countries finds that adult cognitive skills are associated with higher incomes and more prestigious occupations, particularly in more innovative economies (Smith et al., 2022). Research on inventors also shows that early inventive success predicts higher inventive productivity over the rest of their careers (Michlbauer & Zwick, 2024).

Data and methods

PISA data

PISA, run by the Organisation for Economic Co-operation and Development (OECD), is an international assessment of 15-year-olds' capacity to apply knowledge and skills in mathematics, reading, and science to unfamiliar, real-world problems. Advanced proficiency is defined as mathematics Level 5 or above, consistent with the OECD's designation of Levels 5 and 6 as "top performance". Level 5 students can develop and work with models for complex situations and can select, compare, and evaluate appropriate problem-solving strategies (OECD, 2023b). Level 6 would isolate a more extreme tail but leaves very few observations, so Level 6 estimates have greater relative sampling uncertainty, especially in smaller countries. Every tested student has a sampling weight equal to the number of students in the population they represent, and summing the weights of students at Level 5+ gives the estimated absolute number of high performers in each country and cycle.

PISA reports each student's proficiency as a set of plausible values (five per domain through 2012, ten from 2015) drawn from the proficiency distribution consistent with the student's answers, and sampling variance is estimated with 80 replicate-weight sets (OECD, 2014, 2017). We compute every statistic for each plausible value and replicate-weight set and combine the results with Fay balanced-repeated-replication for sampling variance and Rubin's rules for imputation variance (Rubin, 1987).

Scores from different cycles are comparable through the linking of successive test forms, which is estimated with error. Comparisons with 2025 use the released pairwise linking errors (OECD, 2025, Annex Table 15.A.20). In mathematics the linking error between 2003 and 2025 is 5.67 score points, and between 2022 and 2025 it is 1.22. Score-scale uncertainty was converted to rate and count uncertainty using the local score density at the proficiency cut-point, and the linking shift is treated as common to all countries. Endpoint calculations use a symmetric allocation of the relative scale shift. Multi-cycle trend intervals use a first-order upper bound that allows arbitrary correlations among cycle errors relative to 2025; the pairwise table does not by itself identify a unique covariance model for the fitted trends. Design and linking variances are added under an independence assumption (see supplementary materials S3.4).

PISA samples enrolled 15-year-olds in eligible grades, not all residents, so our counts are numbers of high performers in PISA-covered student population. Coverage changes over time. If a school system adds more weak students to the covered population, the measured Level 5+ rate can fall even when nothing changed among previously covered students.

The frame for the main analysis has 38 countries (18 post-socialist and 20 non-post-socialist). We define the geographic scope as UN M49 Europe (United Nations Statistics Division, 2026) plus Kosovo, use national reporting units, and require at least three comparable mathematics cycles. Mathematics is the main domain and its reporting scale is the most consistently maintained over time; reading and science provide descriptive validation series within their own comparable windows. The UK's 2003 observation is

excluded throughout because inadequate school/student response prevents comparability (OECD, n.d.-a), so the UK series starts in 2006 (see S1.1 and Table S3.3 in the supplementary materials). The post-socialist grouping captures the shared demographic shock of the 1990s transition, the abrupt drop in birth rates, but baseline educational performance and institutional trajectories vary widely within the group.

Decomposing the change

Our first decomposition is the symmetric Kitagawa method (Kitagawa, 1955). The demographic component is the change in the covered population weighted by the average Level 5+ rate, and the rate component is the change in the Level 5+ rate weighted by the average covered population.

For the three-factor decomposition we write the count as the product of the resident population aged 15, a coverage ratio (PISA-covered population divided by resident population), and the Level 5+ rate. Because the numerator and denominator come from different statistical systems, the coverage ratio can exceed one and should be read as an alignment index. We adopt the logarithmic-mean Divisia index type I (LMDI-I; Ang, 2005), which gives an additive decomposition with no residual and does not depend on factor ordering. As a cross-check, a Das Gupta decomposition (Das Gupta, 1993) agrees closely with LMDI-I. Standard errors for the coverage and rate components come from re-running the decomposition inside every plausible-value and replicate-weight combination; the resident population is treated as fixed.

The resident population figures come from the OECD's PISA annex tables for the 2003 to 2022 cycles (OECD, 2023c, Table II.A2.2) and for the 2025 cycle (OECD, 2025, Table 14.A.1). Where OECD figures were unavailable, we used Eurostat population counts for all 15-year-olds (Eurostat, 2022b).

Trends in countries and regions

Within single countries we describe trends with Mann–Kendall tests (Mann, 1945) and Theil–Sen slopes (Sen, 1968), non-parametric methods suitable for the three to eight comparable observations available per country. Tests on series this short have limited power. We report raw and Benjamini–Hochberg-adjusted p-values (Benjamini & Hochberg, 1995), but the tests use point estimates and do not include linking-error uncertainty. Regional comparisons pool country slopes in random-effects meta-regressions that contrast post-socialist with non-post-socialist countries, with REML and Knapp–Hartung inference (Knapp & Hartung, 2003). Country-and-cycle fixed-effects models with clustered standard errors give separate design-based diagnostics.

How much of cohort contraction reflects earlier birth declines?

We approximate the birth cohort of children tested at age 15 in year t using live births in year t − 15 (Eurostat, 2022a). In logarithms, the covered population is the sum of three terms, one each for births 15 years earlier, the ratio of resident 15-year-olds to those births (which absorbs migration, mortality, and timing mismatches), and school-system coverage. For the regional comparison, all three terms are pooled with common weights so that they remain exactly additive.

Code and Data

R programming language (R Core Team, 2026) was used for all analyses and visualizations with the help of Claude Code using Claude Opus 4.6 generative AI model. The study repository is *https://osf.io/y65ja*. Code and derived tables identify the raw PISA files and archived external series needed for replication.

Results

High-performer counts fell across most countries

In the fixed set of 21 countries observed in every mathematics assessment from 2003 to 2025, the estimated number of PISA-covered students reaching Level 5 or above fell by about half. The total describes the same countries throughout; it is neither a total for Europe nor an estimate for all resident 15-year-olds.

The long-period decline remained evident after incorporating the released score-linking errors; it was already visible by 2018 and remained large when Germany was excluded. Part of that established pattern is the regional cohort contrast and the dominance of the rate component in non-post-socialist countries. The 2025 results are consistent with the pattern already observed through 2022. The additional decline after 2022 also had an interval excluding zero. Table 1 separates the long-period and recent comparisons; the full trajectory and alternative country sets appear in Table S3.3.

Estimated counts fell in 31 of the 38 countries between their own first and last comparable assessments. Declines in 23 countries had endpoint intervals excluding zero; Romania was the only country with an increase whose interval excluded zero. Endpoint changes do not imply a steady decline at every assessment. In Poland, for example, advanced-proficiency rates rose and then fell back to roughly their starting level (Table S5.1).

Table 1
High-performer count changes in fixed-country comparisons.

Comparison and period	First count	Last count	Count change	Change (%)	95% interval for count change
Fixed 21 countries 2003–2025	583,840	291,484	−292,357	−50.1	[− 389,628, − 195,086]
Same 21 countries 2003–2018	583,840	463,069	−120,771	−20.7	[− 184,459, − 57,084]
Same 21 countries 2022–2025	328,577	291,484	−37,094	−11.3	[− 63,950, − 10,237]
Germany excluded (20) 2003–2025	440,404	235,220	−205,184	−46.6	[− 281,774, − 128,595]

Note. Counts refer to PISA-covered students reaching mathematics Level 5 or above. The fixed panel excludes the UK, whose comparable series starts in 2006. Endpoint intervals combine BRR/PV design variance with released pairwise score-linking errors under the symmetric shift approximation. Full trajectories, alternative frames and uncertainty details appear in supplementary materials (Table S3.3 and S3.4 to S3.5).

Population decline and falling proficiency contributed in different ways

The fixed-country total fell mainly because a smaller share of students reached advanced proficiency, not because there were far fewer students in the covered population. That population declined only modestly, whereas the advanced-proficiency rate nearly halved. The aggregate decomposition assigns most of the count loss to the rate component (supplementary materials S3.5).

Resident-population contraction accounted for more than half of Lithuania's count loss, while falling proficiency accounted for most of Germany's. In France, the rate decline more than offset growth in the resident cohort. Separating resident population from alignment also matters, because a change in the PISA-covered cohort is not necessarily a change in the number of resident 15-year-olds (Fig. 2; Table S5.3). Component shares are not reported when the total change is small or its interval includes zero.

Regional differences depended on the period and specification

Over the full available period, covered cohorts contracted faster in post-socialist countries than in non-post-socialist countries. The faster contraction remained when Russia was excluded, but it was not clearly present in the separately fitted recent period (Table 2).

Advanced-proficiency rates showed the opposite regional contrast. They declined more slowly in post-socialist countries, by about a quarter of a percentage point per year. The estimated difference remained positive in all window checks, but its size and precision varied. The common 2003–2025 comparison (22 countries) produced a smaller estimate with an interval that included zero, whereas the common 2006–

2025 comparison (31 countries) retained a positive estimate with an interval excluding zero (Table S3.2; supplementary materials S3.3).

Quality restrictions mainly changed the precision of the rate comparison. Excluding countries with flagged response or exclusion profiles gave estimates close to the main result, but wider intervals included zero. Adjustment for initial proficiency also reduced the estimated magnitude and left the comparison inconclusive.

Table 2
Regional contrasts and selected sensitivity checks.

Comparison	Countries	P − N contrast	95% interval
A. Covered-population trend (log-percentage points per year)			
Full available window	38	−1.517	[− 2.129, − 0.906]
Excluding Russia	37	−1.440	[− 2.037, − 0.843]
Recent calendar window, 2015–2025	36	0.114	[− 0.795, 1.024]
B. Advanced-proficiency rate trend (percentage points per year)			
Primary available window	38	0.247	[0.092, 0.401]
Common 2003–2025 endpoints	22	0.147	[− 0.090, 0.384]
Excluding flagged/poor 2025 profiles	21	0.232	[− 0.003, 0.466]
Excluding flagged 2022 or 2025 profiles	19	0.248	[− 0.013, 0.509]

Note. P − N is the post-socialist-minus-non-post-socialist contrast. Negative cohort contrasts indicate faster contraction in post-socialist countries; positive rate contrasts indicate slower decline there. Rate intervals incorporate released linking errors using a first-order arbitrary-correlation bound; cohort-only trends do not depend on score linking.

The descriptive score-distribution decomposition placed the regional difference mainly in changes in mean performance rather than dispersion. Germany illustrated the same pattern. The falling mean accounted for most of its modelled upper-tail decline. The regional rate contrast had the same sign when we used alternative proficiency thresholds (Table S5.2).

Earlier birth declines accounted for most of the regional cohort gap

Over the full available period, the larger contraction in covered cohorts in post-socialist countries mainly reflected smaller birth cohorts fifteen years earlier. Earlier births accounted for an estimated 88% of the between-group gap under the common-weight decomposition, although uncertainty around that share was wide (Table S5.5).

The remaining components partly offset one another. Changes in the resident-to-birth ratio added to the regional contraction gap, whereas changes in population alignment reduced it. The resident-to-birth component is consistent with migration and survival, but it also absorbs cohort-timing differences and population-register revisions, and excluding the four countries with major register corrections did not remove its negative direction (Table S5.5).

Migration-background and cross-domain patterns

Estimated high-performer counts among students with an immigrant background increased in the United Kingdom and Ireland; the estimated changes in Austria and Germany were inconclusive. The estimates use design uncertainty only (Table S5.6). When restricted to native/non-immigrant students, the regional proficiency-rate contrast was similar (0.252 versus 0.247), describing a pattern within the subgroup rather than identifying immigration's contribution.

In 25 of 38 countries the direction of the count change agreed in mathematics, reading and science, but not everywhere. The separate tertiary comparison showed a different broad pattern. Attainment generally rose during periods when its definition remained unchanged, while adolescent high-performer counts often fell. We do not evaluate individual transitions from PISA performance to degree completion; rather, we contrast two contemporaneous indicators used by European policymakers. While attainment indicators suggest an increase in human capital, the number of high-performing adolescents is falling. These indicators do not follow the same people and their divergence does not establish a change in graduates' skills.

Discussion

Shrinking cohorts did not become higher performing cohorts

Our empirical finding of a declining absolute count of advanced adolescent proficiency could be interpreted in light of Jones's (2022) "Empty Planet" scenario, although that model concerns the global stock of researchers and depends on assumptions about the idea production function that are not tested here. If economic growth relies on the absolute number of researchers and inventors, Europe's shrinking pool of top-performing youth poses a threat to future innovation. Recent macroeconomic models suggest that demographic decline need not lead to economic stagnation, provided that shrinking cohorts are offset by rising human capital and educational quality (Boikos et al., 2023; Strulik, 2024). At the household level, classic human capital theory predicts a quantity-quality trade-off in which families deciding to have fewer children invest more in each (Becker & Lewis, 1973), a micro-level mechanism that macroeconomic models often extrapolate to national cohorts (e.g., Strulik, 2024). The analysis assesses whether changes in measured proficiency offset changes in cohort size; it does not test the household-level relationship between fertility decisions, educational investment, and children's outcomes. In fact, the Western European upper tail count is shrinking mostly because fewer 15-year-olds reach the advanced proficiency level.

The absolute count has not been part of any European monitoring framework, which tracks shares and credentials. Measured directly, it fell in 31 of 38 countries over each country's observed period, and not only due to smaller cohorts. In Germany, France, and Finland, demography accounts for 23%, − 8%, and − 4% of the loss respectively (three-way LMDI decomposition; Table S5.3), and they lost most of their high performers from relatively stable cohorts. Tertiary attainment generally increased within the observed definition segments in the 33-country comparison (Table S4.1). Pritchett and Viarengo (2009) showed a big gap in absolute counts of advanced performers between the US and Mexico, and using the same approach we show how countries' absolute counts can change within a generation: Germany in 2025 had a smaller Level 5 + count than a school system half its 2003 size would have produced at Germany's own 2003 rate. Germany's assessment of grade 9 students in German language (a different domain) showed a similar trend (Stanat et al., 2023).

Migration

The decomposition presented above can be regarded as an accounting identity rather than an explanation of how migration influences the distribution of proficiency among populations. In keeping with the standard demographic convention, a decrease in the number of individuals composing cohorts is considered to have no effect on ability levels. After EU accessions, the flow out of Central and Eastern Europe was younger and better-educated (Atoyan et al., 2016), and parents' education influences offspring's success (Ichou, 2014). Emigration may affect both population size and measured proficiency (if selective), so the accounting partition cannot establish whether it increased or reduced high-performer counts relative to a no-emigration counterfactual. Migration prospects can encourage investment in education in developing countries, although the net effect on human capital depends on the balance between these incentives and the loss of skilled emigrants (Beine et al., 2008). Restricting the analysis to non-immigrant students gives a similar regional (East-West) contrast in proficiency-rate trends. Recruitment is a legitimate strategy for an individual country, but at the continent-wide scale it also redistributes workers among countries competing with one another (Kerr et al., 2016).

PISA score decline

A recent study (Crato & Marôco, 2024) argues that most European students now lag one to two school years behind their peers in the world's most advanced educational systems, and this performance gap continues to widen. Ireland's 2009 results showed the largest reading decline among 38 countries since 2000 and the second-largest mathematics decline among 39 countries since 2003 (Cosgrove & Cartwright, 2014). The authors caution that changes in cohort composition, administration and student engagement complicate interpretation. Educational poverty rose in many European countries between 2006 and 2015 (Agasisti et al., 2021), a finding from the opposite end of the same distributions. Decomposition shows that it is the changing mean (not dispersion) that is behind the regional gap. France could be seen as a partial exception to the rule since it demonstrates the largest growth in dispersion of outcomes among all European countries during an earlier period, which Goussé and Le Donné (2014) link to the quality of the education system itself and not student composition.

School and institutional characteristics account for more of the movement in educational inequality than student background (Oppedisano & Turati, 2015). COVID-19 contributed to a decline that had already begun, and the OECD attributes only part of the roughly 15-point 2022 mathematics loss to the pandemic (OECD, 2023a), and our series agrees, with the fixed 21-country total already 20.7% below its 2003 level by 2018 and 58.7% of the full 2003 to 2025 loss occurring after 2018. Neither explanation is regionally differentiated, and we do not identify one. The contrast is consistent with post-socialist systems improving from a low base while non-post-socialist countries show faster measured rate decline. The full-window rate contrast is positive, but its precision depends on the window and sample restrictions.

While the known demographic outlook of Eastern Europe makes it easy to project cohort constrictions, there is also a larger opportunity to improve the scores that can at least partially offset the absolute loss due to demography for the near future. In Western Europe the mean shift of the entire distribution points to a system-wide problem (not one specific to the right tail).

Implications

Human capital quality measures predict cross-country differences in income better than proxies relying solely on credentials (Wößmann, 2003). The link between human capital quality and productivity is realised with long lags (Égert et al., 2024). The credential premium is susceptible to educational expansion whereas the skills premium is resilient to skills diffusion, implying that policies focused solely on credential attainment may affect the labour market value of degrees without building the cognitive capital necessary for economic returns (Araki, 2020). Approximately 30 million EU workers are projected to be either overqualified or unemployed by 2060, in spite of medium- and low-skilled vacancy rates quadrupling (Marois et al., 2026).

The results motivate reporting credential and cognitive-performance indicators separately in population projections. While there are education-augmented projections (Lutz et al., 2014; Lutz & KC, 2011) that stratify populations by credentials, there are also skills-adjusted indicators (Lutz et al., 2021), which combine credentials with measured skills, taking the skills of new adult cohorts from PISA reading trends through 2018. However, an adjustment based on the means does not show a contracting upper tail, nor a falling count at a stable rate.

If lower adolescent proficiency counts translate into fewer highly skilled labor-market entrants, they could intensify challenges associated with population ageing.

An indicator reporting the estimated absolute number of 15-year-olds reaching PISA Level 5 + in each member state, published alongside the existing tertiary-attainment rate in the EU Education and Training Monitor, would make contractions of the kind documented here visible in routine reporting rather than recoverable only from microdata, at no additional collection cost. The EU's main education targets are attainment rates, and a rate target can be met even while the absolute number it describes contracts. An indicator of advanced proficiency within successive adolescent cohorts would register what rate-based targets do not and would be a good complement to the current attainment rate focus.

Limitations

PISA covers enrolled 15-year-olds in eligible schools and grades, who are only part of the resident population. Writing the count as P × C × r isolates numerical coverage but does not correct selection into the tested population, so a near-zero regional coverage term is compatible with compositional bias in r. The main frame includes 38 countries (18/20) within the stated geographic scope, each with at least three comparable waves. Even with mean score equating, the 2015 transition from paper-and-pencil to computer-based testing could introduce psychometric drift at high proficiency thresholds (≥ 606.99 points). Paper-only and computer-only subsets, selected by actual administration mode, give regional contrasts of 0.252 (95% interval − 0.024 to 0.529; p = .072) and 0.268 (95% interval 0.106 to 0.431; p = .002). The observational checks cannot establish cross-mode scale invariance in the upper tail. Nor can they separate administration mode from all concurrent changes. PISA is a low-stakes assessment, and measured performance reflects effort as well as proficiency, with experimental and questionnaire-based evidence showing that effort responds to incentives and varies among countries and over time (Akyol et al., 2021; Gneezy et al., 2019; Zamarro et al., 2019). While the demographic components are counts of people and do not depend on test-taking effort, the decline we observe might be affected by lower test taking effort. For changes in effort to explain the regional rate contrast, the decline in effort would have to be greater in non-post-socialist countries. In conscript-based cognitive series from Norway and Denmark, gains halted and reversed for cohorts born from the mid-1970s onward (Bratsberg & Rogeberg, 2018; Teasdale & Owen, 2008). The linking-error calculations do not establish cross-cycle invariance of the full upper-tail distribution. Trend intervals also use a conservative correlation bound.

Conclusion

Education stratified population projections assume equivalence of a college degree awarded in 2005 to a similar one awarded in 2030, considering both as units of human capital. It seems clear that in order for such projections to prove useful for modeling purposes, they have to take the evolution of meaning/value of the said credential into account. While PISA tells us nothing about tertiary education quality, it tells us a lot about the students preparing to go into it.

The students who will participate in PISA in 2041 are mostly born in 2025 and we know that the cohort contraction persists in the East and is arriving in countries that have been experiencing the decline in number of high performers through lower proficiency rates. Although improvement in PISA scores may be a worthwhile goal, whether such gains would offset losses associated with shrinking cohorts (and for how long) remains to be seen. Reporting of both absolute numbers and proficiency rates would allow monitoring frameworks to differentiate the change due to cohort size and the change in proficiency rate.

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Figures

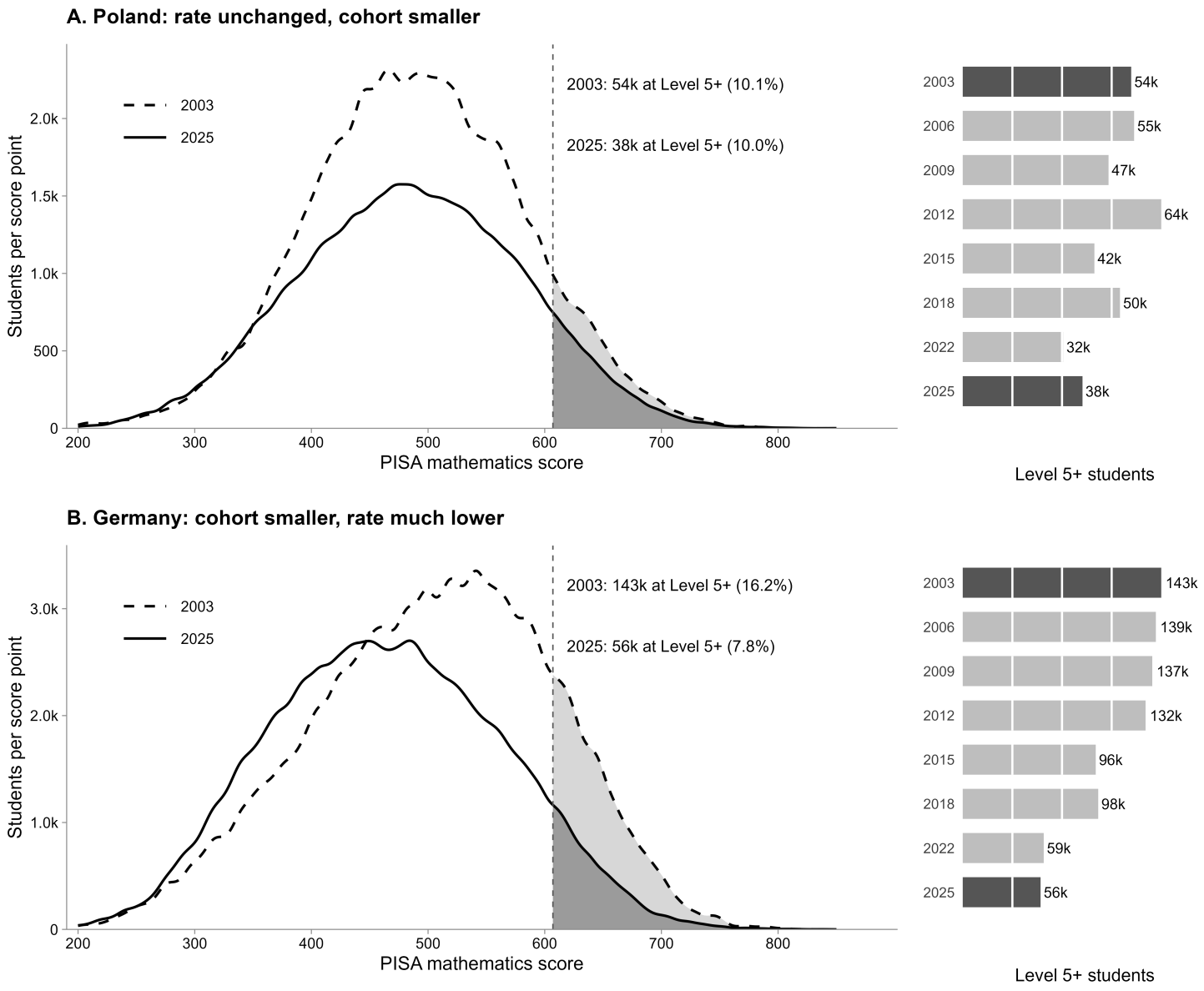


Figure 1

Figure 1. The number of 15-year-olds at mathematics Level 5 or above (score ≥ 606.99): Poland (A) and Germany (B), 2003 and 2025. Curves show the number of PISA-covered students per score point, Gaussian-smoothed (5-point bandwidth) from 7-point weighted histograms of all plausible values; shaded areas lie above the Level 5 cut-point. Labelled counts and rates are computed directly from all plausible values.

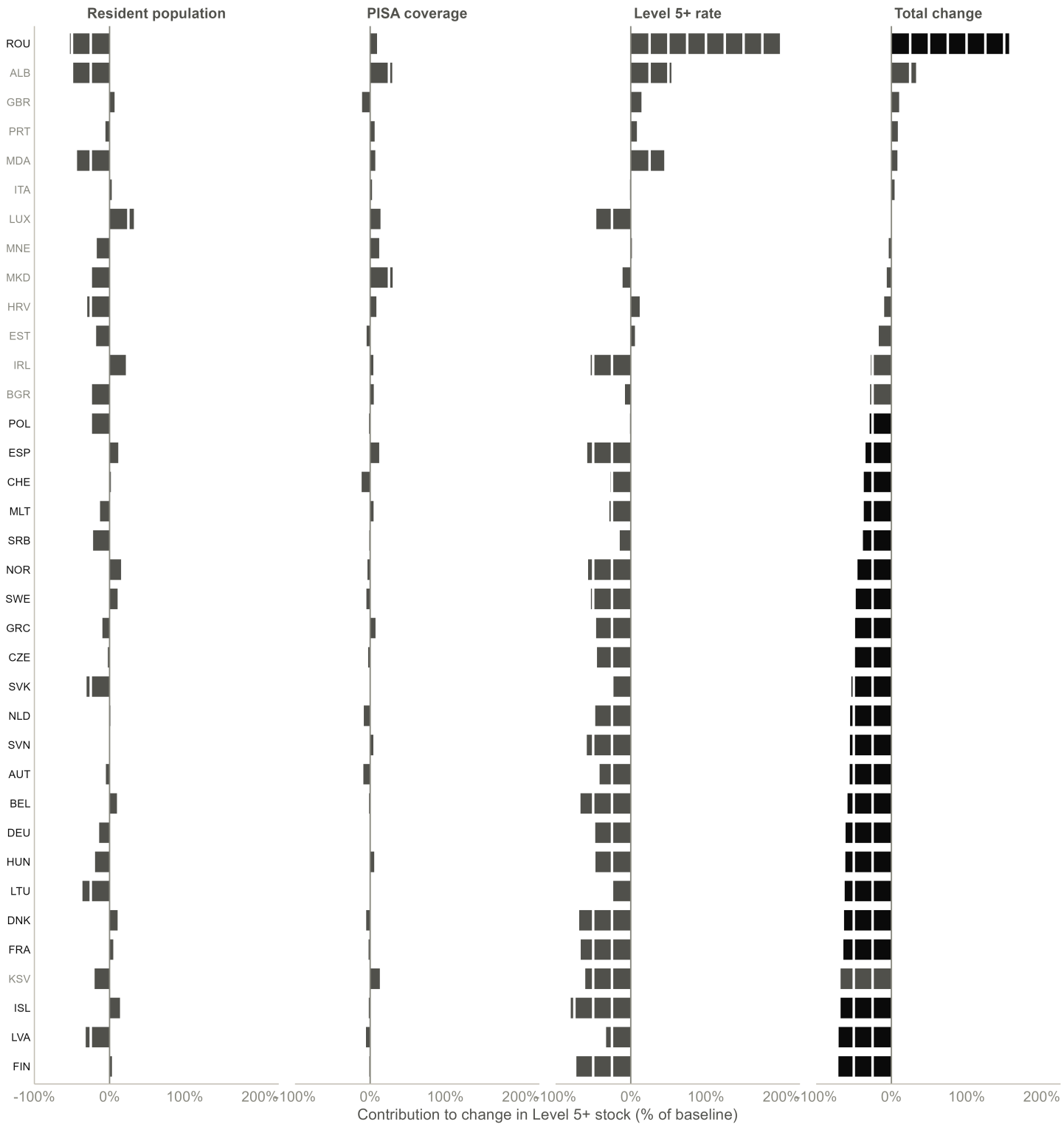


Figure 2

Figure 2. Three-way decomposition of high-performer count change: resident population, population alignment and Level 5+ rate, through each country's latest comparable assessment.

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