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DOES EDUCATIONAL INEQUALITY WEAKEN THE AGGREGATE INCOME PAYOFF TO SCHOOLING? EVIDENCE FROM OECD COUNTRIES

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Abstract

This study examines whether educational inequality moderates the relationship between schooling and income per capita in OECD countries from 1995 to 2024. Average years of schooling are combined with an attainment-based education Gini index to capture both the level and distribution of human capital. Given cross-sectional dependence and slope heterogeneity, the Common Correlated Effects Mean Group estimator is used as the main method, with the Augmented Mean Group estimator and System GMM employed as robustness checks. The results show a positive association between average schooling and income per capita. The interaction between schooling and educational inequality is negative and statistically significant. Marginal effects indicate that the income gain associated with an additional year of schooling decreases as educational inequality rises. The findings suggest that the economic returns to educational expansion depend on both average attainment and its distribution, supporting policies that expand schooling while reducing disparities in educational attainment.

Keywords: educational inequality, education Gini, average schooling, aggregate income payoff, human capital distribution, OECD countries

1. INTRODUCTION

Education is widely regarded as a central driver of economic and social development. A large body of research shows that human capital accumulation,

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commonly measured by average years of schooling, is positively associated with productivity, income levels, and long-run growth. This relationship is particularly important when schooling contributes to productive skills and when economies are able to absorb educated workers effectively (Gemmell, 1996; Ahsan & Haque, 2017; Glawe & Wagner, 2022). Recent evidence also points to mismatches between the competencies developed through higher education and those demanded in the labour market, highlighting the importance of skill alignment for the productive use of education (Štimac & Bilandžić Tanasić, 2023). However, the income payoff from education is not automatic. The ability of firms to access and retain skilled workers may also condition how effectively accumulated human capital is translated into economic performance (Dula & Krasniqi, 2025). It may depend on labor market conditions, structural characteristics, and the extent to which societies can transform schooling into broadly shared productive capacity.

This raises an important distributional question. If education is a key component of human capital, then its contribution to income performance should depend not only on the average level of schooling but also on how educational attainment is distributed across society. Educational inequality, whether shaped by socioeconomic background, gender, or regional disparities, can limit social inclusion and reduce the effective use of human capital. Unequal access to education may reduce the supply of skilled labor, increase misallocation, and weaken aggregate productivity (Klasen, 2002; Fleisher et al., 2011; Benos & Karagiannis, 2016). It can also reinforce labor market segmentation, wage gaps, and unequal employment prospects, thereby limiting the broader social and economic benefits of educational expansion (Kampelmann et al., 2018; He et al., 2020).

Educational inequality also operates through wider social mechanisms. Unequal education systems can restrict social mobility and strengthen the intergenerational transmission of disadvantage, which in turn limits skill diffusion and adaptive capacity (Jerrim & Macmillan, 2015; Blanden et al., 2022). At the macro level, such inequalities may narrow the pool of potential innovators and entrepreneurs, slow structural transformation, and weaken social cohesion. From this perspective, educational inequality is not only an equity concern. It is also a factor that may shape how effectively societies transform schooling into broad-based income gains.

The relationship between schooling and income may therefore be conditional on the distribution of education. When average schooling levels are low, limited educational inequality may coexist with early-stage income gains driven by skill formation among a relatively small segment of the population. Yet, as educational attainment expands, unequal distribution can increasingly constrain spillovers and reduce aggregate productivity gains, leading to diminishing aggregate income gains from further schooling (Sauer & Zagler, 2014; Coady & Dizioli, 2017). In advanced economies, where average schooling is already high, raising educational attainment without addressing disparities may therefore deliver weaker income gains than expected (Makhlouf & Lalley, 2023; Haller, 2023).

Despite this growing literature, the macroeconomic evidence has largely treated average schooling and educational inequality as separate determinants of economic performance. Existing studies typically ask either whether higher average education is associated with better income outcomes or whether educational inequality has an independent effect on growth and productivity. This leaves a distinct question less directly examined: whether the economic payoff associated with additional schooling itself depends on how educational attainment is distributed. The distinction matters because a statistically significant direct effect of educational inequality does not reveal whether inequality changes the effectiveness of further educational expansion. Two countries with similar average years of schooling may therefore obtain different aggregate income payoffs if educational attainment is broadly shared in one country but concentrated among narrower groups in another.

The present study addresses this issue by treating educational inequality as a conditioning factor in the schooling–income relationship rather than only as an additional explanatory variable. The central parameter is therefore the interaction between average schooling and the education Gini, which captures whether the aggregate income payoff associated with schooling changes systematically with the distribution of educational attainment. Applied to OECD countries over 1995–2024, this framework shifts the empirical question from whether educational inequality is directly associated with income to whether it alters the effectiveness with which additional schooling is translated into aggregate income performance.

The concept of an aggregate income payoff used in this study should be distinguished from the individual return to schooling commonly estimated within a Mincerian earnings framework. The latter refers to the wage or earnings premium associated with an additional year of schooling at the individual level. By contrast, the present analysis is conducted at the country level and examines the conditional association between average years of schooling and real GDP per capita. Accordingly, the estimated schooling coefficients are interpreted as macroeconomic semi-elasticities rather than individual wage returns.

The study contributes to the literature in three related ways. First, it reframes educational inequality from a separate correlate of economic performance into a conditioning mechanism that may determine how effectively additional schooling is translated into aggregate income. The contribution therefore lies not simply in including schooling and the education Gini in the same model, but in making their interaction the central object of analysis. Second, it provides a parsimonious theoretical framework in which unequal educational attainment reduces the efficiency with which average schooling is transformed into productive human capital, yielding a directly testable prediction that the marginal income payoff to schooling declines as educational inequality rises. Third, the study evaluates this mechanism across OECD countries using heterogeneous panel estimators that account for cross-sectional dependence and slope heterogeneity, complemented by System GMM for income persistence and potential endogeneity.

Together, these elements connect the distribution of human capital to the effectiveness of educational expansion and thereby extend the conventional human-capital–income relationship beyond average attainment alone.

2. LITERATURE REVIEW

A substantial body of literature emphasizes that human capital accumulation is a fundamental driver of long-run economic performance. However, this relationship depends not only on the average level of education but also on how educational opportunities are distributed across the population. Early and influential contributions consistently document a positive association between average years of schooling and economic growth, particularly once countries surpass certain development thresholds and when education quality is sufficiently high. In this regard, secondary and tertiary education tend to exert stronger growth effects than primary education alone, while quality-adjusted measures of schooling outperform simple attainment indicators in explaining long-run income dynamics (Gemmell, 1996; Wang & Liu, 2016; Ahsan & Haque, 2017; Glawe & Wagner, 2022; Carillo, 2024). At the same time, the literature increasingly acknowledges that the marginal contribution of additional schooling may diminish in high-income or structurally rigid economies, especially when labor markets fail to efficiently absorb skilled workers or when education systems are misaligned with productive needs (Balog, 2021; Almutairi, 2024; Laverde-Rojas et al., 2019). This concern is also reflected in recent evidence showing that employers, practitioners, and students may differ in how they assess the importance of occupational skills, further highlighting the role of skill alignment in translating formal education into productive labour-market outcomes (Mijoč et al., 2024).

While the income-enhancing role of average education is well established, a parallel strand of research highlights that educational inequality can substantially weaken these gains. Education inequality – whether defined along gender, regional, or socioeconomic dimensions – tends to reduce aggregate human capital, limit productivity, and suppress innovation, thereby constraining economic performance. Empirical studies show that unequal access to education lowers the effective supply of skilled labor and amplifies misallocation, with particularly adverse consequences for productivity and long-run output (Klasen, 2002; Benos & Karagiannis, 2016; Fleisher et al., 2011; Magableh et al., 2022). Moreover, disparities in educational attainment translate into segmented labor markets characterized by wage gaps, higher unemployment risks for less-educated workers, and weaker aggregate demand, reinforcing growth-inhibiting dynamics (Jones, 2001; Kampelmann et al., 2018; He et al., 2020).

Beyond direct productivity effects, the literature identifies several interrelated social channels through which education inequality affects economic performance. Unequal education systems restrict social mobility and entrench the intergenerational transmission of disadvantage, thereby limiting the diffusion of skills and constraining the economy's adaptive capacity. In this context, parental

education and socioeconomic background strongly shape educational outcomes, which in turn influence labor market trajectories and lifetime earnings (Jerrim & Macmillan, 2015; Blanden et al., 2022; Schindler et al., 2023). Furthermore, education inequality narrows the pool of potential innovators and entrepreneurs, reducing technological dynamism and slowing structural transformation. These effects are often compounded by weaker social cohesion and heightened political instability, both of which further undermine long-run economic performance (Goczek et al., 2021; Zhao, 2024; Laidin & Sidek, 2025).

Importantly, recent research suggests that the growth impact of education inequality is not uniform but conditional on the level of average schooling. When average educational attainment is low, limited inequality may coexist with modest growth gains driven by early-stage skill formation among a small elite. However, as average schooling rises, the negative effects of unequal educational distribution become increasingly pronounced, since concentrated human capital prevents broad spillovers and limits aggregate productivity gains. Empirical evidence indicates that in highly unequal education systems, further increases in average schooling yield diminishing or even negligible growth effects, underscoring the importance of inclusive human capital accumulation (Sauer & Zagler, 2014; Coady & Dizioli, 2017). In this sense, education expansion without corresponding reductions in inequality may fail to deliver sustained growth benefits.

Relatedly, several studies argue that higher average education alone does not fully offset the adverse effects of educational inequality. While more educated populations tend to be more productive, unequal access to quality education can still significantly hinder growth, particularly by weakening externalities and limiting the diffusion of cognitive skills. Evidence from both developing and advanced economies suggests that education quality and equitable access matter at least as much as average attainment levels, and that ignoring distributional aspects may even exacerbate income inequality over time (Yu et al., 2015; Goczek et al., 2021; Makhlouf & Lalley, 2023; Haller, 2023). Consequently, policies focused solely on raising average years of schooling are unlikely to generate inclusive and durable income gains unless accompanied by measures that address educational disparities.

From a measurement perspective, the literature predominantly relies on attainment-based indicators to capture education inequality, with the education Gini coefficient emerging as the most widely used measure. Adapted from income inequality analysis, the education Gini summarizes the dispersion of years of schooling across the population and is well suited for cross-country and intertemporal comparisons. Its flexibility allows for computation using either individual-level data or grouped attainment distributions, such as those provided by the Barro–Lee dataset (Thomas et al., 2001; Torpey-Saboe, 2019; Luo et al., 2022). Although alternative measures – such as the coefficient of variation, Theil index, and multidimensional composite indicators – offer valuable insights into specific dimensions of inequality, the education Gini remains the standard choice in macroeconomic analyses due to its interpretability and empirical tractability.

Finally, while the dominant empirical finding points to a negative relationship between education inequality and growth, a limited number of studies report insignificant or context-dependent effects. These exceptions often arise in specific historical periods, early development stages, or under alternative model specifications, highlighting the sensitivity of results to measurement choices, sample composition, and time horizons (Thomas et al., 2001; Emara & Raouf, 2017; Shahabadi et al., 2018; Maneejuk & Yamaka, 2021; Makhlouf & Lalley, 2023). Rather than contradicting the broader literature, such findings underscore the importance of accounting for heterogeneity and interaction effects when assessing the income implications of educational inequality.

The reviewed literature shows that higher average education generally supports long-run income performance, but unequal distribution of educational attainment can weaken these gains by reducing effective labor supply, limiting productivity, and constraining human capital spillovers. More importantly, the adverse implications of education inequality may become more pronounced as economies accumulate human capital. This perspective provides the conceptual and empirical basis for examining whether educational inequality weakens the aggregate income payoff to schooling in OECD countries.

3. THEORETICAL FRAMEWORK

This section develops a simple theoretical framework that links average schooling, educational inequality, and income per capita. The main argument is that average schooling raises productive human capital, but the aggregate income payoff to schooling depends on how broadly educational attainment is distributed across the population. This perspective is consistent with human-capital-based growth models and with studies emphasizing the joint role of the level and distribution of education in economic development (Lucas, 1988; Mankiw et al., 1992; Sauer & Zagler, 2014).

When education is concentrated among a limited group, societies may fail to transform average schooling into broad-based productivity and income gains. In such a setting, the same average level of schooling may generate different income outcomes depending on whether educational attainment is widely shared or concentrated among narrower groups. Therefore, educational inequality is treated not only as a possible direct correlate of income, but also as a factor that may weaken the aggregate income payoff associated with average schooling.

Let output in country i at time t be produced by physical capital and effective human capital:

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{it}^{1-\alpha} \tag{1}$$

where Y_{it} denotes aggregate output, A_{it} is total factor productivity, K_{it} is physical capital, H_{it} is effective human capital, and $0 < \alpha < 1$. In the standard human capital framework, higher schooling increases effective human capital and thereby

raises output (Lucas, 1988; Mankiw et al., 1992). However, this relationship depends not only on the average level of schooling but also on the distribution of schooling across individuals.

To capture this mechanism, effective human capital is defined as:

$$H_{it} = L_{it}\exp(\eta AS_{it})\phi(EG_{it}) \tag{2}$$

where L_{it} is the labor force, AS_{it} represents average years of schooling, and EG_{it} denotes educational inequality, measured by the education Gini index. The parameter η captures the productivity-enhancing effect of an additional year of schooling. The exponential form implies that each additional year of schooling increases effective human capital by a constant proportion, which is consistent with the logic of semi-log human-capital specifications. The education Gini index is widely used to summarize the dispersion of schooling attainment across individuals or population groups (Thomas et al., 2001; Sauer & Zagler, 2014). The term $\phi(EG_{it})$ captures the efficiency with which average schooling is transformed into productive human capital. It is assumed that:

$$\phi'(EG_{it}) < 0 \tag{3}$$

This assumption means that higher educational inequality reduces the effective use of schooling. The economic intuition is straightforward. If educational attainment is unequally distributed, a larger part of the population may remain below the skill level required to benefit from technology, participate in high-productivity sectors, or generate human capital spillovers. As a result, the same average level of schooling may produce smaller aggregate income gains when educational attainment is more unequally distributed.

Substituting Equation (2) into Equation (1) gives:

$$Y_{it} = A_{it}K_{it}^{\alpha}[L_{it}\exp(\eta AS_{it})\phi(EG_{it})]^{1-\alpha} \tag{4}$$

Taking logarithms and expressing the model in per capita terms yields the following reduced-form relationship:

$$ln\, Y_{it} = a_{it} + \alpha k_{it} + (1-\alpha)\eta AS_{it} + (1-\alpha)\, ln\, \phi(EG_{it}) \tag{5}$$

where $\ln Y_{it}$ denotes the logarithm of income per capita and k_{it} denotes the logarithm of physical capital per capita. Equation (5) shows that average schooling has a positive effect on income per capita, while educational inequality may reduce the efficiency with which schooling is converted into productive human capital.

A convenient functional form satisfying $\phi'(EG_{it}) < 0$ is:

$$\phi(EG_{it}) = \exp(-\theta EG_{it}),\ \ \theta > 0, \tag{6}$$

which implies:

$$ln\, \phi(EG_{it}) = -\theta EG_{it}$$

This specification implies that higher educational inequality lowers the efficiency of schooling in the formation of effective human capital. It also provides

a direct link between the theoretical framework and the empirical specification, where the education Gini index enters the model as an explanatory variable.

Substituting Equation (6) into Equation (5) gives:

$$\ln Y_{it} = a_{it} + \alpha k_{it} + (1-\alpha)\eta AS_{it} - \theta(1-\alpha)EG_{it} \quad (7)$$

Equation (7) suggests that average schooling is expected to increase income per capita, while educational inequality may reduce the efficiency of human capital formation. However, the main mechanism of this study is not limited to the direct effect of educational inequality. The central hypothesis is that educational inequality changes the marginal income effect associated with schooling. This approach follows the idea that the effect of average education on development may vary with the distribution of educational attainment (Sauer & Zagler, 2014).

The marginal effect of average schooling on income per capita can be expressed as:

$$\frac{\partial \ln Y_{it}}{\partial AS_{it}} = \beta_1 + \beta_3 EG_{it} \quad (8)$$

Because the dependent variable is expressed in logarithmic form while AS_{it} is measured in years of schooling, this marginal effect is interpreted as a semi-elasticity. It shows the percentage change in income per capita associated with a one-year increase in average schooling, conditional on the level of educational inequality. If $\beta_1 > 0$ and $\beta_3 < 0$, average schooling increases income per capita, but this positive effect becomes weaker as educational inequality rises. This is the main theoretical prediction tested in the empirical analysis.

Based on this framework, the baseline empirical model can be written as:

$$\ln Y_{it} = \beta_0 + \beta_1 AS_{it} + \beta_2 EG_{it} + \beta_3 (AS_{it} \times EG_{it}) + \gamma X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (9)$$

where $\ln Y_{it}$ is the logarithm of income per capita, AS_{it} is average schooling, EG_{it} is educational inequality, and $(AS_{it} \times EG_{it})$ is the interaction between average schooling and educational inequality. The vector X_{it} includes control variables such as physical capital formation, the working-age population share, and inflation. Country-specific effects are captured by μ_i, time-specific effects by τ_t, and the error term by ε_{it}.

In the empirical specification, β_1 captures the reduced-form counterpart of the composite theoretical effect $(1-\alpha)\eta$ while β_2 captures the reduced-form association between educational inequality and income per capita. The coefficient β_3 captures whether educational inequality weakens the marginal aggregate income payoff to schooling. Therefore, β_3 is the main parameter of interest in this study.

The expected signs are $\beta_1 > 0, and\ \beta_3 < 0$. The coefficient β_2 is expected to be negative in line with Equation (7), which suggests that educational inequality reduces the efficiency of human capital formation. However, in a sample of OECD countries where educational inequality is relatively low and exhibits

limited within-country variation, this direct effect may be empirically weak or statistically insignificant. Therefore, the main welfare and policy-relevant parameter is β_3, which captures whether inequality moderates the aggregate income payoff to further schooling.

The framework is intentionally kept parsimonious in order to focus on the moderating role of educational inequality in the schooling–income relationship. It does not model skill-biased technological change, education quality, or intergenerational human capital accumulation explicitly. Instead, common shocks affecting OECD countries are controlled for through time effects, while country-specific factors account for time-invariant institutional and structural differences. Therefore, the model should be interpreted as a long-run reduced-form framework rather than a full dynamic theory of human capital accumulation.

4. EMPIRICAL ANALYSIS

This section examines the relationship between average schooling, educational inequality, and income per capita within a heterogeneous panel data framework. Building directly on the theoretical framework, the empirical analysis tests whether average educational attainment supports income performance and whether the unequal distribution of education weakens this effect. To this end, the analysis focuses on OECD countries over the period 1995–2024 and exploits both cross-country and time-series variation in education levels and their distribution.

4.1. Methodology

The empirical strategy is designed to account for cross-sectional dependence, slope heterogeneity, income persistence, and potential endogeneity. Since the diagnostic tests indicate strong cross-sectional dependence and heterogeneous slope coefficients across OECD countries, the main estimations are conducted using the Common Correlated Effects Mean Group (CCEMG) estimator. CCEMG is appropriate for this study because it controls for unobserved common factors through cross-sectional averages and allows slope coefficients to vary across countries.

The Augmented Mean Group (AMG) estimator is also employed as a complementary heterogeneous panel estimator. AMG accounts for common dynamic processes and country-specific heterogeneity, providing an additional check on whether the main findings remain valid under cross-sectional dependence and heterogeneous responses.

System GMM is used as an additional robustness check to address income persistence and potential endogeneity. The relationship between income, schooling, and educational inequality may involve reverse causality, since higher income levels can also affect educational attainment and its distribution. System

GMM incorporates the lagged dependent variable and uses internal instruments based on lagged values of the variables. Its validity is assessed using the Arellano–Bond serial correlation tests and the Hansen test of overidentifying restrictions.

Before estimation, several diagnostic tests are conducted to examine cross-sectional dependence, slope heterogeneity, stationarity, panel effects, heteroskedasticity, serial correlation, and multicollinearity. Across all models, the dependent variable is the natural logarithm of GDP per capita. Physical capital formation and the working-age population share enter the model in logarithmic form, while inflation is included in level form because it may take negative values. The key parameter of interest is the interaction coefficient between average schooling and educational inequality. A negative and statistically significant coefficient indicates that educational inequality reduces the aggregate income payoff to schooling.

4.2. Data and variables

This study relies on a panel dataset constructed to reflect both the level and the distribution of human capital across OECD countries over the period 1995–2024. The variables in the empirical analysis, together with their definitions and data sources, are summarized in Table 1.

Table 1 Variables

Variable	Notation	Description
Income	Y	GDP per capita (constant 2015 US$)
Education	AS	Average years of schooling of the population aged 15–64
Educational inequality	EG	Attainment-based education Gini index
Education-inequality interaction	AS × EG	Interaction term capturing the moderating effect of educational inequality on the aggregate income payoff associated with average schooling
Capital formation	K	Gross fixed capital formation per capita (constant 2015 US$)
Working-age share	POP	Population ages 15-64 (% of total population)
Inflation	INF	Inflation, consumer prices (annual %)

Note: Y, K, POP, and INF variables are sourced from World Development Indicators. AS is obtained from the Barro and Lee (2013, updated 2021) educational attainment dataset. EG and AS×EG are author's calculations. Variables expressed in monetary or scale terms are used in logarithmic form in the empirical analysis, while AS, EG, and INF enter the model in levels.

Source: Author's compilation.

Table 1 reports the dependent variable, the core education-related indicators, and a set of standard control variables commonly used in growth regressions. Economic performance is captured by the natural logarithm of real GDP per capita. Average educational attainment is measured by years of schooling of the working-age population, while educational inequality is proxied by an

attainment-based education Gini index. The interaction term between average schooling and educational inequality is constructed to test whether unequal distribution of education weakens the aggregate income payoff to schooling.

In addition, the model includes physical capital formation, the working-age population share, and inflation to account for capital accumulation, demographic structure, and macroeconomic stability. These variables are included as controls in order to isolate the relationship between schooling, educational inequality, and income per capita from other major determinants of long-run economic performance.

Average educational attainment (AS) is measured by the average years of schooling of the population aged 15–64 and is obtained directly from the Barro–Lee educational attainment dataset. Educational inequality (EG) is measured by an attainment-based education Gini index constructed by the author from the corresponding Barro–Lee educational attainment distributions. Following Thomas et al. (2001), the education Gini is calculated as:

$$EG = \frac{1}{\mu}\sum_{i=2}^{n}\sum_{j=1}^{i-1} p_i p_j \left| y_i - y_j \right| \tag{10}$$

where p_i denotes the population share in educational category i, y_i denotes the years of schooling assigned to that category, and

$$\mu = \sum_{i=1}^{n} p_i p_j \tag{11}$$

is the weighted mean years of schooling used in the Gini calculation. Seven mutually exclusive educational attainment categories are distinguished: no schooling, incomplete primary, completed primary, incomplete secondary, completed secondary, incomplete tertiary, and completed tertiary. Following the grouped-attainment approach, these categories are assigned 0, 3, 6, 9, 12, 14, and 16 years of schooling, respectively. Since the Barro–Lee data report both total and completed attainment shares at the primary, secondary, and tertiary levels, the shares corresponding to incomplete education are obtained as the difference between the relevant total and completed categories.

The historical Barro–Lee series through 2015 is combined with the corresponding post-2015 projection series to cover the full study period. Since the underlying educational attainment data are reported at five-year intervals, annual observations between benchmark years are generated by linear interpolation. This preserves the observed or projected benchmark values while providing a consistent annual panel for 1995–2024. Accordingly, year-to-year movements between benchmark dates reflect smooth interpolated transitions rather than independently observed annual changes.

Before proceeding to the econometric analysis, the basic statistical properties of the variables are presented in Table 2, which reports descriptive statistics for the full sample.

Table 2 Descriptive statistics

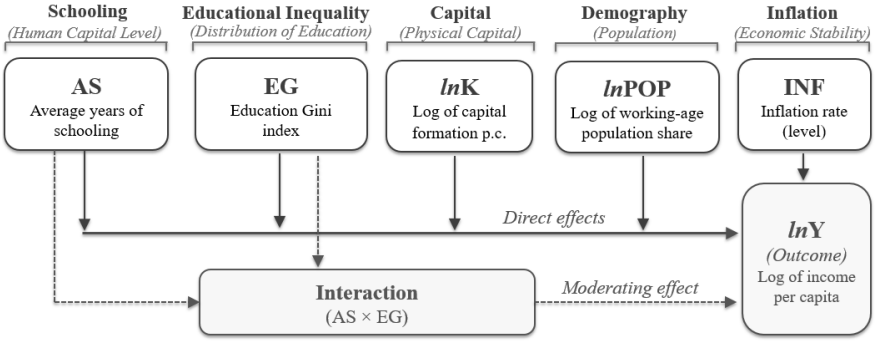
Variable	Obs	Mean	Std. Dev.	Min	Max
Y	1140	33396	22043	3967	112419
AS	1140	11.173	1.473	5.882	13.962
EG	1140	0.166	0.059	0.064	0.367
K	1140	7348	4993	470	38835
POP	1140	66.31	2.50	58.74	73.28
INF	1140	4.14	7.71	-4.45	89.11

Source: author's calculations.

The descriptive statistics in Table 2 indicate substantial cross-country variation in income levels, schooling outcomes, and educational inequality among OECD economies. While average years of schooling are relatively high on average, the education Gini index reveals non-negligible dispersion in educational attainment across countries and over time. Control variables also display considerable heterogeneity, reflecting differences in capital accumulation, demographic structure, and inflation dynamics. This variation provides a suitable empirical setting for examining how education levels and their distribution jointly shape income outcomes.

Building on these variable definitions and summary statistics, Figure 1 summarizes the conceptual structure linking schooling, educational inequality, and income per capita. The next section then introduces the empirical model specifications used to formally assess this relationship within a panel data framework.

Figure 1 Conceptual Framework



Source: Author's own elaboration.

As shown in Figure 1, average schooling is expected to have a positive direct association with income per capita, while educational inequality is expected to weaken this relationship through the AS × EG interaction term. The figure also shows that capital formation, the working-age population share, and inflation enter

the model as control variables. This conceptual structure provides the basis for the empirical specifications presented below.

4.3. Empirical model specification

The empirical specifications are designed to test the theoretical mechanism developed in Section 3. The dependent variable is the natural logarithm of income per capita, while the main explanatory variables are average schooling (AS), educational inequality (EG), and their interaction. The analysis proceeds through two main models. The first model estimates the direct associations between average schooling, educational inequality, and income per capita. The second model introduces the interaction term between average schooling and educational inequality in order to test the main moderation hypothesis of the study.

Since income per capita may be persistent over time, the System GMM specification additionally includes the lagged dependent variable. In the CCEMG and AMG estimations, the models are estimated without the lagged dependent variable in order to focus on the long-run heterogeneous relationship between schooling, educational inequality, and income per capita.

Model 1: Baseline Model

$$lnY_{it} = \beta_0 + \beta_1 AS_{it} + \beta_2 EG_{it} + \gamma X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (12)$$

where lnY_{it} denotes the natural logarithm of GDP per capita, AS_{it} is average years of schooling, and EG_{it} is the education Gini index. The vector X_{it} includes the control variables used in the growth specification. Country-specific effects are represented by μ_i, time-specific effects by τ_t, and the error term by ε_{it}.

In Model 1, β_1 captures the association between average schooling and income per capita, while β_2 captures the association between educational inequality and income per capita, conditional on the control variables.

Model 2: Moderation Model

$$\ln Y_{it} = \beta_0 + \beta_1 AS_{it} + \beta_2 EG_{it} + \beta_3 (AS_{it} \times EG_{it}) + \gamma X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (13)$$

Model 2 directly tests whether educational inequality moderates the aggregate income payoff associated with schooling. A negative and statistically significant interaction coefficient (β_3) would indicate that the marginal effect of average schooling on log income per capita becomes smaller as educational inequality increases

In Model 2, β_1 represents the marginal effect of schooling when educational inequality is zero ($EG = 0$), while β_3 captures how this marginal effect changes as educational inequality increases. Therefore, the marginal effect of average schooling on income per capita is given by:

$$\frac{\partial ln\, Y_{it}}{\partial AS_{it}} = \beta_1 + \beta_3 EG_{it} \quad (14)$$

Because the dependent variable is expressed in logarithmic form while AS_{it} is measured in years of schooling, this marginal effect is interpreted as a semi-elasticity. It shows the percentage change in income per capita associated with a one-year increase in average schooling, conditional on the level of educational inequality.

Across both specifications, X_{it} includes physical capital formation, the working-age population share, and inflation. In the empirical analysis, physical capital formation and the working-age population share enter the model in logarithmic form as lnK and lnPOP, while inflation (INF) enters in level form because it can take negative values. The expected sign of β_1 is positive, while the expected sign of β_3 in Model 2 is negative. The sign of β_2 is treated as an empirical question because the direct association between educational inequality and income may reflect composition effects rather than a causal income-enhancing role of inequality.

4.4. Panel diagnostics and model selection

Before estimating the empirical models, several diagnostic tests are conducted to determine the appropriate econometric strategy. Given the multi-country structure of the dataset, particular attention is paid to cross-sectional dependence, slope heterogeneity, stationarity, panel effects, heteroskedasticity, serial correlation, and multicollinearity.

Cross-sectional dependence is examined using several complementary tests, as reported in Table 3. The results indicate strong cross-sectional dependence for both individual variables and model residuals. This suggests that OECD countries are affected by common shocks and spillover effects. Therefore, estimators that assume cross-sectional independence may produce biased inference, and methods that account for common factors are required.

Table 3 CD Test

Variables	CD	CDw	CDw+	CD*
lnY	127 (0.000)	-3.29 (0.001)	3364 (0.000)	-0.07 (0.941)
AS	111 (0.000)	-2.58 (0.010)	3293 (0.000)	-3.54 (0.000)
EG	91 (0.000)	-3.47 (0.001)	2827 (0.000)	-1.51 (0.132)
lnK	78 (0.000)	-2.31 (0.021)	2356 (0.000)	-1.18 (0.238)
lnPOP	65 (0.000)	-1.98 (0.048)	1987 (0.000)	-0.92 (0.358)
INF	52 (0.000)	-1.72 (0.086)	1562 (0.000)	-0.54 (0.589)
residual	9.8 (0.000)	9.92 (0.000)	1845 (0.000)	5.62 (0.000)

Note: p-values in parentheses. CD: Pesaran (2015, 2021); CDw: Juodis and Reese (2022); CDw+: CDw with power enhancement from Fan et al. (2015); CD*: Pesaran and Xie (2021) with 4 PCs. All variables except residuals are in logarithms where applicable. INF (consumer price inflation) is in percentage points (not log-transformed due to negative values). Residuals are obtained from Model 2 (Moderation Model).

Source: author's calculations.

Next, slope homogeneity is tested to assess whether the relationship between income per capita and the explanatory variables is uniform across countries. The results in Table 4 strongly reject the null hypothesis of homogeneous slopes. This finding indicates that OECD countries differ in their structural responses, supporting the use of heterogeneous panel estimators.

Table 4 Slope Homogeneity

Delta (Δ)	Adj. (Δ)	Swamy's (χ^2):
30.674 ($p = 0.000$)	35.819 (p=0.000)	1.9×10^5 (p=0.000)

Source: author's calculations.

The time-series properties of the variables are examined using complementary unit-root tests that address different features of the panel. As shown in Table 5, the Pesaran (2007) CIPS test, which accounts for cross-sectional dependence, provides mixed evidence in levels, with several variables becoming stationary after first differencing. The Karavias and Tzavalis (2014) test, which explicitly allows for a structural break, rejects the unit-root null for all variables at the 1% significance level. The difference between the two sets of results is relevant given that the sample period includes several major disruptions, notably the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic. In this setting, tests that do not explicitly accommodate structural breaks may have reduced power to distinguish persistent but stationary processes from unit-root behaviour. The break-adjusted evidence is therefore considered particularly informative for the present sample, while the mixed CIPS results are retained as a caution in interpreting the level relationships. The mixed unit-root evidence nevertheless warrants caution regarding the possibility of spurious long-run relationships. Accordingly, the models are estimated in levels to preserve the long-run variation in the data, while the resulting coefficients are interpreted as long-run associations rather than as evidence of causal effects.

Table 5 Unit-root test

	Pesaran (CIPS stat.)		Karavias and Tzavalis (minZ-stat.)	
Variables	Level	1st diff.	Level	1st diff.
lnY	-1.560	-3.624***	-0.0631***	
AS	-1.441	-5.091***	-0.2652***	
EG	-1.665	-5.005***	-0.0004***	
lnK	-1.754	-4.237***	-0.2182***	
lnPOP	-2.101	-4.564***	-0.1452***	
INF	-3.851***		-0.2013***	
residual	-4.214***		-0.5214***	

Note: *** p<0.01, ** p<0.05, * p<0.1. The Karavias and Tzavalis (2014) test allows for one structural break and is implemented with bootstrap critical values (100 replications). The test statistics are min-Z values. The null hypothesis is that the series contains a unit root. Rejection of the null indicates stationarity.

Source: author's calculations.

Panel effect and model specification tests are then conducted to examine whether unobserved country-specific and time-specific effects should be considered. The results in Table 6 indicate significant individual effects, time effects, and joint effects. The LM and Hausman test results also reject simpler pooled or random-effects structures. These findings show that unobserved country-level heterogeneity and common time shocks are relevant for the empirical model.

Table 6 Panel effects and model selection tests

	Individual Effect	Time Effect	Joint Effect
LR	$\chi2$= 2611 (0.000)	$\chi2$= 166.59 (0.000)	$\chi2$= 2698 (0.000)
F	F= 8762 (0.000)	F= 84.46 (0.000)	F= 10309 (0.000)
LM	$\chi2$= 5463.48 (0.000)		
Hausman Test	$\chi2$ = 154.32 (0.000)		

Note: p-values in parentheses.

Source: author's calculations.

Finally, model validity tests are performed to assess heteroskedasticity, serial correlation, and multicollinearity. As reported in Table 7, the modified Wald test indicates groupwise heteroskedasticity, while the Jochmans portmanteau test does not provide evidence of serial correlation. The mean VIF value remains below conventional thresholds, suggesting that multicollinearity is not a serious concern.

Table 7 Model validity tests

Modified Wald (heteroskedasticity)	$\chi2$= 5557.92 (0.000)
Jochmans portmanteau test (autocorrelation)	$\chi2$= 38.00 (0.4695)
Mean VIF	3.10 < 5

Note: p-values in parentheses.

Source: author's calculations.

Taken together, the diagnostic results indicate an empirical setting characterized by cross-sectional dependence, slope heterogeneity, groupwise heteroskedasticity, and relevant country and time effects. These findings justify the use of heterogeneous panel estimators that account for common shocks and country-specific responses. Accordingly, CCEMG is used as the main estimator, AMG is employed as a complementary heterogeneous panel estimator, and System GMM is used as an additional robustness check for income persistence and potential endogeneity.

4.5. Estimation results

Table 8 reports the estimation results for the baseline and moderation models. Since the diagnostic tests indicate cross-sectional dependence and slope heterogeneity, the CCEMG estimator is treated as the main estimator. The AMG estimates are reported as an additional heterogeneous panel robustness check, while System GMM is used to assess whether the results remain valid after accounting for income persistence and potential endogeneity.

Table 8 Estimations

	CCEMG		AMG		System GMM	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
L.lnY	-	-	-	-	0.861***	0.852***
					(0.021)	(0.022)
AS	0.048***	0.091***	0.051***	0.095***	0.058***	0.115***
	(0.015)	(0.024)	(0.014)	(0.022)	(0.012)	(0.019)
EG	-0.352	-0.112	-0.385	-0.131	-0.412	-0.168
	(0.378)	(0.395)	(0.342)	(0.372)	(0.298)	(0.318)
AS × EG		-0.125**		-0.132**		-0.148***
		(0.058)		(0.058)		(0.051)
lnK	0.165***	0.159***	0.168***	0.165***	0.182***	0.178***
	(0.024)	(0.025)	(0.022)	(0.022)	(0.019)	(0.019)
lnPOP	0.038	0.035	0.045	0.041	0.052*	0.048
	(0.036)	(0.037)	(0.033)	(0.034)	(0.030)	(0.031)
INF	-0.007	-0.006	-0.007	-0.007	-0.006	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Obs.	1064	1064	1064	1064	1064	1064
id	38	38	38	38	38	38
CD test	0.438	0.421	0.372	0.365	-	-
AR(2)	-	-	-	-	0.341	0.352
Hansen J	-	-	-	-	0.285	0.298

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. AMG (Augmented Mean Group) and CCEMG (Common Correlated Effects Mean Group) estimators account for cross-sectional dependence and slope heterogeneity. System GMM addresses potential endogeneity concerns and incorporates dynamics through the lagged dependent variable.

Source: author's calculations.

In Table 8, the CCEMG results show that average schooling is positively and statistically significantly associated with income per capita in both Model 1 and Model 2. In the baseline specification, the coefficient of average schooling is 0.048, while it increases to 0.091 after the interaction term is introduced. This suggests that higher average years of schooling are associated with higher income per capita in OECD countries. The AMG and System GMM estimates confirm this positive relationship, indicating that the income-enhancing role of schooling is robust across alternative estimation strategies.

The coefficient of educational inequality is negative in all specifications, but it is not statistically significant. Therefore, the direct coefficient of the education Gini index should be interpreted with caution. This result suggests that educational inequality does not have a precise direct association with income per capita once average schooling, control variables, and the interaction term are included. Accordingly, the main focus should be placed on the interaction between average schooling and educational inequality.

The interaction term AS × EG is negative and statistically significant in all Model 2 specifications. In the main CCEMG model, the coefficient is −0.125 and statistically significant at the 5% level. The AMG estimate is also negative and significant, with a coefficient of −0.132, while the System GMM estimate is −0.148 and statistically significant at the 1% level. This consistent evidence supports the main hypothesis of the study: educational inequality weakens the aggregate income payoff associated with average schooling. In other words, average schooling remains positively associated with income per capita, but its marginal effect becomes smaller when educational attainment is more unequally distributed.

Among the control variables, physical capital formation is positive and statistically significant across all specifications, confirming the importance of capital accumulation for income per capita. The working-age population share has a positive coefficient, but it is generally not statistically significant. Inflation enters with a negative coefficient in all specifications, although it is not statistically significant. These results suggest that capital accumulation is the most robust control variable in the model, while the demographic and inflation variables provide weaker statistical evidence.

The robustness estimates support the main findings. AMG confirms the positive coefficient of average schooling and the negative moderating role of educational inequality under slope heterogeneity and cross-sectional dependence. System GMM also produces similar results after controlling for income persistence and potential endogeneity. The lagged dependent variable is positive and statistically significant in the System GMM models, confirming the persistence of income per capita. Moreover, the AR(2) and Hansen J test p-values are above conventional significance levels, suggesting that the dynamic specification does not suffer from second-order serial correlation and that the instrument set is valid. The results provide consistent evidence that educational inequality reduces the aggregate income payoff to schooling in OECD countries.

4.6. Conditional marginal effects of schooling

The interaction coefficient reported in Model 2 shows that educational inequality weakens the aggregate income payoff to schooling. However, the coefficient itself does not directly show the size of the schooling effect at different levels of educational inequality. Therefore, this section computes the marginal effect of average schooling on income per capita at low, medium, and high values

of the education Gini index. The marginal effect is calculated using Equation (14), where low, medium, and high levels of educational inequality are defined as

$$\frac{\partial ln\, Y_{it}}{\partial AS_{it}} = \beta_1 + \beta_3 EG_{it}$$

where low, medium, and high levels of educational inequality are defined as the mean minus one standard deviation, the mean, and the mean plus one standard deviation, respectively.

Table 9 Marginal Effect of Average Schooling

EG	EG Value	CCEMG	AMG	System GMM
Low	0.107	0.078*** (0.022)	0.081*** (0.019)	0.099*** (0.017)
Medium	0.166	0.070*** (0.024)	0.073*** (0.022)	0.090*** (0.019)
High	0.225	0.063** (0.027)	0.065*** (0.024)	0.082*** (0.021)

Notes: EG values are based on descriptive statistics from Table 2 (Mean = 0.166, SD = 0.059). *** p<0.01, ** p<0.05.

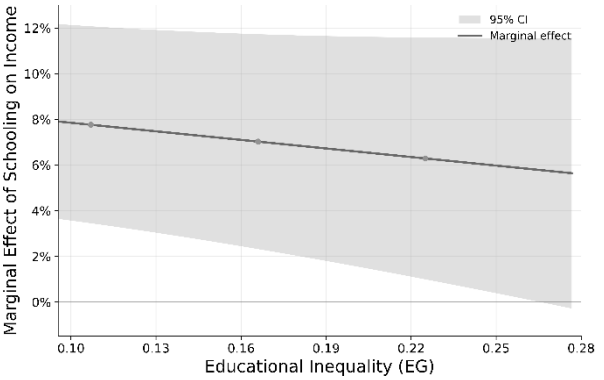
Source: author's calculations.

Table 9 reports the marginal effect of average schooling on income per capita at low, medium, and high levels of educational inequality. The marginal effects are semi-elasticities and indicate the change in log GDP per capita associated with a one-year increase in average schooling, conditional on the education Gini index.

The results show a clear declining pattern. In the main CCEMG specification, the marginal effect of average schooling decreases from 0.078 at low educational inequality to 0.070 at the mean level and 0.063 at high educational inequality. This suggests that the aggregate income payoff to schooling remains positive, but becomes weaker as educational attainment is more unequally distributed. The AMG and System GMM estimates confirm the same pattern, with marginal effects declining from 0.081 to 0.065 and from 0.099 to 0.082, respectively.

The marginal effect results support the central hypothesis of the study. Educational inequality reduces the magnitude of the positive income effect associated with schooling. While Table 9 reports marginal effects at three representative levels of educational inequality, Figure 2 extends the analysis over a broader range of observed EG values. Specifically, the figure plots the CCEMG-based marginal effect across the 5th–95th percentile range of the observed education Gini distribution, together with 95% confidence intervals.

Figure 2 Marginal effect of schooling across educational inequality



Note: The solid line represents the CCEMG-based marginal effect of a one-year increase in average schooling, and the shaded area denotes the 95% confidence interval. The plotted range corresponds to the 5th–95th percentiles of the observed education Gini distribution (approximately 0.095–0.277).

Source: Author's calculations based on the CCEMG estimates.

The figure shows a steady decline in the estimated schooling effect as educational inequality increases. The confidence interval remains above zero over most of the plotted range but widens toward the upper tail, indicating greater uncertainty at relatively high levels of educational inequality.

5. DISCUSSION

The findings provide consistent empirical support for the central argument that the aggregate income payoff to schooling depends not only on the average level of education but also on how educational attainment is distributed across society. Across the CCEMG, AMG, and System GMM estimations, average schooling is positively associated with income per capita. More importantly, the interaction between average schooling and educational inequality is negative and statistically significant in all moderation models. This indicates that the positive income effect of schooling becomes weaker as educational attainment is more unequally distributed.

This result has an important social and economic interpretation. Educational inequality is not only a matter of unequal opportunity; it also shapes how efficiently societies convert schooling into income gains. When educational attainment is more evenly distributed, an additional year of average schooling is more likely to generate broad-based productivity improvements, stronger human capital spillovers, and wider participation in productive activities. By contrast, when schooling is concentrated among a narrower segment of the population, the aggregate income payoff associated with further educational expansion becomes

smaller. This finding is consistent with the theoretical framework of the study, which argues that educational inequality reduces the effective transformation of schooling into productive human capital.

The magnitude of this moderation effect is also economically meaningful. Based on the main CCEMG estimates, the marginal effect associated with an additional year of average schooling declines from 0.078 at relatively low educational inequality to 0.063 at relatively high educational inequality. Since the dependent variable is expressed in logarithmic form, these estimates correspond approximately to a 7.8% and 6.3% difference in income per capita associated with an additional year of average schooling, respectively. Thus, moving from the low- to the high-inequality benchmark is associated with a reduction of about 1.5 percentage points, or roughly 19% relative to the schooling payoff observed at the lower level of inequality. The result therefore represents more than a statistically significant interaction: it indicates a quantitatively meaningful attenuation in the aggregate income payoff associated with educational expansion.

This pattern is consistent with the broader evidence that the economic benefits of education depend on both the level and the distribution of human capital. Sauer and Zagler (2014) emphasize that educational inequality can constrain the growth benefits associated with human-capital accumulation, while Coady and Dizioli (2017) show that the relationship between education and economic inequality is heterogeneous and sensitive to distributional conditions. The present findings extend this line of research by identifying a specific moderating channel: educational inequality is associated not only with economic outcomes in its own right, but also with a weaker marginal income payoff to additional schooling. The results are likewise consistent with more recent evidence emphasizing that high average attainment does not necessarily compensate for unequal access and distribution of education (Makhlouf & Lalley, 2023; Haller, 2023). The OECD evidence presented here therefore complements earlier studies by showing that distributional constraints remain relevant even among relatively high-education economies.

The marginal-effect analysis also shows that educational expansion continues to be positively associated with income performance across the representative levels of educational inequality considered in Table 9, although its effectiveness declines systematically as the education Gini rises. The results therefore do not imply that schooling loses its economic relevance; rather, they indicate that unequal human-capital distribution limits the extent to which additional schooling translates into higher aggregate income.

The direct coefficient of educational inequality is negative in all specifications, but it is not statistically significant. This result should be interpreted carefully. It does not imply that educational inequality is irrelevant. Instead, it suggests that in OECD countries, where educational inequality is relatively lower and less variable than in many developing economies, its direct association with income per capita may be difficult to identify once average schooling, control

variables, and interaction effects are included. The more relevant finding is the interaction effect, which consistently shows that educational inequality weakens the aggregate income payoff to schooling. In this sense, the main implication is not that educational inequality directly lowers income in every specification, but that it reduces the productivity of further educational expansion.

The robustness results strengthen this interpretation. The main CCEMG estimates are supported by the AMG estimator, which also accounts for cross-sectional dependence and heterogeneous country responses. System GMM further confirms the negative moderating effect after controlling for income persistence and potential endogeneity. This consistency suggests that the main finding is not driven by a specific estimator or by restrictive assumptions about cross-country homogeneity. Rather, the evidence points to a stable pattern across alternative empirical approaches: schooling contributes positively to income performance, but its aggregate income payoff is lower when educational inequality is higher.

The control variables generally show economically plausible patterns. Physical capital formation is positive and statistically significant across all specifications, confirming the importance of capital accumulation for income per capita. The working-age population share has a positive coefficient, but it is generally not statistically significant. Inflation enters with a negative coefficient in all models, although the estimates are not statistically significant. These results suggest that capital accumulation is the most robust control variable, while the demographic and inflation variables provide weaker statistical evidence.

From a policy perspective, the findings imply that education policy should not focus only on increasing average years of schooling. Educational expansion remains important, but its income payoff depends on whether educational attainment is broadly shared. Policies that reduce disparities in educational attainment, improve access to quality education, and support disadvantaged groups can contribute not only to equity but also to the effectiveness of human capital accumulation. In this sense, educational equality and human capital accumulation should be viewed as complementary objectives rather than separate policy goals.

These findings are particularly relevant for OECD countries, where average schooling levels are already high. In such contexts, further income gains may depend less on simply increasing the quantity of schooling and more on improving the inclusiveness and distribution of educational attainment. The results therefore suggest that education-driven income performance requires both a high level of schooling and a more equal distribution of educational opportunities. This perspective links human-capital policy to broader debates on inclusive growth and broad-based development.

6. CONCLUSIONS

This study examines whether educational inequality moderates the aggregate income payoff to schooling in OECD countries over the period 1995–

2024. The main argument is that average schooling supports income performance, but its effectiveness depends on how educational attainment is distributed across the population. To examine this relationship, the study combines a theoretical framework with a heterogeneous panel empirical strategy centred on the CCEMG estimator. AMG is employed as a complementary heterogeneous panel estimator, while System GMM serves as an additional robustness check for income persistence and potential endogeneity.

The findings show that average schooling is positively associated with income per capita across all model specifications. However, the interaction between average schooling and educational inequality is negative and statistically significant. This indicates that the aggregate income payoff to schooling declines as the education Gini increases. Therefore, the results support the central hypothesis of the study: educational inequality weakens the aggregate income payoff to schooling, even where average educational attainment is relatively high.

The marginal effect analysis further strengthens this conclusion. A one-year increase in average schooling is associated with a higher income gain when educational inequality is low, but this effect becomes smaller as educational inequality rises. This pattern suggests that educational expansion continues to matter for income performance, but its effectiveness is reduced when educational attainment is more unequally distributed. In this respect, the findings show that the distribution of education is not only an equity issue but also an important factor shaping the productivity of human capital accumulation.

The robustness checks confirm the main results. The main CCEMG estimates are supported by the AMG estimator, which accounts for cross-sectional dependence and heterogeneous country responses. System GMM also confirms the negative moderating effect after controlling for income persistence and potential endogeneity. Taken together, these results suggest that the central finding is not driven by a particular estimation method or by restrictive assumptions regarding cross-country homogeneity.

From a policy perspective, the findings imply that policies focused only on increasing average years of schooling may deliver limited income gains if educational inequality remains high. Expanding education is still essential, but its income payoff is likely to be stronger when educational opportunities are more evenly distributed. Therefore, policies that reduce disparities in educational attainment, improve access to quality education, and support disadvantaged groups can contribute both to equity and to long-run income performance.

The study concludes that education-driven income performance depends on both the level and the distribution of human capital. For OECD countries, increasing average schooling remains important, but it is not sufficient on its own. Sustainable income gains require a more inclusive process of human capital accumulation in which educational opportunities are more broadly shared across society. These findings suggest that improving the distribution of education is not only an equity objective but also an essential component of long-run income performance.

7. LIMITATIONS

This study has several limitations that should be considered when interpreting the findings. First, the analysis relies on attainment-based measures of education, namely average years of schooling and the education Gini index. Although these indicators are widely used in cross-country studies, they do not fully capture differences in education quality, learning outcomes, or field-specific skills. This limitation is particularly relevant for OECD countries, where differences in years of schooling are comparatively modest but meaningful variation in skills and learning outcomes may remain. Future research could therefore complement attainment-based measures with quality-adjusted human-capital indicators, including internationally comparable assessments such as PISA.

Second, the education Gini index is calculated from grouped educational attainment data. This allows for broad country coverage and long time-series construction, but it may not capture within-group variation or more detailed dimensions of educational inequality. Future studies could use micro-level data, where available, to examine how different forms of educational inequality shape the aggregate income payoff to schooling.

Third, the study focuses on OECD countries. This improves comparability across relatively advanced economies, but it limits the generalizability of the findings to developing and emerging economies. The moderating role of educational inequality may differ in countries with lower average schooling, weaker institutions, or different labor market structures. Extending the analysis to broader country groups would help assess whether the mechanism identified in this study also applies outside the OECD context.

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REFERENCES

Ahsan, H., & Haque, M. E. (2017). Threshold effects of human capital: Schooling and economic growth. *Economics Letters, 156*, 48–52. https://doi.org/10.1016/j.econlet.2017.04.014

Almutairi, N. T. (2024). Does investment in human capital via education stimulate economic growth in an oil-rich country? A case study of Saudi Arabia. *Journal of the Knowledge Economy, 15*, 2933–2955. https://doi.org/10.1007/s13132-023-01265-1

Balog, I. I. (2021). How effective are school years? Examining the link between human capital and economic growth in European countries, 2014–2019. *Public Finance Quarterly, 66*(4), 467–481. https://doi.org/10.35551/pfq_2021_4_1

Barro, R. J., & Lee, J.-W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics, 104*, 184–198. https://doi.org/10.1016/j.jdeveco.2012.10.001

Benos, N., & Karagiannis, S. (2016). Do education quality and spillovers matter? Evidence on human capital and productivity in Greece. *Economic Modelling, 54*, 563–573. https://doi.org/10.1016/j.econmod.2016.01.015

Blanden, J., Doepke, M., & Stuhler, J. (2022). *Educational inequality* (NBER Working Paper No. 29979). National Bureau of Economic Research. https://doi.org/10.3386/w29979

Carillo, M. F. (2024). Human capital composition and long-run economic growth. *Economic Modelling, 137*, Article 106760. https://doi.org/10.1016/j.econmod.2024.106760

Coady, D., & Dizioli, A. (2017). *Income inequality and education revisited: Persistence, endogeneity, and heterogeneity* (IMF Working Paper No. 2017/126). International Monetary Fund. https://doi.org/10.5089/9781475595741.001

Dula, A., & Krasniqi, B. (2025). Firm-level hiring difficulties in manufacturing SMEs: The role of workforce migration, firm characteristics, and growth expectations. *Ekonomska misao i praksa, 34*(1), 3–22. https://doi.org/10.17818/EMIP/2025/7

Emara, A., & Raouf, E. (2017). The role of education inequality in the growth-volatility relationship in MENA region. *E3 Journal of Business Management and Economics, 8*(1), 18–25. https://doi.org/10.18685/EJBME(8)1_EJBME-17-012

Fan, J., Liao, Y., & Yao, J. (2015). Power enhancement in high-dimensional cross-sectional tests. *Econometrica, 83*(4), 1497–1541. https://doi.org/10.3982/ECTA12749

Fleisher, B. M., Hu, Y., Li, H., & Kim, S. (2011). Economic transition, higher education and worker productivity in China. *Journal of Development Economics, 94*(1), 86–94. https://doi.org/10.1016/j.jdeveco.2010.01.001

Gemmell, N. (1996). Evaluating the impacts of human capital stocks and accumulation on economic growth: Some new evidence. *Oxford Bulletin of Economics and Statistics, 58*(1), 9–28. https://doi.org/10.1111/j.1468-0084.1996.mp58001002.x

Glawe, L., & Wagner, H. (2022). Is schooling the same as learning? The impact of the learning-adjusted years of schooling on growth in a dynamic panel data framework. *World Development, 151*, Article 105773. https://doi.org/10.1016/j.worlddev.2021.105773

Goczek, Ł., Witkowska, E., & Witkowski, B. (2021). How does education quality affect economic growth? *Sustainability, 13*(11), Article 6437. https://doi.org/10.3390/su13116437

Haller, A.-P. (2023). Reducing inequalities through higher education and economic growth. Gender analysis by educational degrees: Bachelor's, master's and doctoral degrees. *Engineering Economics, 34*(3), 258–274. https://doi.org/10.5755/j01.ee.34.3.29972

He, Y., Peng, X., & Xu, H. (2020). Overeducation, market recognition, and effective labour supply. *China Economic Review, 59*, Article 101384. https://doi.org/10.1016/j.chieco.2019.101384

Jerrim, J., & Macmillan, L. (2015). Income inequality, intergenerational mobility, and the Great Gatsby curve: Is education the key? *Social Forces, 94*(2), 505–533. https://doi.org/10.1093/sf/sov075

Jones, P. (2001). Are educated workers really more productive? *Journal of Development Economics, 64*(1), 57–79. https://doi.org/10.1016/S0304-3878(00)00124-3

Juodis, A., & Reese, S. (2022). The incidental parameters problem in testing for remaining cross-section correlation. *Journal of Business & Economic Statistics, 40*(3), 1191–1203. https://doi.org/10.1080/07350015.2021.1906687

Kampelmann, S., Rycx, F., Saks, Y., & Tojerow, I. (2018). Does education raise productivity and wages equally? The moderating role of age and gender. *IZA Journal of Labor Economics, 7*, Article 1. https://doi.org/10.1186/s40172-017-0061-4

Karavias, Y., & Tzavalis, E. (2014). Testing for unit roots in short panels allowing for a structural break. *Computational Statistics & Data Analysis, 76*, 391–407. https://doi.org/10.1016/j.csda.2012.10.014

Klasen, S. (2002). Low schooling for girls, slower growth for all? Cross-country evidence on the effect of gender inequality in education on economic development. *The World Bank Economic Review, 16*(3), 345–373. https://doi.org/10.1093/wber/lhf004

Laidin, J., & Sidek, N. Z. M. (2025). The role of education in mitigating income inequality: A conceptual framework. *International Journal of Research and Innovation in Social Science, 9*(15), 906–916. https://doi.org/10.47772/IJRISS.2025.915EC0067

Laverde-Rojas, H., Correa, J., Jaffe, K., & Caicedo, M. (2019). Are average years of education losing predictive power for economic growth? An alternative measure through structural equations modeling. *PLOS ONE, 14*(3), Article e0213651. https://doi.org/10.1371/journal.pone.0213651

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

Luo, G., Zeng, S., & Baležentis, T. (2022). Multidimensional measurement and comparison of China's educational inequality. *Social Indicators Research, 163*, 857–874. https://doi.org/10.1007/s11205-022-02921-w

Magableh, S., Alalawneh, M., & Alqalawi, U. (2022). An empirical study on the effect of education on labor productivity. *Journal of Governance & Regulation, 11*(2), 301–308. https://doi.org/10.22495/jgrv11i2siart9

Makhlouf, Y., & Lalley, C. (2023). Education expansion, income inequality and structural transformation: Evidence from OECD countries. *Social Indicators Research, 169*, 255–281. https://doi.org/10.1007/s11205-023-03161-2

Maneejuk, P., & Yamaka, W. (2021). The impact of higher education on economic growth in ASEAN-5 countries. *Sustainability, 13*(2), Article 520. https://doi.org/10.3390/su13020520

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

Mijoč, I., Dropulić, I., & Galant, A. (2024). Analysis of skills for the accounting manager profession: The perspective of employers, accountants and students in Croatia. *Ekonomska misao i praksa, 33*(1), 271–295. https://doi.org/10.17818/EMIP/2024/1.13

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews, 34*(6–10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics, 60*(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H., & Xie, Y. (2021). *A bias-corrected CD test for error cross-sectional dependence in panel data models with latent factors* (CESifo Working Paper No. 9234). CESifo. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3904536; https://doi.org/10.2139/ssrn.3904536

Sauer, P., & Zagler, M. (2014). (In)equality in education and economic development. *Review of Income and Wealth, 60*, 335–379. https://doi.org/10.1111/roiw.12142

Schindler, S., Bar-Haim, E., Barone, C., Birkelund, J., Boliver, V., Capsada-Munsech, Q., Erola, J., Facchini, M., Feniger, Y., Heiskala, L., Herbaut, E., Ichou, M., Karlson, K., Kleinert, C., Reimer, D., Traini, C., Triventi, M., & Vallet, L. (2023). Educational tracking and social

inequalities in long-term labor market outcomes: Six countries in comparison. *International Journal of Comparative Sociology, 65*(1), 39–62. https://doi.org/10.1177/00207152231151390

Shahabadi, A., Nemati, M., & Hosseinidoust, S. (2018). The effect of education on income inequality in selected Islamic countries. *International Journal of Asia Pacific Studies, 14*(2), 61–78. https://doi.org/10.21315/ijaps2018.14.2.3

Štimac, H., & Bilandžić Tanasić, K. (2023). Competencies and skills: Gap between higher education and labour market. *Ekonomska misao i praksa, 32*(2), 615–628. https://doi.org/10.17818/EMIP/2023/2.15

Thomas, V., Wang, Y., & Fan, X. (2001). *Measuring education inequality: Gini coefficients of education* (Policy Research Working Paper No. 2525). World Bank. https://doi.org/10.1596/1813-9450-2525

Torpey-Saboe, N. (2019). Measuring education inequality. In *Measuring education inequality in developing countries* (pp. 51–74). Springer. https://doi.org/10.1007/978-3-319-90629-4_4

Wang, Y., & Liu, S. (2016). Education, human capital and economic growth: Empirical research on 55 countries and regions (1960–2009). *Theoretical Economics Letters, 6*(2), 347–355. https://doi.org/10.4236/tel.2016.62039

Yu, N., Yu, B., Jong, M., & Storm, S. (2015). Does inequality in educational attainment matter for China's economic growth? *International Journal of Educational Development, 41*, 164–173. https://doi.org/10.1016/j.ijedudev.2015.02.008

Zhao, W. (2024). The role of education quality in economic growth. *Highlights in Business, Economics and Management, 45*, 97–105. https://doi.org/10.54097/ncvbh380

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SLABI LI NEJEDNAKOST U OBRAZOVANJU AGREGATNI DOHODOVNI UČINAK ŠKOLOVANJA? DOKAZI IZ ZEMALJA OECD-A

Sažetak

Ovo istraživanje ispituje moderira li nejednakost u obrazovanju agregatni dohodovni učinak školovanja u zemljama OECD-a od 1995. do 2024. godine. Nejednakost u obrazovanju promatra se kao čimbenik koji može mijenjati odnos između prosječnog broja godina školovanja i dohotka po stanovniku. Prosječan broj godina školovanja kombinira se s Ginijevim indeksom obrazovanja, temeljenim na obrazovnim postignućima, kako bi se obuhvatile i razina i raspodjela ljudskog kapitala. Zbog međuzavisnosti među presječnim jedinicama i heterogenosti koeficijenata nagiba, kao glavna metoda procjene primjenjuje se procjenitelj zajedničkih koreliranih učinaka srednjih grupa (CCEMG), dok AMG i sistemski GMM služe kao provjere robusnosti. Rezultati pokazuju pozitivan odnos školovanja i dohotka po stanovniku, dok je interakcija školovanja i obrazovne nejednakosti negativna i statistički značajna. Pozitivan dohodovni učinak dodatne godine školovanja slabi s porastom obrazovne nejednakosti, što upućuje na važnost istodobnog povećanja obrazovnih postignuća i smanjenja nejednakosti u njihovoj raspodjeli.

Ključne riječi: nejednakost u obrazovanju, Ginijev indeks obrazovanja, prosječan broj godina školovanja, agregatni dohodovni učinak, raspodjela ljudskog kapitala, zemlje OECD-a.

JEL klasifikacija: I24, I25, O47, C33.