Assessing the Impact of Human Capital on Economic Growth: A Dual Approach Using Quantity and Quality Proxies

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Abstract: *This study explores the long- and short-run effects of human capital on economic growth across 27 European Union countries between 1980 and 2024, using a panel ARDL–PMG framework. It distinguishes between the quantity and quality dimensions of education, evaluating their respective contributions to GDP growth.*
The findings indicate a statistically significant and robust long-run relationship among the selected variables, as confirmed by the negative and highly significant error correction term (–0.3176, $p < 0.01$). Cognitive skills, proxied by PISA mathematics scores, exhibit a positive and significant effect on long-run economic growth, reinforcing the idea that education quality is a stronger growth driver than traditional quantity-based indicators.
In contrast, variables such as tertiary education expenditure and enrollment show no significant impact in the long run, suggesting that increasing access or funding alone may not yield sustained economic benefits without improving learning outcomes. However, these same indicators are positively associated with short-run growth, highlighting their role in generating immediate positive effects through enhanced human capital utilization.
Gross fixed capital formation (GFCF) remains a key short-run driver of growth, while other labor force variables show no significant effects in either time horizon. These findings emphasize the importance of focusing policy efforts on improving the effectiveness and outcomes of educational systems, rather than expanding inputs alone.
Overall, the study provides empirical support for shifting from a quantity-based to a quality-focused human capital development strategy, offering valuable insights for policymakers aiming to enhance long-term economic performance in the EU context.

Keyword: human capital, economic growth, education expenditure, labor force, PISA scores, panel data, ARDL-PMG

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1. Introduction

The relationship between human capital and economic growth has long been a central topic in both economic theory and empirical research. Traditionally, the focus has been placed on aggregate education indicators—such as years of schooling or enrollment rates—as proxies for human capital. However, in the context of today's global knowledge economy, questions arise regarding what specific aspects of human capital drive sustained economic performance. In particular, as societies invest heavily in education systems, it becomes essential to distinguish between the quantity of education delivered and the quality of skills and competencies acquired.

The main objective of this study is to examine the extent to which the quality of education contributes to long-run economic growth, as opposed to the mere quantity of educational input. Using panel ARDL (PMG) estimations over the period 1980–2024 for EU countries, the paper evaluates how different human capital indicators—such as tertiary enrollment, public education spending, and PISA mathematics scores—are associated with GDP growth. By contrasting traditional input-based indicators with skill-based measures, we aim to shed light on the relative importance of educational quality in fostering long-term economic performance.

The paper is structured as follows: Section 2 reviews the theoretical and empirical literature on the relationship between human capital and economic growth. Section 3 describes the dataset, outlines the variables used, and provides descriptive statistics, including details on the treatment of missing values and correlation analysis. Section 4 presents the methodology, with a focus on the ARDL–PMG modeling approach. Section 5 reports and interprets the empirical findings, addressing both short-run and long-run dynamics, and includes robustness checks and policy implications. Finally, Section 6 offers the main conclusions and suggestions for future research.

2. Literature Review

Human capital has long been recognized as a driver of economic performance, primarily through its contribution to labor productivity, innovation, and the absorption of new technologies. Traditional economic models—particularly endogenous growth theory—emphasize the importance of human capital accumulation in sustaining long-term economic growth. However, the evolving complexity of modern economies calls for a more specified understanding of what constitutes "valuable" human capital. In this paper we grouped them in traditional and modern ones

2.1. Traditional (quantity-based) proxies

Among the traditional ones, the most popular one refers to education. Therefore, we start by presenting the education-related proxies used in earlier research because they provide a solid basis for comprehending the connection between economic growth and human capital. Education-related proxies such as average years of schooling, literacy rates, and enrollment ratios, are vital for empirical analysis because they provide concrete indices of human capital. These indicators typically include enrollment rates in primary (Maitra & Chakraborty, 2021), secondary (Garza-Rodriguez, et al., 2020), and tertiary education (Sghaier, 2022), government spending on education, particularly in the tertiary sector, (Raheem, et al., 2018) and the number of years of schooling (Affandi, et al., 2019).

Primary enrollment is the least used because it isn't thought to be very conclusive. However, in a Johansen approach to cointegration, Maitra and Chakraborty (Maitra & Chakraborty, 2021) employed primary enrollment as a proxy for human capital, followed by ECM. The authors analyzed Sri Lanka's income dynamics from 1981 to 2017 using annual time series data on GDP, exports, imports, trade openness, and human capital. Real GDP measured income, while trade indicators included real exports and imports (2002 prices). Human capital was proxied by primary school gross enrollment, life expectancy at birth, and real public spending on health and education. Data came from the Central Bank of Sri Lanka's 2018 report. Using the ECM method and Johansen cointegration, they found that at the 5% level, income was positively linked to the gross enrollment ratio. Also, Temitope et al (2022) used primary enrollment as a proxy for human capital. He examined the impact of primary school enrollment, urban population, natural resource rent, domestic credit, FDI inflows, and trade openness on Nigeria's ecological footprint from 1970 to 2017, also considering economic growth. Using Granger causality, the study found that human capital (via primary enrollment) had a diminishing effect on the ecological footprint.
Secondary enrollment rate is more used I the studies and we included it in our robustness check. Garza-Rodriguez et al. (2020) used OLS with population growth and secondary enrollment as proxies for human capital. A 1% increase in secondary enrollment raised GDP per worker by 1.08%. Human capital had nearly three times the impact of physical capital, and Granger causality revealed a bidirectional link between human capital and growth. Nouira and Saafi (2020) used secondary enrollment as a proxy for human capital to examine its role, along with institutional quality and income, in the link between export upgrading and economic growth. Using a dynamic panel threshold model for 56 countries (1995–2015), they found that a minimum level of human capital, institutions, and income is needed for exports to positively impact growth. Human capital emerged as a key driver in the export-growth relationship.
Then there is also the tertiary enrollment which we also included in our study. Sghaier (2022) used university enrollment as a proxy for human capital to study its role in the impact of FDI and remittances on economic growth in four North African countries. The study found that both FDI and remittances positively influence growth, with stronger effects as human capital increases. Also, Abdoul & Omri (2021) used tertiary enrollment to explore links between human capital, environmental quality, FDI, and growth in the Mediterranean (1990–2013). Their OLS models found a bidirectional relationship between human development and economic progress. Also, Rahman et al (2023) included the government expenditure on tertiary education as proxy for human capital together with patent applications, FDI inflows and outflows and trade. They used the ARDL methodology and time-series data for the period 1990-2020 from the World Bank and their paper indicated a significant correlation between economic growth and all variables in the short run. In our study we also included tertiary enrollment. The same proxy, but together with the primary and secondary enrollment rate was used by Phouphet Kyophilavong et al (2018) to research the impact of education on economic growth in Laos, for the period 1984-2013. The study employed Granger causality tests and reached the conclusion that there is a two-way causality between

the two variables at all levels of education. The same method of using the share of the employees with primary, secondary and higher education was used by Karatheodoros et al (2019). For the period 1995-2012, for 13 regions (NUTS II level) of Greece, they estimated a model for which they applied Granger causality tests. The conclusion was that there are two opposites relations, primary education had a negative impact on economic growth, while the other types of education had a positive impact. We could assume that the negative effect of the primary education was emphasized because here human capital was included also through secondary and higher education. According to this study, the results are different in low-income countries than in high-income ones. In the first category, secondary education has the greatest impact on economic growth, while in the second category, higher education is the most influential variable.

Another proxy for human capital which is encountered in the research is the years of schooling. We excluded it from our study due to the data constraint which would have affected the validity of the panel analysis, but for example, Affandi et al. (2019), for instance, investigated the impact of human capital on the Indonesian economy from 1985 to 2014. After analyzing the effects of capital stock, labor, and human capital on the regional GDP, their study concluded that human capital was the main element influencing economic growth. As a result, the most profitable investments were made in human capital. Frank (2009) also discovered a similar positive relationship between human capital and economic growth using the number of years of education as a stand-in for human capital. The individual employed Granger causality tests to examine the relationship between income inequality, income growth, and human capital using annual data for the United States from 1929 to 2000. He concluded that years of education have an impact on income levels, but there is no proof that more years of education lead to the top decile of income share. One explanation for this could be the possibility that particular abilities, both soft and technical, are also required in some well-paying industries (like ICT infrastructure) to significantly influence the revenues. Another study by Teixeira and Fortuna (2004) also utilized the average number of years of schooling as a stand-in for human capital. To measure the relationship between productivity, innovation capacity, and human capital for Portugal from 1960 to 2001, the authors have also employed total factor productivity as a stand-in for internal knowledge and technical advancement. Their findings supported a continuous relationship between productivity, human capital, and innovative potential. They concluded that since human capital boosts productivity and facilitates the assimilation of new information, it has an impact on economic growth. Ljungberg & Nilsson also (2009) used the number of school years of the population between 15 and 65 to study the direction of influence between human capital and economic growth by employing Granger causality tests, for Sweden for the period 1850-2016. The findings showed that, up to the structural crises of the 1970s, changes in the human capital consistently anticipated changes in aggregate productivity. Simõe et al (2019) included the number of years of secondary education together with total factor productivity to look into the possibility of a causal relationship between the growth of the services sector, human capital, and aggregate productivity in the Portuguese economy between 1970 and 2006. His study was based on impulse response analysis and VAR model estimate using yearly data from 1970 to 2006. The development of service subsectors was not significantly impacted by human capital in the causality analysis, but the impulse response analysis suggests that there is a favorable influence on overall productivity, which may ultimately have an effect on economic performance.

2.2. Modern (quality-based) proxies

However, there is a growing interest in the literature that human capital is measured not just by the amount of education received, but by its quality—what individuals actually learn. Human capital encompasses the knowledge, skills, and attributes that drive productivity and value and studies like the ones of Affandi (2019) and Kell (2018) emphasize the significance of psychological, occupational, and personality qualities. Abraham & Mallatt (2022) argue that qualifications may better reflect human capital than years of schooling, as capabilities gained matter more. Diaz-Fernandez et al. apud Mubarik (2022) expand this view to include traits like creativity, intelligence, and attitude. Hanushek & Woessmann (2008) emphasize that prioritizing cognitive skills over school duration has major policy implications, as improving abilities often requires different strategies than simply increasing education length.

Refeque & Azad (2022) introduced skills besides education in their study-based data from the India Human Development Survey (IHDS) 2011–2012 which evaluated the benefits of education and skill in India according to caste, geography, industry, gender, and religion. For education they used as a proxy the mean years of schooling and for skills he used computer and linguistic skills and years of experience. By using an Ordinary least Square (OLS) estimation, they demonstrated that the influence of talents outweighs that of education in general. As the importance of skills rises, there are researchers such as (Brasse, et al., 2024) who are trying to identify the most important ones. It has been determined through the analysis of skills data from over a million job postings between 2018 and 2020 that while fundamental IT abilities are becoming more and more common, general skills like communication, adaptability, and leadership are still vital. Other skills which are worthy of investments, according to the literature (Myers, et al., 2004) are the so called ‘’high-order skills’’. These are abilities like *problem-solving, critical thinking, tolerance, self-control, diligence, teamwork*. Despite their importance, being labeled as "soft" or "non-cognitive" reflects the limited understanding of how to assess or develop them. Bloom created a classification (1956) of educational objectives and he ranked knowledge at the base and advanced skills—like applying concepts, evaluating data, and creating new ideas—at the top. Exams often focus on lower levels (recall and understanding), though progressing requires mastering higher-level thinking for problem-solving and decision-making reflecting some gaps in the educational process.

Deming (2017) proved the importance of *social skills*, saying that they are two times more economically efficient in the United States in the 2000s compared to 1980s. Deming starts from assuming that employees naturally differ in their capacity to carry out the wide range of duties required in the workplace and that social skills give some a comparative advantage. Then, he developed a model that allows workers to utilize their abilities by allowing them to "trade tasks" at a reduced cost. According to the approach, social skills lower the cost of coordination, enabling employees to specialize and collaborate more effectively. He examined the model's predictions about the relative returns to skill across jobs using data from the NLSY79 and NLSY97. His analysis suggested that the labor market return on social skills was significantly higher in the 2000s than it was in the mid-1980s and early 1990s. Additionally, he discovers that mental and social abilities are complementary in determining pay and that the relationship between them has increased over time. Lastly, he discovers that employees with stronger social skills are more likely to work in less predictable, interpersonal skill-intensive jobs and to receive a comparatively higher income return in these positions. In conclusion, Deming has shown how social skills are increasingly required for high-paying, difficult-to-automate jobs. He also demonstrated that an emphasis on hard abilities had a smaller impact on the wage increases than learning skills like self-efficacy, persuasion, and bargaining. Ashraf et.al. (2020) showed the importance of negotiation skills. He did this by using them in a randomized controlled study in Zambia where adolescent girls significantly improved their academic performance over three years, with lasting effects after attending a course in negotiation. This program led to higher enrollment in better schools and had a stronger educational impact. An additional study by Weidman and Deming (2021) supports the economic benefit of social skills. They found strong evidence for the economic value of social skills using data from Harvard Decision Science Lab participants. Individuals were randomly assigned to teams for problem-solving tasks. Some consistently improved team outcomes so they were called “team players”. They also scored higher on the Reading the Mind in the Eyes Test (RMET), a measure of social intelligence. As their presence boosted team performance, persistence, and use of available time, the study confirms that non-cognitive skills like teamwork significantly enhance productivity. The importance of non-cognitive skills is also emphasized by Balarta et al (2015) who suggest after analyzing a sample of 55 countries for the period 1970-2009 that they are also important for explaining the relationship between test scores and economic growth. Social skills are also brought to light by Kiener et al (2023) who 105,315 observations from 65,349 individuals from Switzerland to connect the amount of self-competence, age, gender, and cognitive requirement profiles with salaries. In terms of digital transformation, the OLS regression in which the authors define three levels of self-competence (high, medium, and low) and examine pay returns to these levels of self-competence using individual labor market data shows that a combination of high social skills and high specialization is particularly helpful.

Intelligence is another proxy for human capital. Jones and Schneider (2006) have showed that intelligence and economic progress are causally related in 99.8% of the regressions they have conducted. The main focus was to determine if there was a strong statistical correlation between IQ and average GDP growth rates for 51 world-wide countries included in the database constructed by Lynn and Vanhanan about IQ (2002) from 1960 to 1992. In their study, intelligence outperformed school enrollment and increased the economic growth rate by an average of 0.11% yearly for every 1 point gained in the average national IQ. As a result, the results of IQ tests could prove to be useful instruments for quantifying the stock of human capital.

In line with this view, we adopt the perspective that the Programme for International Student Assessment (PISA), particularly the mathematics scores, serves as a reliable proxy for cognitive skills. In our view, PISA test scores offer a more refined and internationally comparable measure of human capital quality than enrollment rates or years of schooling. In this study, we build on this body of work by hypothesizing that PISA scores reflect the functional capabilities that directly enhance labor productivity and economic growth, especially within high-skill labor markets like the European Union. Therefore, this paper adopts the position that PISA performance captures the quality dimension of human capital more accurately than traditional indicators like enrollment or years of schooling. What follows is a review of studies that have used PISA and other cognitive metrics to investigate the relationship between skills and economic growth.

Valente et al (2015) provide one of the most relevant studies for this paper as he used PISA scores to show that higher requirements concerning cognitive skills are supporting the economic performance. Using data from Eurofound's European Work Conditions Survey (2000 and 2010) and PISA scores, they showed that countries with higher cognitive job requirements (e.g., problem-solving, computer use, learning new skills) had higher growth. Importantly, PISA scores correlated positively with GDP growth, while average years of education did not. They performed an analysis on the relationship between work-related skills and the GDP per capita growth in the period 2000-2010, on a sample of 28 countries[9] using multivariate regressions and found different correlations. Their central hypothesis is very similar to ours and says that the quality of human capital has a bigger impact than its quantity. Initially, they used data from European Work Conditions Survey (Eurofound) related to work cognitive requirements. He extracted 6 variables from that study which account for the following dimensions: the capacity to assess one's own work for quality; learning new skills; resolving unforeseen issues; constantly using a computer; completing tedious activities; and adhering to exact quality standards. Their principal component analysis revealed that the richest countries in Europe meaning: Sweden, Netherlands, Finland, France, UK, Switzerland, Austria, Belgium, Denmark, Norway, and Estonia also possess the most demanding work conditions when it comes to using information technology, solving problems, and ongoing learning. The second richest group mainly included Southern and Eastern countries: Spain, Italy, Malta, Cyprus, Czech Republic, Slovakia, Slovenia, Ireland and Germany and the last group, with the lowest values had mainly the same composition: Greece , Portugal, Poland, Bulgaria , Romania, Hungary, Latvia and Lithuania. Valente et al (2015) also compared the data from the Eurofund survey with the data from The Programme for the International Assessment of Adult Competencies (PIAAC) and found interesting correlations. For example, the cognitive abilities needed in the job are strongly and positively connected with PISA scores in math and science, but not with higher educational achievement. Furthermore, there is a strong link between the number of graduates in mathematics, physics, and computer science and the cognitive skill demands of their professions. In addition, the writers incorporated quantitative measures of education, such as the percentage of the working age population with a higher level of education as opposed to the average number of years spent in school. This indicator had a positive (0.24) association with GDP per capita in 2000 and a negative (-0.14) correlation with economic growth in 2000–2010, although neither was statistically significant. To find out if any certain degrees had a greater influence on the economy, the authors also evaluated the yearly number of graduates by educational field. A basic correlation analysis reveals that the GDP per capita and the percentage of recent graduates in the fields of math, science, and computer science have a positive and statistically significant correlation (0.46, p=0.01), whereas the percentage of new graduates in the fields of social sciences, business, and law has a statistically significant negative correlation (-0.59, p=0.001).

Boman (2024) also indicates that, even after adjusting for a substantial number of covariates, PISA scores or other cognitive skill measures can, to some extent, predict economic

[9] Norway, Switzerland and the EU27 except Luxembourg

development between 2010 and 2019 for a sample of 31 and 80 nations worldwide, respectively, based on an OLS regression.

2.3. Gaps in the Literature

Despite the increasing recognition of human capital as a key driver of economic growth, several important gaps remain in the existing literature. First, many studies rely on national-level time series data, which limits the ability to generalize findings across countries with different institutional settings. Second, while the role of cognitive skills has gained attention, empirical applications using PISA scores in long-run growth models like ARDL-PMG remain scarce, especially in multi-country panel settings. This study addresses these gaps by combining both types of indicators within a unified model and applying it to a balanced EU panel from 1980 to 2024.

3. Data and Descriptive Statistics

3.1. Description of Variables

To meet the objective of our study, we use a balanced panel dataset of the 27 members of the European Union, for the period 1980-2024. The focus on European Union (EU) countries is motivated by their shared economic, educational, and policy frameworks, which enhance comparability. The names of the variables used in this study and their data sources are presented in the following table. The data was obtained from the World development indicators database published by the World Bank.

Table 1: Variables used

Variable	*Description*	*Source*	*Expected Sign*
GDP	GDP growth (annual %)	World Bank [NY.GDP.MKTP.KD.ZG]	+
GFCF	Gross fixed capital formation (% of GDP)	World Bank [NE.GDI.FTOT.ZS]	+
LBR	Labor force, Total	World Bank, [SL.TLF.TOTL.IN], interpolated	+
UA	Unemployment with advanced education (% of total labor force with advanced education)	World Bank, [SL.UEM.ADVN.ZS], interpolated	-
EXS	Expenditure on secondary education (% of government expenditure on education)	World Bank, [SE.XPD.SECO.ZS], interpolated	+
ENS	School enrollment, tertiary (% gross)	World Bank, [SE.TER.ENRR], interpolated	+
EXT	Expenditure on tertiary education (% of government expenditure on education)	World Bank, [SE.XPD.TERT.ZS], interpolated	+
ENT	School enrollment, tertiary (% gross)	World Bank, [SE.TER.ENRR], interpolated	+
PISAM	PISA score at the mathematics test	World Bank, [LO.PISA.MAT]	+

		interpolated	

Source: author's compilation based on data retrieved from the World Bank (World Development Indicators). All variables were processed and interpolated by the author as needed

Descriptive statistics were computed for all variables included in the model, including the dependent variable GDP growth. This allows for a better understanding of the variability in economic performance across countries and over time.

Table 2 - Summary statistics

Variables	*Mean*	*Min*	*Max*	*Std. Dev.*
GDP	*2.33*	*-32.11*	*24.61*	*4.19*
GFCF	*22.61*	*4.45*	*53.22*	*4.05*
LBR	*7614382*	*135236*	*4.40*	*1.00*
UA	*4.88*	*0.79*	*20.85*	*2.94*
EXS	*40.90*	*11.47*	*71.51*	*7.72*
EXT	*20.64*	*0.11*	*36.09*	*6.07*
ENS	*102.74*	*53.52*	*164.07*	*16.83*
ENT	*49.46*	*1.42*	*11.66*	*25.69*
PISAM	*489.23*	*413.44*	*548.35*	*26.11*

Panel: European Union (N=27)
Source: authors computation using Stata 18.00

Given the long-time span of the dataset, several variables presented missing values for specific countries and years. To address this issue and maintain the integrity of the panel structure, linear interpolation was applied within countries using the ipolate command combined with bysort in Stata.

Table 3: Correlation Matrix

Correlation	*GDP*	*GFCF*	*LBR*	*UA*	*EXS*	*ENS*	*EXT*	*ENT*	*PISAM*
GDP	*1*								
GFCF	*0.21*	*1*							
LBR	*-0.12*	*-0.13*	*1*						
UA	*0.01*	*-0.07*	*0.002*	*1*					
EXS	*0.10*	*-0.02*	*0.17*	*0.19*	*1*				
ENS	*-0.05*	*-0.10*	*-0.01*	*0.13*	*-0.01*	*1*			
EXT	*-0.04*	*-0.10*	*0.03*	*0.08*	*-0.01*	*0.30*	*1*		
ENT	*-0.07*	*-0.17*	*0.08*	*0.16*	*-0.06*	*0.55*	*0.47*	*1*	
PISAM	*-0.10*	*-0.01*	*0.10*	*-0.12*	*-0.12*	*0.51*	*0.31*	*0.43*	*1*

Panel: European Union (N=27)
Source: authors computation using Stata 18.00

Table 3 presents the correlation matrix among the variables included in the Panel ARDL model, offering a preliminary assessment of the linear relationships between them. The results show that GDP, the dependent variable, exhibits relatively weak correlations with the explanatory variables, supporting the use of a dynamic model such as Panel ARDL, which captures both short-run adjustments and long-run relationships rather than relying solely on contemporaneous correlations. The strongest positive correlations are observed among education- and innovation-related variables—for instance, between tertiary education (ENT) and education expenditure (ENS) (r = 0.55), as well as between ENT and PISA scores (PISAM) (r = 0.43). These moderate correlations suggest some degree of collinearity that may warrant further investigation (e.g., through Variance Inflation Factor analysis) to ensure the robustness of the model. Overall, all correlation coefficients fall well below the conventional multicollinearity threshold of 0.8, indicating no serious multicollinearity concerns. This supports the simultaneous inclusion of the selected variables in the ARDL framework and sets the stage for exploring their dynamic and long-term effects on economic growth. To ensure the absence of multicollinearity among the independent variables included in the ARDL model, a Variance Inflation Factor (VIF) diagnostic was conducted. The VIF values were calculated after estimating a pooled OLS regression using the same set of regressors. All VIF scores were below the commonly accepted threshold of 5, with a mean VIF of 1.34, indicating no serious multicollinearity issues. Therefore, all variables were retained in the final model specification.

4. Methodology

4.1. Justification for using ARDL PMG Model

The ARDL-PMG (Pooled Mean Group) model was selected due to its ability to handle a mix of I(0) and I(1) variables, which characterizes the current panel dataset. Moreover, the PMG estimator captures both short-run dynamics and long-run equilibrium relationships, allowing for heterogeneous short-run coefficients across countries while constraining the long-run coefficients to be homogeneous. This is particularly suitable for the European Union panel, where countries may respond differently to shocks in the short run but exhibit common long-term structural behaviors.

Table 4 - Unit root test

Variables	*Im-Pesaran-Shin*	*Status*
GDP	*-32.11****	*I(0)*
GFCF	*-5.3619****	*I(0)*
LBR	*-10.9416****	*I(1)*
UA	*-10.6924****	*I(1)*
EXS	*-13.2941****	*I(1)*
EXT	*-13.3280****	*I(1)*
ENS	*-12.2525****	*I(1)*
ENT	*-4.4351****	*I(1)*
PISAM	*-3.4521****	*I(1)*

Panel: European Union (N=27)
Note: IPS test performed with lags (1), with trend
Source: authors computation using Stata 18.00

Given that the explanatory variables are a mix of I(0) and I(1, the ARDL-PMG estimator was employed. This model is suitable for mixed integration orders and avoids the restrictive assumptions required by cointegration tests such as Kao. The significance of the error correction term confirms the existence of a long-run relationship among the variables

4.2. ARDL Model Specification

To investigate the impact of human capital on economic growth, we employ a panel ARDL model using the PMG estimator. This approach allows for heterogeneous short-run dynamics across countries while constraining long-run coefficients to be homogeneous. The following ARDL-PMG model was specified:

$$\Delta GDP_{it} = \theta EC_{i,t-1} - \sum \alpha_j \Delta X_{i,t-j} + \varepsilon_{it} \tag{1}$$

where $\mathrm{EC}_{\mathrm{i,t-1}}$ is the error correction term:

$$EC = X_{i,t-1} - (\beta_i GFCF_{i,t-1} + \beta_2 LBR_{i,t-1} + \beta_3 EXT_{i,t-1} + \beta_4 ENT_{i,t-1} + \beta_5 PISA_{i,t-1}) \tag{2}$$

derived from the long-run equilibrium equation:

$$\Delta GDP_{it} = \beta_i GFCF_{i,t-1} + \beta_2 LBR_{i,t-1} + \beta_3 EXT_{i,t-1} + \beta_4 ENT_{i,t-1} + \beta_5 PISA_{i,t-1} + \varepsilon_{it}$$

The short run follows:

$$\Delta GDP_{it} = \theta EC_{i,t-1} + \alpha_1 \Delta GFCF_{i,t} + \alpha_2 \Delta LBR_{i,t} + \alpha_3 \Delta UA_{i,t} + \alpha_4 \Delta EXT_{i,t} + \alpha_5 \Delta ENT_{i,t} + \varepsilon_{it}$$

The dependent variable is GDP growth, while the explanatory variables include gross fixed capital formation (GFCF), labor participation, education expenditure and enrollment (at secondary or tertiary level), and the performance in PISA mathematics. The model accounts for both short-term fluctuations and long-term relationships among the variables. The selection of variables is guided by economic theory and prior empirical research.

5. Results and Discussion

5.1. Estimation Results

Table 5 presents the results of the ARDL–PMG estimation, where the dependent variable is the GDP growth. The estimated model captures both the short-run dynamics and the long-run equilibrium relationships between economic growth and selected explanatory variables related to labor force and education. The coefficient of the error correction term (ECT) is negative and statistically significant (–0.3176, $p < 0.01$), confirming the existence of a long-run cointegrating relationship among the variables. This implies that approximately 31.76%

of the deviation from the long-run equilibrium is corrected each year, indicating a moderate but meaningful speed of adjustment.

Table 5 –PMG-ARDL
Estimation Results for the determinants of GDP growth, 1980-2024

Long-run Equation			*Short-run Equation*		
Variable	*Coefficient*	*P-Value*	*Variable*	*Coefficient*	*P-Value*
GFCF	*-*	*-*	*D(GFCF)*	*0.6423****	*0.000*
LBR	*1.55e-07*	*0.527*	*D(LBR)*	*3.94e-06*	*0.787*
UA	*-*	*-*	*D(UA)*	*-0.3639*	*0.189*
EXT	*0.0147*	*0.769*	*D(EXT)*	*0.2277****	*0.008*
ENT	*0.0034*	*0.874*	*D(ENT)*	*0.3461****	*0.001*
PISAM	*-0.0804****	*0.000*	*-*		
ECT	*-*	*-*	*ECT*	*-0.3176****	*0.000*

Panel: European Union (N=27)
Source: authors computation using Stata 18.00

Based on the estimated ARDL-PMG model, the long-run cointegrating equation derived from the PMG-ARDL estimates is:

$$\Delta GDP_{it} = 1.55x10^{-7}\, LBR_{i,t-1} + 0.0147\, EXT_{i,t-1} + 0.0034\, ENT_{i,t-1} - 0.0804\, PISA^{***}_{i,t-1} + \varepsilon_{it}$$

The full ARDL error-correction model can be expressed as:

$$\Delta GDP_{it} = -0.3176 EC_{i,t-1} + 0.6423 \Delta GFCF_{i,t} + 3.94x10^{-6} \Delta LBR_{i,t} - 0.3639 \Delta UA_{i,t} + 0.2277 \Delta EXT_{i,t} + 0.3461 \Delta ENT_{i,t} + 18.38492 + \varepsilon_{it}$$

Although the coefficient for PISA performance in the long-run block is negative (–0.0804), the error correction mechanism is negative (–0.3176), which implies that in the long term, an increase in PISA mathematics scores is associated with a positive effect on GDP growth. This reflects a meaningful and significant contribution of cognitive skills to long-run economic performance.

5.2. Long-run and short-run interpretation

In the long run, given the negative ECT coefficient, the signs of the long-run coefficients should be interpreted in reverse. Therefore, PISA mathematics mean shows a statistically significant positive long-run effect on economic growth ($p < 0.01$). This suggests that better student performance in mathematics is associated with higher long-term GDP growth, reinforcing the role of cognitive skills in fostering productivity and development. The significance of the PISA mathematics score in the long-run model underscores the idea that quality of education—as reflected in measurable cognitive skills—is more relevant to economic growth than the quantity of education alone. Simply increasing funding or access to tertiary education does not guarantee improved productivity unless it translates into actual learning outcomes. Therefore, policies aiming to foster growth through human capital accumulation should prioritize educational effectiveness and target skill acquisition, not just institutional expansion. EXP (Expenditure on tertiary education) and ENT (Enrolment in tertiary education) exhibit negative long-run effects on GDP growth; however, their coefficients are not statistically significant ($p = 0.769$ and 0.874, respectively). These findings suggest that, in the long run, government expenditure on tertiary education and enrollment rates may not contribute directly to growth in this dataset. Labor (total labor force) has a long-run coefficient close to zero and is not statistically significant, indicating a negligible direct long-term effect in the presence of education-related factors.

In the short-run, GFCF (Gross Fixed Capital Formation) has a positive and highly significant short-run effect ($p < 0.01$), confirming the crucial role of physical investment in stimulating economic activity. EXP (Expenditure on tertiary education) and ENT (Enrolment in tertiary education) also have positive and statistically significant short-run effects ($p = 0.008$ and $p = 0.001$, respectively). These results suggest that education investment and access at the tertiary level can generate immediate economic benefits, possibly through increased human capital utilization. UA (unemployment with advanced education) and LBR (Labor) do not exhibit statistically significant effects in the short run, indicating that broader labor indicators may have a more structural or indirect influence.

5.3. Robustness Tests

To assess the robustness of the long-run relationship between human capital and economic growth, we introduced two alternative proxies for education: secondary education public expenditure (EXS) and secondary school enrolment (ENS). These variables were added alongside the previously used cognitive skills proxy (PISA). Despite the inclusion of these additional education indicators, the PISA mathematics scores remain statistically significant and negatively associated with GDP per capita growth in the long run ($p = 0.005$). This reinforces the central claim of the analysis: education quality, rather than mere spending or enrolment levels, plays a more critical role in long-term growth. Meanwhile, neither EXS nor ENS exhibited significant effects in the long-run specification, suggesting that traditional quantity-based measures of education alone may be insufficient to explain long-run economic performance.

The error correction term (ECT) is negative and highly significant (-0.2693, $p < 0.01$), indicating a stable long-run equilibrium exists among the variables. About 27% of the deviations from this equilibrium are corrected annually, supporting the validity of the ARDL framework. The results from the PMG-ARDL estimation confirm that PISA mathematics scores (PISAM) remain a significant long-run determinant of economic growth, consistent with previous model specifications. The coefficient is negative and statistically significant (-0.0595, $p < 0.01$), reinforcing the idea that higher cognitive skills, as captured by international assessment results, are crucial for sustaining long-term economic performance., this result holds even after including additional education-related controls such as secondary education expenditure (EXS) and enrollment rates (ENS), which are found to be insignificant in the long run. In the short run, gross fixed capital formation (GFCF) continues to exert a strong positive and statistically significant impact on growth (0.6416, $p < 0.01$), while secondary school enrollment (ENT) also shows a meaningful and positive association (0.0130, $p < 0.05$). These results point to the importance of physical investment and short-term improvements in educational access for boosting output.

Table 6 –PMG-ARDL Estimation Results for the determinants of GDP growth, 1980-2024

Long-run Equation			Short-run Equation		
Variable	Coefficient	P-Value	Variable	Coefficient	P-Value
GFCF	-	-	D(GFCF)	0.6416***	0.000
LF	-3.38e-08	0.908	D(LBR)	0.0001	0.110
UA	-	-	D(UA)	-0.3278	0.304
EXS	0.0171	0.613	D(EXT)	-0.0057	0.953
ENS	-0.0202	0.541	D(ENT)	0.0130**	0.016
PISAM	-0.0595***	0.005	-		
ECT	-	-	ECT	-0.2693***	0.000

Panel: European Union (N=27)
Source: authors computation using Stata 18.00

6. Conclusion

This study investigates the relationship between human capital, investment, and economic growth in EU countries using an ARDL–PMG framework applied to panel data from 1980 to 2024. The results confirm the existence of a long-run cointegrating relationship. In particular, student performance measured by PISA scores exhibits a positive and statistically significant effect on GDP growth in the long term. By contrast, variables such as tertiary education spending and enrollment are found to be insignificant in the long run but show positive effects in the short run. Gross fixed capital formation remains a key short-run driver of growth, while some labor market indicators (e.g., unemployment with advanced education) have limited explanatory power.

Based on the findings, several policy directions emerge. First, enhancing educational quality—particularly in core competencies like mathematics—is crucial for fostering sustainable long-term growth. Governments should go beyond increasing funding or access and instead prioritize outcome-based reforms that boost learning effectiveness. Second, while short-run benefits can be derived from investment in tertiary education, such efforts must be aligned with labor market needs and monitored for efficiency. Finally, broader economic growth strategies should integrate human capital development policies that combine skill-building with educational equity and quality assurance.

However, this study is subject to several limitations. First, the availability of annual data for certain educational quality indicators (e.g., PISA, Barro-Lee) is limited, which required the use of interpolation or country-level means—potentially reducing the precision of estimated effects. Second, the model assumes long-run homogeneity across EU countries, which may not fully capture cross-country institutional differences. Third, the analysis focuses on linear relationships and does not explore potential threshold or nonlinear effects of education on growth. Future work will include further robustness checks such as estimations for sub-samples, sub-periods and including dummies for financial crisis such as the one from 2009-2010 and the pandemic year 2020. Also, we intend to employ alternative estimators in order to better capture the characteristics of our data.

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