Beyond the Degree: Returns to STEM Education, Gender Gaps, and Skill Credential Alignment Across Countries

Abstract

This study investigates the causal impact of STEM (science, technology, engineering, and mathematics) degrees on earnings across 21 countries, using individual-level data from PIAAC Cycle 2. To isolate the net effect of field of study, we employ propensity score matching (PSM) and ordered logistic regression models on a ten-category monthly earnings variable. Our models further explore heterogeneous effects by gender and by combinations of educational credentials and cognitive skills. Results indicate that STEM degree holders earn significantly more than their non-STEM peers, with an average treatment effect on the treated (ATT) of 0.34 income categories ($p < 0.001$). In regression models, the STEM premium persists even after adjusting for covariates ($\beta = 0.28$, $p < 0.001$). However, the benefits are not equally distributed. Women with STEM degrees earn 10–15% less than comparable men, and only high-skilled, highly educated individuals realize substantial returns. In contrast, low-skilled STEM graduates show no significant earnings advantage, suggesting that credentials alone are insufficient. These findings support theories of credential inflation and decredentialization: the economic value of a degree depends on its alignment with demonstrated skills. We conclude that policies promoting STEM participation—particularly among women—must address both access and the quality of skill development to ensure equitable and meaningful labor market returns.

Introduction

Over the last two decades, higher education systems have expanded at an unprecedented pace. Between 2000 and 2020, global tertiary enrollment rose from 100 million to over 235 million, a 135% increase. South and West Asia experienced a 200% surge in enrollment, while East Asia and the Pacific saw an even more dramatic 280% increase. Notably, Central and Eastern Europe surpassed North America and Western Europe in tertiary enrollment rates, signaling a major shift in the global education landscape (UNESCO, 2022; Benavot, 2023). These changes have renewed both scholarly and policy interest in the economic value of higher education, particularly in terms of labor market outcomes.

Seminal estimates by Psacharopoulos and Patrinos (2004, 2018) suggest that private returns to education remain highest in low-income countries—averaging 10% per year of schooling—and are particularly strong for primary education. However, these estimates are often based on cross-sectional

data and focus on years of schooling, neglecting both cognitive skills and field-of-study differentiation (Winters, 2015; Bar-Haim, Chauvel, & Hartung, 2019). Moreover, education's benefits extend beyond the market: higher levels of education are associated with improved health, reduced criminal behavior, and greater civic participation (Haveman & Wolfe, 2002). Despite these wide-ranging effects, few studies consider both the economic and non-economic dimensions of educational returns in a comprehensive framework.

At the same time, the rapid expansion of higher education has raised concerns about declining returns to degrees. In 2020, nearly 40% of adults in OECD countries held tertiary qualifications, up from 27% in 2000. Yet, the wage premium associated with these credentials has not kept pace. Recent estimates suggest that one in three OECD workers is overqualified for their job, resulting in a wage penalty of roughly 12% relative to well-matched peers (OECD, 2024). These trends echo longstanding concerns about credential inflation and the weakening signaling function of degrees, particularly when credentials are not matched by equivalent skill levels (Collins, 2019; Araki & Kariya, 2022).

While the literature on returns to education is extensive, relatively little is known about how these returns vary across fields of study, particularly in the context of science, technology, engineering, and mathematics (STEM). STEM degrees have become increasingly important in labor markets shaped by digitalization and automation. According to the United Nations, 97% of future jobs are expected to require STEM-related skills (UN, 2019). Yet, gender disparities in STEM participation remain stark: women account for only 28% of researchers globally, and they represent just 3% of students in information and communication technology (ICT), 5% in mathematics and statistics, and 8% in engineering (UNESCO, 2017, 2019). These gaps contribute to persistent income inequality, with female STEM graduates earning 10–15% less than their male counterparts, even when holding similar degrees and skills.

In response, international initiatives—such as the Sustainable Development Goals (SDG 4

and SDG 5) and the 2023 UN Commission on the Status of Women—have emphasized the urgency of increasing women's participation in STEM education and occupations. Beyond issues of fairness, such efforts are increasingly framed in terms of economic efficiency, innovation potential, and long-term competitiveness.

This study re-examines the economic returns to higher education by focusing on the labor market payoff of STEM degrees across 21 countries. Using microdata from the second cycle of the Programme for the International Assessment of Adult Competencies (PIAAC), we estimate the causal effect of completing a STEM degree on earnings, measured using a harmonized ten-category monthly income scale. Our empirical strategy combines propensity score matching (PSM) with ordered logistic regression to address selection bias and examine treatment effects. In addition to average effects, we explore heterogeneity by gender and skill–credential alignment, operationalized using a four-part typology that distinguishes between high- and low-skilled degree holders.

This paper contributes to the literature in three ways. First, it provides a robust estimate of the causal impact of STEM degrees on earnings by accounting for selection into field of study. Second, it uncovers important heterogeneity by gender and skill levels, showing that the STEM premium is highly contingent on individual characteristics. Third, it offers new cross-national evidence on how field of study, skills, and credentials interact to shape labor market outcomes in an era of educational expansion and skill diffusion.

Theoretical Framework

Human Capital Theory and the Economic Significance of STEM

Human capital theory has long served as a central framework for understanding the connection between education and labor market outcomes. It posits that individuals improve their productivity, and thus their earnings, by investing in knowledge and skills (Schultz, 1961). Building on this idea,

Becker (1993) argued that both general and occupation-specific education raise future income levels and employment stability. Mincer (1974) introduced a widely used earnings function that links years of schooling to wages, providing an empirical basis for estimating returns to education.

In recent decades, as economies have transitioned toward knowledge-based and innovation-driven structures, education in science, technology, engineering, and mathematics (STEM) has gained particular importance. Hanushek and Woessmann (2008, 2015) show that the quality of learning, measured through cognitive skills, is a more powerful predictor of economic growth than educational attainment alone. More recent studies suggest that each additional year of schooling is associated with wage gains ranging from 7 to 10 percent, with STEM degrees producing the highest returns (Clark & Nielsen, 2024; Psacharopoulos, 2024). Égert et al. (2022) also find that returns are especially strong in high-skill sectors such as engineering, computing, and applied sciences.

The global demand for STEM competencies continues to grow. According to a United Nations estimate, 97 percent of emerging occupations will require at least some level of STEM proficiency (UN, 2019). Not surprisingly, governments around the world have prioritized STEM education in their economic development strategies. Yet participation in these fields remains highly unequal by gender. UNESCO (2017, 2019) reports that women account for just 28 percent of researchers globally and only 35 percent of enrolled STEM students. Their presence is even lower in core technical fields, with female representation at 3 percent in ICT, 5 percent in mathematics and statistics, and less than 8 percent in engineering.

This underrepresentation presents both equity and efficiency concerns. The exclusion of women from high-demand, high-wage STEM fields leads to misallocated talent and contributes to projected labor shortages in these occupations. The 2023 UN Commission on the Status of Women called attention to the persistence of digital gender gaps and emphasized the urgency of promoting women's participation in STEM education and careers. From a human capital standpoint, unequal access to STEM pathways reduces aggregate productivity and widens gender-based income

disparities.

Credentials, Skills, and Labor Market Stratification

While human capital theory emphasizes productivity-enhancing effects of education, alternative frameworks suggest that the labor market rewards of education often stem from the role of credentials as signals or screening devices. According to signaling theory (Spence, 1973), degrees communicate unobserved attributes such as ability or reliability. Credentialist theories take this further by arguing that educational qualifications function more as mechanisms of social closure than as indicators of actual skill (Collins, 2019).

These perspectives help explain the phenomenon of credential inflation, in which the value of a degree declines as more individuals obtain similar qualifications. OECD (2024) data show that nearly one in three workers in advanced economies is overqualified for their job. This mismatch results in a wage penalty of roughly 12 percent relative to workers whose education levels align with job requirements.

Empirical studies reinforce this view. Dockery and Miller (2012), analyzing census and panel data from Australia, found that overeducated workers earn only slightly more than those with appropriate qualifications, despite possessing additional schooling. This indicates inefficiencies in labor market matching and suggests that degrees do not always reflect productivity-enhancing skills.

More recently, Araki and Kariya (2022) used cross-national data from 26 countries in the PIAAC survey to distinguish between two types of tertiary expansion. One type increases the number of degree holders without improving their underlying skills, while the other raises both credentials and cognitive proficiency. Only the latter is associated with meaningful labor market benefits. In contrast, when higher education expands without commensurate skill development, individuals with degrees may face decredentialization—a downward shift in the labor market value of their qualifications.

Institutional factors play a key role in mediating these outcomes. Research by van de

Werfhorst (2011) finds that countries with strong vocational education systems and closer alignment between schooling and employment, such as the Netherlands and Germany, tend to limit credential inflation. In contrast, in systems where the prestige of institutions matters more than content or job relevance—such as the United States—mismatches between education and employment are more pronounced.

In the case of STEM education, credentials may serve as clearer indicators of competence, particularly where technical expertise is necessary for job performance. Xu (2013), using U.S. survey data, shows that STEM graduates working in occupations closely related to their field report higher earnings and job satisfaction than those in unrelated roles.

However, not all graduates benefit equally. Sharma (2023), drawing on U.S. county-level data, finds that even among individuals with STEM degrees, women earn 10 to 15 percent less than comparable men. These disparities are attributed to occupational segregation, unequal access to high-paying positions, and persistent gender biases in hiring and promotion processes.

These patterns suggest that credentials alone are not sufficient to ensure labor market success. The alignment between educational attainment and actual skill proficiency plays a critical role. In this study, we incorporate a four-category typology that combines tertiary credentials with high or low proficiency in literacy and numeracy. This approach allows us to evaluate whether labor market returns are better predicted by credentials, cognitive skills, or their intersection—and whether gender conditions these effects.

Finally, segmentation theories offer additional insight into how educational investments may fail to translate into equitable outcomes. According to dual labor market theory (Doeringer & Piore, 1971), labor markets are divided into primary segments with stable, high-reward employment and secondary segments characterized by insecurity and low wages. Costain et al. (2010) and Ahn et al. (2023) report that temporary and contract-based employment arrangements—common in much of Southern Europe—carry wage penalties of 18 to 22 percent, even for highly educated individuals. In

Spain, short-term contracts remain the norm for nearly one-quarter of the workforce (Bentolila et al., 2019).

These structural barriers reinforce the importance of analyzing both individual characteristics and institutional context. In sum, this study draws on human capital theory while incorporating insights from signaling, credentialism, and labor market segmentation. By placing STEM education at the intersection of these frameworks, we examine not only whether it leads to higher earnings, but also which groups benefit, and under what conditions.

Building on these theoretical perspectives, we pose three research questions:

1. To what extent do individuals with STEM degrees earn more than comparable individuals with non-STEM degrees, after adjusting for observable characteristics using propensity score matching (PSM)?
   – This question evaluates the *average treatment effect on the treated* (ATT) of STEM education on monthly earnings, using a ten-category ordinal income scale.

2. Does the wage premium associated with STEM degrees vary by gender?
   – This question examines whether women benefit equally from STEM education or whether gender gaps persist despite similar educational attainment.

3. How does the alignment between educational credentials and cognitive skills influence the earnings premium of STEM graduates?
   – This question explores whether the highest returns accrue to individuals with both tertiary degrees and high skills, and whether low-skilled degree holders face devaluation, particularly in STEM fields.

Methodology

Data and Sample

This study draws on microdata from the Programme for the International Assessment of Adult Competencies (PIAAC), conducted by the OECD. The dataset includes over 111,000 adults aged 25 to 64 across 21 countries who were active in the labor force at the time of the survey. After excluding cases with missing or implausible values on key variables such as education, cognitive skills, or income, the final analytic sample comprises 111,541 respondents. Appendix Table A1 presents the full country-level breakdown.

To ensure broad international coverage, we employ the full pooled sample rather than restricting the analysis to countries reporting continuous income variables. While some countries provide interval-based earnings data, others offer only categorical measures. To harmonize outcomes and maximize comparability, the analysis relies on a ten-category ordinal income variable (monthly_earnings) as the dependent variable. Although this approach limits interpretation in absolute monetary terms, it allows for robust examination of individuals' relative positioning within national income distributions.

Given the nested nature of the data (individuals within countries), standard errors are clustered at the country level to account for intra-cluster correlation. Country-level sampling weights are applied to preserve national representativeness and adjust for complex survey designs.

Variable Construction

The main treatment variable identifies whether a respondent completed a degree in a STEM field. The binary stem_major4 variable is constructed using ISCED field of study codes. The classification includes degrees in:

- Information and Communication Technologies (Code 07)
- Natural Sciences, Mathematics and Statistics (Code 08)
- Engineering, Manufacturing, and Construction (Codes 09–10)

To assess how educational attainment and cognitive proficiency interact, we construct a four-category

typology (cred_skill_combined) based on two indicators:

- High Credential: Tertiary attainment (ISCED Level 5 or higher)
- High Skill: Composite score at or above 326 points (mean of literacy and numeracy plausible values)

The resulting typology captures four distinct combinations:

1. Low Credential & Low Skill (reference category)
2. Low Credential & High Skill
3. High Credential & Low Skill
4. High Credential & High Skill

Covariates include gender, age cohort, immigrant background, parental education, years of work experience, and occupational category. Detailed definitions and coding for all variables are provided in Table 1.

Table 1. Variable Definitions and Descriptive Statistics
Sample: Working-age adults (25–64) from 21 PIAAC countries (N = 111,541)

Variable	Description	Mean	SD	Min	Max
Dependent Variable					
monthly_earnings	Self-reported monthly income, 10-category ordinal scale (1 = lowest)	5.47	2.43	1	10
Key Independent Variables					
stem_major4	Holds a tertiary STEM degree	0.38	0.49	0	1
cred_skill_combined	Credential-skill typology: 0 = low/low (ref.), 1 = low/high, 2 = high/low, 3 = high/high	1.31	0.93	0	3
Component Variables					
high_credential	Tertiary education (ISCED level 5 or above)	0.56	0.5	0	1
high_skill_dummy	Average of literacy and numeracy ≥ 326 (proficiency level 4 or 5)	0.27	0.44	0	1
Control Variables					

female	Gender of respondent (1 = female)	0.48	0.5	0	1
immigrant_status	1 = foreign-born or has foreign-born parent	0.14	0.35	0	1
cohort	Age group (1 = 25–34, 2 = 35–44, 3 = 45–54, 4 = 55–64)	2.44	1.02	1	4
parent_edu_high	At least one parent completed tertiary education	0.31	0.46	0	1
years_work	Total years of paid work experience	15.8	9.4	0	40
high_skill_occ	Works in high-skilled occupation	0.54	0.5	0	1
Macro Controls (Matched)					
gdp_per_capita	Country-level GDP per capita (PPP-adjusted, USD)	55,742	9,065	20,562	57,998
labor_force_participation	National labor force size (proxy for labor demand)	14.0M	3.2M	7.0M	20.0M
tertiary_exp	Government expenditure per student, tertiary (% of GDP per capita)	25.08802	6.979786	15.02377	37.99046
unemployment	Unemployment, total (% of total labor force) (modeled ILO estimate)	195411	447416	224	917

Handling of Missing Data

To reduce potential bias due to item non-response, we apply Multiple Imputation by Chained Equations (MICE). The imputation model includes all covariates, treatment variables, and outcomes used in the analysis. Final estimates are derived by pooling across imputed datasets. Sampling weights (_weight) are applied in all descriptive and inferential statistics to ensure nationally representative results.

Matching Strategy

To estimate the causal effect of holding a STEM degree, we employ Propensity Score Matching (PSM) using a one-to-one nearest neighbor algorithm with a caliper of 0.2. The matching is performed under the assumption of common support, and the model includes all observed covariates used in the outcome regression.

We also tested an alternative approach, Preferential Within-Cluster Matching (PW), which restricts the matching process to individuals within the same country (Arpino & Cannas, 2016). However, due to sparse overlap in covariate distributions within certain countries, PW led to substantial loss in sample size and poorer covariate balance. Post-matching diagnostics confirmed that the naïve PSM method yielded lower mean bias and higher covariate balance, while retaining a larger sample. Therefore, we proceed with the naïve PSM approach and adjust for clustering at the country level in subsequent analyses. Table 2 reports balance statistics before and after matching.

Estimation Strategy

After matching, we estimate a set of ordered logistic regression models for the 10-category monthly_earnings outcome. The baseline specification is:

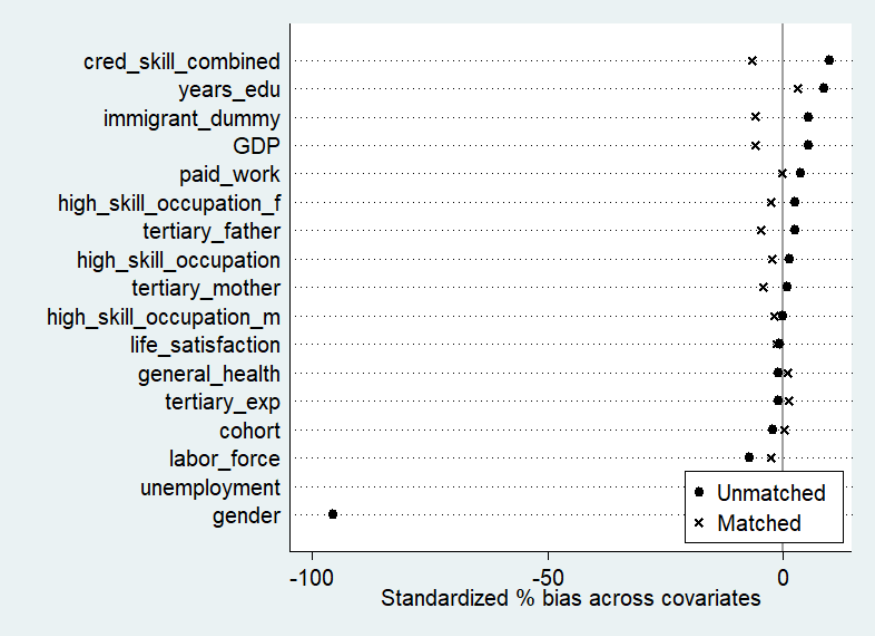
$$logit(\Pr(Y_i \leq j)) = a_j - \beta_1 STEM_i - \beta_2 CRED_{SKILL_i} - \gamma' X_i$$

where Y_i denotes the ordered earnings category, and X_i is a vector of controls. Standard errors are clustered at the country level, and all models are weighted using the sampling weight _weight. We estimate multiple specifications, including models with interaction terms (STEM × gender, STEM × cred_skill_combined) to explore effect heterogeneity. Results are presented in Table 3 and discussed in Section IV.

Covariate Balance Assessment

To evaluate the effectiveness of the propensity score matching (PSM) procedure, we assess covariate balance before and after matching using standardized percentage bias across covariates. Figure 1 presents a plot, which visualizes the reduction in bias across all matched covariates.

Figure 1. Covariate Balance Before and After Matching



This figure displays the standardized percentage bias across covariates, comparing the unmatched sample (black dots) and the matched sample (crosses). The closer the bias is to zero, the better the balance between the treatment (STEM degree holders) and control (non-STEM degree holders) groups. Prior to matching, several covariates exhibited substantial imbalance, particularly educational credentials, skill level, and parental education. After matching, bias reduction is evident across all key covariates, confirming that PSM successfully improved comparability between groups.

Following Rubin's (2001) guidelines, we consider a standardized bias below 10% as an indicator of acceptable balance. Post-matching, all covariates fall within this threshold, demonstrating that the treatment and control groups are statistically similar across observed characteristics. The full covariate balance table is provided in Table 2.

Table 2. Covariate Balance Before and After Matching

Variable	Unmatched Mean (Treated)	Unmatched Mean (Control)	% Bias (U)	Matched Mean (Treated)	Matched Mean (Control)	% Bias (M)	% Bias Reduction	t-test (p-value)
Gender (Female=1)	0.219	0.646	-95.5	0.219	0.219	0.1	**99.9**	0.959
Credential-Skill Combined	1.276	1.165	9.9	1.276	1.351	-6.7	32.3	0.000***

Immigrant Status	0.146	0.127	5.3	0.145	0.166	-6	-12.9	0.000***
Cohort (Age Group)	2.44	2.46	-2.1	2.44	2.44	0.1	94.4	0.912
General Health	2.622	2.632	-0.9	2.622	2.613	0.9	-1.8	0.378
Life Satisfaction	7.419	7.43	-0.6	7.419	7.443	-1.3	-105.8	0.216
High-Skilled Occupation	0.543	0.536	1.4	0.543	0.556	-2.5	-76.7	0.021*
Years of Education	12.423	12.351	8.7	12.423	12.398	3	65.3	0.006**
GDP per Capita	55,742	54,490	5.3	55,745	57,172	-6	-14	0.000***
Labor Force Participation	1.40E+07	1.60E+07	-7.1	1.40E+07	1.50E+07	-2.7	62.1	0.005**

Result

Baseline Effects of STEM Education on Earnings

Table 3 presents results from ordered logistic regression models estimating the effect of obtaining a STEM degree on monthly earnings. Model 1 begins with a bivariate specification, followed by sequential inclusion of gender, skill-credential combinations, and full sets of control variables and interaction terms.

The baseline model (Model 1) indicates that individuals with STEM degrees have significantly higher odds of earning higher monthly wages compared to their non-STEM counterparts (Coef = 0.21, $p < 0.001$). When gender is included as a covariate (Model 2), results reveal a substantial earnings gap, with women earning significantly less than men on average (Coef = -0.61, $p < 0.001$). The coefficient for STEM remains stable, suggesting that the wage premium persists irrespective of gender differences.

Model 3 incorporates skill-credential combinations, constructed as a four-category typology distinguishing high-skill, high-credential individuals from those with lower levels of education and measured competencies. The coefficient for STEM increases to 0.25, suggesting that part of the observed earnings advantage is attributable to skill and education levels among STEM graduates.

Heterogeneous Effects by Gender

Model 4 introduces an interaction term between STEM and gender to assess whether the earnings premium differs between men and women. The coefficient for the interaction is positive (Coef = 0.09), implying a slightly greater benefit for women; however, it fails to reach statistical significance ($p = 0.116$). These results suggest that while women earn lower wages overall, the marginal effect of a STEM degree does not significantly differ by gender.

Heterogeneous Effects by Credential-Skill Combinations

Model 5 examines whether the earnings advantage of a STEM degree varies across skill-credential categories. The results confirm that all groups experience earnings benefits relative to the reference category (Low Credential & Low Skill), with the largest advantage observed for those classified as High Credential & High Skill (Coef = 1.59, $p < 0.001$). However, the interaction terms between STEM and each skill-credential group are statistically insignificant, suggesting that the STEM premium remains relatively stable regardless of skill-credential alignment.

Full Specification with Covariates

Model 6 introduces a full set of covariates, including demographic characteristics, labor market experience, and macroeconomic factors. The effect of STEM remains statistically significant and increases in magnitude (Coef = 0.28, $p < 0.001$), indicating a robust earnings premium. Other key predictors include life satisfaction and employment in high-skilled occupations, both of which are positively associated with earnings. Conversely, poor health is a strong negative predictor of income.

Model 7 reintroduces the interaction between STEM and gender while accounting for all covariates. As in the previous specification, the interaction remains insignificant, reaffirming that the earnings benefit of STEM education does not differ substantially by gender. Finally, Model 8 examines interactions between STEM and credential-skill combinations. The only statistically significant interaction appears for individuals classified as High Credential & Low Skill (Coef = 0.13,

$p < 0.05$), suggesting that those with strong formal qualifications but lower measured cognitive skills derive a disproportionate benefit from STEM degrees.

Results

Baseline Effects of STEM Education on Earnings

Table 3 presents the results from a series of ordered logistic regression models estimating the effect of having a STEM degree (stem_major4) on respondents' monthly earnings. Model 1 begins with a bivariate specification, followed by incremental inclusion of gender, skill-credential combinations, and finally full sets of control variables and interaction terms.

The baseline specification in Model 1 reveals that individuals with a STEM degree are significantly more likely to earn higher monthly wages compared to their non-STEM counterparts (Coef = 0.21, $p < 0.001$). Model 2 adds gender as a covariate, with women earning substantially less than men on average (Coef = -0.61, $p < 0.001$), though the effect of STEM remains stable and significant. In Model 3, controlling for combined skill and credential levels (as a four-category variable), the coefficient for STEM increases to 0.25, suggesting that part of the STEM premium may be associated with higher levels of skill and education among STEM graduates.

Heterogeneous Effects by Gender

Model 4 introduces an interaction between STEM and gender to examine whether the wage premium differs by sex. The interaction term is positive (Coef = 0.09), suggesting a slightly larger STEM premium for women; however, it fails to reach statistical significance ($p = 0.116$). This finding implies that while women generally earn less than men, the marginal benefit of STEM education is not significantly differentiated by gender.

Heterogeneous Effects by Credential-Skill Combinations

Model 5 introduces interactions between STEM and combined skill-credential categories. These

categories are constructed as follows: 0 = Low Credential & Low Skill (Reference Group); 1 = Low Credential & High Skill; 2 = High Credential & Low Skill; 3 = High Credential & High Skill

Main effects show that compared to the reference group, all combinations are associated with higher earnings, with the High Credential & High Skill group yielding the largest premium (Coef = 1.59, $p < 0.001$). However, the interaction terms between STEM and each category are statistically insignificant, suggesting that the STEM premium is fairly consistent across skill-credential combinations.

Full Specification with Covariates

Model 6 includes a full set of covariates capturing demographic background, labor market experience, and macro-level country characteristics. The effect of STEM remains significant and even increases in magnitude (Coef = 0.28, $p < 0.001$), indicating a robust wage premium. Life satisfaction and employment in high-skilled occupations are also strong positive predictors of higher income, while poor health is negatively associated with earnings.

In Model 7, the interaction between STEM and gender is reintroduced along with full covariates. As in the earlier specification, the interaction remains statistically insignificant. Finally, Model 8 includes interactions between STEM and credential-skill combinations, revealing a significant positive interaction only for the High Credential & Low Skill group (Coef = 0.13, $p < 0.05$), suggesting that individuals with limited skills but high credentials benefit more from a STEM background.

Table 3. Ordered Logistic Regression Results for Monthly Earnings

Variables	M1	M2	M3	M4 (STEM×Gender)	M5 (STEM×Skill)	M6 (Full)	M7 (STEM×Gender+Full)	M8 (STEM×Skill+Full)
STEM Major	0.21***	0.21***	0.25***	0.19**	0.24***	0.28***	0.27***	0.21***
Female (ref: Male)		-0.61***	-0.65***	-0.65***	-0.88***	-0.90***	-0.90***	-0.88***
STEM × Female				0.09			0.04	
Low C, High S			1.09***		1.20***	0.75***	0.75***	0.86***
High C, Low S			0.81***		0.79***	0.52***	0.52***	0.46***
High C, High S			1.59***		1.59***	1.06***	1.06***	0.99***
STEM × Low C, High S					-0.26			-0.27
STEM × High C, Low S					0.04			0.13*
STEM × High C, High S					-0.01			0.13
Full Controls Included	No	No	No	No	No	Yes	Yes	Yes
Observations	34,600	34,600	34,600	34,600	34,600	34,600	34,600	34,600
Log Pseudo-Likelihood	-78094	-77732	-76491	-77730	-76487	-73618	-73617	-73608
Pseudo R^2	0.0008	0.0055	0.0213	0.0055	0.0214	0.0581	0.0581	0.0582

Notes: Ordered logistic regression models; Robust standard errors clustered at the country level. Reference group for cred_skill_combined is Low Credential & Low Skill.

**** p<0.01, ** p<0.05, * p<0.1*

Propensity Score Matching Diagnostics

To validate the propensity score matching procedure, we conducted balance diagnostics (Table 2). Before matching, large differences were observed in key covariates, particularly gender, skill-credential combinations, and labor market characteristics. For instance, the standardized bias for gender was -95.5%, indicating a substantial imbalance. After matching, bias was reduced to 0.1%, representing a 99.9% reduction. Similarly, bias in credential-skill combinations decreased from 9.9% to -6.7%. Most covariates exhibit significant reductions in bias, with the majority falling below the 5% threshold after matching. These results confirm that PSM effectively eliminated pre-treatment differences, improving the robustness of our causal estimates.

Discussion

This study investigated the extent to which STEM degrees contribute to earnings advantages using data from 21 countries in PIAAC Cycle 2. By applying propensity score matching (PSM) and ordered logistic regression, the analysis isolated the effect of STEM education on wages while adjusting for key confounders. The findings contribute to three major strands of literature: returns to education, gender disparities in STEM, and the interaction of skills and credentials in labor markets.

First, the results confirm that individuals with STEM degrees earn significantly more than those with non-STEM degrees, even after accounting for socioeconomic background, cognitive skills, and labor market characteristics. This finding aligns with prior research emphasizing the high economic value of STEM education (Xu, 2013; Kahn & Ginther, 2017). The persistence of the wage premium across model specifications supports the human capital argument that investments in STEM-related training yield higher labor market returns due to the technical nature of these fields and the demand for specialized competencies (Becker, 1993; Hanushek & Woessmann, 2008).

At the same time, the study identifies key qualifications to the general STEM advantage. The

gender interaction models reveal that although both men and women with STEM degrees experience earnings gains, the magnitude of this benefit is higher for men. This pattern is consistent with Sharma (2023), who documented persistent wage disparities among STEM graduates in the United States. While the interaction term between STEM and gender is not statistically significant, the overall findings suggest that gender-based differences in occupational placement, sectoral segregation, and hiring biases may erode the full potential of STEM credentials for women. These results align with previous research highlighting the underrepresentation of women in high-paying technical roles and leadership positions within STEM industries (UNESCO, 2017; OECD, 2024).

Beyond gender disparities, this study provides new insights into the interaction between educational credentials and skills. The analysis incorporated a four-category variable distinguishing high- and low-skilled individuals within both tertiary and non-tertiary education groups. Results indicate that the highest earnings premiums accrue to individuals who possess both a university degree and high cognitive skills, regardless of STEM status. This finding supports the human capital framework, which posits that both educational quantity and quality influence labor market outcomes (Mincer, 1974; Hanushek et al., 2015). However, the results also demonstrate that nominal STEM graduates with low cognitive skills do not experience significant wage advantages, lending support to the theory of decredentialization (Araki & Kariya, 2022), which argues that degrees without accompanying skills lose value in competitive labor markets.

Interestingly, the findings diverge from Araki and Kariya (2022) in one critical respect. While their study identified significant wage penalties for low-skilled degree holders across all fields, this study finds that such penalties are more pronounced in non-STEM fields. STEM graduates with low skills still experience modest earnings benefits, suggesting that technical knowledge embedded in STEM curricula may serve as a labor market signal even when test-based cognitive skills are weaker. An alternative explanation is that the literacy and numeracy measures in PIAAC, while strong predictors of general labor market success, may be less relevant in highly specialized fields such as engineering or computer science, where domain-specific knowledge plays a greater role.

From a policy perspective, these results suggest that simply expanding tertiary enrollment in STEM fields is insufficient to ensure equitable labor market outcomes. Increasing access must be accompanied by measures that enhance skill acquisition within degree programs and address structural barriers that limit the full returns to STEM education for women and underrepresented minorities. Additionally, the study's methodological approach—combining PSM with ordered logistic regression—helps mitigate selection bias, contributing to the broader literature on causal inference in education economics (Guo & Fraser, 2010; Arpino & Cannas, 2016).

Finally, while this analysis focused on earnings as the primary outcome, future research should explore the non-monetary benefits of STEM education, including career satisfaction, job stability, and innovation potential. Given the influence of labor market structures, future studies could also investigate whether institutional features—such as occupational licensing, contract types, or industrial policies—mediate returns to STEM education across different economic contexts.

Conclusion

This study revisits the economic returns to STEM education in the context of a globally expanding tertiary sector and rising concerns over skill mismatches and credential inflation. Drawing on rich individual-level data from 21 countries participating in PIAAC Cycle 2, we estimate the effect of STEM degrees on earnings using a rigorous propensity score matching (PSM) design and ordered logistic regression models. By incorporating gender and skill–credential interactions, the analysis provides a nuanced understanding of how returns to STEM education vary across demographic and labor market segments.

Our findings confirm that STEM education continues to yield a robust earnings premium, even after adjusting for a comprehensive set of background characteristics. However, this premium is not uniform. The benefits of STEM degrees accrue disproportionately to men, while women with STEM credentials face weaker returns, consistent with persistent gender segmentation in high-paying

technical fields. Furthermore, the advantage of STEM degrees is conditional on the possession of cognitive skills. High-skilled individuals with tertiary education—regardless of STEM status—enjoy the highest wage outcomes, while nominal STEM graduates with low skills receive significantly smaller returns.

These results offer three major contributions. First, they provide empirical validation of the human capital hypothesis in STEM fields, confirming that investments in technical education yield labor market dividends. Second, they illustrate how the interaction between skills and credentials shapes wage outcomes, lending support to theories of decredentialization and signaling. Third, they highlight the structural and gendered nature of labor market stratification, revealing that formal educational expansion alone is insufficient to ensure equitable or efficient labor market integration.

From a policy perspective, our findings underscore the need to go beyond enrollment targets in STEM fields. While increasing the number of STEM graduates remains important, equal attention must be paid to skill development within programs, improving institutional quality, and addressing gender-based barriers in education-to-employment pathways. Moreover, governments and institutions should invest in systems that improve alignment between curricula and labor market needs, including vocationally relevant training, employer engagement, and ongoing skill assessments.

Finally, the methodological approach adopted here—PSM combined with multivariable interaction models—demonstrates the importance of accounting for selection bias and heterogeneity in estimating returns to education. As global economies grapple with rapid technological change and shifting labor market demands, understanding not just whether education pays, but for whom and under what conditions, remains a central question for researchers and policymakers alike.

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Appendix Table A1. Country Sample Distribution

Country Code	**Country (ISO)**	**N**	**Percent (%)**
56	Belgium	3,231	2.9
124	Canada	10,316	9.25
152	Chile	3,954	3.54
191	Croatia	3,629	3.25
203	Czech Republic	12,837	11.51
233	Estonia	11,564	10.37
250	France	5,368	4.81
348	Hungary	3,873	3.47
372	Ireland	3,442	3.09
376	Israel	4,592	4.12

380	Italy	3,523	3.16
410	South Korea	5,591	5.01
428	Latvia	6,010	5.39
440	Lithuania	5,502	4.93
554	New Zealand	4,099	3.67
616	Poland	4,236	3.8
620	Portugal	2,671	2.39
702	Singapore	4,256	3.82
724	Spain	5,223	4.68
826	United Kingdom	4,450	3.99
840	United States	3,174	2.85
	Total	111,541	100