ESRI Working Paper No. 812

October 2025

An Industry-Level Measure of Quality-Adjusted Human Capital in the European Union

Juan Duran[a,b], Michelle Alicia Jordan [c,b], and Iulia Siedschlag[a,b]

a: Economic and Social Research Institute (ESRI)
b: Department of Economics, Trinity College Dublin
c: School of Research, Sciences Po

* Corresponding author:
Juan Duran
Economic and Social Research Institute (ESRI)
Whitaker Square, Sir John Rogerson's Quay, Dublin 2
Email: juan.duranvanegas@esri.ie

An Industry-Level Measure of Quality-Adjusted Human Capital in the European Union*

Juan Duran[1, 2], Michelle Alicia Jordan[3, 1], and Iulia Siedschlag[1, 2]

[1]The Economic and Social Research Institute (ESRI)
[2]Department of Economics, Trinity College Dublin
[3]School of Research, Sciences Po

October 2025

Abstract

This paper examines the role of human capital in driving labour productivity growth across industries in the EU and the UK from 2010 to 2021. Building on Égert et al. (2022), we introduce a novel quality-adjusted human capital (QAHC) measure that combines both the quantity and quality of education, incorporating data from OECD's Programme for International Student Assessment (PISA) and Programme for the International Assessment of Adult Competencies (PIAAC) on test scores and mean years of schooling, alongside employment composition from the EU KLEMS & INTANProd database. We show that this measure yields reasonable output elasticities in a Stochastic Frontier model and that it has statistically significant link to labour productivity growth, particularly in goods-producing industries, unlike traditional proxies such as education attainment shares.

Keywords— Human Capital, Labour Productivity, Education, Education Quality

JEL Codes— J24, I21, I26

*This research is part of the EFFEct project funded from the European Union's Horizon Europe Programme (Grant No. 101129146). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the granting authority. Neither the European Union nor the granting authority can be held responsible for them.

1 Introduction

In recent decades, developments in growth theory have placed human capital at the centre of explanations for international differences in income. Foundational works by Lucas (1988), Romer (1990), and Mankiw et al. (1992) have established human capital as a key driver of long-run growth, and have demonstrated its importance in accounting for observed variation in living standards across countries. Reflecting this consensus, policy agendas also prioritise human capital: education and skills reforms are repeatedly identified as key priorities for both advanced and emerging economies in international reports (OECD, 2019, 2023a).

Despite significant progress in theory, measures of human capital used in empirical research have struggled to explain macroeconomic variables in a satisfactory manner, a challenge that has been referred to as the "human capital paradox" (Botev et al., 2020). At the macro level, efforts have recently focused on bringing together measures of both the quantity and quality of human capital (Égert et al., 2022; Angrist et al., 2020; Botev et al., 2019; Fournier & Johansson, 2016). In particular, Égert et al. (2022) assemble a measure incorporating quality (adult and student test scores) and quantity (mean years of schooling) at the country level and find that the elasticity of the stock of human capital with respect to the quality of education largely outsizes that of quantity. At the industry level, while there have been improvements in measuring investments in continuous training (O'Mahony, 2012), the existing literature using explicit measures has only considered the quantity of education proxied by years of schooling or educational attainment (Ciccone & Papaioannou, 2009).[1]

In this paper, we contribute to the literature by constructing a quality-adjusted human capital (QAHC) measure for 19 one-digit NACE industries across 21 EU countries and the UK between 2010-2021. We follow Égert et al. (2022) and use country-level data on the quality of education, proxied by adult and student test scores, and the quantity of education, proxied by mean years of schooling, across ten age cohorts. We then estimate the elasticities of adult skills with respect to student test scores and mean years of schooling and construct the human capital measure as a cohort-weighted average of student test scores and mean years of schooling using employment shares by age from the EU-KLEMS & INTANProd database. Therefore, our measure leverages cohort-country differences in the quality and quantity of education with country-industry variation in the employment composition over time.

To determine the link of our measure with industry-level productivity, we use two complementary approaches. First, we use a Stochastic Frontier model to estimate the output elasticities of input accumulation. Our analysis reveals that including QAHC yields output elasticities with respect to

[1] Another strand of the literature estimates human capital at the individual or household level relying on wages, schooling years, and labour experience and generally finds robust evidence on the impact of education on earnings at the micro level. See Folloni & Vittadini (2010) for a survey of this literature.

human capital that are in line with prior macroeconomic literature (0.36% to 0.44%). Second, we examine the drivers of labour productivity growth more broadly by considering the accumulation of both tangible and intagible capital. While most human capital proxies display positive but statistically insignificant effects, QAHC stands out as it exhibits a significant positive association with productivity growth in goods-producing sectors alongside non-ICT tangible capital and intangible economic competencies capital.

The remainder of the paper is structured as follows: Section 2 presents a literature review of different approaches to measure human capital at the macro and industry level; Section 3 describes the data; Section 5 presents the analysis of the link between the new human capital measure and industry-level productivity; Section 6 concludes.

2 Literature Review

In this section, we summarize selected work on the literature on human capital that employ similar approches and measures to the ones employed in this paper. For more comprehensive literature reviews see Wilson & Briscoe (2004), Folloni & Vittadini (2010), and Benos & Zotou (2014).

2.1 Country-level Measures

Much of the modern empirical research has attempted to proxy human capital using a simple measure, mean years of schooling in a country. This measure quantifies the accumulated educational investment in the workforce by treating human capital as proportional to years spent in formal education (Benos & Zotou, 2014), under the implicit assumption that rates of return to education do not vary across countries or over time (Botev et al., 2019). Mean years of schooling are often adjusted to account for decreasing marginal returns to education, traditionally through piecewise linear transformations (see, for instance, Hall & Jones, 1999), based on estimated rates of return to education (for example, from Psacharopoulos, 1994; Psacharopoulos & Patrinos, 2004; Montenegro & Patrinos, 2014). Other studies focused on improving the quality of the underlying attainment data. de la Fuente & Doménech (2006) argue that the quality of data used in estimations of human capital in growth regressions is a major contributor to the lack of economically or statistically significant estimates. The authors document substantial inconsistencies across widely used attainment datasets, including in the widely used Barro & Lee (2001) series, such as implausible short-run jumps and breaks attributable to shifts in statistical classification. Leveraging previously unpublished OECD materials and national statistical sources, they compile a new educational attainment series for 21 OECD countries and find a systematic positive relationship between data quality and the magnitude and precision of the human capital coefficient, suggesting that measurement error is a central driver of weaker empirical results. More recently, polynomial specifications have been used to achieve a smoother adjustment in rates of returns across education levels (as in Morrisson & Murtin, 2013).

In practice, most human capital measures relying on mean years of schooling are often not statistically significant and can even display a negative sign (Égert, 2017). This issue is also reflected in the wider literature, with a meta-analysis of 60 studies from 1989 to 2011 showing that approximately 20% of estimated coefficients for human capital had the "wrong" (negative) sign (Benos & Zotou, 2014).

Botev et al. (2019) propose an improved proxy for human capital that incorporates both time and country variation in returns to education. By combining country-specific rates of return with updated data on mean years of schooling, they capture substantial heterogeneity and temporal dynamics in returns to education. Their results show that returns to education have increased over time in OECD and BRICS countries. Notably, the authors identify a U-shaped profile of returns to additional years of education, with higher returns at the primary and tertiary levels compared to secondary, in contrast to much of the earlier literature which assumed a monotonic decline. They identify an optimal specification for capturing time and country heterogeneity, and demonstrate a positive, statistically significant, and robust relationship between their human capital measure and multi-factor productivity.

Despite such advances, adjusted measures of mean years of schooling as a proxy for human capital remain subject to criticism. This approach makes a strong assumption that learning translates directly into schooling, while there is evidence that the gap between years of schooling and actual learning can be considerable and vary widely across countries (UNESCO, 2017; Angrist et al., 2020). To address this limitation, some empirical studies employ learning-adjusted years of schooling, combining measures of educational quantity and quality. In the literature, this is typically implemented either as two separate indicators, one for quality and one for quantity, or as a composite measure formed by multiplying mean years of schooling by a proxy for education quality, such as standardised student test scores that are benchmarked to a reference country. The underlying rationale is that learning outcomes may be more closely linked to economic growth than schooling alone.

Botev et al. (2019) attempt to incorporate quality into their human capital proxy by multiplying their mean years of schooling measure (adjusted for time- and country-specific returns) by the ratio of a country's student test scores to those of the USA, which serves as the benchmark in a sample year (2000). However, they do not find robust evidence of a positive relationship between productivity and this quality-adjusted measure, with most estimated coefficients negative. Additionally, as Égert et al. (2022) note, Botev et al. (2019)'s approach does not provide a clear separation between the quantity and quality components underlying the changing rate of return to education. Moreover, observed differences in rates of return across countries and over time may be partly driven by institutional factors or other influences, meaning that these rates may not reflect potential productivity gains that could be realised through policy alone.

Fournier & Johansson (2016), in contrast, find a significant positive effect when using the product of mean years of schooling and student test scores as a composite measure in explaining long-term GDP per capita. However, a limitation of this approach is that it relies on PISA scores from just one single year (2006), implicitly assuming that education quality is constant across all workforce cohorts and over time. When both quality and quantity components are included separately, the quality component has a larger and more statistically significant effect, while the quantity component becomes smaller and less significant. This seems to confirm the suggestion that education quality may be a more important driver of growth than years of schooling alone.

Angrist et al. (2020) develop a stock measure of human capital using a Mincerian framework, weighting mean years of schooling by an estimated return of 0.10 per year (from Psacharopoulos & Patrinos, 2004) and learning (student test scores) by 0.20 per standard deviation (from Hanushek & Zhang, 2009). Incorporating learning quality substantially improves the explanatory power of human capital for cross-country differences in output per worker, and their quality-adjusted measure exhibits a much stronger and more statistically significant association with economic growth than traditional measures.

However, the learning-adjusted years of schooling approach has its own limitations and has attracted several methodological criticisms. As Égert et al. (2022) observe, the weights assigned to quality and quantity in these composite measures are typically imposed rather than empirically estimated, often assumed to be equal, or, as in Angrist et al. (2020), taken from returns reported in the microeconomic literature. Furthermore, student test scores generally capture the skills of current students rather than those of the existing workforce. As a result, improvements in education quality will only gradually affect economic outcomes as new cohorts enter the labour market. It is therefore important to interpret current test scores as a flow into the broader stock of human capital, rather than as a direct measure of the skills currently embodied in the workforce. This distinction is particularly relevant for assessing the short-run macroeconomic impact of education quality reforms, since gains in student learning will be reflected in productivity only over time.

Building on the work of Angrist et al. (2020), Égert et al. (2022) address key limitations of earlier composite measures by empirically estimating the relative contributions of educational quality and quantity to human capital. The authors regress adult cognitive skills (from PIAAC) on both past student test scores (from PISA and World Bank datasets[2]) and mean years of schooling by cohort, directly estimating the respective elasticities. To ensure accuracy, the authors lag student test scores appropriately, so that each cohort's adult outcomes are matched to the relevant historical student-level assessments, and employ a heterogeneous approach for older cohorts to allow for the depreciation of skills with age. Their findings indicate that the elasticity of human capital with respect to the quality of education is three to four times greater than that of quantity, chal-

[2]See Altinok et al. (2018) and Angrist et al. (2020).

lenging previous assumptions of equal or other arbitrarily imposed weights in composite human capital measures. Incorporating these empirically derived elasticities, the authors construct a new cohort-weighted human capital measure by aggregating past student test scores and mean years of schooling for all current working-age cohorts, weighted by their shares in the workforce. This measure is shown to be more strongly and robustly associated with multi-factor productivity than traditional proxies. Importantly, their analysis suggests that while both educational quantity and quality matter, improvements in quality have a far greater potential impact on long-run productivity, though these gains accrue gradually as successive cohorts enter the labour market.

Beyond issues of measurement, a complementary strand of this literature examines how human capital affects technology diffusion and convergence to the world technology frontier. Madsen (2014) emphasises the central role of human capital its affects on productivity directly and indirectly through the adoption of frontier technologies. Using a harmonised series of educational attainment for 21 industrialised economies over 1870–2009, the author finds a strong positive link between productivity growth and the interaction of human capital with distance to the frontier. Whilst changes in human capital, its level, and frontier distance are all positively associated with growth, once the interaction is included, the effect of human capital levels becomes negative and distance becomes insignificant. This suggests that education facilitates convergence but yields only temporary growth effects once convergence is achieved. To capture education quality, Madsen (2014) incorporates teacher–pupil ratios adjusted for weekly hours, finding similar results to the baseline and concluding that resource availability has little effect on productivity. However, this quality adjustment is limited, since it captures only one dimension of educational quality, relies on scarce data for the nineteenth century, and uses average hours worked in the population as a proxy for teacher hours, which may be imperfect. Despite the limitations to the quality adjustment, the findings reinforce the fact that human capital primarily supports productivity growth by enabling technology adoption and convergence to the frontier, rather than by permanently raising growth rates once the frontier is reached.

2.2 Industry-level Measures and Studies

Studies at the industry and sector level have focused on differentiating between initial education before individuals join the workforce and investments in continuous education while being part of the workforce (O'Mahony, 2012; Wilson & Briscoe, 2004). The education component of human capital is typically measured with educational attainment or mean years of schooling sourced from labour surveys (Wilson & Briscoe, 2004).

In this line, Ciccone & Papaioannou (2009) examines whether human capital shapes sectoral growth patterns, particularly through facilitating the adoption of skilled-labour-augmenting technologies. Their industry-level approach leverages variation across manufacturing sectors with different schooling intensities measured as the average years of employee schooling across 28 industries, as well as the share of employees with at least twelve years of education (secondary school completion) and at least sixteen years (college completion), based on 1980 US Census microdata. Due to limited international data, they proxy industry human capital intensities in all countries using the US distribution, arguing that cross-industry differences in human capital intensity observed in the US broadly reflect global patterns. They find that countries with higher initial education levels, as well as those with faster improvements in schooling, experienced stronger value-added and employment growth in schooling-intensive industries during the 1980s and 1990s. In addition to educational quantity, they incorporate a human capital quality index from Hanushek & Kimko (2000) at the country level based on six international mathematics and science assessments and find that higher schooling quality is associated with faster growth in schooling-intensive sectors, with the effect particularly pronounced in open economies. However, when both quality and quantity interactions are included, the quality component remains significant only for employment growth, not value-added growth, suggesting its independent contribution is less robust in this setting.

Extending this perspective, other industry-level studies have examined how human capital conditions technology diffusion from the world frontier. Kneller (2005) provides evidence that the productivity gains from frontier technology depend both on countries' absorptive capacity and their geographical distance from the source of innovation. Human capital, measured by mean years of schooling in the population aged 25 and over from Barro & Lee (2001), enters the model through the absorptive capacity channel. The results show a positive and statistically significant interaction between foreign productivity and human capital, suggesting that the productivity benefits of frontier innovation are greater in countries with higher levels of human capital and are attenuated by greater geographical distance from the frontier.

Similarly, Kneller & Stevens (2006) apply a stochastic frontier framework to a similar unbalanced panel of nine manufacturing industries in twelve OECD economies (1974–1991) to examine whether differences in absorptive capacity account for cross-country productivity gaps. In this paper, human capital is proxied by the mean years of schooling in the population (de la Fuente & Doménech, 2006). The results indicate that human capital has a large and statistically significant direct effect on output, roughly three to four times larger than the effect of the world technology stock (R&D). Through the efficiency channel, human capital also significantly reduces technical inefficiency, with heterogeneous gains across industries (particularly pronounced in machinery and equipment, other manufacturing, and chemicals).

Corvers (1997) complements these findings, by examining how skill composition relates to labour productivity across fifteen manufacturing sectors in seven EU countries between 1988 and 1991. The employment share of highly skilled workers is positively and statistically significantly associated with the level of sectoral labour productivity, with magnitudes that exceed the average high-skill shares across manufacturing. By contrast, the medium-skill share is positive but not statistically significant in levels, and changes in either the high- or medium-skill shares are not significantly related to productivity growth over the 1988–1991 period.

In sum, advances in the human capital measurement literature stress the need to incorporate quality alongside quantity, and industry-level evidence points to human capital as a key channel for technology diffusion and efficiency gains. However, the most recent developments in human capital measurement have not yet been applied in sectoral settings, and there is limited work combining quality-adjusted measures with industry data.

3 Data

In this section, we detail the data sources employed to construct the industry-level human capital measure and the subsequent productivity analysis.

3.1 Adult Test Scores

The Programme for the International Assessment of Adult Competencies (PIAAC), administered by the OECD, is a large-scale, international household survey testing literacy, numeracy, and problem-solving skills of adults aged 16 to 64 (OECD, 2024).

Two cycles of PIAAC have been conducted thus far: Cycle 1 between 2011 and 2017, and Cycle 2 in 2023. Results are reported by country, survey cycle, and ten five-year age cohorts, allowing for detailed age-cohort analysis.

We calculate the average skill score for each country, cycle, and cohort, combining results from both cycles. Using both cycles increases coverage across EU-28 countries; however, some countries are missing entirely (Bulgaria, Cyprus, Luxembourg, Malta, Romania) or only participated in one cycle (Greece and Slovenia in Cycle 1; Croatia, Latvia, Portugal in Cycle 2). Additionally, only England and Flanders participated for the United Kingdom and Belgium respectively; these are recoded as national-level data, but this limitation should be kept in mind.

3.2 Student Test Scores

For our measure of student skills, we use the OECD's Programme for International Student Assessment (PISA), which tests 15-year-olds in mathematics, reading, and science every three years from 2000 to 2022 (OECD, 2023b). Participation in PISA is uneven across EU-28 countries and survey waves, resulting in gaps in the panel. We average the three subject scores for each country and year to form our student skills measure.

To extend coverage before 2000, we incorporate a dataset compiled by Altinok & Diebolt (2024), which links standardised, psychometrically robust international and regional achievement test scores at five-year intervals from 1970, enabling comparability with PISA scores.

STS coverage before 1990 is not available for Slovenia, the Slovak Republic, Lithuania, Latvia, Estonia, Croatia, and Czechia. To address other missing country-year observations and improve panel balance, we apply linear interpolation for countries with historical test scores in 1995 that lack PISA participation in every survey year, bridging gaps between the last STS observation and subsequent PISA waves.

3.3 Mean Years of Schooling

To capture educational attainment quantity, we use mean years of schooling (MYS) data from the Wittgenstein Centre (Wittgenstein Centre for Demography and Global Human Capital, 2018), based on Lutz et al. (2018). The data covers the EU-28 countries and is available in ten five-year age cohorts ranging from 15 to 64 years, similar to PIAAC's cohort structure.

Minor differences exist between cohort age brackets between MYS and PIAAC: cohort 1 covers ages 15–19 rather than 16–19, and cohort 10 covers ages 60-64 rather than 60-65, but these are unlikely to significantly affect results.

Linear interpolation was applied for the years in which both PIAAC cycles were administered (2011, 2014, 2017, and 2023), since the original data is only available at five-year intervals.

3.4 Country-Level Data

To weight the country-level human capital measures appropriately, we incorporate data on the active population by country and five-year age cohort from Eurostat (2025). This dataset provides annual observations of the number of active persons (in thousands) for each country, disaggregated by five-year age groups, covering 1995 to 2024. For the United Kingdom, data is available only through 2019.

Each five-year age group was assigned a cohort number from 1 to 10 to ensure consistency with the PIAAC and MYS data. Minor discrepancies exist between cohort definitions: cohort 1 covers ages 15–19 rather than 16–19 in PIAAC, and cohort 10 covers ages 60–64 rather than 60–65. Similar to the MYS data, these differences are unlikely to materially affect the analysis.

For each country and year, the number of persons in each cohort was divided by the total active population to calculate cohort proportions. This weighting procedure follows Égert et al. (2022) and ensures that skill and schooling measures accurately reflect the demographic composition of the active labour force in each country.

3.5 Industry-Level Data

To capture the distribution of employment across age cohorts and industries, we use the 2025 release of the EU KLEMS & INTANProd dataset (Bontadini et al., 2023). This source provides detailed employment shares by age and education levels for industries across EU-28 countries, covering the period 2008–2021.

We construct the measure for 19 NACE industries, covering sections A through S, and exclude the categories Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T) and Activities of extraterritorial organisations and bodies (U).

For each country-industry pair, we calculate the proportion of total employment with upper secondary education or higher accounted by the three age cohorts defined in EU KLEMS & INTANProd: 15–29, 30–49, and 50–65 years. Additionally, we compute the share of employees within each industry and country who have attained intermediate level (upper secondary and post-secondary non-tertiary education, levels 3 and 4 of the International Standard Classification of Education - ISCED) or higher and high (first and second stage of tertiary education, ISCED levels 5 and 6) education, to enable comparison with our industry-level human capital stock measure.

In addition to these employment composition metrics, we also employ data on value-added and capital stocks in our productivity analysis. A detailed description of the construction of these variables and the dataset is provided by Bontadini et al. (2023) and Stehrer (2024).

4 An Industry-Level Measure of Quality-Adjusted Human Capital

We build on Égert et al. (2022) and start by estimating the relative weights of the quality and quantity factors explaining adult skills across cohorts. To do so, following Égert et al. (2022), we first match PIAAC scores to the corresponding PISA scores and MYS for each country (c), age cohort (k), survey year (T). Since years can slightly vary across datasets, we apply 1-2 year lags or leads as needed. For example, a 25-year-old Irish PIAAC respondent in 2011 is matched to Ireland's PISA score from 2001 (when they were 15) and the corresponding MYS for that cohort in 2001, applying a one-year lag since PISA assessments occur triennially. In order to maximize the sample size, we focus on cohorts 1 to 8 (up to 50-54 years-old) to include countries with available information on the PIAAC Cycle 2 in 2023 but no available information on PISA results before 1990. Once we have performed the matching, we estimate the following equation:

$$\log\left(ATS_{k,c,T}\right) = \beta_0 + \beta_1 \log\left(STS'_{k,c,T}\right) + \beta_2 \log\left(STS'_{k=8,c,T}\right) + \beta_3 \log\left(MYS_{c,T}\right) + \varepsilon_c \tag{1}$$

where $ATS_{k,c,T}$ denotes adult test scores of age cohort k in country c at time T, $STS'_{k,c,T}$ denotes the corresponding matched student test scores for that cohort at the age of 15, $MYS_{c,T}$ is the mean years of schooling in the country as a proxy of the quantity of education.The coefficients β and γ capture the elasticity of cohort-specific adult skills with respect to the quality and quantity proxies of education, while δ is a decay parameter that captures potential decreases in the relationship between adult skills and student test scores for the oldest cohort.

While the constant term β_0 in Eq. 1 country-invariant in Égert et al. (2022), we allow it to vary by groups of country-wave observations that we determine using the k-means partitional clustering algorithm (Makles, 2012). The Within-group Sum of Squares (WSS) component of the analysis of variance (ANOVA) for ten clusters plotted in Figure A1 indicates that the optimal solution occurs at $g = 4$, after which the reduction in WSS and the increase in the explained proportion of total variance is very small. Figure A2 presents the scatterplot matrix of the clusters across for the three variables.

Table 3 presents the estimated coefficients. Column 1 displays the estimates of the baseline version of Eq. 1, while Column 2 includes country and PIAAC cycle fixed-effects. In Column 3, we present the estimates of our preferred specification in which we allow the intercepts to vary by cluster and omit country and wave fixed effects since the clustering method was done at the country-wave level. The estimates of this specification are statistically significant at the 1% level and are very similar to the ones in Égert et al. (2022) (included in parentheses): the intercept varies between 3.589 to 3.704 (3.732), and the elasticities with respect to student test scores and mean years of schooling are 0.279 (0.278) and 0.082 (0.083), respectively. The decay parameter of -0.006 is less comparable as Égert et al. (2022) include interaction terms for cohorts 50-59 (-0.009) and 60-65 (-0.015).

We now turn to construct the industry-level QAHC measure using the estimated elasticities as weights and EU KLEMS & INTANProd data on labor composition of workers with formal qualifications by age cohort in the following equation:

$$\log(QAHC_{j,g,c,t}) = \hat{\beta}_{1_g} + \sum_{k=1}^{7} \phi_{k,c=1,2,t} \hat{\beta}_1 \log(\overline{STS'}_{k,c}) \tag{2}$$

$$+ \phi_{k=3,c,t} (\hat{\beta}_1 + \hat{\beta}_2) \log(\overline{STS'}_{k=8,c}) + \hat{\beta}_3 \log(MYS_{c,t}) \tag{3}$$

where j indexes 1-digit NACE industries, g indexes clusters, $\phi_{k,c,t}$ are the labor shares of each cohort in total employment of industry j, country c and year t, while $\overline{STS'}_{k,c}$ denotes the mean student test scores across waves for each cohort k.

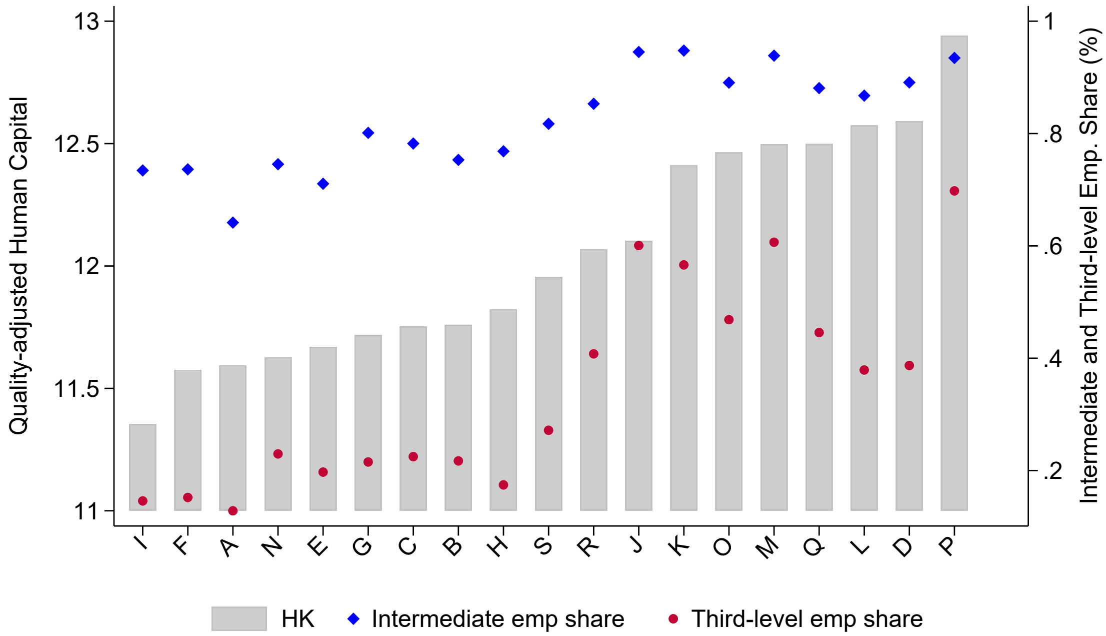
Table 1: Weights Estimates

	(1)	(2)	(3)
β_0	0.703	2.976***	3.586***
	(0.529)	(0.513)	(0.491)
Cohort 2			0.083***
			(0.008)
Cohort 3			0.115***
			(0.008)
Cohort 4			0.071***
			(0.007)
log(STS′)	0.759***	0.381***	0.279***
	(0.089)	(0.084)	(0.081)
log(STS′) $\times$ Cohort 50-54	-0.006***	-0.006***	-0.006***
	(0.002)	(0.001)	(0.001)
log(MYS)	0.068**	0.106***	0.082***
	(0.033)	(0.028)	(0.025)
Observations	359	359	359
Adjusted R^2	0.268	0.634	0.577
Country FE		✓	
Cycle FE		✓	

Notes: Number of countries=23. Heteroscedasticity-robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

We standardise the resulting measure and re-scale it to the mean years of schooling range for ease of exposition. Figure 1 presents the mean QAHC by industry over the studied period and compares it to the mean employment share of workers with intermediate and higher educational attainment. Patterns across industries are similar when comparing the new measure with the employment share of workers with intermediate or higher educational attainment, while there are larger differences when contrasting it to the employment share of workers with high education. In particular, our measure assigns higher positions to electricity and gas supply (D), real estate activities (L), and health and social work (Q), relative to information and communication (J), financial and insurance activities (K), and professional, scientific and technical activities (M).

Figure 1: Mean QAHC per Industry, 2010-2021



Notes: The graph plots the mean measure of QAHC between 2010-2021 (grey bars) calculated following Eq. 1 using the weights estimated in Column 3 of Table 3 and labour shares of workers with formal qualifications by three age cohorts (15-25, 30-49, and +50) from the labour module of the EU KLEMS & INTANProd database. The measure is re-scaled to the MYS range. The mean employment share of workers with intermediate and higher (blue diamonds) and higher (red dots) educational attainment over the same period are plotted in the secondary axis for comparison.

5 QAHC and Labour Productivity

In this section, we examine the relationship of the industry-level QAHC and labour productivity using two complementary frameworks. First, following Pieri et al. (2018), we use a Stochastic Frontier Model (SFM) to estimate the output elasticities of input accumulation using a translog production function:

$$y_{j,c,t} = \gamma_i x_{i,j,c,t} + \gamma_{i,n} x_{i,j,c,t} \times x_{n,j,c,t} + tfp_{j,c,t} + \mu_j + \mu_c + v_{j,c,t} \tag{4}$$

where x denotes production inputs in industry j, country c, and year t indexed with i and n: labour (hours worked), human capital, and tangible (ICT and non-ICT capital). The interaction terms then include squared and cross-product among inputs. Additionally, account for time-invariant country and industry characteristics by including fixed-effects (μ_j, μ_c). Total Factor Productivity (TFP) is modelled as a function of R&D and ICT capital stocks and the inefficiency term capturing the distance from the production boundary ($u_{j,c,t}$) which is assumed to be positive, identically distributed as a half normal and independent from the error term $v_{j,c,t}$. In turn, R&D and ICT capital stocks can also affect efficiency through the inefficiency term variance function.

Second, following Adarov & Stehrer (2019), we examine the drivers of labour productivity growth across industries more broadly by distinguishing between labour (hours worked), tangible (ICT and non-ICT) capital, and intangible capital (economic competencies, Software and data bases -DB-, research and development -R&D-, and other innovative properties) alongside the QAHC and other proxies of human capital available on EU KLEMS & INTANProd. In this part of the analysis, we start from the following production function:

$$Y_{j,c,t} = A_{j,c,t} L_{j,c,t} H_{j,c,t} T_{j,c,t} I_{j,c,t} \tag{5}$$

where $Y_{j,c,t}$ is the value-added, Aj, c, t is a multi-factor productivity shifter, $L_{j,c,t}$ denotes labour inputs, $H_{j,c,t}$ denotes human capital, and $T_{j,c,t}, I_{j,c,t}$ denote sets of tangible and intangible capital inputs, respectively. Dividing by labour on both sides of Eq. 5, taking logs, and differentiating we get:

$$\Delta y_{j,c,t} = \theta_0 + \theta_1 \Delta h_{j,c,t} + \Lambda \Delta T_{j,c,t} + \Omega \Delta I_{j,c,t} + \mu_{j,t} + \mu_{c,t} + u_{j,c,t} \tag{6}$$

where we also add industry-year and country-year fixed effects ($\mu_{j,t}, \mu_{c,t}$), while $u_{j,c,t}$ is an error term that also models the productivity shifter term Aj, c, t. Alongside our QAHC measure, we use alternative human capital measures available on EU-KLEMS & INTANProd: i) the log change in labour services, a Törnqvist volume index of hours worked weighted by the nominal input shares of each age and education labour type; ii) the labour composition effect, obtained from deducing the log change in hours worked from the log change in labour services (Stehrer et al., 2019); iii) the change in the labour share of workers with secondary or higher, and higher educational attainment. Moreover, we consider the interactions between each human capital measure and each intangible capital component to capture any complementarity effects.

Through this section, we restrict the analysis to the market economy excluding agriculture and mining (C-S, excluding O, P, and Q) over the period 2010-2021.

5.1 Stochastic Frontier Analysis

Table 3 presents the estimation results of the SFM. Odd columns report the baseline specifications without inefficiency determinants, while even columns include R&D and ICT capital stocks as determinants of the technical inefficiency component variance function.

The output elasticities of the production function in Columns (1) and (2) - Panel A are slightly lower than previous estimates in the literature although not directly comparable as most studies focus on manufacturing industries. Estimates of the inefficiency variance distribution in Column (2) - Panel B are consistent with Pieri et al. (2018) finding that ICT and R&D reduce technical inefficiency. Similarly, the output elasticities of these types of technological capital fall in panel A as we account for the efficiency effects in Column (2) compared to Column (1), with the input accumulation effect of ICT being no longer statistically significant.

We include QAHC as an additional production input in Columns (3) and (4). According to the estimates in Panel A, the elasticity of output with respect to human capital ranges between 0.36% to 0.44%, which falls within the range of 0.2%-0.6% found in previous macroeconomic studies (Mankiw et al., 1992; de la Fuente & Doménech, 2006; Cohen & Soto, 2007). The output elasticity estimates of other production inputs remain stable, while the coefficient of R&D increases in magnitude relative to the one of ICT in the inefficiency variance distribution (Column 4, Panel B).

5.2 Labour Productivity Growth Drivers

Table 3 presents the estimation results of specification Eq. 6. In each Column (1)-(5), we estimate the model using a different industry-level measure of human capital and standardize these coefficients for ease of interpretation. Overall, results point at tangible non-ICT and intangible economic competencies and innovation property as the main drivers of labour productivity growth. Regarding human capital, all signs are positive except for higher educational attainment, but only the QAHC coefficient is statistically significant at the 5% level. According to this estimate, a one standard deviation increase in QAHC (equivalent to about 0.85% increase) is associated with a 0.004 percentage point (pp) increase in labour productivity growth. Regarding the interaction effects, we do not find robust evidence of complementarities.

In table Table 4, we further examine the results by considering heterogeneity across goods-producing sectors (C-F) and services (O-S). While we do not find a statistically significant association for services, the association between our QAHC measure and labour productivity growth in the case of goods sectors is stronger (0.009% increase per each standard deviation) and statistically significant at the 5% level.[3] Non-ICT capital and economic competencies remain inputs associated with labour productivity growth.

[3] It is possible that the effecs are stronger for knowledge-based industries compared to other service sectors. In our case, the results do not differ substantially when looking at 1-digit business services J-N versus other services. These results are available from the authors upon request.

Table 2: STOCHASTIC FRONTIER AND EFFICIENCY ESTIMATES

	Panel A: Frontier			
	(1)	(2)	(3)	(4)
ln(ICT)	0.028***	-0.001	0.032***	-0.000
	(0.0065)	(0.0078)	(0.0066)	(0.0077)
ln($Non-ICT$)	0.183***	0.184***	0.181***	0.184***
	(0.0101)	(0.0103)	(0.0100)	(0.0103)
ln($Labour$)	0.505***	0.514***	0.523***	0.535***
	(0.0156)	(0.0155)	(0.0158)	(0.0157)
ln($R\&D$)	0.012***	0.008*	0.011***	0.009**
	(0.0042)	(0.0045)	(0.0042)	(0.0044)
ln($QAHC$)			0.443***	0.361**
			(0.1481)	(0.1452)
Constant	-0.198***	-0.121***	-0.167**	-0.087**
	(0.0672)	(0.0386)	(0.0789)	(0.0398)
	Panel B: Inefficiency			
ln(ICT)		-0.502***		-0.595***
		(0.0980)		(0.0994)
ln($R\&D$)		-0.109***		-0.066
		(0.0421)		(0.0451)
Constant	-12.444	-4.386***	-11.709	-4.337***
	(71.1601)	(0.3034)	(60.3487)	(0.3170)
	Panel C: Idiosyncratic error variance			
Constant	-3.031***	-3.262***	-3.080***	-3.358***
	(0.0283)	(0.0439)	(0.0285)	(0.0488)
Observations	2508	2508	2508	2508
Log-likelihood	242.0	281.6	303.9	358.0

Notes: Standard errors in parentheses. All models include country and industry dummies. Squared terms and additional inputs cross-products not reported.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 3: Labour Productivity Growth Drivers

	(1)	(2)	(3)	(4)	(5)
Labour services	0.054				
	(0.0384)				
Labour composition		0.003			
		(0.0017)			
Secondary att. share			0.005*		
			(0.0024)		
Tertiary att. share				-0.002	
				(0.0015)	
QAHC					0.004**
					(0.0015)
Non-ICT	0.464***	0.469***	0.456***	0.458***	0.450***
	(0.0546)	(0.0548)	(0.0542)	(0.0528)	(0.0517)
ICT	-0.005	-0.012	-0.011	-0.013	-0.013
	(0.0096)	(0.0125)	(0.0123)	(0.0126)	(0.0125)
Economic comp.	0.199***	0.182***	0.191***	0.187***	0.195***
	(0.0514)	(0.0492)	(0.0500)	(0.0470)	(0.0451)
Software and DB	0.020	0.022*	0.017	0.020*	0.011
	(0.0139)	(0.0128)	(0.0119)	(0.0114)	(0.0099)
R&D	-0.020*	-0.018	-0.018*	-0.022*	-0.019*
	(0.0117)	(0.0113)	(0.0103)	(0.0116)	(0.0107)
Other innov. property	0.039*	0.042**	0.038**	0.054***	0.047***
	(0.0202)	(0.0170)	(0.0180)	(0.0200)	(0.0180)
ICT × Labour services	0.323***				
	(0.1235)				
Economic comp. × Labour services	-0.640				
	(0.5896)				
Software and DB × Labour services	0.032				
	(0.1562)				
R&D × Labour services	0.367				
	(0.2734)				
Other innov. property × Labour services	-0.089				
	(0.5703)				
Hours worked		0.068	0.033	0.038	0.036
		(0.0434)	(0.0439)	(0.0442)	(0.0443)
ICT × Labour composition		0.006*			
		(0.0033)			
Economic comp. × Labour composition		-0.034			
		(0.0237)			
Software and DB × Labour composition		-0.013			
		(0.0095)			
R&D × Labour composition		-0.000			
		(0.0069)			
Other innov. property × Labour composition		-0.001			
		(0.0227)			
ICT × Secondary att. share			0.018*		
			(0.0100)		
Economic comp. × Secondary att. share			0.018		
			(0.0519)		
Software and DB × Secondary att. share			-0.018		
			(0.0189)		
R&D × Secondary att. share			-0.003		
			(0.0190)		
Other innov. property × Secondary att. share			-0.035		
			(0.0267)		

	(1)	(2)	(3)	(4)	(5)
ICT × Tertiary att. share				0.014	
				(0.0132)	
Economic comp. × Tertiary att. share				-0.033	
				(0.0297)	
Software and DB × Tertiary att. share				0.010	
				(0.0158)	
R&D × Tertiary att. share				-0.012	
				(0.0106)	
Other innov. property × Tertiary att. share				0.021**	
				(0.0100)	
ICT × QAHC					0.011
					(0.0117)
Economic comp. × QAHC					0.001
					(0.0220)
Software and DB × QAHC					-0.021**
					(0.0099)
R&D × QAHC					-0.020*
					(0.0116)
Other innov. property × QAHC					0.015
					(0.0270)
Observations	2184	2184	2184	2184	2184
Adjusted R^2	0.507	0.503	0.501	0.501	0.505

Notes: Standard errors clustered at the country-industry level in parentheses. All models include country-year and industry-year fixed-effects. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 4: Labour Productivity Growth Drivers - Sector Heterogeneity

	Production C-F	Services G-S ex. O-Q
	(1)	(2)
QAHC	0.009***	0.000
	(0.0027)	(0.0014)
Hours worked	0.050	0.030
	(0.1075)	(0.0467)
Non-ICT	0.597***	0.414***
	(0.1039)	(0.0606)
ICT	-0.056***	0.022*
	(0.0124)	(0.0112)
Economic comp.	0.230**	0.189***
	(0.0933)	(0.0504)
Software and DB	0.013	0.011
	(0.0237)	(0.0092)
R&D	-0.004	-0.017
	(0.0160)	(0.0121)
Other innov. property	-0.100*	0.060***
	(0.0579)	(0.0195)
ICT × QAHC	0.013	0.010
	(0.0178)	(0.0110)
Economic comp. × QAHC	0.068*	-0.020
	(0.0353)	(0.0295)
Software and DB × QAHC	-0.032***	-0.012
	(0.0107)	(0.0160)
R&D × QAHC	0.021*	-0.023**
	(0.0112)	(0.0111)
Other innov. property × QAHC	-0.111***	0.042
	(0.0330)	(0.0267)
Observations	683	1501
Adjusted R^2	0.391	0.583

Notes: Standard errors clustered at the country-industry level in parentheses. All models include country-year and industry-year fixed-effects. * p<0.1, ** p<0.05, *** p<0.01.

6 Conclusion

This paper contributes to the ongoing debate on human capital's role in driving economic growth by introducing a novel quality-adjusted human capital (QAHC) measure at the industry-level across the EU and the UK from 2010 to 2021. Building on (Égert et al., 2022), we leverage PISA and PIAAC data on the quality and quantity of education across countries and age cohorts alongside country-industry variation in the employment composition by age over time from the EU KLEMS & INTANProd database. We show that this QAHC measure produces reasonable output elasticities when used in the estimation of a Stochastic Frontier model and it has a statistically significant link with labour productivity growth in the goods-producing industries unlike other available proxies of human capital at the industry level such as intermediate and high education attainment shares.

Further research could examine the effects of human capital quantity and quality on other economic outcomes such as the adoption of digital and green technologies.

References

Adarov, A., & Stehrer, R. (2019). *Tangible and intangible assets in the growth performance of the eu, japan and the us.*

Altinok, N., Angrist, N., & Patrinos, H. A. (2018). *Global data set on education quality (1965–2015)* (Policy Research Working Paper No. WPS 8314). Washington, D.C.. Retrieved from http://documents.worldbank.org/curated/en/706141516721172989

Altinok, N., & Diebolt, C. (2024). Cliometrics of learning-adjusted years of schooling: evidence from a new dataset. *Cliometrica*, *18*, 691–764. Retrieved from https://doi.org/10.1007/s11698-023-00276-x

Angrist, N., Djankov, S., Goldberg, P. K., & Patrinos, H. A. (2020). *Measuring human capital* (Policy Research Working Paper No. 8742). Retrieved from https://documents1.worldbank.org/curated/en/540801550153933986/pdf/Measuring-Human-Capital.pdf

Barro, R. J., & Lee, J.-W. (2001). International data on educational attainment: Updates and implications. *Oxford Economic Papers*, *53*(3), 541–563. Retrieved from https://doi.org/10.1093/oep/53.3.541

Benos, N., & Zotou, S. (2014). Education and economic growth: A meta-regression analysis. *World Development*, *64*, 669–689. Retrieved from https://doi.org/10.1016/j.worlddev.2014.06.034

Bontadini, F., Corrado, C., Haskel, J., Iommi, M., & Jona-Lasinio, C. (2023). EUKLEMS & INTANProd: industry productivity accounts with intangibles—Sources of growth and productivity trends: methods and main measurement challenges. *The Luiss Lab of European Economics. https://euklems-intanprod-llee. luiss. it/(Data extracted on 21 February 2023)*.

Botev, J., Égert, B., Smidova, Z., & Turner, D. (2019). *A new macroeconomic measure of human capital with strong empirical links to productivity* (Working Paper No. 1575). Paris: OECD Economics Department. Retrieved from https://doi.org/10.1787/d12d7305-en

Botev, J., Égert, B., Smidova, Z., & Turner, D. (2020, March). *The human capital paradox: A measurement issue?* OECD Economics Department (ECOSCOPE). Retrieved from https://oecdecoscope.blog/2020/03/18/the-human-capital-paradox-a-measurement-issue/

Ciccone, A., & Papaioannou, E. (2009). Human capital, the structure of production, and growth. *The Review of Economics and Statistics*, *91*(1), 66–82. Retrieved from https://doi.org/10.1162/rest.91.1.66

Cohen, D., & Soto, M. (2007). Growth and human capital: good data, good results. *Journal of economic growth*, *12*(1), 51–76.

Corvers, F. (1997, 08). The impact of human capital on labour productivity in manufacturing sectors of the european union. *Applied Economics*, *29*, 975-987. doi: 10.1080/000368497326372

de la Fuente, A., & Doménech, R. (2006, 03). Human capital in growth regressions: How much difference does data quality make? *Journal of the European Economic Association*, *4*(1), 1-36. Retrieved from https://doi.org/10.1162/jeea.2006.4.1.1 doi: 10.1162/jeea.2006.4.1.1

Eurostat. (2025). *Active population by sex, age and citizenship (code: Lfsa_agan).* Eurostat, European Commission. Retrieved from https://ec.europa.eu/eurostat/databrowser/view/LFSA_AGAN/default/table?lang=en (Accessed: 2025-07-09)

Folloni, G., & Vittadini, G. (2010). Human capital measurement: a survey. *Journal of economic surveys*, *24*(2), 248–279.

Fournier, J., & Johansson, Å. (2016). *The effect of the size and the mix of public spending on growth and inequality* (OECD Economics Department Working Papers No. 1344). Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/f99f6b36-en

Hall, R., & Jones, C. (1999). Why do some countries produce so much more per worker than others? *The Quarterly Journal of Economics*, *114*(1), 83–116. Retrieved from http://dx.doi.org/10.1162/003355399555954

Hanushek, E. A., & Kimko, D. D. (2000, December). Schooling, labor-force quality, and the growth of nations. *American Economic Review*, *90*(5), 1184–1208. Retrieved from https://doi.org/10.1257/aer.90.5.1184

Hanushek, E. A., & Zhang, L. (2009). Quality-consistent estimates of international schooling and skill gradients. *Journal of Human Capital*, *3*(2), 107–143. Retrieved from http://dx.doi.org/10.1086/644780

Kneller, R. (2005, 02). Frontier technology, absorptive capacity and distance. *Oxford Bulletin of Economics and Statistics*, *67*, 1-23. doi: 10.1111/j.1468-0084.2005.00107.x

Kneller, R., & Stevens, P. A. (2006, 02). Frontier technology and absorptive capacity: Evidence from oecd manufacturing industries. *Oxford Bulletin of Economics and Statistics*, *68*, 1-21. doi: 10.1111/j.1468-0084.2006.00150.x

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

Lutz, W., Stilianakis, N., Stonawski, M., Goujon, A., & KC, S. (2018). *Demographic and human capital scenarios for the 21st century: 2018 assessment for 201 countries* (W. Lutz, N. Stilianakis, M. Stonawski, A. Goujon, & S. KC, Eds.). Publications Office of the European Union. Retrieved from https://data.europa.eu/doi/10.2760/835878

Madsen, J. B. (2014, 10). Human capital and the world technology frontier. *Review of Economics and Statistics*, *96*, 676-692. doi: 10.1162/rest_a_00381

Makles, A. (2012). Stata tip 110: How to get the optimal k-means cluster solution. *The stata journal*, *12*(2), 347–351.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992, May). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, *107*(2), 407–437. Retrieved from https://doi.org/10.2307/2118477

Montenegro, C., & Patrinos, H. A. (2014). *Comparable estimates of returns to schooling around the world* (Policy Research Working Paper No. 7020). World Bank. Retrieved from https://hdl.handle.net/10986/20340

Morrisson, C., & Murtin, F. (2013). The kuznets curve of human capital inequality: 1870–2010. *Journal of Economic Inequality*, *11*(3), 283–301. Retrieved from http://dx.doi.org/10.1007/s10888-012-9227-2

OECD. (2019). *Economic policy reforms 2019: Going for growth*. Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/aec5b059-en

OECD. (2023a). *Economic policy reforms 2023: Going for growth*. Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/9953de23-en

OECD. (2023b). *PISA: Programme for International Student Assessment*. https://www.oecd.org/en/about/programmes/pisa.html. (Accessed: 2025-08-05)

OECD. (2024). *PIAAC: Programme for the International Assessment of Adult Competencies*. https://www.oecd.org/skills/piaac/.

O'Mahony, M. (2012). Human capital formation and continuous training: Evidence for EU countries. *Review of Income and Wealth*, *58*(3), 531–549.

Pieri, F., Vecchi, M., & Venturini, F. (2018). Modelling the joint impact of r&d and ict on productivity: A frontier analysis approach. *Research Policy*, *47*(9), 1842–1852.

Psacharopoulos, G. (1994). Returns to investment in education: A global update. *World Development*, *22*(9), 1325–1343. Retrieved from https://doi.org/10.1016/0305-750X(94)90007-8

Psacharopoulos, G., & Patrinos, H. A. (2004). Returns to investment in education: A further update. *Education Economics*, *12*(2), 111–134. Retrieved from http://dx.doi.org/10.1080/0964529042000239140

Romer, P. M. (1990, October). Endogenous technological change. *Journal of Political Economy*, *98*(5, Part 2), S71–S102. Retrieved from https://doi.org/10.1086/261725 (Originally NBER Working Paper No. 3210 (December 1989))

Stehrer, R. (2024). *wiiw growth and productivity database – release 2024.* Retrieved from https://euklems.eu/wp-content/uploads/2024/12/wiiw-GPD_Release2024.pdf

Stehrer, R., Bykova, A., Jäger, K., Reiter, O., & Schwarzhappel, M. (2019). Industry level growth and productivity data with special focus on intangible assets. *Vienna Institute for International Economic Studies Statistical Report*, *8*.

UNESCO. (2017). *More than one-half of children and adolescents are not learning worldwide* (No. Fact Sheet No. 46). Retrieved from https://uis.unesco.org/sites/default/files/documents/fs46-more-than-half-children-not-learning-en-2017.pdf

Wilson, R. A., & Briscoe, G. (2004). The impact of human capital on economic growth: a review. *Impact of Education and Training, the Third Report on Vocational Research in Europe: Background Report, Luxembourg: Office for Official Publications of the European Communities*.

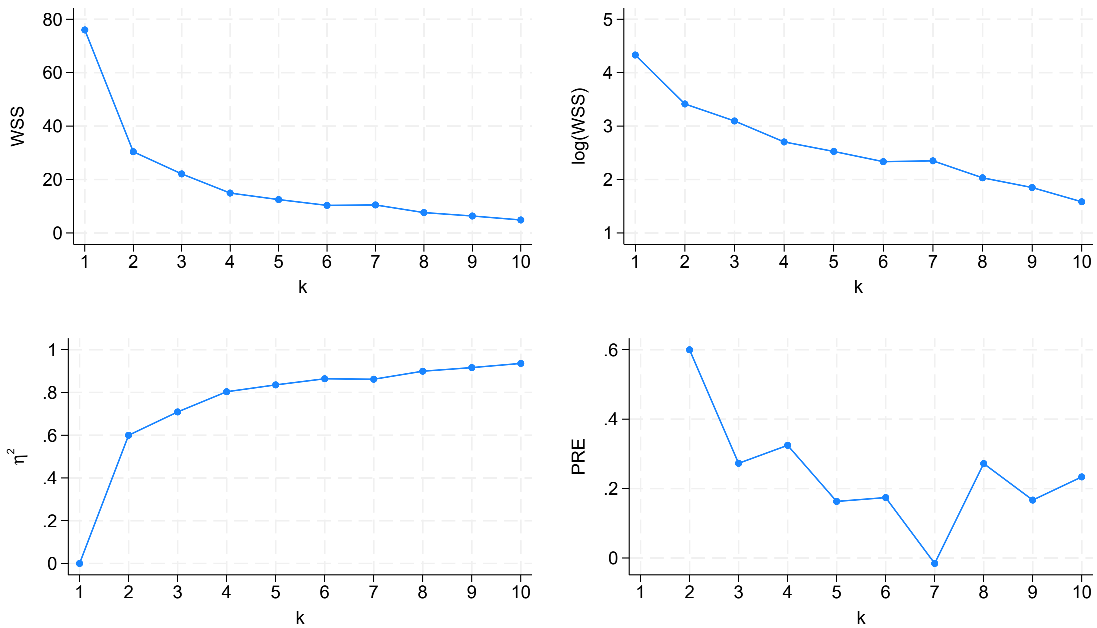
Wittgenstein Centre for Demography and Global Human Capital. (2018). *Wittgenstein centre data explorer version 2.0.* https://dataexplorer.wittgensteincentre.org/wcde-v2/. (Accessed: 2025-07-04)

Égert, B. (2017). *Regulation, institutions and productivity: New macroeconomic evidence from oecd countries* (OECD Economics Department Working Papers No. 1393). Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/579ceba4-en

Égert, B., de la Maisonneuve, C., & Turner, D. (2022). *A new macroeconomic measure of human capital exploiting pisa and piaac: Linking education policies to productivity* (Working Paper No. 1709). OECD Publishing. Retrieved from https://doi.org/10.1787/a1046e2e-en

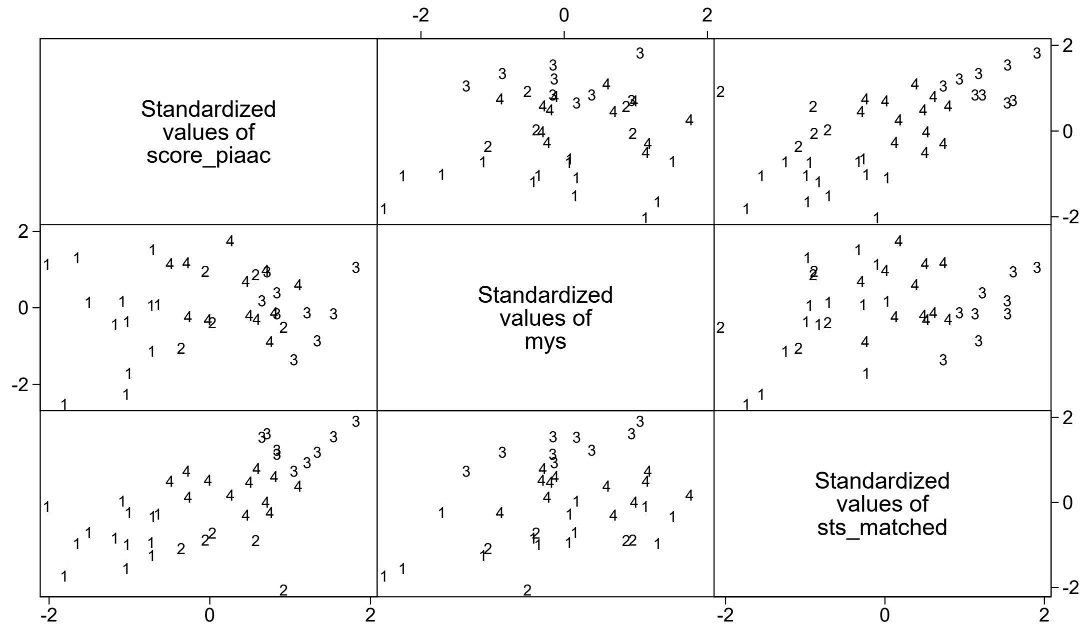
Appendix

Figure A1: K-Means Clusters: ANOVA Analysis



Notes: The graph plots the Within-group Sum of Squares (WSS) component of the analysis of variance (ANOVA) for ten clusters.

Figure A2: K-Means Clusters: Scatterplot Matrix of the Components



Notes: All variables are standardised.