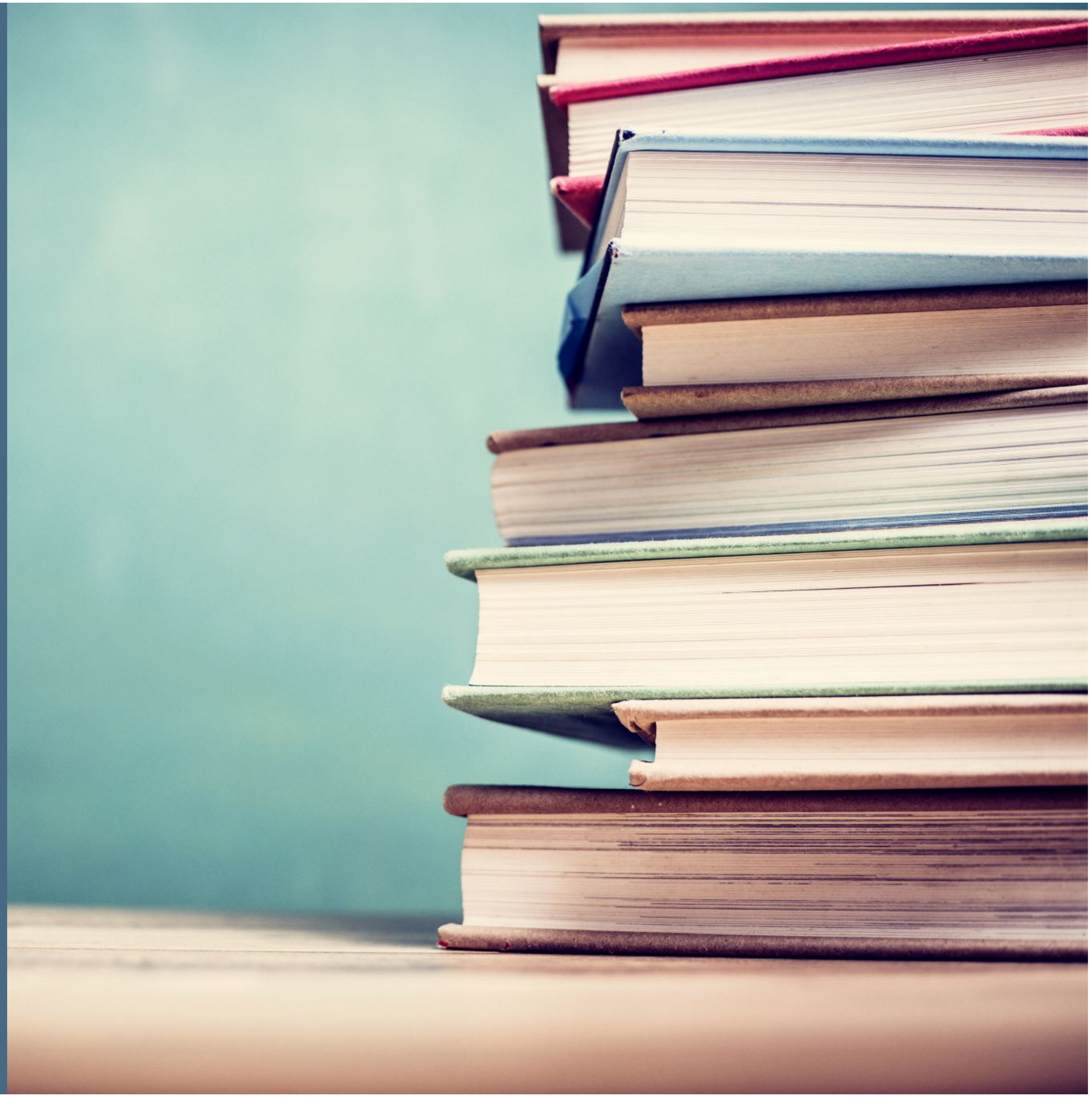
EDUCATION AND INEQUALITY

EE473



- **Human capital theory** – investment in higher levels of educational attainment improves labor market outcomes through improved productivity
- **Private returns to education** – the benefits accruing to individuals from obtaining additional education. These includes higher earnings and reduced likelihood of unemployment. ‘Returns’ to education are causal impacts rather than associations
- **Skilled-biased technical change** – changes in technology lead to increases in the productivity which differentially favors high-skilled workers. This is in part responsible for increases in inequality as earnings for high-skilled workers rise more quickly than the earnings of lower- skilled workers
- **Social returns to education** – the benefits of an individual obtaining additional education for other members of society. These can include higher productivity, reduced impacts from crime a healthier workforce, and more civic engagement

INTRODUCTION

- We consider the extent to which educational achievement is unequally spread through the population
- We look at the implications of inequalities in education for economic and social well-being
- The analysis we present studies several dimensions of inequality in education experiences and achievement: social background; ethnicity and immigrant status; and gender

INEQUALITIES BY SOCIAL BACKGROUND

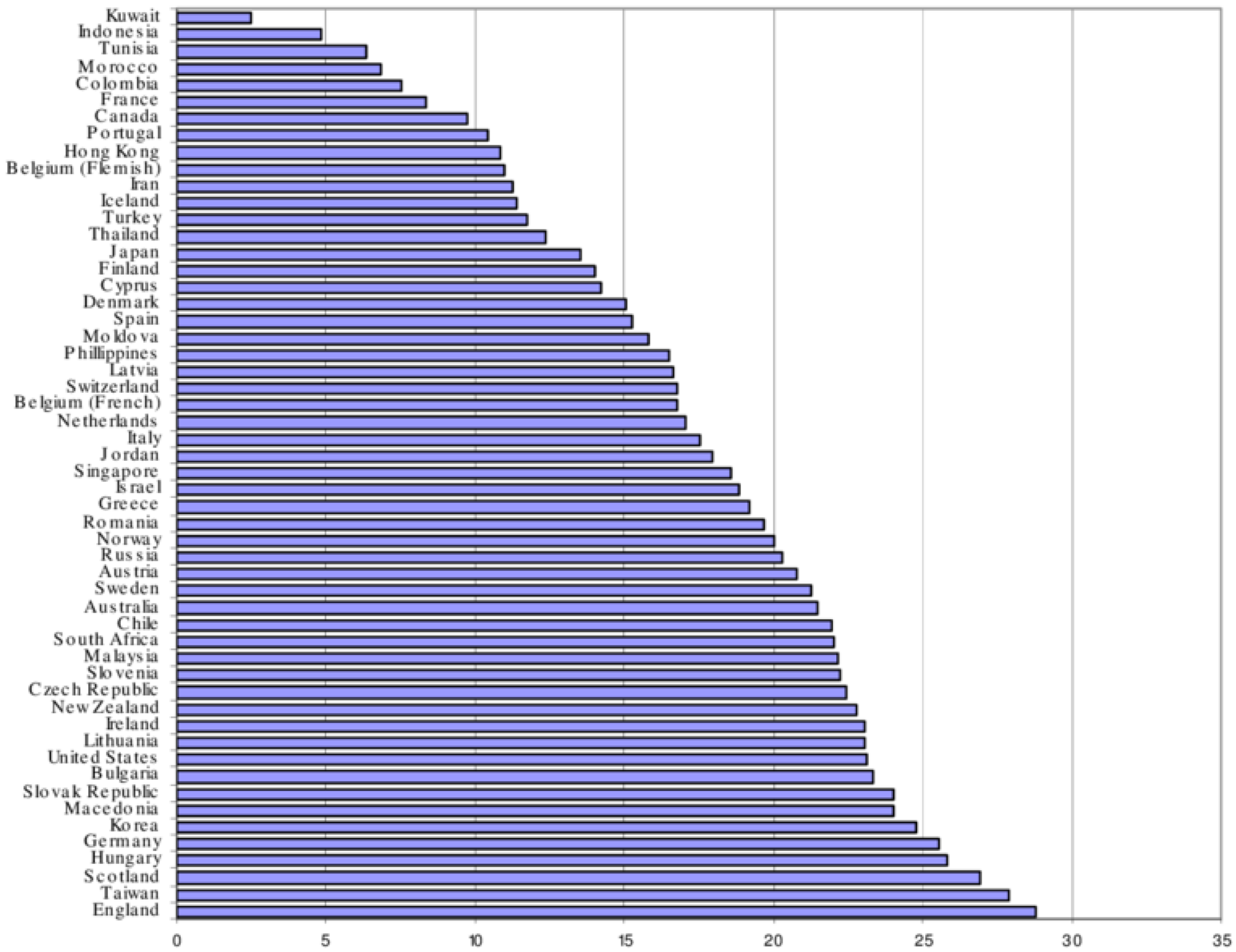
- The observation that **children from poorer backgrounds do worse in terms of educational outcomes has a long history**
- **Gaps in educational attainment between children from richer and poorer backgrounds continue to be marked** at the start of the twenty-first century
- A large literature indicates that gaps in attainment emerge very early in children's lives. **Substantial gaps in test-score attainment are found by income group before children start school** (Carnerio & Heckman, 2004; Blanden &Machin, 2008)
- Some evidence links these **differences to the sizable disparities in preschool enrolment between children from high- and low- education parental backgrounds** (Mayers et al., 2004)
- Recent international surveys that **test school-age children enable comparisons to be made of the strength of the influence of family background on achievement across many countries**

FIGURE 1
ESTIMATED EFFECTS OF FAMILY BACKGROUND ON STUDENTS' TEST SCORES ACROSS COUNTRIES

Family background effects are based on reported measures of the number of books at home; test scores are average mathematics and science scores from TIMSS

The family background effects are estimated from statistical regressions explaining standardized test scores based on the number of books at home

As standardized test scores have an international standard deviation of 100, these effects can be interpreted as percentages of an international standard deviation by which test achievement increases if the number of books is raised by one category



- Figure 1 shows family background effects on test scores from an interesting recent paper by Schuetz et al. (2005) - this uses cross-country data from the Third International Mathematics and Science Study (TIMSS) from 1995 and its repeat survey from 1999
- In 53 out of 54 countries the family background effect is statistically significant and the implied gaps in test scores are large
- Unsurprisingly, **these substantial gaps in test scores lead to inequality in final educational attainments – this includes a higher probability of dropping out of school and lower qualification attainment**
- There is evidence that **inequalities continue to grow so that parental background influences final educational outcomes even once earlier achievements are taken into account**

INEQUALITIES BY RACE, ETHNICITY, AND IMMIGRANT STATUS

- Given the diversity of the racial and ethnic dimensions pertinent in different countries, it is difficult to provide a concise summary across countries.
- Cameron and Heckman (2001) find that **minority groups are actually more likely to attend college given their test scores.**
- Carneiro et al. (2005) have sought to investigate the time path in differences in cognitive and noncognitive skills by race – there is evidence that this gap widens somewhat with age between blacks and whites, but with gaps appearing so early; it is difficult to state that the school system is the major source of racial inequality in the US.
- Platt(2007) finds substantial differences in education attainment among the UK's 16 to 24 years old in 2001, with young people from Chinese and Indian backgrounds exceeding the performance of whites.

- Figure 2, 3, and 4 attempts this by considering the differences between reading, science, and problem-solving performance test scores in the Programme for International Student Assessment (PISA) between both first- and second- generation immigrants and native students (that is third generation or higher).
- In almost all countries (Canada being the exception), natives are outperforming immigrant groups at age 13 and, in most, gaps are larger for first-generation immigrants than second-generation immigrants, this suggests assimilation.

FIGURE 2
DIFFERENCES IN READING PERFORMANCE BY IMMIGRANT STATUS

Note: statistically significant differences are marked in darker tones.
Source: Oecd pisa 2003 database

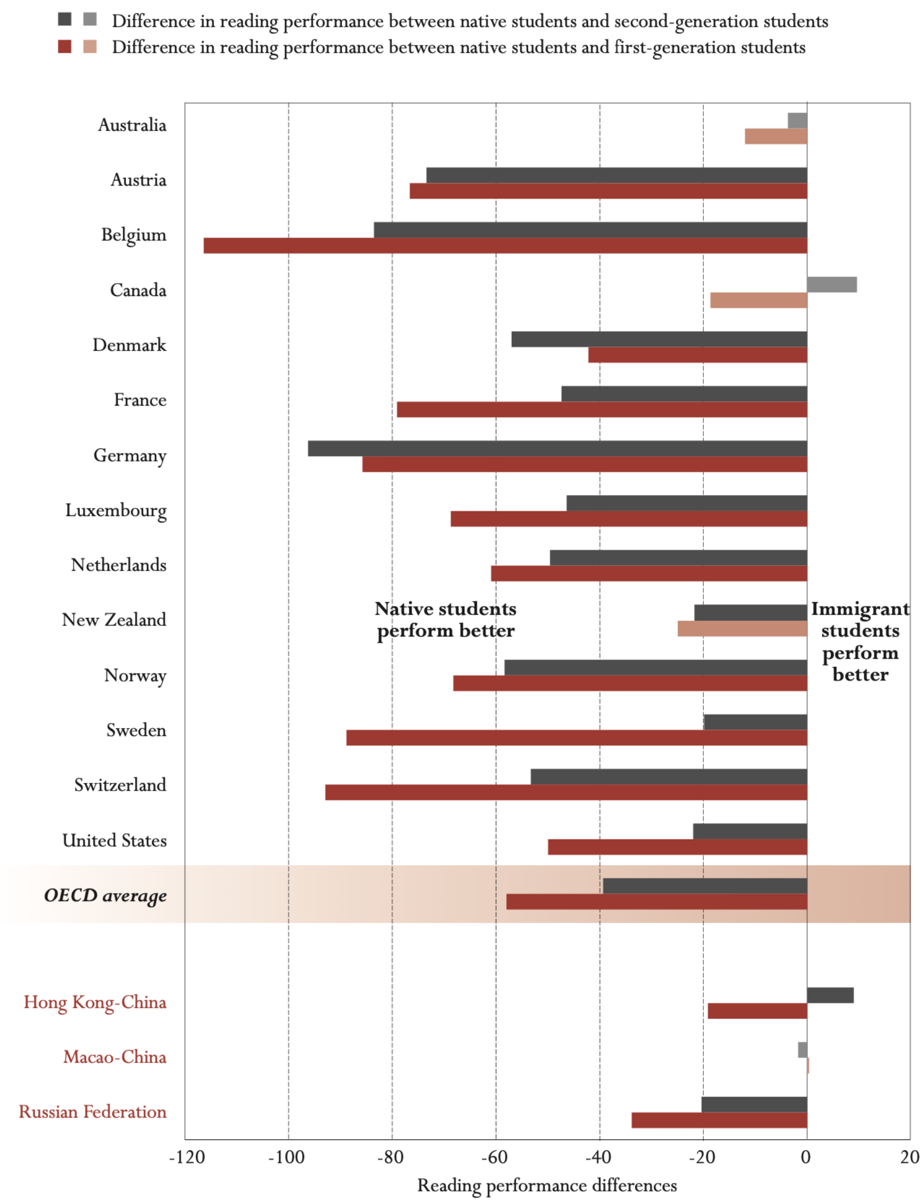


FIGURE 3 DIFFERENCES IN SCIENCE PERFORMANCE BY IMMIGRANT STATUS

Note: statistically significant differences are marked in darker tones.
Source: Oecd pisa 2003 database

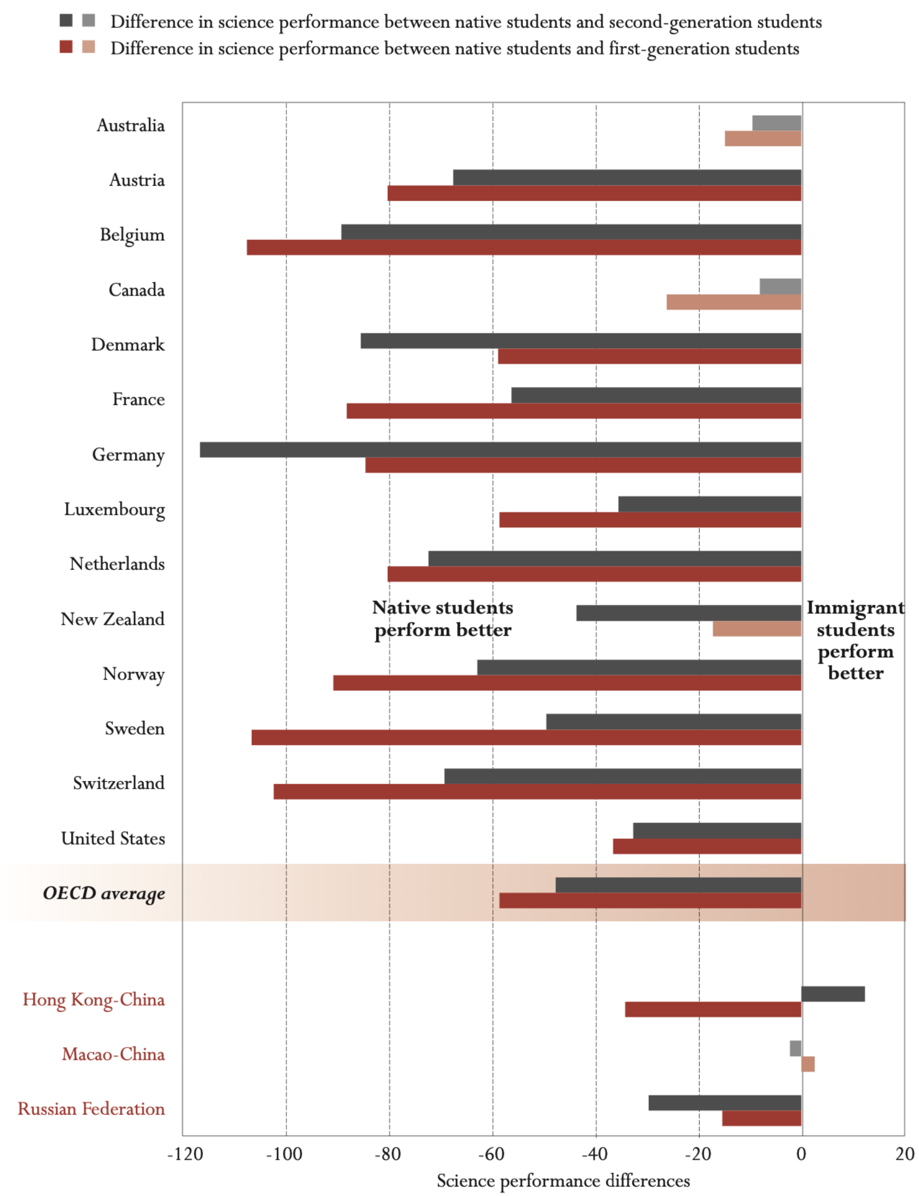
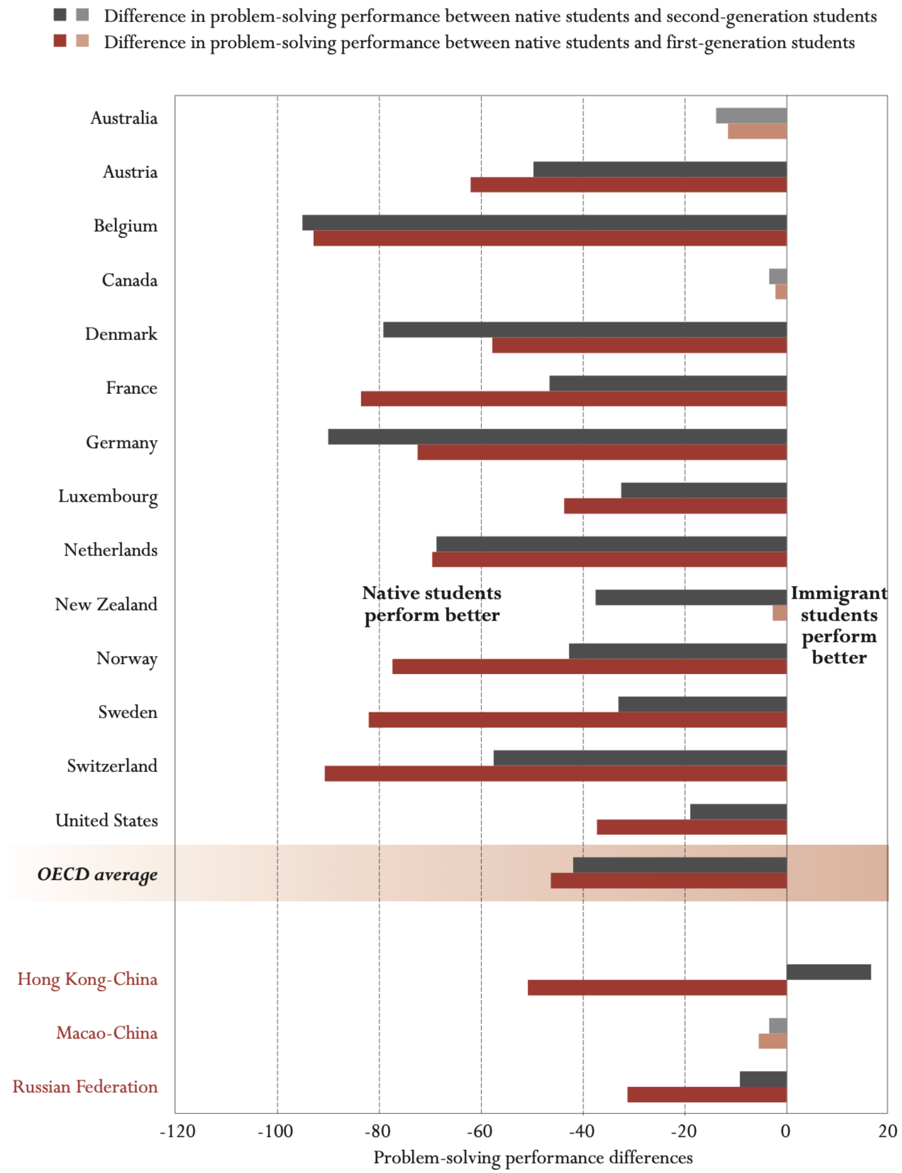


FIGURE 4 DIFFERENCES IN PROBLEM-SOLVING PERFORMANCE BY IMMIGRANT STATUS

Note: statistically significant differences are marked in darker tones.
Source: Oecd pisa 2003 database



- In the three other PISA assessment domains (reading, science and problem solving), there are also significant differences in performance between native students and immigrant students (see figures 2, 3 and 4).
- The trends between **second-generation and native students are similar across domains**.
- There are **larger differences in performance between first-generation and native students in reading and science than in mathematics and problem solving**.
- The more pronounced **disadvantages of immigrant students in reading and science may result from the greater need to master language in these subject domains**.
- Previous research indicates that **immigrant students whose native or home languages differ from the language of instruction may therefore be at a particular disadvantage in these domains** (abedi, 2003).

INEQUALITIES BY GENDER

- The relative performance of women compared to men in terms of qualifications gained has improved across the world in the past three or four decades.
- Jacob (2002) uses a decomposition approach to analyze why women in the US are now more likely to go to college than men.
- He finds that 90% of the attendance gap can be explained by women's higher returns to degrees and women's greater noncognitive skills.
- Noncognitive skills are measured as middle school grades, grade retention, and the number of hours spent on homework – a measure of behavior problems.
- The idea is that measures of school-based attainment will reflect effort and application once cognitive test scores are also taken into account.
- Jacob does not find any differences in cognitive scores between girls and boys conditional on other characteristics.

- We can say that **inequalities by family background are large, persistent, and show little sign of reducing, while the picture for race/ethnicity and gender is more positive, at least in some countries.**

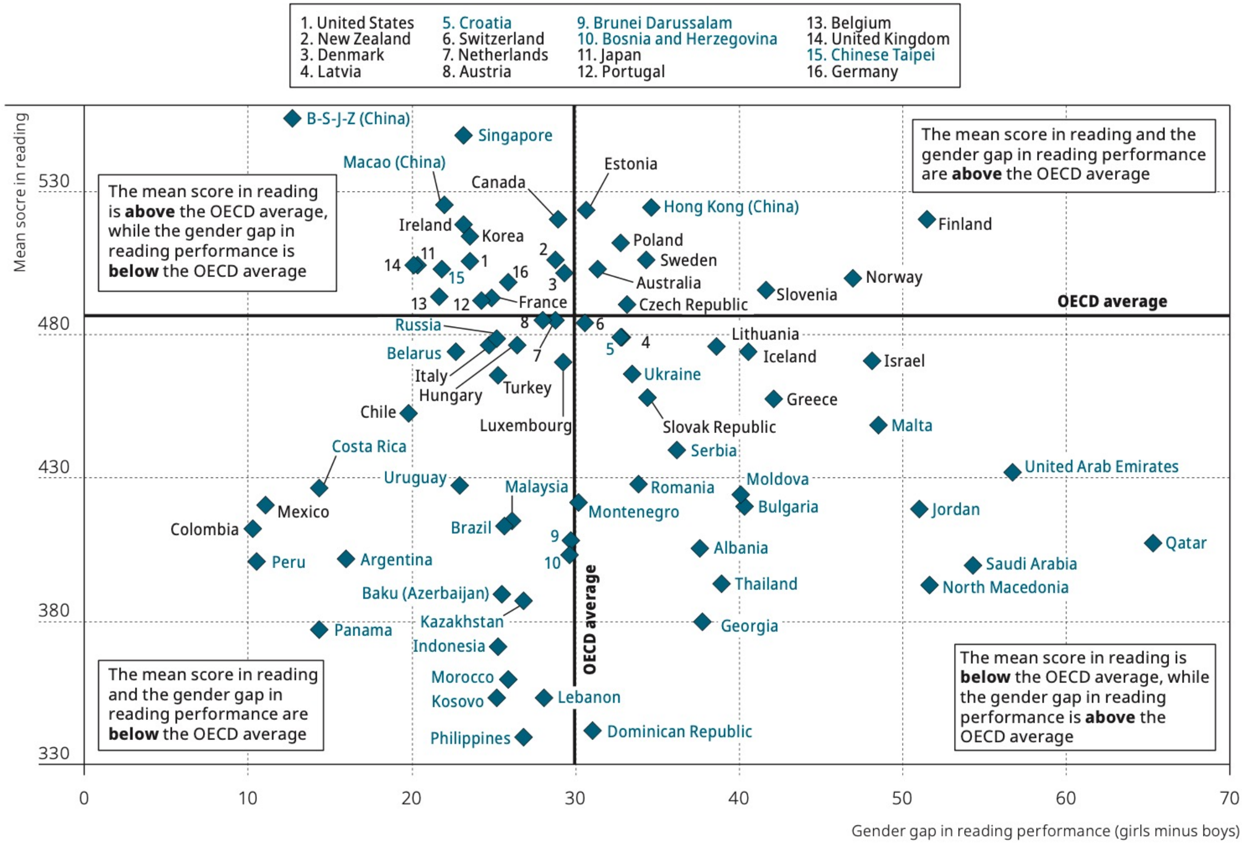
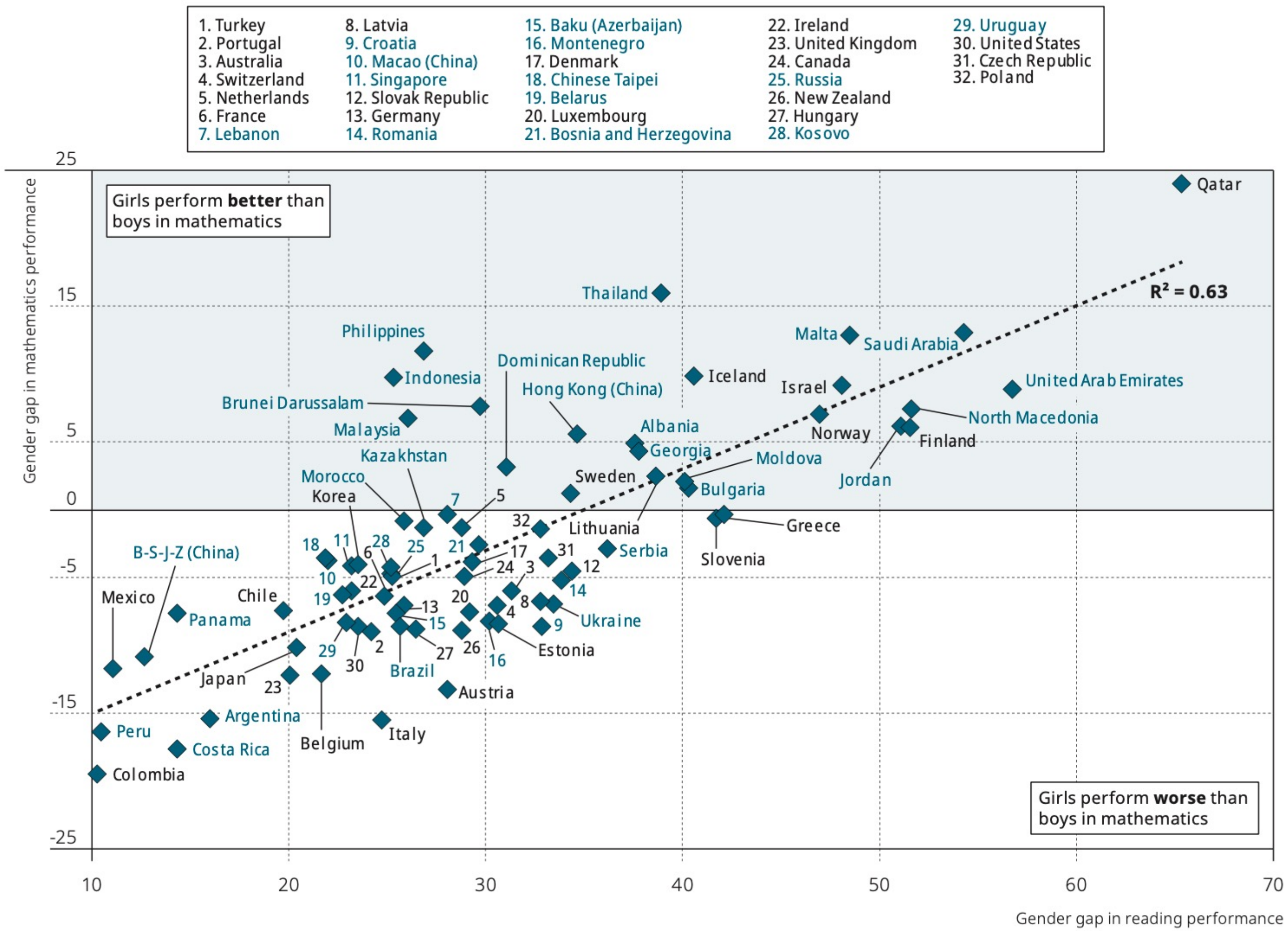


FIGURE 5 MEAN SCORE AND GENDER GAP IN READING PERFORMANCE

Source: OECD, PISA 2018 Database, Tables I.B1.4 and II.B1.7.1.

FIGURE 6 GENDER GAP IN READING AND MATHEMATICS PERFORMANCE



Note: Gender gap refers to the difference between girls and boys (girls minus boys).
Source: OECD, PISA 2018 Database, Tables II.B1.7.1 and II.B1.7.3.

EDUCATION AND ECONOMIC OUTCOMES

- Higher levels of educational attainment are **strongly associated** with higher earnings and better employment prospects

$$\log w = \beta_1 + \beta_2 S + \beta_3 S^2 + u$$

- Psacharopoulos and co-authors have written numerous papers comparing the coefficient β_2 across the world and have found evidence that earnings returns to schooling are widespread and tend to be higher for primary education and in countries with lower levels of development

- Table 1 shows OECD evidence on educational wage differentials that accrue to people with tertiary education levels relative to post- secondary nontertiary levels in 15 countries
- The existence of sizable gaps in earnings is seen for all countries
- According to these earnings differentials, acquisition of more education leads to significantly higher earnings

TABLE 3: EDUCATION AND EARNINGS : DIFFERENCES IN EARNINGS BETWEEN FEMALE AND MALE WORKERS, BY EDUCATIONAL ATTAINMENT

ISC11A			Below upper secondary education	Upper secondary or post-secondary non-tertiary education	Tertiary education	All levels of education
Country	Unit					
Australia	Percentage, 2021		96	81	82	87
Austria	Percentage, 2021		85	85	76	83
Belgium	Percentage, 2020	i	78	82	87	91
Canada	Percentage, 2020		73	73	80	82
Chile	Percentage, 2017		81	76	68	82
Colombia	Percentage, 2020		85	85	84	109
Costa Rica	Percentage, 2021		87	89	101	124
Czechia	Percentage, 2020		89	84	75	83
Denmark	Percentage, 2021		82	81	77	82
Estonia	Percentage, 2021		62	74	78	83
Finland	Percentage, 2020		81	78	76	81
France	Percentage, 2019		72	76	74	79
Germany	Percentage, 2021		95	80	71	76
Greece	Percentage, 2018		72	83	78	84
Hungary	Percentage, 2021		87	85	70	84
Ireland	Percentage, 2020	i	79	85	70	79
Israel	Percentage, 2020		68	69	69	73
Italy	Percentage, 2020		79	80	70	83
Korea	Percentage, 2021		75	72	73	72
Latvia	Percentage, 2021	i	76	68	73	83
Lithuania	Percentage, 2018		85	80	76	83
Luxembourg	Percentage, 2021	i	67	87	82	86
Mexico	Percentage, 2018	i	66	72	75	75
Netherlands	Percentage, 2021		83	84	78	89
New Zealand	Percentage, 2021		80	81	81	83
Norway	Percentage, 2021		82	79	76	82
Poland	Percentage, 2020		78	82	74	88
Portugal	Percentage, 2021		80	77	74	84
Slovak Republic	Percentage, 2021		81	81	75	83
Slovenia	Percentage, 2021		89	88	85	97
Spain	Percentage, 2020		78	75	84	91
Sweden	Percentage, 2021		86	84	80	87
Switzerland	Percentage, 2021		82	84	82	83
Türkiye	Percentage, 2021	i	74	79	81	89
United Kingdom	Percentage, 2021		77	73	77	81
United States	Percentage, 2021		74	76	72	78

Relative earnings - men = 100

EMPLOYMENT RATES OF TERTIARY-EDUCATED ADULTS, BY FIELD OF STUDY (2021)

- Workers with educational qualifications also tend to correlate with improved employment probabilities.
- Table 4 compares the employment rates of those who do not complete upper secondary schools (equivalent to US high school) with employment rates for those who have high school but no college education.
- Obtaining at least the typical level of education increases employment probabilities.

TABLE 4 EMPLOYMENT RATES OF 25-64 YEARS-OLD, BY EDUCATIONAL ATTAINMENT (2021)

PERCENTAGE OF EMPLOYED 25-64 YEARS-OLD AMONG ALL 25-64 YEARS-OLD

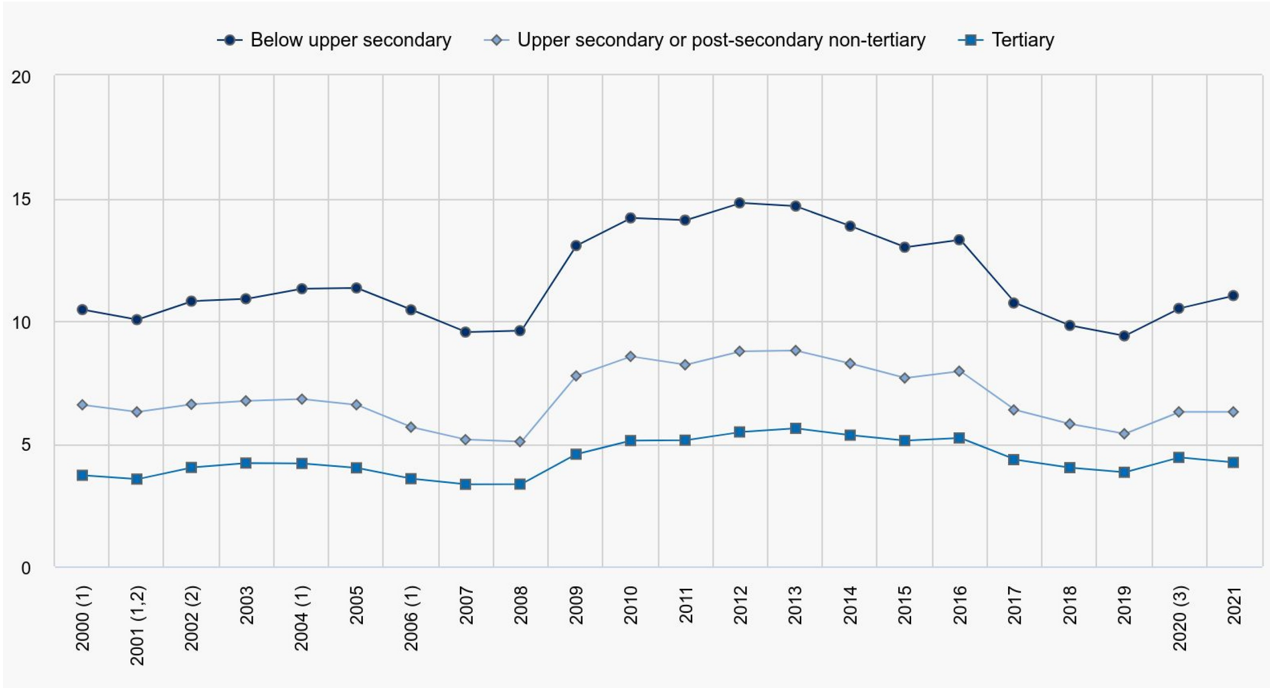
		Below upper secondary	Upper secondary or post-secondary non-tertiary			Tertiary					All levels of educatio
			Upper secondary	Post-secondary non-tertiary	Total	Short-cycle tertiary	Bachelor's or equivalent	Master's or equivalent	Doctoral or equivalent	Total	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OECD	Countries										
	Australia	60	78	84	79	81	86	88	95	86	79
	Austria	54	75	85	76	85	80	89	93	86	76
	Belgium	45	72	85	73	86	85	89	95	87	74
	Canada	56	69	79	72	79	83	87[d]	x(7)	82	77
	Chile[1]	52	63	a	63	73	83	91[d]	x(7)	80	65
	Colombia	65	76[d]	x(2)	68	x(6)	87[d]	x(6)	x(6)	77	69
	Costa Rica	60	66	c	66	72	83	89	c	81	66
	Czech Republic	56	83[d]	x(2)	83	89	82	88	94	87	83
	Denmark	62	82	91	82	87	86	90	93	88	81
	Estonia	64	79	80	79	83	86	89	92	87	81
	Finland	54	76	95	77	82	88	90	m	88	79
	France	53	74	61	74	85	84	89	91	86	75
	Germany	62	80	86	82	88	87	89	93	88	81
	Greece	53	62	68	63	71	73	84	93	76	65
	Hungary	59	81	91	82	91	89	92	99	91	82
	Iceland	71	80	91	82	85	87	92	93	89	83
	Ireland	52	70	75	72	81	86	88	92	86	77
	Israel	48	70	a	70	84	86	90	92	87	76
	Italy	51	70	74	70	70	75	85	92	82	66
	Japan[2]	x(2)	82[d]	x(5)	m	82[d]	89[d]	x(6)	x(6)	86[d]	84
	Korea	61	70	a	70	76	77	86[d]	x(7)	77	73
	Latvia	62	73	75	73	82	86	86	97[r]	86	77
	Lithuania	58	74	74	74	a	88	92	96	90	80
	Luxembourg	62	72	78	72	81	81	89	89	86	77
	Mexico	64	69	a	69	72	78	86	92	78	68
	Netherlands	66	83	79	83	90	87	91	96	89	82
	New Zealand	72	82	86	83	90	89	88	89	89	83
	Norway	61	81	83	81	83	90	93	95	89	82
	Poland	49	74	74	74	76	89	91	97	91	78
	Portugal	70	82	81	82	78	83	92	95	90	80
	Slovak Republic	30	79	82	79	c	76	90	92	88	78
	Slovenia	50	75	a	75	86	89	91	94	90	79
	Spain	58	71	64	71	79	80	84	87	81	71
	Sweden	62	85	82	84	82	89	93	94	89	83
	Switzerland	67	82[d]	x(2)	82	x(6, 7, 8)	88[d]	89[d]	93[d]	89	83
	Türkiye	50	59	a	59	63	75	82	91	72	57
	United Kingdom[3]	64	79	a	79	82	87	88	91	86	80
	United States	52	67[d]	x(2)	67	75	80	85	88	81	72
	OECD average	58	75	80	75	81	84	89	93	85	76
	EU22 average	56	76	79	76	82	84	89	93	87	77
Partners	Argentina	66	73	a	73	x(6)	85[d]	x(6)	93	86	74
	Brazil	55	68	a	68	x(6)	80[d]	83	90	80	65
	China	m	m	m	m	m	m	m	m	m	m
	India[1]	61	63	75	64	x(6)	61[d]	x(6)	64	62	62
	Indonesia	73	73[d]	x(2)	73	75	82	82	89	81	74
	Saudi Arabia	m	m	m	m	m	m	m	m	m	m
	South Africa[1]	40	53	m	53	67	77	84[d]	x(7)	73	49
	G20 average	58	71	m	70	m	81	m	87	81	71

Note: In most countries, data refer to ISCED 2011. For Argentina and India, data refer to ISCED-97. See *Definitions* and *Methodology* sections for more information. Data and more breakdowns are available at: http://stats.oecd.org/, *Education at a Glance Database*.

Source: OECD/ILO (2022). See *Source* section for more information and Annex 3 for notes (https://www.oecd.org/education/education-at-a-glance/EAG2022_X3-A.pdf).

FIGURE 7 TRENDS IN UNEMPLOYMENT RATES, BY EDUCATIONAL ATTAINMENT (2000 TO 2021)

PERCENTAGE OF UNEMPLOYED 25-34 YEARS OLD AMONG 25-34 YEARS OLD IN THE LABOUR FORCE, OECD AVERAGE



Note: Because of a lack of data for many years, the following countries are excluded from the OECD average: Austria, Chile, Colombia, France, Iceland, Japan, Lithuania, Luxembourg, Norway and Slovenia. There are breaks in the time series following methodological change in the ISCED classification with minor impact on the aggregate levels of educational attainment.

1: Missing data for Israel.

2: Missing data for Finland.

3: Missing data for Türkiye.

Source: OECD (2022), *Education at a Glance Database,* http://stats.oecd.org/. See *Source* section for more information and Annex 3 for notes (https://www.oecd.org/education/education-at-a-glance/EAG2022_X3-A.pdf).

CAUSALITY

- The empirical study of education-related earnings differentials was developed in tandem with human capital theory
- Educational attainment has a casual impact on labor market outcomes through improved productivity
- There is robust cross-country evidence that the more educated get higher monetary rewards in the labor market

TABLE 5: EVIDENCE ON THE CAUSAL IMPACT OF EDUCATION ON EARNINGS

Study	Data	Basic Return	Causal return	Means to generate causal estimate
Angrist and Krueger (1991)	US census	5-7%	6-11%	Variations in years of education generated by different quarter of birth
Card (1995)	1966 Cohort of Young Men, United States	7%	13%	Variations in years of education from proximity to college when growing up
Conneely and Uusitalo (1997)	Finnish men in the army in 1982	8%	11%	Variations in years of education from proximity to college when growing up
Harmon and Walker (1995)	Family Expenditure Survey, United Kingdom	6%	15%	Variations in education induced by raising of compulsory school leaving age
Ashenfelter and Rouse (1998)	1991-93 Princeton Twins Study	7%	9%	Variation in education within twin pairs
Miller et al. (1995)	Australian Twins Register	3%	5%	Variation in education within twin pairs

CHANGES OVER TIME

- Differential educational attainments can lead to substantial differences in earnings, employment probabilities, and other outcomes that matter for individuals' welfare.
- Employers are prepared to pay higher wages to more educated workers; this reflects in part their scarcity value.
- As simple demand and supply analysis indicates that, ceteris paribus, as more workers become highly educated, the earnings returns to being educated will decline.

- An increase in the supply of educated workers will lead to a decline in the wage premium they receive unless demand for them increases further.

- Large increases in the demand for graduates have occurred so that wage differentials related to education have stayed constant or increased in the face of the expansion of tertiary education in many countries.

- The leading expansion for the rise in demand for skilled workers is skill-biased technical change (SBTC).
- This hypothesis states that **the rise in demand for more skilled workers has been driven by new technologies in the workplace.**
- These new technologies lead to higher productivity, but that **only some workers possess the necessary skills to use them**.
- Employers are prepared to increase the wages of the skilled workforce **who are complements with the new technology**.

AUTOR, D. H., LEVY, F., & MURNANE, R. J. (2003). HAVE PROPOSED A MORE SOPHISTICATED VERSION OF THE SBTC HYPOTHESIS

- Their argument is that **computerization reduces the demand for routine tasks (for manual and nonmanual workers) but results in an increase in demand for analytic or nonroutine skills.**
- Routine nonmanual tasks (e.g. clerical work) may be replaced by computers while some nonroutine tasks done by manual workers (like cleaning) are largely unaffected.
- Increased demand for workers with the skills and capabilities to do jobs involving nonroutine tasks.
- This shows that education that confers these skills on workers is likely to have a bigger payoff in the labor market and generate earnings returns.

TABLE 6: PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASK

	Routine tasks	**Nonroutine tasks**
Example	**Analytic and interactive tasks**	
	• Record-keeping • Calculation • Repetitive customer service (e.g. bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	• Substantial substitution	• Strong complementarities
Example	**Manual tasks**	
	• Picking or sorting • Repetitive assembly	• Janitorial services • Truck driving
Computer impact	• Substantial substitution	• Limited opportunities for substitution or complementarity

Source: Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. The Quarterly Journal of Economics, 118(4), 1279–1333. http://www.jstor.org/stable/25053940

TABLE 7: COMPUTERIZATION AND INDUSTRY TASK INPUT 1980-1998: OVERALL AND BY EDUCATION GROUP
DEPENDENT VARIABLE: 10X ANNUAL CHANGE IN QUANTILES OF TASK MEASURE, MEASURED IN PERCENTILES OF 1960 TASK DISTRIBUTION

- These estimates in panel A show striking correlations between industry computerization, rising labor input of routine cognitive and manual tasks, and declining labor input of nonroutine interactive and analytic tasks.

Panels B through E present analogous models estimated separately for the four education groups

- Industry-level computerization is strongly predictive of shifts toward nonroutine and against routine tasks within essentially all education groups.
- A large portion of the within-education group changes are accounted for by cross-industry patterns of computer adoption. This suggest to us that task change ins antecedent to educational upgrading, rather than merely a reflection of it.

	1. Δ Nonroutine analytic	2. Δ Nonroutine interactive	3. Δ Routine cognitive	4. Δ Routine manual
	A. Aggregate within-industry change			
Δ Computer use	12.95	15.97	−15.84	−14.32
1984–1997	(3.68)	(4.32)	(4.73)	(4.73)
Intercept	−0.33	1.27	0.38	0.54
	(0.77)	(0.90)	(0.99)	(0.99)
Weighted mean task Δ	2.20	4.39	−2.71	−2.25
	B. Within industry: High school dropouts			
Δ Computer use	4.64	11.92	−2.64	−8.85
1984–1997	(6.07)	(8.73)	(7.95)	(6.76)
Intercept	−2.51	−4.39	0.02	1.11
	(1.26)	(1.82)	(1.66)	(1.41)
Weighted mean task Δ	−1.61	−2.07	−0.49	−0.62
	C. Within industry: High school graduates			
Δ Computer use	0.04	13.49	−28.18	−25.50
1984–1997	(4.17)	(5.40)	(6.13)	(6.05)
Intercept	−1.49	1.07	1.55	0.48
	(0.87)	(1.13)	(1.28)	(1.26)
Weighted mean task Δ	−1.48	3.70	−3.95	−4.49
	D. Within industry: Some college			
Δ Computer use	7.95	18.14	−15.68	−17.77
1984–1997	(5.03)	(5.54)	(5.27)	(5.61)
Intercept	−1.88	−0.58	0.35	1.39
	(1.05)	(1.15)	(1.10)	(1.17)
Weighted mean task Δ	−0.33	2.96	−2.71	−2.08
	E. Within industry: College graduates			
Δ Computer use	1.61	5.57	−0.78	−4.46
1984–1997	(3.42)	(3.35)	(4.85)	(5.70)
Intercept	0.25	0.10	−0.96	−0.12
	(0.71)	(0.70)	(1.01)	(1.19)
Weighted mean task Δ	0.57	2.22	−1.48	−1.98
	F. Decomposition into within and between education group components			
Explained task Δ	2.52	3.11	−3.09	−2.79
Within educ groups (%)	23.7	77.9	91.7	111.1
Between educ groups (%)	76.3	22.1	8.3	−11.1

CONCLUSION

- Education and inequality are closely related.
- Education yields a private return in the labor market and there are social returns to education, it is clear that the uneven patterns of education acquisition have the potential to generate inequalities in economic and social outcomes.
- Depending on how these uneven patterns of acquisition are distributed across the population, it is evident that education can have an equalizing or disequalizing effect on outcomes.
- The recent experience of increased labor market inequality being linked to changing patterns of educational attainment suggests that it has, at least in this recent time period, been disequalizing and therefore had a tendency to raise inequality.

SOURCES

Brewer, Dominic and Patrick J. McEwan (2010). *Economics of Education*. New York: Elsevier

OECD (2006), “Performance of Immigrant Students in 2003”, in Where Immigrant Students Succeed: A Comparative Review of Performance and Engagement in PISA 2003, OECD Publishing, Paris.

DOI: https://doi.org/10.1787/9789264023611-4-en

OECD (2023), *Education at a Glance 2023 Sources, Methodologies and Technical Notes*, OECD Publishing, Paris, https://doi.org/10.1787/d7f76adc-en.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. The Quarterly Journal of Economics, 118(4), 1279–1333. http://www.jstor.org/stable/25053940