Revista de Științe Politice. Revue des Sciences Politiques • No. 89 • 2026: 21 - 37

ORIGINAL PAPER

From PISA to Prosperity: How Education Quality Is Associated with Economic Development in the EU (2018, 2022)

George Teodor Mitu[1], Narcis Eduard Mitu[2], Mihaela Zglavoci[3]

Abstract:
This paper provides a descriptive benchmark on the association between learning quality and economic development in the European Union. Using two reference points, 2018 and 2022, it links PISA performance (PISA_mean, defined as the average of national mean scores in mathematics, reading, and science) to real GDP per capita (chain-linked volumes, base year 2015). The institutional frame is the EU-27, while the effective sample size varies by year due to PISA coverage, and the paper reports year-specific N transparently. Cross-sectional comparisons indicate a positive association between PISA_mean and GDP per capita in both 2018 and 2022, although the relationship is not tight. By contrast, changes over 2018-2022 show weak co-movement between ΔPISA_mean and Δln(GDP per capita), supporting cautious interpretation of short-run dynamics in a period marked by major educational and economic disruptions. A brief regional contrast (CEE versus the rest of the EU) points to persistent average gaps in prosperity accompanied by lower average learning outcomes, alongside substantial heterogeneity within groups. The results are presented as comparative benchmarks and starting points for deeper, covariate-rich analysis, suggesting that convergence debates have solid reasons to incorporate learning quality explicitly.

Keywords: *PISA, education quality, real GDP per capita, EU-27, convergence.*

[1] Master's degree in Economics, University of Craiova, Faculty of Economics and Business Administration; Email: tedimitu@ymail.com, ORCID ID: https://orcid.org/0000-0003-0551-2497
[2] Associate Professor, PhD, University of Craiova, Faculty of Economics and Business Administration, Public Finances specialization, Phone: 0040251411317, Email: narcis.mitu@edu.ucv.ro, ORCID ID: https://orcid.org/0000-0003-0265-7658
[3] Master's degree in Economics, University of Craiova, Faculty of Economics and Business Administration;
Email: mihaelazglavoci2001@gmail.com, ORCID ID: https://orcid.org/0009-0002-1704-1274

1. Introduction

Educational outcomes and economic performance are often discussed separately in EU policy debates (Olimid & Olimid, 2025), yet they are linked by a shared concern: the capacity of member states to sustain productivity growth and convergence in living standards (Mitu & Stanciu, 2023). Large-scale learning assessments have made it possible to compare skills across countries with a degree of consistency that was difficult to achieve with older attainment-based measures. In parallel, macroeconomic statistics provide robust benchmarks of income levels that remain central in convergence analysis. Bringing these two lenses together, even in a compact descriptive framework, can clarify whether differences in skills and differences in prosperity point in the same direction across the Union.

The present study examines this alignment using a two-point comparison anchored in internationally comparable learning outcomes and harmonized national income statistics. The analysis relies on PISA-based performance as an empirical proxy for cognitive skills and uses real GDP per capita, expressed in chain-linked volumes with a common base year, as the indicator of economic development. The education indicator is operationalized as PISA_mean, a summary indicator of PISA performance, so that the cross-country comparison is not driven by a single domain. The two reference years are chosen to capture a meaningful shift in the European environment: one observation precedes the period of major disruption to schooling, while the other reflects the first subsequent measurement of learning outcomes at scale (OECD, 2023). While the institutional frame is the EU-27, the effective sample size may vary by year because the composite requires complete domain scores; the paper reports year-specific N transparently and does not impute missing PISA values. This setup supports a focused question: how strongly do skill differences correspond to income differences within the EU, and do short-run movements in measured learning outcomes map onto short-run movements in income levels?

The conceptual rationale draws on the human-capital channel in growth theory, which treats skills as a productive asset that supports technology absorption, innovation, and the efficiency of resource use (Lucas, 1988; Romer, 1990). Contemporary research has sharpened this rationale by emphasizing learning quality rather than schooling duration, and by arguing that achievement-based indicators can be more informative for long-run economic potential than traditional quantity measures. Recent EU-oriented contributions further suggest that learning outcomes may not follow a uniform convergence path across member states, which makes comparative benchmarking of learning quality particularly relevant for a union concerned with cohesion (Glawe & Mendez, 2023). Evidence that system-level effectiveness differs across countries also motivates attention to outcomes rather than inputs alone (Dincă et al., 2021).

Two features of the analysis are worth stating upfront. First, the empirical exercise is intended to be interpretable and replicable with a limited number of indicators. This choice prioritises transparency over model complexity, and it is meant to provide a baseline that can be extended in later work. Second, the article does not treat the observed relationships as causal. Cross-country comparisons are exposed to multiple confounders, and education and macroeconomic indicators operate on different time scales. The paper therefore uses the evidence to structure interpretation and policy discussion, not to claim that one variable mechanically generates the other.

The remainder of the paper proceeds as follows. Section 2 positions the study within recent research on learning quality and economic performance. Section 3 describes data sources, variable construction, and the descriptive strategy. Section 4 presents the cross-sectional patterns in each reference year, a comparison of changes across the two points, and a brief regional contrast. Section 5 discusses interpretation and policy implications in light of country heterogeneity. Section 6 concludes with limitations and key takeaways.

2. Conceptual framework and relevant literature

A standard starting point in growth economics is that persistent income differences across countries reflect more than short-run fluctuations in capital accumulation. In endogenous-growth frameworks, human capital and innovation are treated as internal drivers of long-run development: skill formation raises the productivity of workers directly and supports the creation, diffusion, and effective use of new technologies (Lucas, 1988; Romer, 1990). In this conceptual lens, education matters economically because it builds capabilities that translate into higher productivity, better technology adoption, and stronger innovative potential over time, not merely because it increases time spent in formal schooling.

Within this broad view, the empirical literature has progressively shifted from "education quantity" to "education quality". In recent research, "education" is increasingly treated not as a simple quantity of schooling, but as a multidimensional form of human capital whose economic relevance depends on what learners actually know and can do. While years of schooling and attainment remain useful descriptors of educational expansion, they are imperfect proxies for the skills that shape productivity, and cross-country differences in learning outcomes are often persistent. A growing strand of European-focused work therefore separates schooling from learning and explicitly models heterogeneity across countries and "clubs" in the quality dimension of human capital (Glawe & Mendez, 2023).

Within this perspective, cognitive skills measured through large-scale assessments are widely used as operational proxies for education quality. In the EU context, PISA is particularly influential because it offers comparable cross-country measures of student performance and distributions of achievement. The PISA 2022 cycle, for example, places learning outcomes and equity at the center of cross-country comparisons and provides an updated benchmark for post-pandemic educational performance (OECD, 2023). In this paper, education quality is operationalised as PISA_mean. This choice aligns with the idea that "quality" is multidimensional, while keeping the indicator transparent enough to support replication in a compact descriptive design.

Recent empirical work has continued to reinforce the relevance of the "quality" channel, while also refining it. For the European Union specifically, Hanushek and Woessmann (2020) quantify the macroeconomic stakes of meeting EU education goals and show that improvements in achievement (as captured by PISA points) have large projected long-run effects on GDP. At the same time, newer studies emphasize that average achievement is not the whole story. Learning inequality can shape the aggregate payoff to education by limiting how broadly cognitive skills are distributed in the population. Evidence using global learning data suggests that reducing inequality in learning outcomes can matter for economic development alongside raising mean scores (Piao, 2024). For the present article, this insight is most useful as context: the analysis relies on national means and therefore cannot test how within-country dispersion or equity-related distributional patterns mediate the education–income relationship.

Another important refinement is that education quality is increasingly discussed alongside institutional capacity and policy implementation constraints. EU member states may converge in schooling attainment yet diverge in learning outcomes, generating "learning clubs" rather than uniform convergence. For Europe, the club-convergence approach highlights how learning outcomes can follow different trajectories even under shared policy frameworks, implying that regional and institutional spillovers, and not only funding levels, can influence long-run patterns (Glawe & Mendez, 2023). Complementary EU-focused evidence from efficiency analysis also points to cross-country differences in how educational inputs translate into outputs, consistent with the idea that institutions and policy design shape the productivity of education spending (Dincă et al. 2021). This institutional lens motivates a cautious interpretation of cross-sectional associations: observed alignment between skills and income may reflect both human-capital mechanisms and differences in governance, policy execution, and economic structure.

Post-2020 literature also reflects structural changes in the skill content of human capital. Two developments are frequently emphasized. First, the diffusion of digital technologies and the organization of work increase the economic relevance of combinations of cognitive and socio-emotional skills. A systematic review on "Education 4.0" within competence frameworks illustrates how digital and innovation-related competencies are increasingly embedded in educational agendas (Akimov et al., 2023). Second, labour-market research framed around "Industry 5.0" underlines that soft skills remain economically valuable even as technology intensity rises, suggesting that education quality cannot be reduced to test scores alone, even if test scores remain a practical macro proxy (Poláková et al., 2023). In a related vein, higher education is discussed as part of national competitiveness strategies in the post-pandemic environment, reinforcing the idea that education systems interact with broader development models rather than functioning in isolation (Arredondo-Trapero et al., 2024). For this study, these strands reinforce a boundary condition: PISA-based measures are informative for benchmarking cognitive skills, but they capture only one component of a broader, evolving skill set.

Against this background, a practical empirical strategy for an EU-27 article in 2026 is to focus on a small set of clearly interpretable indicators and a limited number of comparison points, instead of attempting a full panel model with many controls. Two reference years are especially informative: 2018 (the last pre-pandemic PISA cycle with broadly comparable results) and 2022 (the first post-pandemic cycle). This pairing supports a compact, policy-relevant narrative: (i) where EU countries stood before the shock, (ii) where they are after it, and (iii) how the relative positions and dispersion changed. Because GDP per capita remains a standard proxy for economic performance, the core descriptive question can be framed as whether countries with higher education quality in these two years tend to exhibit higher income levels, and whether shifts in learning outcomes between 2018 and 2022 align with relative income dynamics over the same period.

Finally, the measurement problem deserves brief but explicit handling. Although PISA is triennial, recent work has experimented with constructing annual measures of education quality by combining mixed-frequency learning assessments with annual macro data, which shows that researchers are actively trying to reduce the temporal mismatch between education metrics and economic indicators (Musibau et al., 2024). For the present article, however, the two-point comparison (2018 vs. 2022) is methodologically coherent and transparent: it uses observed PISA outcomes, avoids strong interpolation assumptions, and directly targets the most policy-salient interval for benchmarking pre- and post-disruption learning performance.

3. Data and method

3.1. Data sources and coverage

The empirical analysis uses two harmonised sources to build a compact EU-27 comparison for *2018* and *2022*. The 2018 and 2022 cycles are chosen because they provide two comparable reference points, with 2018 as the last pre-pandemic benchmark and 2022 as the first post-pandemic cycle.

Education outcomes are taken from PISA national mean scores (PISA_mean) in *mathematics, reading*, and *science*, using the OECD International Data Explorer export underlying this paper (OECD, 2019, 2023).

Economic development is measured using real GDP per capita from Eurostat (2026), dataset *"tipsna40"*, reported as *chain-linked volumes (2015), euro per capita*. This indicator captures income levels net of inflation effects and is suitable for cross-country comparison when applied consistently.

The unit of analysis is the member state of the European Union. The paper keeps "EU-27" as the institutional frame, but it reports the *effective sample size (N)* used in each result because coverage differs by year in the working PISA extract:

- ***2018 cross-section: N = 26.*** In the export used here, Spain's 2018 reading mean is not available, so the composite PISA_mean cannot be constructed for Spain in 2018 (OECD, 2019).
- ***2022 cross-section: N = 26.*** Luxembourg did not participate in PISA 2022, so no 2022 PISA domain means exist for constructing the composite (Ministry of Education, Children and Youth, Luxembourg, 2023).
- ***Changes 2018-2022 (balanced sample): N = 25,*** restricted to countries with complete information in both years.

This treatment is deliberate: the paper does not impute missing PISA values, to avoid adding modelling assumptions in a descriptive design (OECD, 2019, 2023).

3.2. Variable construction

Education quality (PISA_mean). For each country $i$and year $t \in \{2018{,}2022\}$, the composite indicator is defined as the simple average of the three PISA domain means:

$$\text{PISA\_mean}_{i,t} = \frac{\text{PISA\_math}_{i,t} + \text{PISA\_read}_{i,t} + \text{PISA\_sci}_{i,t}}{3}$$

All three components are measured in PISA scale points (OECD, 2019, 2023). If any domain mean is missing for a country-year, $\text{PISA_mean}_{i,t}$is treated as missing for that observation.

Economic development (GDPpc_real). Let $\text{GDPpc\_real}_{i,t}$ denote real GDP per capita from Eurostat *"tipsna40"*, expressed as chain-linked volumes (2015), euro per capita (Eurostat, 2026). *"Chain-linked volumes"* refer to a standard real-measure construction based on annual chain-linking, aimed at removing price effects in volume comparisons (Eurostat, 2025).

Log transform. Figures and country tables report GDP per capita in levels for readability. For correlations and regression benchmarks, the paper also uses the natural logarithm:

$$\ln\left(\text{GDPpc\_real}_{i,t}\right)$$

which reduces scale effects from very high-income observations and supports proportional interpretation.

3.3. Empirical strategy and reported statistics

The design is deliberately *descriptive*. The goal is to benchmark how strongly learning outcomes align with living-standard differences across EU member states, not to estimate causal effects. The empirical outputs therefore consist of:

Cross-sectional association (2018; 2022). For each year, Section 4 reports:

- a scatterplot of $\text{PISA\_mean}_{i,t}$ against $\text{GDPpc\_real}_{i,t}$ (Figures 1-2);
- the Pearson correlation between $\text{PISA\_mean}_{i,t}$ and $\ln\left(\text{GDPpc\_real}_{i,t}\right)$;
- and a bivariate OLS benchmark:

$$\ln\left(\text{GDPpc\_real}_{i,t}\right) = \alpha_t + \beta_t \cdot \text{PISA\_mean}_{i,t} + \varepsilon_{i,t}$$

Here, α_t is the intercept, β_t is the fitted slope, and $\varepsilon_{i,t}$ is the residual. The slope β_t summarises the average change in ln (GDPpc) associated with a one-point difference in PISA_mean. As a local approximation, $100 \cdot \beta_t$ can be read as an approximate percent difference in GDP per capita per one PISA point, used strictly for description.

Goodness-of-fit (R²). R^2 is not part of the regression equation. It is a separate output of the OLS fit:

$$R_t^2 = 1 - \frac{\sum_i \hat{\varepsilon}_{i,t}^2}{\sum_i \left(\ln\left(\text{GDPpc\_real}_{i,t}\right) - \ln\left(\overline{\text{GDPpc\_real}}_t\right)\right)^2}$$

and indicates the share of cross-country variation in ln (GDPpc) captured by the linear benchmark.

Changes between 2018 and 2022. For countries observed in both years (balanced sample), the paper constructs:

$$\Delta\text{PISA\_mean}_i = \text{PISA\_mean}_{i,2022} - \text{PISA\_mean}_{i,2018}$$

$$\Delta\ln\left(\text{GDPpc\_real}\right)_i = \ln\left(\text{GDPpc\_real}_{i,2022}\right) - \ln\left(\text{GDPpc\_real}_{i,2018}\right)$$

and examines their association in Figure 3, complemented by correlation and an OLS benchmark analogous to the cross-sectional specification.

Regional contrast (CEE vs rest of EU). The paper reports a compact group comparison (Table 4) between Central and Eastern European member states and the rest of the EU, using the balanced sample and presenting group means for 2018, 2022, and the 2018-2022 changes.

3.4. Interpretation rules and limitations of inference

All relationships are interpreted as associations. Cross-country comparisons are vulnerable to reverse causality (higher income enabling better schooling conditions) and omitted variables (institutions, sectoral structure, innovation intensity, demographic structure). In addition, using real GDP per capita in euro (chain-linked volumes) is transparent and consistent across time, but it is not a full welfare metric and does not correct for cross-country price-level differences (Eurostat, n.d., 2025).

4. Results

4.1. Cross-sectional association in 2018

To anchor the analysis, this subsection first examines the 2018 cross-sectional pattern between *PISA_mean* and *real GDP per capita* across the EU country.

Figure 1 plots the 2018 EU cross-section (N=26) relating education outcomes to economic development, with education proxied by *PISA_mean* (average of mathematics, reading, and science mean scores) and development measured by *real GDP per capita* (Eurostat tipsna40, chain-linked volumes, reference year 2015).

The pattern is broadly upward sloping: countries with higher PISA_mean tend to have higher real GDP per capita, but dispersion is substantial. A compact descriptive summary is given by:

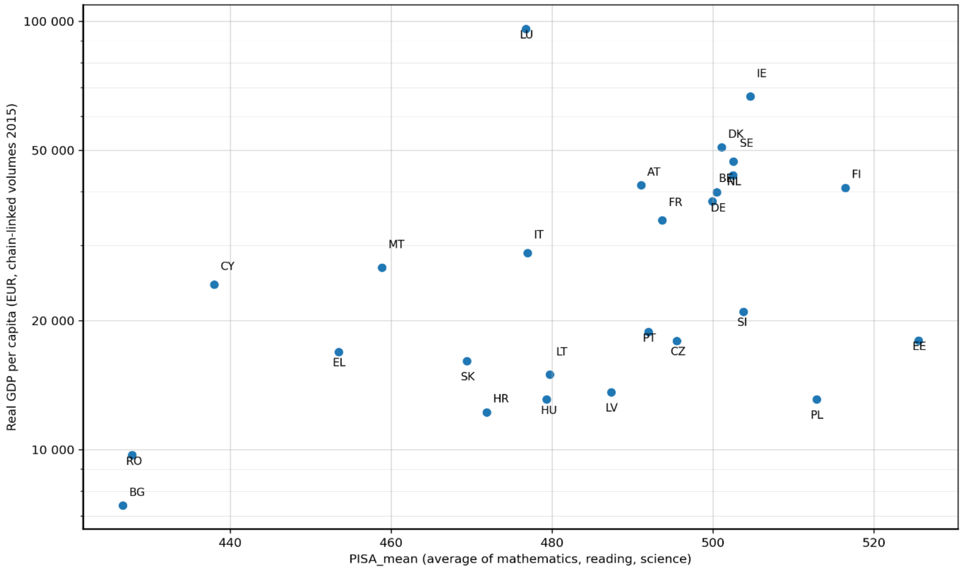
- the *Pearson correlation* between PISA_mean and ln(GDPpc): $r \approx 0.466$ (N=26);
- a simple bivariate OLS benchmark:

$$\ln(GDPpc_i) = \alpha + \beta \cdot PISA\_mean_i + \varepsilon_i$$

estimated on the same cross-section, where $\ln(\cdot)$is the natural logarithm. In 2018, the fitted slope is $\beta \approx 0.0113$, with $R^2 \approx 0.217$. Here, R^2 is not part of the regression equation; it is a separate statistic reported from the estimated model and indicates the share of cross-country variation in $\ln(GDPpc)$captured by this linear fit.

For interpretation, $\beta$is read as the average difference in $\ln(GDPpc)$associated with a one-point difference in PISA_mean. As a local approximation, $100 \cdot \beta$can be read as an approximate percent difference in GDP per capita per one PISA point, but this is used strictly as a readable summary of the scatterplot, not as a causal estimate.

Figure 1. *EU cross-section: PISA_mean and real GDPpc (2018)*



Note: y-axis in log scale for readability.
Source: authors' compilation based on OECD (2019) PISA and Eurostat tipsna40.

Table 1. Cross-sectional dataset (2018)

Country	Code	Math	Reading	Science	PISA_mean	GDPpc_real (EUR, 2015)	lnGDPpc
Austria	AT	498.9	484.4	489.8	491.0	41430	10.632
Belgium	BE	508.1	492.9	498.8	499.9	38040	10.546
Bulgaria	BG	436.0	419.8	424.1	426.7	7410	8.911
Croatia	HR	464.2	479.0	472.4	471.9	12230	9.412
Cyprus	CY	450.7	424.4	439.0	438.0	24300	10.098
Czechia	CZ	499.5	490.2	496.8	495.5	17960	9.796
Denmark	DK	509.4	501.1	492.6	501.1	50830	10.836
Estonia	EE	523.4	523.0	530.1	525.5	17990	9.798
Finland	FI	507.3	520.1	521.9	516.4	40860	10.618
France	FR	495.4	492.6	493.0	493.7	34320	10.443
Germany	DE	500.0	498.3	503.0	500.4	39930	10.595
Greece	EL	451.4	457.4	451.6	453.5	16920	9.736
Hungary	HU	481.1	476.0	480.9	479.3	13100	9.480
Ireland	IE	499.6	518.1	496.1	504.6	66830	11.110
Italy	IT	486.6	476.3	468.0	477.0	28810	10.268
Latvia	LV	496.1	478.7	487.3	487.4	13630	9.520
Lithuania	LT	481.2	475.9	482.1	479.7	14970	9.614
Luxembourg	LU	483.4	470.0	476.8	476.7	96110	11.473
Malta	MT	471.7	448.2	456.6	458.8	26600	10.189
Netherlands	NL	519.2	484.8	503.4	502.5	43680	10.685
Poland	PL	515.6	511.9	511.0	512.8	13120	9.482
Portugal	PT	492.5	491.8	491.7	492.0	18830	9.843
Romania	RO	429.9	427.7	425.8	427.8	9720	9.182
Slovakia	SK	486.2	458.0	464.0	469.4	16110	9.687

Slovenia	SI	508.9	495.3	507.0	503.7	21010	9.953
Sweden	SE	502.4	505.8	499.4	502.5	47080	10.760

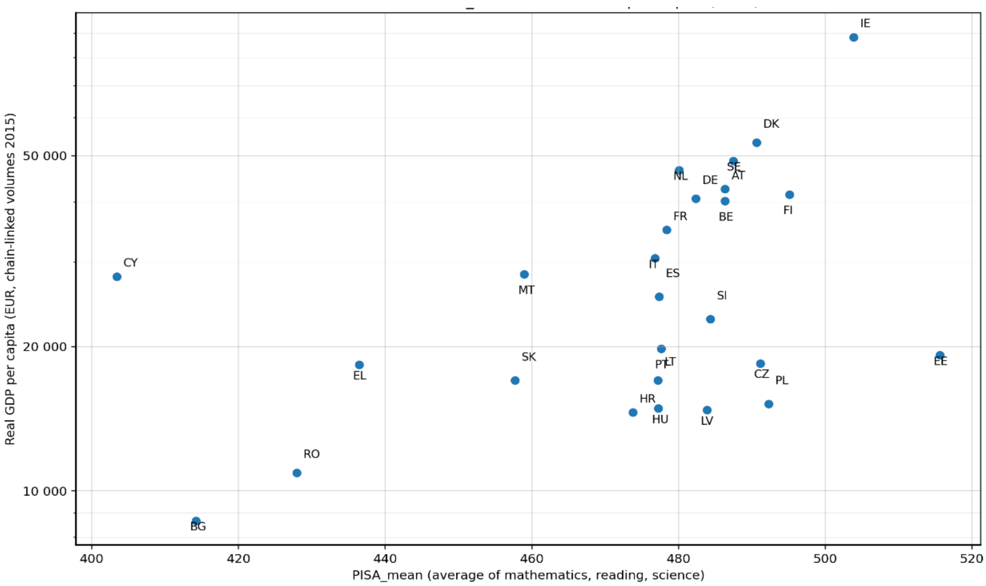
Source: OECD PISA 2018 (International Data Explorer export) and Eurostat tipsna40; authors' calculations.

Table 1 provides the underlying country-level values for 2018 used in Figure 1 and in the descriptive statistics (PISA domain scores, PISA_mean, GDPpc, lnGDPpc).

4.2. Cross-sectional association in 2022

Figure 2 replicates the same cross-sectional comparison for 2022 (N=26). Luxembourg is excluded because it did not participate in PISA 2022.

Figure 2. *EU cross-section: PISA_mean and real GDPpc (2022)*



Note: y-axis in log scale for readability.

Source: authors' compilation based on OECD (2023) PISA and Eurostat tipsna40.

The association remains positive and similarly loose:

- Pearson correlation between PISA_mean and ln(GDPpc): $r \approx 0.456$ (N=26);
- OLS benchmark:

$$\ln\left(GDPpc_i\right) = \alpha + \beta \cdot PISA\_mean_i + \varepsilon_i$$

with $\beta \approx 0.0096$ and $R^2 \approx 0.208$.

Table 2. Cross-sectional dataset (2022)

Country	Code	Math	Reading	Science	PISA_mean	GDPpc_real (EUR, 2015)	lnGDPpc
Austria	AT	487.3	480.4	491.3	486.3	42610	10.660
Belgium	BE	489.5	478.9	490.6	486.3	40190	10.601
Bulgaria	BG	417.3	404.3	421.0	414.2	8660	9.066
Croatia	HR	463.1	475.5	482.7	473.8	14580	9.587
Cyprus	CY	418.3	381.1	410.9	403.4	27990	10.240
Czechia	CZ	487.0	488.6	497.7	491.1	18450	9.823
Denmark	DK	489.3	488.8	493.8	490.6	53290	10.884
Estonia	EE	509.9	511.0	525.8	515.6	19190	9.862
Finland	FI	484.1	490.2	511.0	495.1	41470	10.633
France	FR	473.9	473.9	487.2	478.3	35030	10.464
Germany	DE	474.8	479.8	492.4	482.3	40710	10.614
Greece	EL	430.1	438.4	440.8	436.5	18310	9.815
Hungary	HU	472.8	473.0	485.9	477.2	14860	9.606
Ireland	IE	491.6	516.0	503.8	503.8	88360	11.389
Italy	IT	471.3	481.6	477.5	476.8	30550	10.327
Latvia	LV	483.2	474.6	493.8	483.9	14750	9.599
Lithuania	LT	475.1	471.8	484.5	477.1	17010	9.742
Malta	MT	466.0	445.3	465.6	459.0	28280	10.250
Netherlands	NL	492.7	459.2	488.3	480.1	46670	10.751
Poland	PL	489.0	488.7	499.2	492.3	15190	9.628
Portugal	PT	471.9	476.6	484.4	477.6	19800	9.893
Romania	RO	427.8	428.5	427.5	427.9	10910	9.297
Slovakia	SK	464.0	446.9	462.3	457.7	17000	9.741
Slovenia	SI	484.5	468.5	500.0	484.3	22810	10.035
Spain	ES	473.1	474.3	484.5	477.3	25420	10.143
Sweden	SE	481.8	487.0	493.5	487.4	48780	10.795

Source: OECD PISA 2022 (International Data Explorer export) and Eurostat tipsna40; authors' calculations

4.3. Changes between 2018 and 2022

To evaluate whether short-run changes in learning outcomes co-move with short-run changes in income, the analysis uses the balanced sample with complete information in both 2018 and 2022 (N=25) and computes:

$$\Delta PISA\_mean_i = PISA\_mean_{i,2022} - PISA\_mean_{i,2018}$$

$$\Delta \ln(GDPpc_i) = \ln(GDPpc_{i,2022}) - \ln(GDPpc_{i,2018})$$

Figure 3 plots $\Delta PISA_mean$against $\Delta \ln(GDPpc)$. The relationship is weak:

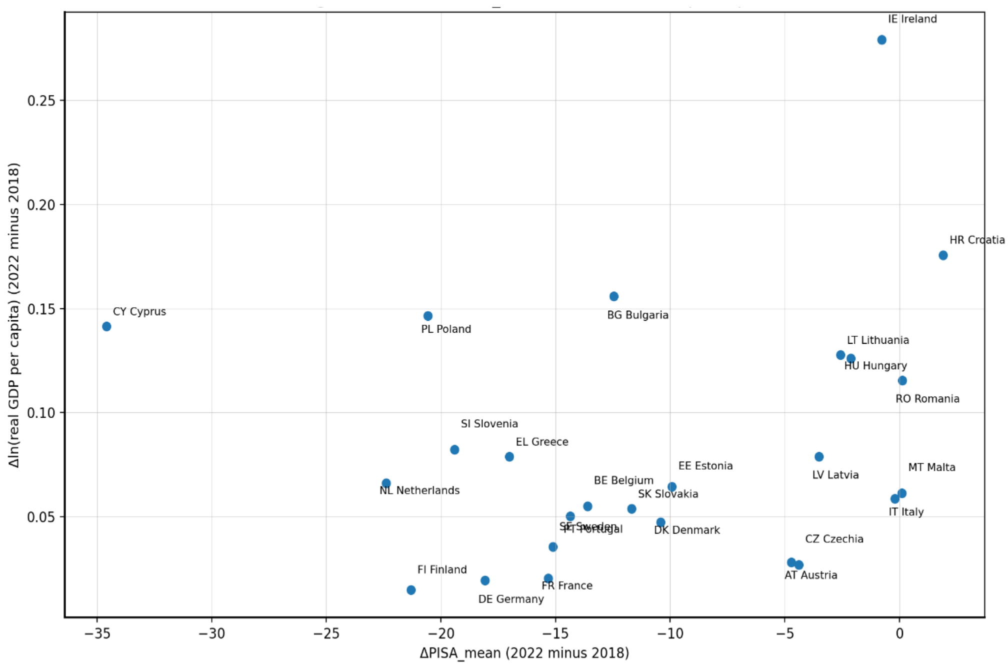
- Pearson correlation: $r \approx 0.219$ (N=25);
- OLS benchmark:

$$\Delta \ln(GDPpc_i) = \alpha + \beta \cdot \Delta PISA\_mean_i + \varepsilon_i$$

with $\beta \approx 0.00148$ and $R^2 \approx 0.048$.

This result is consistent with a cautious reading: over 2018-2022 (a short interval that includes the pandemic shock), learning outcomes and income levels need not adjust at the same speed, and any association between their short-run changes should be interpreted conservatively.

Figure 3. *Changes between 2018 and 2022: ΔPISA_mean and Δln(real GDPpc)*



Source: OECD PISA (IDE export) and Eurostat tipsna40; own calculations.

Table 3. Changes between 2018 and 2022 (balanced sample, N=25)

Country	Code	PISA_mean_2018	PISA_mean_2022	ΔPISA_mean	GDPpc_2018	GDPpc_2022	ΔlnGDPpc
Austria	AT	491.0	486.3	-4.7	41430	42610	0.028
Belgium	BE	499.9	486.3	-13.6	38040	40190	0.055
Bulgaria	BG	426.7	414.2	-12.5	7410	8660	0.156
Croatia	HR	471.9	473.8	1.9	12230	14580	0.176
Cyprus	CY	438.0	403.4	-34.6	24300	27990	0.141
Czechia	CZ	495.5	491.1	-4.4	17960	18450	0.027
Denmark	DK	501.1	490.6	-10.4	50830	53290	0.047
Estonia	EE	525.5	515.6	-9.9	17990	19190	0.065
Finland	FI	516.4	495.1	-21.3	40860	41470	0.015
France	FR	493.7	478.3	-15.3	34320	35030	0.020
Germany	DE	500.4	482.3	-18.1	39930	40710	0.019
Greece	EL	453.5	436.5	-17.0	16920	18310	0.079
Hungary	HU	479.3	477.2	-2.1	13100	14860	0.126
Ireland	IE	504.6	503.8	-0.8	66830	88360	0.279
Italy	IT	477.0	476.8	-0.2	28810	30550	0.059
Latvia	LV	487.4	483.9	-3.5	13630	14750	0.079

Lithuania	LT	479.7	477.1	-2.6	14970	17010	0.128
Malta	MT	458.8	459.0	0.1	26600	28280	0.061
Netherlands	NL	502.5	480.1	-22.4	43680	46670	0.066
Poland	PL	512.8	492.3	-20.6	13120	15190	0.146
Portugal	PT	492.0	477.6	-14.4	18830	19800	0.050
Romania	RO	427.8	427.9	0.1	9720	10910	0.115
Slovakia	SK	469.4	457.7	-11.7	16110	17000	0.054
Slovenia	SI	503.7	484.3	-19.4	21010	22810	0.082
Sweden	SE	502.5	487.4	-15.1	47080	48780	0.035

Source: OECD PISA 2018 and 2022 (International Data Explorer exports) and Eurostat tipsna40; authors' calculations.

Table 3 reports, by country, the 2018 and 2022 levels and the derived changes ($\Delta PISA\_mean$, $\Delta \ln\,(GDPpc)$) used in Figure 3.

4.4. Brief regional contrast

A compact regional contrast is reported between Central and Eastern European (CEE) member states (BG, HR, CZ, EE, HU, LV, LT, PL, RO, SK, SI - *Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia*) and the rest of the EU, using the balanced sample (N=25). Table 4 shows group means for 2018 and 2022 and mean changes over 2018-2022.

Two patterns are visible in this descriptive benchmark:

- In both years, the CEE group records lower average GDP per capita than the rest of the EU, alongside slightly lower average PISA_mean.
- Between 2018 and 2022, average $\Delta PISA_mean$is negative in both groups, while average $\Delta \ln\,(GDPpc)$remains positive, illustrating that income growth over this short window can coexist with declines in measured learning outcomes.

Table 4. Regional contrast (CEE vs rest of EU, balanced sample)

Group	N	PISA_mean _2018	PISA_mean _2022	ΔPISA_ mean	GDPpc _2018	GDPpc _2022	ΔlnGDPpc
CEE	11	480.0	472.3	-7.7	14295	15765	0.105
Rest of EU	14	488.0	474.5	-13.4	37033	40146	0.068

Source: OECD PISA 2018 and 2022 (International Data Explorer exports) and Eurostat tipsna40; authors' calculations.

5. Discussion and policy implications

This paper provides a descriptive benchmark on how learning outcomes and income levels align across EU member states, using a composite indicator of education performance (PISA_mean) and real GDP per capita for 2018 and 2022. Three results matter for interpretation.

First, the cross-sectional evidence in both reference years suggests a positive association between learning outcomes and living standards: countries with higher PISA_mean tend to display higher real GDP per capita. At the same time, the relationship is not tight. Dispersion across member states is substantial, indicating that learning outcomes and income levels do not map one-to-one. From our perspective, the main value of these cross-sectional patterns is that they provide a readable benchmark for where countries stand in a joint skills and prosperity space, not evidence of a causal effect running from schooling to income. Reverse causality and omitted factors such as institutions, innovation capacity, labour-market structure, demographic composition, and inequality remain plausible.

Second, the change comparison over 2018-2022 points to weak co-movement between short-run changes in measured learning outcomes and short-run changes in income. This contrast between “levels” and “changes” is substantively plausible. Learning outcomes and macroeconomic indicators operate on different time scales, and the 2018-2022 window is short and includes major disruption. In addition, measured changes in PISA performance can reflect both real shifts in skills and features of the assessment and schooling environment during the period. From this perspective, weak short-run alignment should not be read as refuting longer-run human-capital mechanisms. Rather, it highlights the limits of short-horizon inference and the risk of expecting rapid macroeconomic responses to changes in measured learning outcomes.

Third, the regional contrast (CEE versus the rest of the EU) is best interpreted as a compact summary of a persistent development gap rather than as a ranking exercise. Average differences in prosperity are, on the whole, accompanied by average differences in learning outcomes, yet heterogeneity within both groups remains substantial. From our perspective, this heterogeneity matters for policy: group labels are less informative than the joint country profile of learning outcomes and development levels, and one-size-fits-all prescriptions are unlikely to be efficient.

Policy implications follow directly from these points and should be framed as priorities compatible with descriptive evidence:

- ***Protect and restore foundational skills as a near-term objective.*** The evidence is consistent with learning recovery being a first-order priority. The most defensible implication is not that education reforms generate immediate macro payoffs, but that skills are a component of long-run productivity potential. Policies that target foundational competencies (reading, numeracy, scientific reasoning) are therefore justified even when income indicators do not respond quickly;
- ***Focus on distribution, not only averages.*** National means are informative for benchmarking, but they mask within-country dispersion. From a policy perspective, raising average performance can be pursued through broad improvements, targeted support to low-performing students, or both. Given fiscal constraints, interventions with credible evidence on cost-effectiveness, such as early remediation, structured tutoring, and curriculum adjustments aligned with core competencies, deserve priority. A practical objective is to reduce the mass of low performance while sustaining pathways for high achievement;
- ***Treat education policy and growth policy as complements with different time horizons.*** The weak short-run alignment in changes reinforces that policymakers should not expect rapid macroeconomic returns from education reforms. Education policy is better understood as a medium- to long-run investment, while short-run income dynamics are shaped by cyclical conditions, external demand, energy prices, and sectoral composition. Coordination remains useful, but evaluation horizons should be realistic;
- ***Strengthen monitoring and comparability.*** Because results depend on consistent measurement, routine monitoring of learning outcomes and transparent documentation of data coverage condition what can be inferred and compared.

At minimum, policy reporting should distinguish clearly between level comparisons and change comparisons, document missing observations and participation issues, and avoid overinterpreting small differences as meaningful movements;

- ***Interpret regional gaps as signals for prioritisation, not labels.*** The CEE and non-CEE contrast can support prioritisation in cohesion discussions: countries that underperform on both dimensions may warrant concentrated support for teacher development, school leadership, and equity-oriented funding, while countries with comparatively strong learning outcomes relative to income may benefit from policies that convert skills into productivity, such as innovation diffusion and stronger school-to-work transitions.

Overall, the evidence supports a cautious but practical message. Cross-country differences in measured learning outcomes align with differences in living standards, yet short-run changes do not move tightly together. From our perspective, policy discussion should therefore avoid simplistic expectations of immediate macroeconomic returns and instead emphasise learning recovery, equity, and institutional capacity for sustained improvement, alongside growth policies that enable skills to translate into productivity.

6. Limitations and conclusions

6.1. Limitations

This paper is intentionally descriptive and several limitations follow directly from that choice.

First, all reported relationships should be read as associations. From our perspective, reverse causality is plausible, higher income can finance better schooling inputs, while omitted factors such as institutional quality, innovation capacity, labour-market structure, demographic composition, and social inequality may jointly shape both learning outcomes and GDP per capita. The bivariate benchmarks (correlations and OLS slopes) are therefore summaries of cross-country patterns, not evidence of causal effects.

Second, measurement and coverage issues matter. The PISA composite used here, $PISA\_mean$, averages domain-specific national mean scores, which improves comparability across domains but remains a limited proxy for "education quality". It does not capture non-cognitive skills, curriculum breadth, early childhood conditions, or within-country dispersion. Moreover, in the working extract used for this paper, Spain is missing the 2018 reading mean and Luxembourg has no 2022 PISA data due to non-participation, which implies year-specific cross-sections (N=26 in 2018 and 2022) and a smaller balanced panel for changes (N=25). In our view, reporting these sample sizes transparently is preferable to imputing missing PISA values, but it constrains comparability in the change analysis.

Third, the short horizon is a substantive limitation. The 2018-2022 interval includes the pandemic period and major shocks, while learning outcomes and macroeconomic variables typically adjust on different time scales. From this perspective, weak co-movement between $\Delta PISA_mean$and $\Delta\ln(GDPpc)$over 2018-2022 should not be overinterpreted, either as confirmation or refutation of longer-run human-capital mechanisms. Finally, real GDP per capita in chain-linked volumes is suitable for real comparisons over time, but it is not a full welfare measure and it does not correct for cross-country price-level differences.

6.2. Conclusions

The paper provides a compact EU benchmark linking learning outcomes and economic development in two reference years, 2018 and 2022, and examines how changes in measured learning relate to changes in income over the same interval.

In our opinion, the most robust message is the cross-sectional one: in both years, higher PISA_mean tends to coincide with higher real GDP per capita, although the relationship is far from tight and substantial heterogeneity remains across member states. This pattern is consistent with the idea that skills and prosperity are connected, but, from our perspective, the evidence presented here supports a careful interpretation limited to association.

The second message concerns dynamics. Using the balanced sample, the association between short-run changes in learning and short-run changes in income over 2018-2022 is weak. From this perspective, education systems and economies should not be expected to move in lockstep over short intervals, especially around large shocks. A plausible reading is that skills may matter for long-run productivity potential even when short-run income dynamics are driven by cyclical and structural factors.

Finally, the regional contrast reinforces that the EU contains persistent development gaps, but also meaningful within-group variation. From our perspective, this is a practical reminder that policy discussions should avoid one-size-fits-all expectations. The descriptive evidence is most useful as a transparent starting point: it highlights where learning outcomes and income levels align or diverge, and it motivates deeper, covariate-rich work on the institutional and socio-economic channels that connect education to prosperity.

Authors' Contributions:

The authors contributed equally to this work.

References:

Akimov, N., Kurmanov, N., Uskelenova, A., Aidargaliyeva, N., Mukhiyayeva, D., Rakhimova, S., Raimbekov, B., & Utegenova, Z. (2023). Components of education 4.0 in open innovation competence frameworks: Systematic review. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(2), 100037. https://doi.org/10.1016/j.joitmc.2023.100037

Arredondo-Trapero, F. G., Guerra-Leal, E. M., Kim, J., & Vázquez-Parra, J. C. (2024). Competitiveness, quality education and universities: The shift to the post-pandemic world. *Journal of Applied Research in Higher Education, 16*(5), 2140–2154. doi:10.1108/JARHE-08-2023-0376 https://doi.org/10.1108/JARHE-08-2023-0376

Dincă, M. S., Dincă, G., Andronic, M. L., & Pasztori, A. M. (2021). Assessment of the European Union's educational efficiency. *Sustainability, 13*(6), 3116. https://doi.org/10.3390/su13063116

Eurostat. (2026). *Real GDP per capita (tipsna40)*. Eurostat Data Browser. https://doi.org/10.2908/TIPSNA40

Eurostat. (n.d.). *Short-term business statistics and (annual) chain linking*. Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Short-term_business_statistics_and_(annual)_chain_linking

Eurostat. (2025). *Resource productivity statistics*. Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Resource_productivity_statistics

Eurostat. (2025.). *National accounts and GDP.* Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=National_accounts_and_GDP

Glawe, L., & Mendez, C. (2023). Schooling ain't learning in Europe: A club convergence perspective. *Comparative Economic Studies, 65*, 324–361. https://doi.org/10.1057/s41294-022-00194-3

Hanushek, E. A., & Woessmann, L. (2020). A quantitative look at the economic impact of the European Union's educational goals. *Education Economics, 28*(3), 225–244. https://doi.org/10.1080/09645292.2020.1719980

Lucas, R. E., Jr. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Ministry of Education, Children and Youth, Luxembourg. (2023). *Programme for International Student Assessment (PISA).* https://men.public.lu/en/systeme-educatif/pilotage-monitoring/etudes-internationales/programme-international-pisa.html

Mitu, N. E., & Stanciu, C. V. (2023). Public Sector Performance and Public Sector Efficiency: An Analysis for CEE Countries. *Eastern European Economics*, *61*(6), 700–722. https://doi.org/10.1080/00128775.2023.2223581

Musibau, H., Vespignani, J., & Yanotti, M. B. (2024). *Education quality and economic growth: A new international measure of quality of education* (MPRA Paper No. 122859). Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/122859/

OECD (2019), *PISA 2018 Results (Volume I and Volume II): What Students Know and Can Do*, and *Where all students can succeed* PISA, OECD Publishing, Paris, https://doi.org/10.1787/5f07c754-en and https://doi.org/10.1787/b5fd1b8f-en.

OECD (2023), *PISA 2022 Results (Volume I): The State of Learning and Equity in Education*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/53f23881-en.

Olimid, D.A., Olimid, A.P. (2025). Computational Methods to Social and Public Perceptions: Focus on Digital Governance, Sustainable Development and International Security. *Revista de Științe Politice. Revue des Sciences Politiques*, no. 87, pp. 122-133. https://cis01.ucv.ro/revistadestiintepolitice/files/numarul87_2025/9.pdf

Piao, X. (2024). Learning quality, its inequality and sustainable development: Evidence from global learning data. *Discover Sustainability, 5*, Article 169. https://doi.org/10.1007/s43621-024-00359-3

Poláková, M., Horváthová Suleimanová, J., Madzík, P., Copuš, L., Molnárová, I., & Polednová, J. (2023). Soft skills and their importance in the labour market under the conditions of Industry 5.0. *Heliyon, 9*(8), e18670. https://doi.org/10.1016/j.heliyon.2023.e18670

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5, Part 2), S71–S102. https://doi.org/10.1086/261725

Article Info

Received: February 03 2026
Accepted: March 23 2026

How to cite this article:

Mitu, N.E., Mitu, G.T., Zglavoci, M. (2026). From PISA to Prosperity: How Education Quality Is Associated with Economic Development in the EU (2018, 2022). *Revista de Științe Politice. Revue des Sciences Politiques,* no. 89, pp. 21 – 37.