Value of the human capital and its implication in economic growth and competitiveness. Inference based on the PISA results from OECD countries

Martin MARIS[1]

Abstract

The main scope of the paper is to provide a critical assessment of PISA testing results and their implications for economic growth and competitiveness. For the purpose of the study, the growth-curve model based on so-called panel waves studying OECD countries over the 2006-2022 period was employed. Based on the PISA testing results, the evidence shows that negative human capital development has accelerated across the countries and in all evaluated fields, particularly since the pandemic. The results highlight a considerable variation in predictive margins across countries, even with similar income levels or the same geographical area. Moreover, the average score based on the PISA testing is positively related to income, implicating the relationship between human capital and economic growth and competitiveness. In turn, the average score tends to decline with increasing inequality and the 'crowding effect' of classrooms. Finally, AHC analyses clustered sampled countries based on their level of dissimilarity. However, the initial assumption that 'similar' countries (regarding income or geographical area) would create exclusive clusters has provided mixed results. Using the PISA testing platform as one of the proxy indicators for future human capital development of the schooling youth with implications for growth cannot be ruled out. However, there is a need to do more research in this area.

Keywords: PISA tests, human capital, economic growth, competitiveness

Introduction

The Programme for International Student Assessment (PISA) is a comprehensive set of standardised tests administered by the Organisation for Economic Co-operation and Development (OECD) to evaluate the academic performance of 15-year-old students in various countries worldwide. The test is performed every three-year cycle and covers a wide range of subjects, primarily focusing on student excellence in reading, mathematics, and science. Testing includes completing a battery of science, reading, and mathematics tests and the additional survey.

Today, two such studies, PISA and TIMSS (Trends in International Mathematics and Science Study), dominate the field. These two projects, however, differ in several important ways. Unlike TIMSS, which is descriptive and analytical, PISA is exciplitly and intentionally normative. Both studies measure trends in test scores over time (Sjøberg and Jenkins, 2022). Overall, PISA has been a remarkable phenomenon. Moreover, the PISA was not merely an educational event. It involved the public rehearsal of reasons for failure or success; in some cases, public, political and academic explanations about why 'failure' was not that and why 'success' was not that either (Pereyra et al., 2011). Grek (2009) admits that over time, PISA has played a somewhat indirect but no less important role in the governance of the European education

[1] Contact adress: Martin Mariš, doc.Ing.,PhD, Slovak University of Agriculture in Nitra

Faculty of European Studies and Regional Development,

Institute of Sustainable Regional and Local Development,

Tr. A. Hlinku 2, 949 76 Nitra, +421 37 641 4562

e-mail: martin.maris@uniag.sk

space. PISA is not limited to Europe and has a far more significant, almost global reach. Even some authors relate the PISA results to increases in GDP (Hanushek & Woessman, 2008; OECD, 2010).

However, some critics have been concerned about the objectivity of the PISA results and stress the need for caution in making decisions, especially in education policy. Kaščák and Pupala (2011) point to the lack of transparency in approaches to the program. Technical reports are methodologically incomplete, presented data are selected, and statistical methods are questionable. Starr (2014) points out the pros and cons of PISA involvement. The PISA tests provide evidence of improvement or deterioration in student learning over time, place and school context. Hence, PISA test results can be diagnostic and helpful in teaching and learning. A common criticism is that information derived from testing instruments gives little value to teachers, who already know what their students know and what they do not know. A second common criticism is that tests do not account for the contextual differences that create educational advantages or disadvantages. School often performs at levels indicative of the social capital available to them in the local community.

Volante and Klinger (2023) are concerned about the OECD's promotion of 'academic resilience' – which refers to the capacity of individuals to prosper despite adverse circumstances. Countries are further compared and contrasted about the disadvantaged students that achieve higher scores in PISA, making associations from drawn school-level factors and resulting implications drawn for policy reform. Furthermore, Tieneken (2014) flatly rejects the importance of the PISA results, and hence, they cannot give policymakers or educators meaningful insights into student preparation for the global economy.

The paper aims to critically assess the PISA results of the involved countries (OECD member states) at the spatial-temporal level. The study sample, which incorporates the OECD group, currently containing 38 member states, mainly developed countries, has been analysed over eight periods from 2000 to 2022. This comprehensive approach ensures a thorough evaluation of the PISA results.

1. First, the theoretical part of the paper covers the fundaments of the PISA testing, its main achievements and the implications of PISA results within the framework of international literature
2. Second, the basic inference of the statistical sample is provided
3. Methodological framework and research methods are outlined.
4. Research results are presented, especially the model fit and subsequent statistics.
5. Discussion and conclusions of the study are provided.

The primary data format for statistical analysis involves longitudinal (short panel) data on two levels with occasions nested in subjects, in which subjects become clusters. The data panel is submitted for various statistical analyses, including the variance-components model, probability distribution, and agglomerated hierarchical clustering. The results' variability is expected to lay the ground for spatial and temporal conditioning factors linked to the studied countries' economic growth and competitiveness.

The paper provides a comprehensive structure covering various aspects of the analysis of PISA results. It aims to highlight potential differences among the countries in spatial-temporal dimensions that could profoundly impact their ability to gain a competitive edge in the global economy architecture.

Literature review

The state of Global Schooling and Education

Barro and Lee (2015) provide a historical overview of the evolution of the global education system. Traditionally, education had belonged to children from privileged backgrounds, who later became the ruling class; however, the shift from this narrow base of education occurred gradually, starting in the second half of the 18^{th} century. Initially, primary education expanded rapidly with the spread of compulsory mass schooling in the industrialised regions of the world. Generally, universal access to secondary education began to grow during the first half of the 20th century; however, it did so at uneven rates.

Over the last decade, global schooling and education have undergone remarkable changes. Several key messages may be highlighted: 1) The global school drop-outs declined only slightly; there were some 244 million children and youth out of school in 2021, 9 million less than in 2015; 2) Completion rates have improved faster than out-of-school rates. Globally, the completion rate increased between 2015 and 2021 from 85% to 87% in primary education, 74% to 77% in secondary education, and 54% to 59% in upper secondary education; 3) In 21 of 32 primarily upper-middle and high-income countries, grade 4 students performed worse in reading in 2021 than in 2016 (UNESCO, 2023). McCowan and Unterhalter (2015) agree that since 2000, there has been a dramatic expansion in education provision worldwide. However, this expansion and development has not been equitable. Some social groups and regions have benefited, while others have been excluded or received inadequate schooling. The World Bank adds that despite the spread of schooling (the years of education completed by the average adult more than tripled over the 1950-2010 period), lower-income countries often rapidly expand secondary education when much of their population has not yet completed primary school. Moreover, it underscores that in nearly every country, parents' wealth and educational attainment are the main determinants of their children's education (World Bank, 2018).

Although the overall returns to higher levels of education are positive, the magnitude of benefits varies considerably. The returns depend on an individual's gender, ethnicity, socio-economic status, and what and where they have studied. Educational inequalities attract substantial policy attention because of the substantive impact of education on later life outcomes – most obviously employment and earnings, but also outcomes such as health, happiness, marriage, crime, and civic participation (Farquharson et al.,2024; Gross et al., 2016). The OECD insists that there continues to be a strong link between labour-market participation and educational attainment, whether participation is measured by employment, unemployment, or inactivity rates. However, the type of programme attainment also does affect employment rates. Vocational attainment can be associated with solid employability in the labour market. On average, in OECD countries, the employment rate among younger adults who achieved upper-secondary or post-secondary non-tertiary education as their highest attainment is 83% for those with vocational qualifications and 73% for those with general ones (OECD, 2023).

Crucial to the analysis of inequalities is the structure of the education system, in particular the available education institutions, how they can be accessed, how people can transit from one to another educational stage, and how they can move between parallel institutions (Gross et al., 2016). Jacobs (1996) relates education inequality to several dimensions: 1) access to higher education, 2) college experiences (like the learning process), and 3) outcomes of education (education success, competencies and skills, etc.). Coleman et al. (1966) and Jencks et al. (1972) argue that student achievement can be predicted by their intelligence and background characteristics (e.g. SES). However, other studies suggest that after controlling for student background factors, much variation at the school level remains (Townsend, 2007). Such unexplained variation is often attributed to the school's effect on student learning outcomes (Thomas et al., 2007).

Langthaler and Malik (2023) noted that the issue of inequalities in education has risen considerably after the COVID-19 pandemic. The school dropout rates and learning losses have increased disproportionately among weak socio-economic groups. While patterns are similar in most countries, the rise in educational inequalities and their socio-economic consequences are markedly wider in the Global South than in the Global North. Their roots go back to the colonial past and are related to the global asymmetric division of labour, power and wealth.

There is also much debate about the efficiency of educational institutions. Agasisti et al. (2019) estimate that, on average, the academic output in European countries can be maintained while reducing the amount of resources invested by 15-18%. Overall, countries from continental Europe and Nordic countries appear to have economically inefficient educational systems because, notwithstanding relatively high outputs (good PISA scores, low drop-out rates), they spend much money per student well above the international average. Pfeffer (2015) and Pfeffer (2012) provide evidence of the equality-quality trade-off in education. Cross-sectional analysis brought somewhat mixed results. The evidence from the Scandinavian countries (Sweden, Finland, Denmark) shows that education systems can perform well in both dimensions. Germany stands out as a country with a higher quality of education and a low level of equality. The duplicate accounts are for Belgium, Switzerland, and Norway. Moreover, countries with less differentiated education systems and higher levels of equality can attain higher education quality.

Despite the apparent benefits of education, Hannum and Buchman (2005) argue that education enhances but does not ensure an individual's economic security. The impact of education expansion on economic growth remains debated, and decades of sociological studies provide evidence that education expansion does not necessarily narrow social inequalities. However, based on the evidence, the authors point out that countries with higher per capita GNPs have higher ratios of educational enrolment, especially at levels beyond primary schools.

Similarly, Petrakis and Stamakis (2002) suggest that the link between growth and education varies with different levels of economic development. Also, primary and secondary education are more important in less developed countries, while the link between growth and higher education plays a more prominent role in OECD countries.

If broadly speaking, the 'knowledge' term captured the preeminent economic position on which the endogenous growth theory is based. The key ideas proposed by Romer (1986), Lucas (1988), and Barro (1990) stress that the role of investments in education and skill development shall enhance human capital, which will become critical for long-term growth.

However, human capital is still underestimated in today's business economy. Information concerning human capital is not reflected in companies' financial statements (Rzempala, 2007). In business practice, the company's market value is often substantially higher than its book value, assuming that the human capital might be the source of the difference (Borowski, 2015).

Human capital is recognised as a population's education and health level and an essential economic growth determinant. There are several ways how to measure human capital. These measures are of two distinct types: monetary and index-based. Currently, two approaches are widely adopted: The Changing Wealth of Nations (CWON) and the Inclusive Wealth Report (IWR) (Lange et al., 2018; Lim et al., 2018; Liu & Fraumeni, 2020). The World Bank measures human capital as the present value of the labour force's expected earnings, a measure consistent with the concept of capital used for other assets. Human capital wealth per capita typically increases in low- and middle-income countries. In some upper-middle- and high-income countries, ageing and stagnant wages are reducing the share of human capital in total capital. It is estimated that the human capital wealth had risen by 22% from 1995-2014 and stood at $108,654 per capital level. However, human capital growth has been uneven. We observe the decline of human capital in high-income economies – in most developing economies, the share of human capital in total wealth is rising (Lange et al., 2018).

Lim et al. (2018) measure human capital as an index based on four components: education attainment, learning, health, and survival. The main findings generally show that countries worldwide improved their expected human capital from 1990 to 2016 and showed changes in the four components relative to 1990. However, countries vary widely in the rate of human capital formation. In 2016, 44 countries had already achieved more than 20 years of expected human capital; 68 countries had less than 10 years of expected capital. Among other metrics, for instance, the World Bank's Human Capital Index (WB HCI), the United Nations Human Development Index (UN HDI) and the United Nations Development Programme (UNDP) are often employed (Liu & Fraumeni, 2020).

Methodology and Methods

For the purpose of the study, we analyse longitudinal data, employing the so-called growth-curve model. We may consider this approach adequate because it exciplitly models the shape of trajectories of individual subjects over time and how these trajectories vary, both systematically, because of occasion-level and subject-level covariates, and randomly.

We use growth-curve models to study pupil attainment based on the scores gained from the PISA testing on three respective levels (math, reading, and science) over the 2006-2022 period. It may be assumed that we may expect an increase in students' PISA attainment over the period because of technological progress, innovations, and the overall transition towards a knowledge society.

We consider a panel dataset comprising 38 units observed across six distinct periods. Let $N = 38$ denote the number of countries in the sample and $T = 6$ denote the number of periods. Hence, the sample consists of N units observed across T periods, resulting in a total of $N \times T = 228$ observations. For each unit $i = 1,2, \dots, N$, and for each period t where $t = 1,2, \dots, T$, we observe the variables Y_{it} and X_{kit} (where $k = 1,2, \dots, K$ represents different covariates).

$$Y_{it} = \beta_0 + \beta_1 D_{2i} + \beta_2 D_{3i} + \beta_3 D_{4i} + \beta_4 D_{5i} + \beta_5 D_{6i} + \gamma_1 X_{1it} + \gamma_2 X_{2it} + \gamma_3 X_{3it} + \xi_i + \epsilon_{it} \quad (1)$$

Or

$$Y_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j D_{ji} + \sum_{k=1}^{3} \gamma_k X_{kit} + \xi_i + \epsilon_{it} \quad (2)$$

Where

Y_{it} – the dependent variable (achieved PISA score) in the country i and time t

Let $D_i$be a categorical dummy variable with six indicators representing the year when the PISA testing was conducted.

D_{2i}- equals 1 if the observation was in 2009, 0 otherwise

D_{3i} - equals 1 if the observation was in 2012, 0 otherwise

D_{4i} - equals 1 if the observation was in 2015, 0 otherwise

D_{5i} - equals 1 if the observation was in 2018, 0 otherwise

D_{6i} - equals 1 if the observation was in 2022, 0 otherwise

The first category (year 2006) is the reference category and does not need a separate dummy variable.

X_{1it} – represents the logarithm of GDP per capita in the country i and time t

X_{2it} – represents the logarithm of the Gini index in the country i and time t

X_{3it} – represents the logarithm of the share of the population in preproduction age (0-15) in the country i and time t

ξ_i – is the random slope

ϵ_{it} – is an idiosyncratic error term for the i and time t

We assume that random intercept

$$\xi_i \sim N(0, \sigma_\xi^2)$$

And error term assumption

$$\epsilon_i \sim N(0, \sigma^2)$$

PISA publishes scores from three fields: mathematics, reading, and science. Hence, three models with the same covariates will be employed.

Finally, the sampled countries are evaluated using the agglomerative hierarchical clustering (AHC) method, which incorporates the latest PISA results (from three respective subjects) and model variables.

Formally, given the set of countries $\{i = 1,2, \dots, n\}$ with corresponding feature vectors $x_i = \{x_{i1}, x_{i2}, \dots, x_{ip}\}^T$, agglomerative clustering process constructs a sequence of partitions

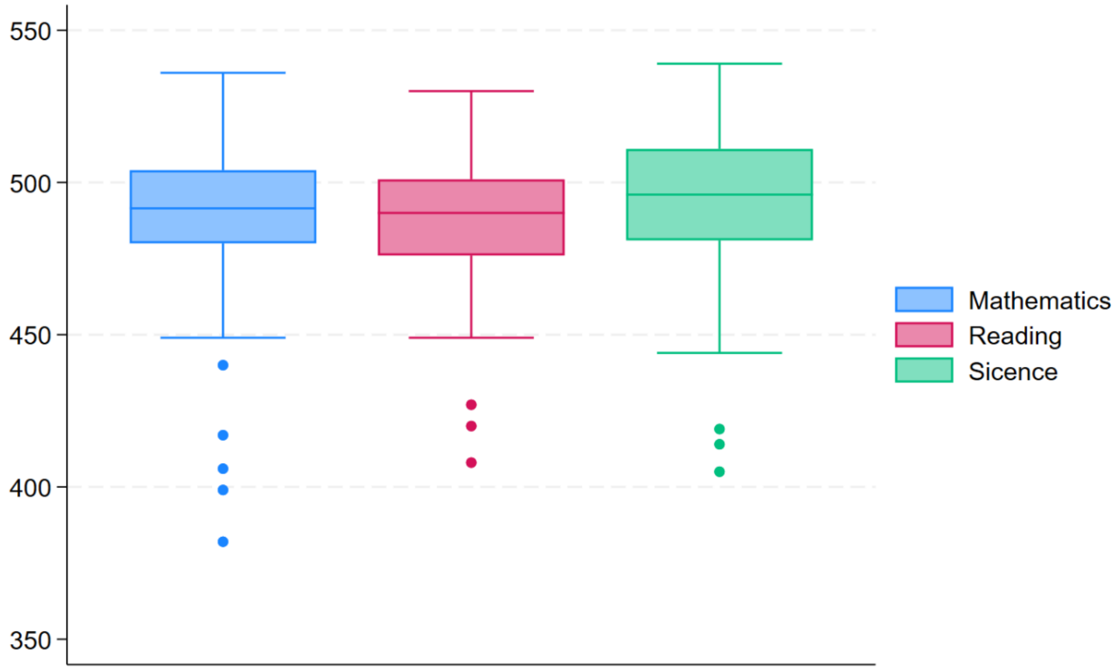
$$C_n \to C_{n-1} \to \cdots \to C_2 \to C_1 \quad (3)$$

Where C_k represents the partition of the dataset into k clusters. The merging criterion selects the pair of clusters (C_r, C_s) that minimises the distance $d(C_r, C_s)$ calculated from the p variables according to the selected linkage method.

Results

We begin by analysing the average score results of the PISA testing at three respected fields over the observed period 2006-2022.

Figure 1: Average PISA score by three respected fields over 2006-2022

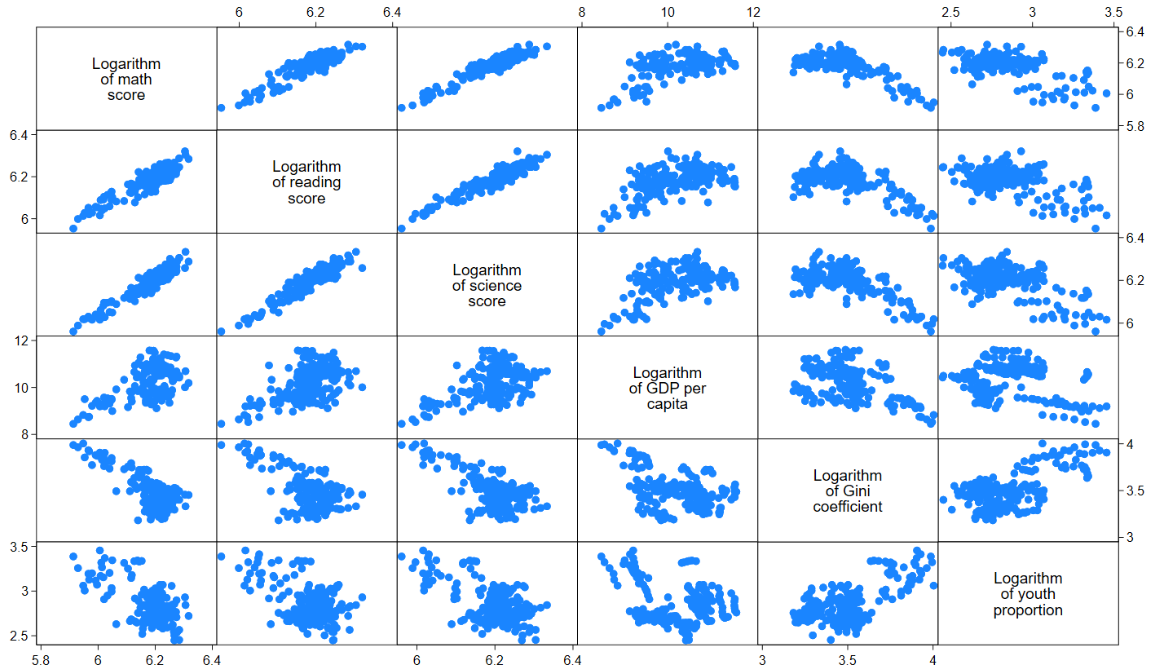


Source: own research, www.oecd.org

Fig.1 shows the average PISA score by field of testing from 2006 to 2022. We may observe similar PISA scores in each testing field; however, there is considerable variation in individual results among the OECD countries. Mathematics logs the highest variation (35.17 Std.dev.), followed by Science (31.82 Std.dev.) and *Reading* (27.32 Std.dev.). Moreover, mathematics also logs the highest record of outliers from the mean.

Next, we assess the relations among the variables that are the study's subjects. We consider the PISA variables (each testing field) and auxiliary variables included in the panel dataset.

Figure 2: Correlation matrix between the PISA variable and auxiliary variables



Source: own research

Fig. 2 shows the correlation matrix between the PISA variables and auxiliary variables. The highest correlation, close to unity, is between the PISA variables, which suggests that a high score in mathematics is related to a high achievement in reading or science and vice versa. The correlations between the PISA variables and auxiliary variables are significant and bi-directional. Hence, the PISA variables (e.g. the score from each testing field) are positively related to the GDP but negatively to the value of the Gini coefficient and share of youth in preproduction age in the country.

The results of the PISA score modelling in each respective field will be presented in the following section.

Table 1: The PISA mathematics model

```
Mixed-effects ML regression                          Number of obs     =    181
Group variable: cntsc                                Number of groups  =     38
                                                     Obs per group:
                                                                  min  =      4
                                                                  avg  =    4.8
                                                                  max  =      5
                                                     Wald chi2(7)      = 133.24
Log likelihood =   404.7983                          Prob > chi2       = 0.0000

------------------------------------------------------------------------------
       lmath | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        year |
       2012  |  -.0037865   .0044399    -0.85   0.394    -.0124885    .0049155
       2015  |   -.014136   .0045972    -3.07   0.002    -.0231465   -.0051256
       2018  |  -.0158181   .0047434    -3.33   0.001     -.025115   -.0065213
       2022  |  -.0494642   .0053291    -9.28   0.000     -.059909   -.0390194
             |
        lgdp |   .0494884   .0097983     5.05   0.000     .0302842    .0686927
       lgini |  -.0877328   .0316713    -2.77   0.006    -.1498075   -.0256581
      lyouth |  -.0707182   .0260553    -2.71   0.007    -.1217856   -.0196508
       _cons |   6.196089   .1745906    35.49   0.000     5.853897     6.53828
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
cntsc: Identity              |
                   sd(_cons) |   .0414641   .0062773      .0308183    .0557875
-----------------------------+------------------------------------------------
                sd(Residual) |   .0184403    .001173      .0162789    .0208888
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 152.00        Prob >= chibar2 = 0.0000
```

Source: own research

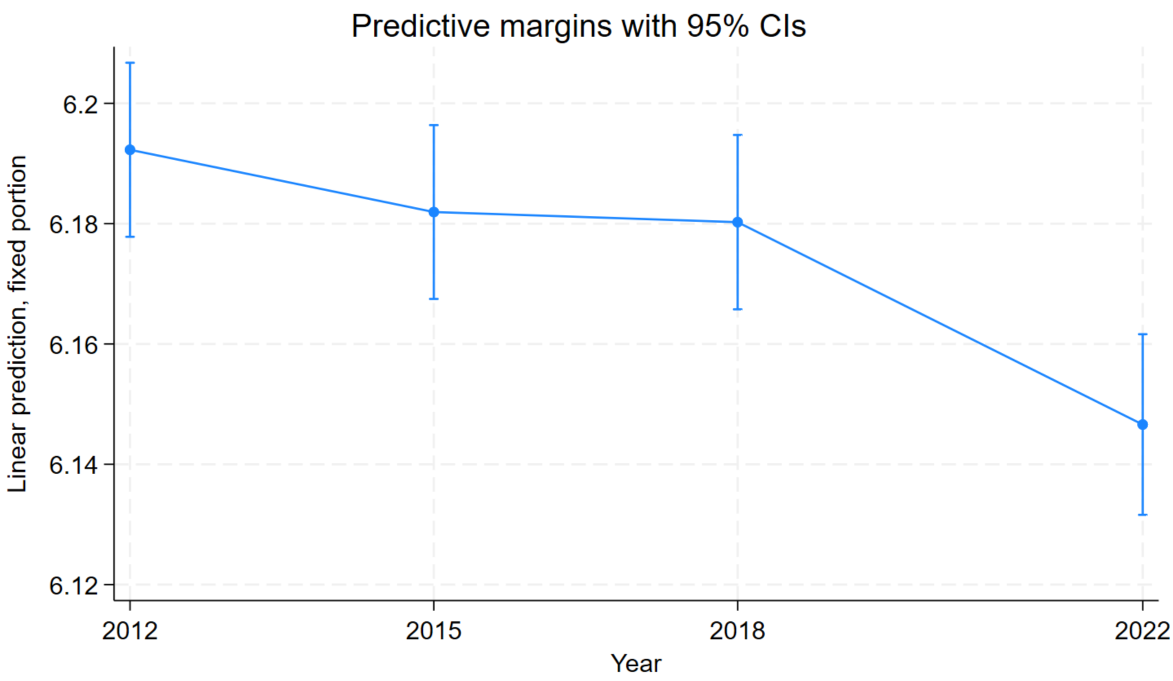
Table 1 presents the first model fitting the mathematics score from PISA testing against the independent covariates. The *maximum likelihood* method was used for the estimation. Overall, the model may be considered statistically significant. Among the indicator variables, the reference period is 2006 (the year

2009 absent because of missing data). It might be seen that all other compared periods (except 2012) became statistically significant and negative, suggesting that overall results from mathematics based on PISA testing have declined compared to the reference period.

Other covariates became statistically significant and showed mixed effects. Higher GDP per capita will support better PISA performance, while a higher Gini coefficient and a higher proportion of youth of preproduction age tend to decrease PISA performance in mathematics.

The random part of the model includes estimating the random-intercept standard deviation (the estimation of the between-subject variance) and the estimate of the within-subject standard deviation (expressed in logarithms). There is considerable variation between the countries, which is substantially higher than the variation within the periods of the same country.

Figure 3: Predictive marginsplot of Mathematics score based on PISA testing



Source: own research

Fig. 3 shows a predictive marginsplot showing predicted means and CI based on achieved results from PISA mathematics testing. We may observe considerable variability among the results of OECD countries and declining mean scores over the observed period.

Table 2: The PISA reading model

Mixed-effects ML regression	Number of obs	= 216
Group variable: cntsc	Number of groups	= 38
	Obs per group:	
	min	= 4
	avg	= 5.7
	max	= 6
	Wald chi2(8)	= 84.62
Log likelihood = 475.00619	Prob > chi2	= 0.0000

lread	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
year						
2009	.0104356	.0049132	2.12	0.034	.000806	.0200653
2012	.0145139	.0049605	2.93	0.003	.0047914	.0242364
2015	.0052371	.005095	1.03	0.304	-.0047489	.015223
2018	-.0053696	.0052496	-1.02	0.306	-.0156587	.0049195
2022	-.026857	.0057552	-4.67	0.000	-.038137	-.015577
lgdp	.042564	.0091372	4.66	0.000	.0246554	.0604726
lgini	-.0468019	.030486	-1.54	0.125	-.1065534	.0129496
lyouth	-.0201837	.0253314	-0.80	0.426	-.0698322	.0294649
_cons	5.969066	.1647045	36.24	0.000	5.646251	6.29188

Random-effects parameters	Estimate	Std. err.	[95% conf. interval]	
cntsc: Identity				
sd(_cons)	.0381732	.0054275	.0288891	.050441
sd(Residual)	.0205758	.001134	.018469	.0229228

LR test vs. linear model: chibar2(01) = 167.77   Prob >= chibar2 = 0.0000

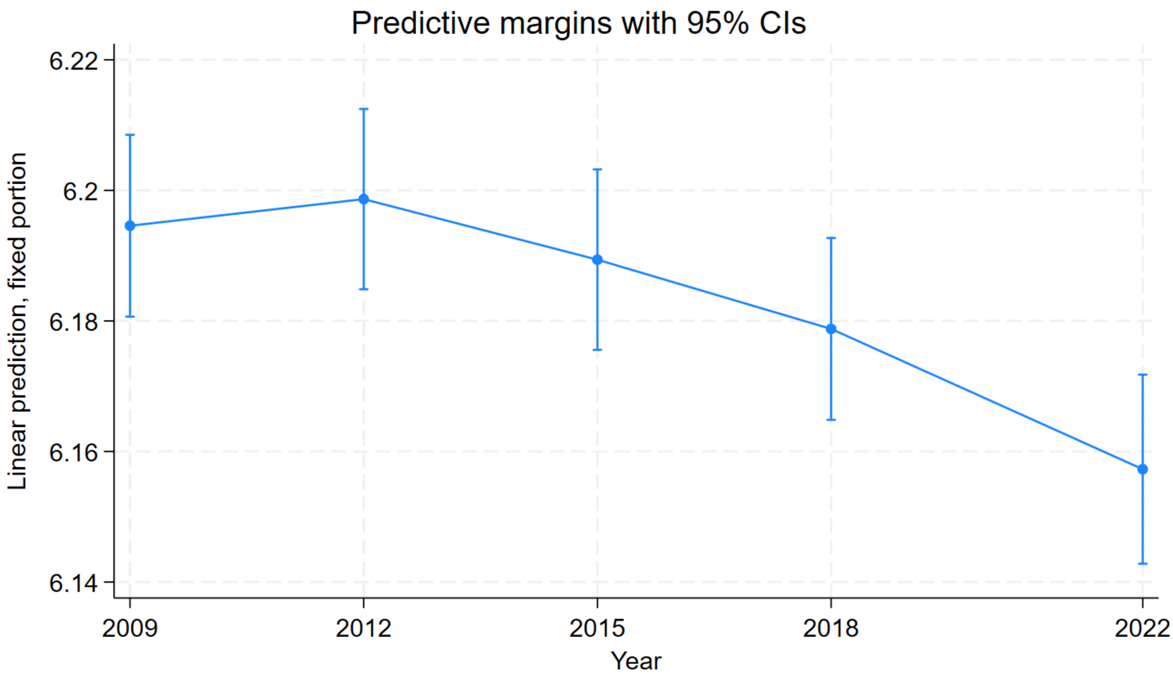
Source: own research

Table 2 shows the results of the second model fitting the reading score from PISA testing against the independent covariates. The model is statistically significant. In model periods, 2009 and 2012 became positive and statistically significant, which suggests that over this period, pupils were able to improve their overall reading scores compared to the reference period (2006). However, in the period 2022, the result became negative and statistically significant, which suggests that this period shows significant deterioration of achieved results in reading.

Among the other covariates, statistically significant and positive became just GDP per capita, suggesting the higher income countries perform better in PISA testing.

The random part shows considerable variation between the countries, which is substantially higher than the variation within the same country's periods.

Figure 4: Predictive marginsplot of Reading score based on PISA testing



Source: own research

Fig. 4 shows a predictive marginsplot showing predicted means and CI based on achieved results from PISA reading testing. We may observe considerable variability among the results of OECD countries and, since 2015, declining mean scores over the observed period.

Table 3: The PISA science model

```
Mixed-effects ML regression                         Number of obs     =    218
Group variable: cntsc                               Number of groups  =     38
                                                    Obs per group:
                                                                 min  =      4
                                                                 avg  =    5.7
                                                                 max  =      6
                                                    Wald chi2(8)      = 118.17
```

```
Log likelihood =  516.96903                          Prob > chi2      = 0.0000

------------------------------------------------------------------------------
       lscie | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        year |
        2009  |   .0030817   .0039266     0.78   0.433    -.0046143    .0107777
        2012  |   .0011344   .0039745     0.29   0.775    -.0066554    .0089242
        2015  |  -.0176685   .0041119    -4.30   0.000    -.0257277   -.0096093
        2018  |  -.0262853   .0042563    -6.18   0.000    -.0346275    -.017943
        2022  |  -.0340693   .0047776    -7.13   0.000    -.0434332   -.0247053
             |
        lgdp |   .0422958   .0089139     4.74   0.000     .0248249    .0597667
       lgini |  -.0380411   .0269136    -1.41   0.158    -.0907906    .0147085
      lyouth |  -.0912448    .022476    -4.06   0.000     -.135297   -.0471925
       _cons |   6.165959   .1540303    40.03   0.000     5.864065    6.467853
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
cntsc: Identity              |
                  sd(_cons) |   .0407242   .0053438      .0314891    .0526679
-----------------------------+------------------------------------------------
               sd(Residual) |   .0165435   .0008931      .0148825    .0183899
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 249.72        Prob >= chibar2 = 0.0000
```

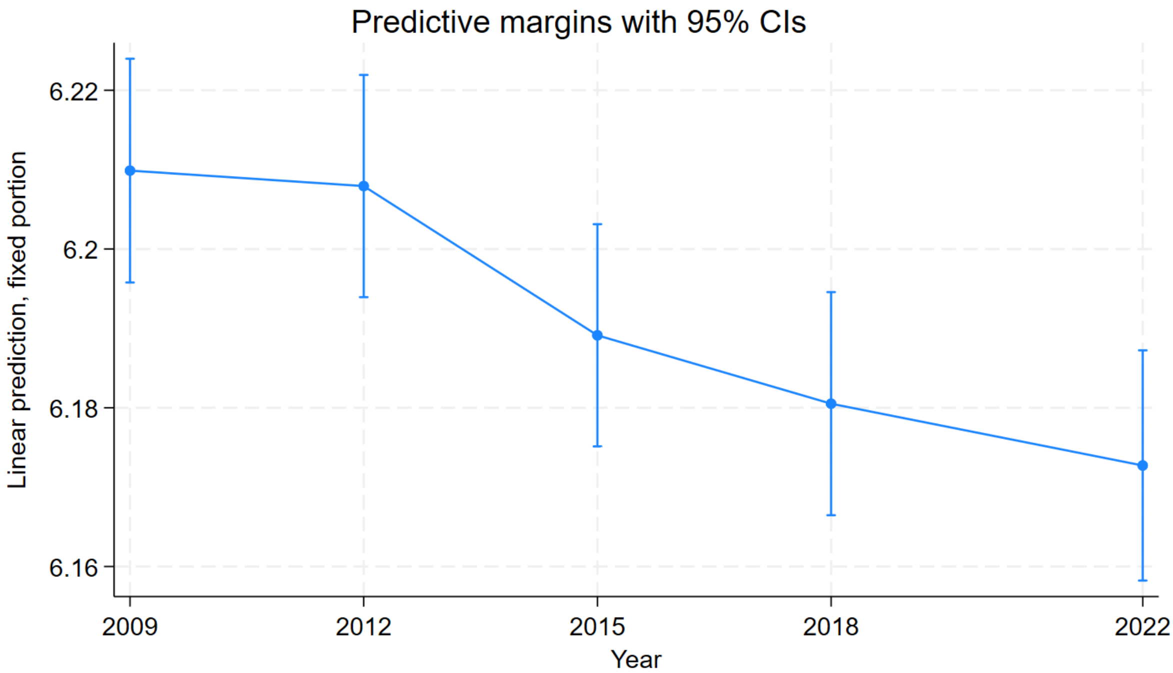
Source: own research

Table 3 shows the results of the third model, which fits the science score from PISA testing against the independent covariates. The model is statistically significant. For the periods 2015, 2018, and 2022, the results became negative and statistically significant, which suggests that over this period, there has been a continuing decline in the overall science scores of pupils compared to the reference period (2006).

Among the other covariates, statistically significant and positive became GDP per capita and share of youth in preproduction age, which turns negative.

The random part shows again considerable variation between the countries, which is substantially higher than the variation within the periods of the same country.

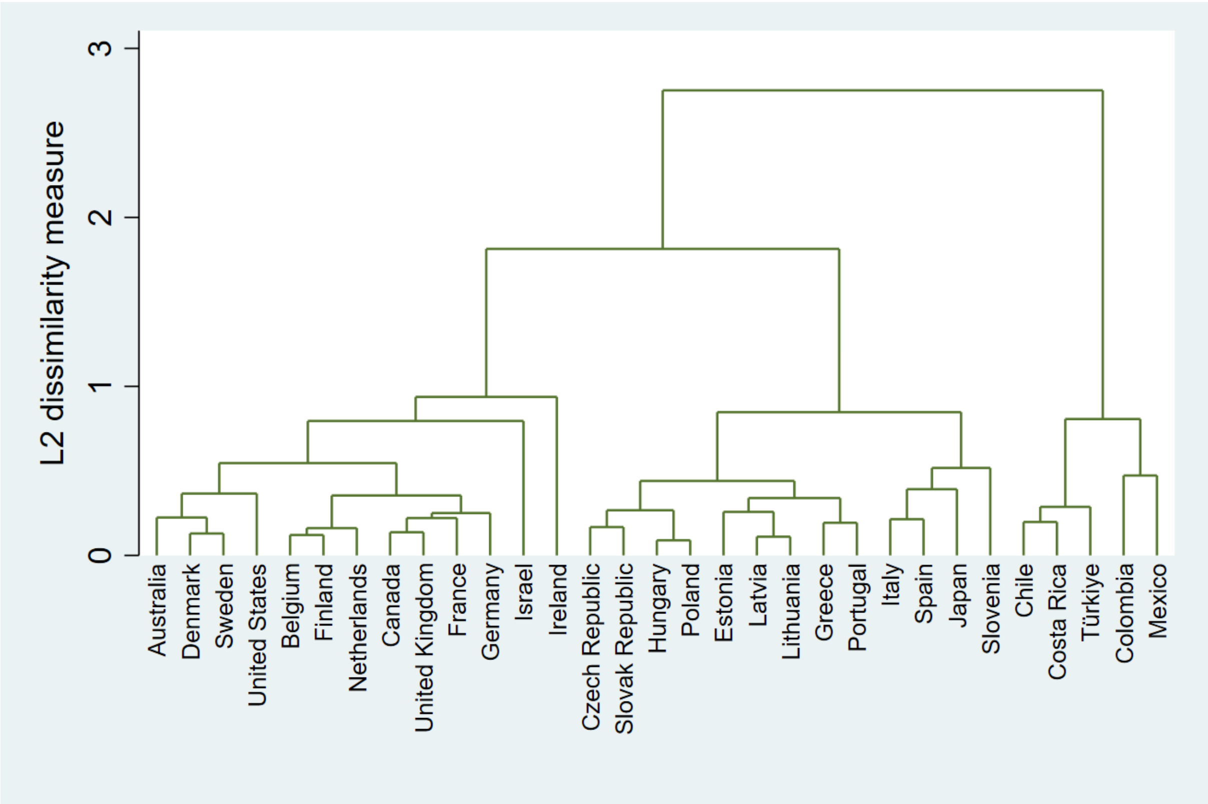
Figure 5: Predictive marginsplot of Science score based on PISA testing



Source: own research

Fig. 5 shows a predictive marginsplot showing predicted means and CI based on achieved results from PISA science testing. We may observe considerable variability among the results of OECD countries. After 2012, we may observe a remarkable decline in the achieved score from the science.

Figure 6: Results of AHC using the Complete linkage method



Source: own research

Fig. 6 shows the AHC results using the Complete linkage method, represented by the dendrogram. We may observe three distinct clusters. Several smaller clusters (sub-clusters) may be recognised on various dissimilarity levels within each cluster. In some cases, the cluster composition reflects a similar geographical composition of sampled countries. The cluster on the far left (Cluster „A") includes four sub-clusters. The first three sub-clusters show smaller level dissimilarity when merging into a single subcluster. It includes Western European countries, the United States and Canada. On the right are two outliers (Israel and Ireland) within cluster A.

Cluster „B"in the centre contains three sub-clusters at the lower dissimilarity level. The left side includes Eastern and South-Eastern European countries, and the right side includes countries with low geographical proximity. Both clusters „A" and „B" represent high-income countries. On the far right is cluster „C", which contains two subclusters showing the lowest dissimilarity from the sampled countries. Cluster „C" includes lower-income countries with similar geographical composition (excluding Türkiye). The clusters „A“ and „B“ show lower dissimilarity than cluster „C“ as they merge on lower nodes.

Discussion

The paper's main objective was to critically evaluate the results of the PISA testing in three fields of study: mathematics, reading, and science at the spatial-temporal level. The study comprises the OECD countries over the 2006-2022 period.

The overall result shows a substantial decrease in the mean PISA testing in each study field compared to the initial period. As visualised by the predictive margins, the sharpest decline was logged in mathematics, whereas reading and science declined similarly steeply. Also, the steepest decline was logged in all studied subjects in the 2018-2022 period, suggesting the detrimental impact of the pandemic on schooling performance worldwide. Moreover, the sampled countries have shown considerable variance within the studied periods and between themselves in each field. The 'between' variance was more significant than the' within', underscoring the disparities even between the most developed countries globally.

Such a decline in the youth skills is cause for concern. However, there is already evidence about this process. Sleicher (2023) highlights a disquieting global trend: average student performance is heading in the wrong direction. Some 25% of 15-year-olds in OECD member states (roughly representing 16 million children) are estimated to be low performers in maths, reading and science. The students have not attained Level 2 proficiency, meaning they can struggle to do tasks such as using basic algorithms or interpreting simple texts. The situation is even worse among many non-OECD member states. In 18 countries and economies, more than 60% of 15-year-olds are considered low performers (Sleicher, 2023).

Compared with similar testing programs, TIMSS 2019 (Mullis et al., 2020) provides mixed results in its assessment. The trends in mathematical achievement in the eighth grade signal more improvements than downturns across the assessment cycle internationally. In the most recent TIMSS testing program in 2015 and 2019, among 33 participating countries, 13 had increases in average achievement, and 4 had declines. The trends between 2007 and 2019 and 1995 and 2019 also show more increases than decreases in average mathematics achievement in the long term.

Regarding science achievement in TIMSS 2015 and 2019, 11 countries had increases in average achievement, and 5 had declines, but the majority stayed the same. However, across the seven assessment cycles since 1995, most countries have had some periods of increases and decreases and periods of stability.

Comparing the PIRLS 2021 and PIRLS 2016 testing programs focusing on reading skills, two-thirds of the PIRLS 2021 countries had a decline in average reading achievement, which suggests the pandemic's negative impact on youth's reading skills. However, pointing at the long-term trend, when comparing the year's trend results (2001 -2021) for the 18 countries participating in both assessments, there were 7 increases, 6 maintaining the same position and 5 decreases (Mullis et al, 2021).

Underscoring the challenges related to the massive use of ICT in daily life, a recent PIRLS 2018 study shows that youth face significant limits. Measuring across four levels of sophistication of ICT use, 18 per cent of students on average across all countries were working below the lowest proficiency level, meaning that they do not have a functional working knowledge of computers. Around 36 per cent of students were working at level 2, meaning they could use the computer to complete basic tasks; 19 per cent of students were working at level 3, and just 2 per cent of students were working on level 4, which demonstrates the capacity to work independently and above (Mullis et al, 2020).

Among the other covariates in the model, national income (GDP per capita) showed a statistically significant relation with higher PISA score achievement, implicating the relationship between human capital achieved and economic growth. Indeed, the relationship between income and economic growth fuels interest in the research.

World Development Report shows the correlation between the national income and the gap between primary and lower secondary completion rates. The widest disparities may be observed in lower-income and low-income countries, especially lower-secondary schools (World Bank, 2018). Hanushek et al. (2000) examine the quality of education apart from the point of quantity as a determinant of economic growth. Using international test scores as a proxy for the quality of education, they find that countries with better educational systems also experience higher economic growth. Similarly, Psacharopoulos et al. (2018) studied evidence on global returns to education, especially regarding the contribution to growth. The returns to investment in education might be substantial and could become the driver of economic growth in lower-income countries. Moreover, education may also create a positive externality. Acemoglu and Angrist (2000) studied the spillover effects of education on economic growth. Increasing human capital in society, for instance, through compulsory schooling, significantly affects economic growth beyond individuals who receive education.

The Gini coefficient and share of youth in preproduction age demonstrate the environmental factors that affect the educational attainment of schooling youth (socioeconomic status in particular). The effect of inequalities on students' educational performance is a topic of ongoing debate. Lagravinese et al. (2020) provide evidence about the effect of economic, social, and cultural status on performances based on the PISA results, highlighting substantial heterogeneity among the students and countries. The economic, social and cultural gaps weigh more on underperformance than the education system. For instance, additional insights about this topic were provided by (Suna et al., 2020; Broer et al., 2019; Teodor, 2012).

The dendrogram from the AHC analysis using the Complete linkage method reveals three distinct clusters. Cluster “A” and “B” predominantly consist of high-income countries with mixed geographical proximity to each other. They experience a lower dissimilarity level, merging into a single cluster on a lower cut-off point. Finally, Cluster “C” includes countries experiencing similar features (geography, income) at far greater distances than Clusters “A” and “B.”

Conclusion

The main scope of the paper is to provide a critical assessment of PISA testing results and their implications for economic growth and competitiveness. Based on the PISA testing results, the evidence shows that negative human capital has accelerated across the countries and in all evaluated fields, particularly since the pandemic.

The evidence also shows a statistically significant relation to national income, suggesting that higher-income countries achieve higher average PISA scores. This link may also have broader implications when considering human capital as a critical economic growth and competitiveness asset.

Among other factors significantly affecting PISA testing results, socio-economic inequality and a higher proportion of schooling youth in society tend to decrease the average PISA scoring. The detrimental effects of social inequalities are already well described in the literature. A higher proportion of schooling youth in society may contribute to the 'crowding effect' of classrooms, making teachers, lecturers, and overall educational process management more demanding.

Finally, AHC provides a sampling of countries to more homogenous clusters, highlighting the similarity within the clusters and the dissimilarity between them. However, the initial assumption that 'similar' countries in income or geographical area create exclusive clusters provided mixed results.

The study also has its limitations. The number of environmental factors with an effect on the PISA results could be expanded. Also, the presented link of the study to growth and competitiveness is only on the level of implication, and more research shall be provided in this area.

References

Acemoglu, D., & Angrist, J. (2000). How large are human-capital externalities? Evidence from compulsory schooling laws. *NBER Macroeconomics Annual, 15*, 9-59. The University of Chicago Press. https://doi.org/10.1086/654403

Agasisti, T., Munda, G., & Hippe, R. (2019). Measuring the efficiency of European education systems by combining data envelopment analysis and multiple-criteria evaluation. *Journal of Productivity Analysis, 51*, 105-124. https://doi.org/10.1007/s11123-019-00549-6

Barro, R. J. (1991). Economic growth in a cross-section of countries. *The Quarterly Journal of Economics, 106*(2), 407-443. https://doi.org/10.2307/2937943

Borowski, A. (Year). Methods of human capital measurement. Publisher.

Broer, M., Bai, Y., & Fonseca, F. (2019). Socioeconomic inequality and educational outcomes: Evidence from twenty years of TIMSS. *IEA Research for Education*. Springer Open.

Coleman, J. S., Campbell, E. Q., Hobson, C. J., McPartland, J., Mood, A. M., Weinfeld, F. D., & York, R. L. (1966). Equality of educational opportunity. *U.S. Department of Health, Education, and Welfare, Office of Education*.

Farquharson, C., McNally, S., & Tahir, I. (2024). Education inequalities. *Oxford Open Economics, 3*, i760–i820. https://doi.org/10.1093/ooec/odad029

Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Duckworth, D. (2018). Preparing for life in a digital world: *IEA International Computer and Information Literacy Study 2018 International Report*. IEA.

Grek, S. (2009). Governing by numbers: The PISA 'effect' in Europe. *Journal of Education Policy, 24*(1), 23-37. https://doi.org/10.1080/02680930802412669

Hadjar, A., & Gross, C. (Eds.). (2016). *Education systems and inequalities: International Comparisons*. Policy Press.

Hannum, E., & Buchmann, C. (2004). Global educational expansion and socio-economic development: An assessment of findings from the social sciences. *World Development, 33*(3), 333-354.

Jacobs, J. A. (1996). Gender inequality and higher education. *Annual Review of Sociology, 22*, 153-185. https://doi.org/10.1146/annurev.soc.22.1.153

Jencks, C., Smith, M., Acland, H., Bane, M. J., Cohen, D., Gintis, H., Heyns, B., & Michelson, S. (1972). *Inequality: A reassessment of the effect of family and schooling in America*. Basic Books Inc.

Kaščák, O., & Pupala, B. (2011). PISA v kritickej perspektíve. *Orbis Scholae, 5*(1), 53–70. ISSN 1802-4637.

Kyriakides, L., Creemers, B. P. M., Panayiotou, A., & Charalambous, E. (2021). *Quality and equity in education: Revisiting theory and research on educational effectiveness and improvement*. Routledge.

Lagravinese, R., Liberati, P., & Resce, G. (2020). The impact of economic, social, and cultural conditions on educational attainments. *Journal of Policy Modeling, 42*(1), 112-132. https://doi.org/10.1016/j.jpolmod.2019.03.007

Langthaler, M., & Malik, J. (2023). Inequalities in education from a global perspective: Theoretical approaches, dimensions, and policy discussions. *ÖFSE Briefing Paper 34*. Austrian Foundation for Development Research. Vienna.

Lange, G.-M., Wodon, Q., & Carey, K. (Eds.). (2018). *The changing wealth of nations 2018: Building a sustainable future*. World Bank Group. https://doi.org/10.1596/978-1-4648-1046-6

Lim, S. S., Updike, R. L., Kaldjian, A. S., Barber, R. M., Cowling, K., York, H., Friedman, J., Xu, R., Whisnant, J. L., Taylor, H. J., Leever, A. T., Roman, Y., Bryant, M. F., Dieleman, J., Gakidou, E., & Murray, C. J. L. (2018). Measuring human capital: A systematic analysis of 195 countries and territories, 1990–2016. *The Lancet, 392*(10154), 1217-1234. https://doi.org/10.1016/S0140-6736(18)31941-X

Liu, G., & Fraumeni, B. M. (2020). A brief introduction to human capital measures. *NBER Working Paper Series, (27561)*. National Bureau of Economic Research. http://www.nber.org/papers/w27561

Mullis, I. V. S., & Martin, M. O. (Eds.). (2021). *Trends in reading achievement: PIRLS 2021 International Results in Reading*. TIMSS & PIRLS International Study Center, Boston College.

Mullis, I. V. S., Martin, M. O., & Loveless, T. (2016). *20 years of TIMSS: International trends in mathematics and science achievement, curriculum, and instruction*. TIMSS & PIRLS International Study Center, Lynch School of Education, Boston College, & International Association for the Evaluation of Educational Achievement (IEA).

Mullis, I. V. S., Martin, M. O., Foy, P., Kelly, D. L., & Fishbein, B. (2019). *TIMSS 2019 International Results in Mathematics and Science*. TIMSS & PIRLS International Study Center, Lynch School of Education and Human Development, Boston College, & International Association for the Evaluation of Educational Achievement (IEA).

OECD. (2023). *Education at a glance 2023: OECD indicators*. OECD Publishing. https://doi.org/10.1787/eag-2023-en

Pereyra, M. A., Kotthoff, H.-G., & Cowen, R. (Eds.). (2011). *PISA under examination: Changing knowledge, changing tests, and changing schools*. Sense Publishers.

Petrakis, P. E., & Stamatakis, D. (2002). Growth and educational levels: A comparative analysis. *Economics of Education Review, 21*(5), 513-521. https://doi.org/10.1016/S0272-7757(01)00050-4

Pfeffer, F. T. (2012). Equality and quality in education. *Population Studies Center Research Report 774*. Institute for Social Research, University of Michigan.

Pfeffer, F. T. (2015). Equality and quality in education: A comparative study of 19 countries. *Social Science Research, 51*, 350-368.

Psacharopoulos, G., & Patrinos, H. A. (2018). *Returns to investment in education: A decennial review of the global literature* (Policy Research Working Paper No. 8402). Education Global Practice, World Bank Group. https://doi.org/10.1596/1813-9450-8402

Rzempała, J. (2007). Kapitał intelektualny jako źródło przewagi konkurencyjnej przedsiębiorstwa. *Zeszyty Naukowe Uniwersytetu Szczecińskiego, 453*.

Schleicher, A. (2022). *Programme for International Student Assessment: Insights and interpretations*. OECD Publishing.

Sorby, S. A., & Panther, G. C. (2020). Is the key to better PISA math scores improving spatial skills? *Mathematics Education Research Journal, 32*, 213–233. https://doi.org/10.1007/s13394-020-00328-9

Starr, K. (2014). The influences and implications of PISA: An Australian perspective. *AASA Journal of Scholarship and Practice, 10*(4), 19-30.

Svein Sjøberg, S., & Jenkins, E. (2022). PISA: A political project and a research agenda. *Studies in Science Education, 58*(1), 1-14. https://doi.org/10.1080/03057267.2020.1824473

Suna, H. E., Tanberkan, H., Gür, B. S., & Perc, M. (2020). Socioeconomic status and school type as predictors of academic achievement. *Journal of Economy, Culture and Society, 61*(1), 41-