Earnings, education and competences: can we reverse inequality ?

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Educational policies are often invoked as good instruments for reducing income inequality. Do we possess strong empirical evidence ?

We know that some reforms (for example increase in compulsory education) increase schooling, with heterogeneous impact among genders and proxies for abilities.

However unobservable ability and/or sorting of individuals makes it difficult to obtain reliable measure of the causal impact of educational policies.

Educational policies are difficult to measure, since they capture an institutional change, which can be more qualitative than quantitative.

from Brunello-Fort-Weber
EJ 2009

Table 3

Quantile Effects When Education is Treated as Exogenous
(Sample size: 18,328) By gender (9,936 males and 8,392 females)

	$\tau = 0.10$	$\tau = 0.30$	$\tau = 0.50$	$\tau = 0.70$	$\tau = 0.90$
Males	0.019***	0.026***	0.033***	0.035***	0.039***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Females	0.027***	0.037***	0.043***	0.050***	0.051***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)

Note. Each regression included a constant, country dummies, q, q^2 and their interaction with country dummies, survey dummies, age, age squared, the lagged country specific unemployment rate and GDP *per capita*, the country and gender specific labour force participation rate at the estimated time of labour market entry, the country specific GDP per head and unemployment rate at the age affected by the country specific reform. Details on these coefficients are available from the authors upon request. τ denotes the quantile of the distribution of wages. Three stars, two stars and one star for statistically significant coefficients at the 1%, 5% and 10% confidence level. Robust standard errors are shown in parentheses.

Table 4

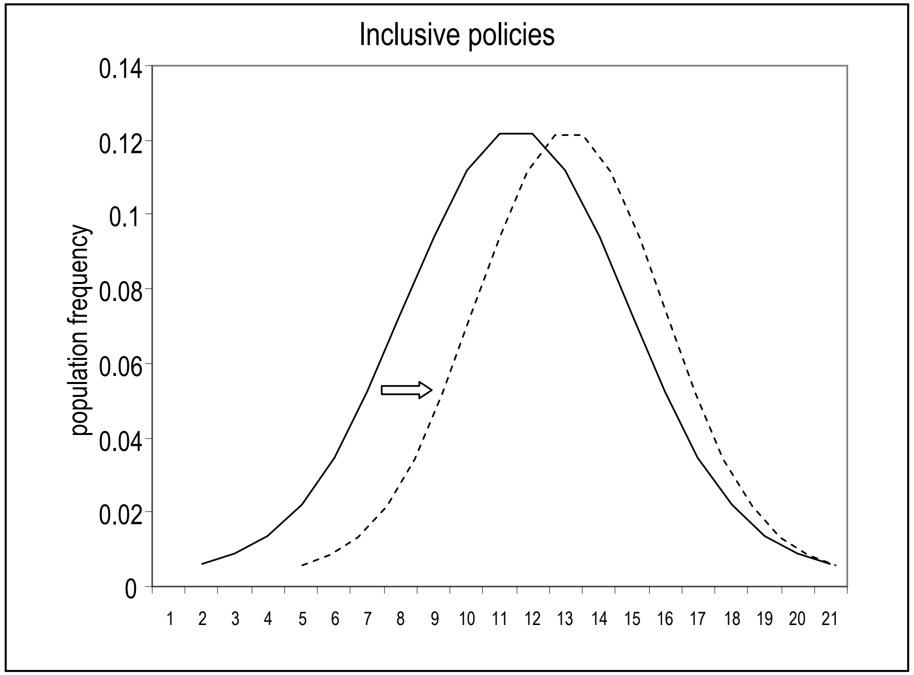
First Stage Effect of ycomp on s (Sample size: 18,328)

Males	$\tau_a = 0.10$	$\tau_a = 0.30$	$\tau_a = 0.50$	$\tau_a = 0.70$	$\tau_a = 0.90$
Coeff. (s.e.)	0.354***	0.056***	0.120***	0.078***	0.026
	(0.007)	(0.012)	(0.006)	(0.035)	(0.071)
F-test (p-value)	2146.6	19.1	307.6	4.86	0.13
	(0.000)	(0.000)	(0.000)	(.027)	(0.714)
Females	$\tau_a = 0.10$	$\tau_a = 0.30$	$\tau_a = 0.50$	$\tau_a = 0.70$	$\tau_a = 0.90$
Coeff. (s.e.)	0.416***	0.284***	0.072***	0.219***	0.135***
	(0.016)	(0.020)	(0.007)	(0.029)	(0.065)
F-test (p-value)	643.8	195.4	88.7	57.4	4.26
	(0.000)	(0.000)	(0.000)	(0.000)	(0.039)

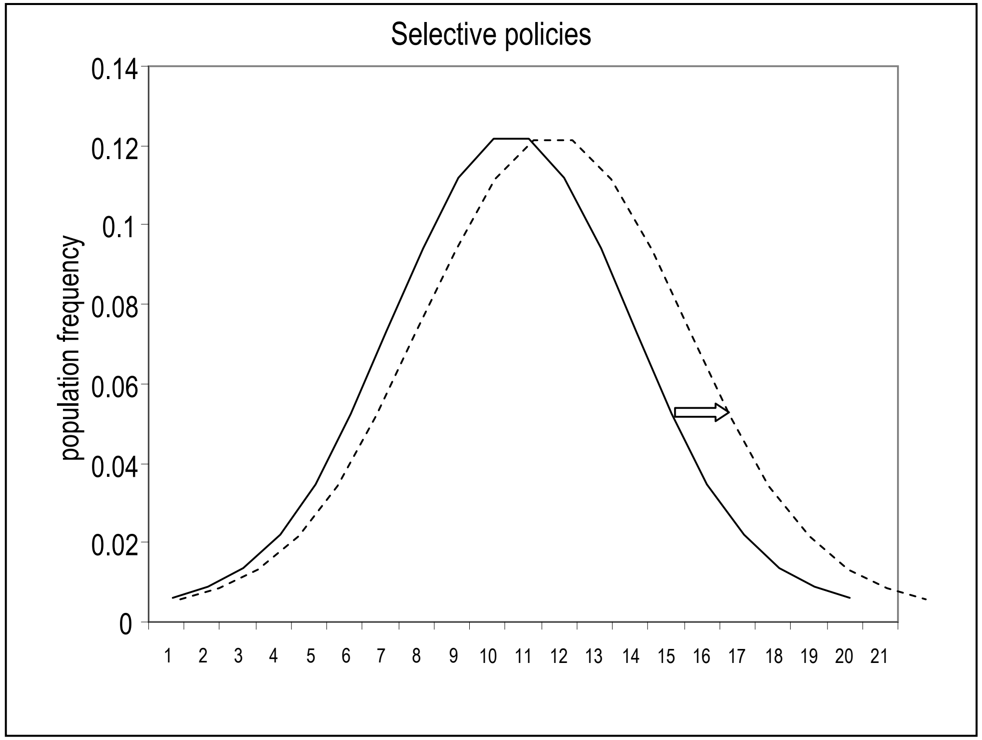
Note. See Table 3. τ_a denotes the quantile of the distribution of ability.

But educational reforms can work in different point of the ability distribution.

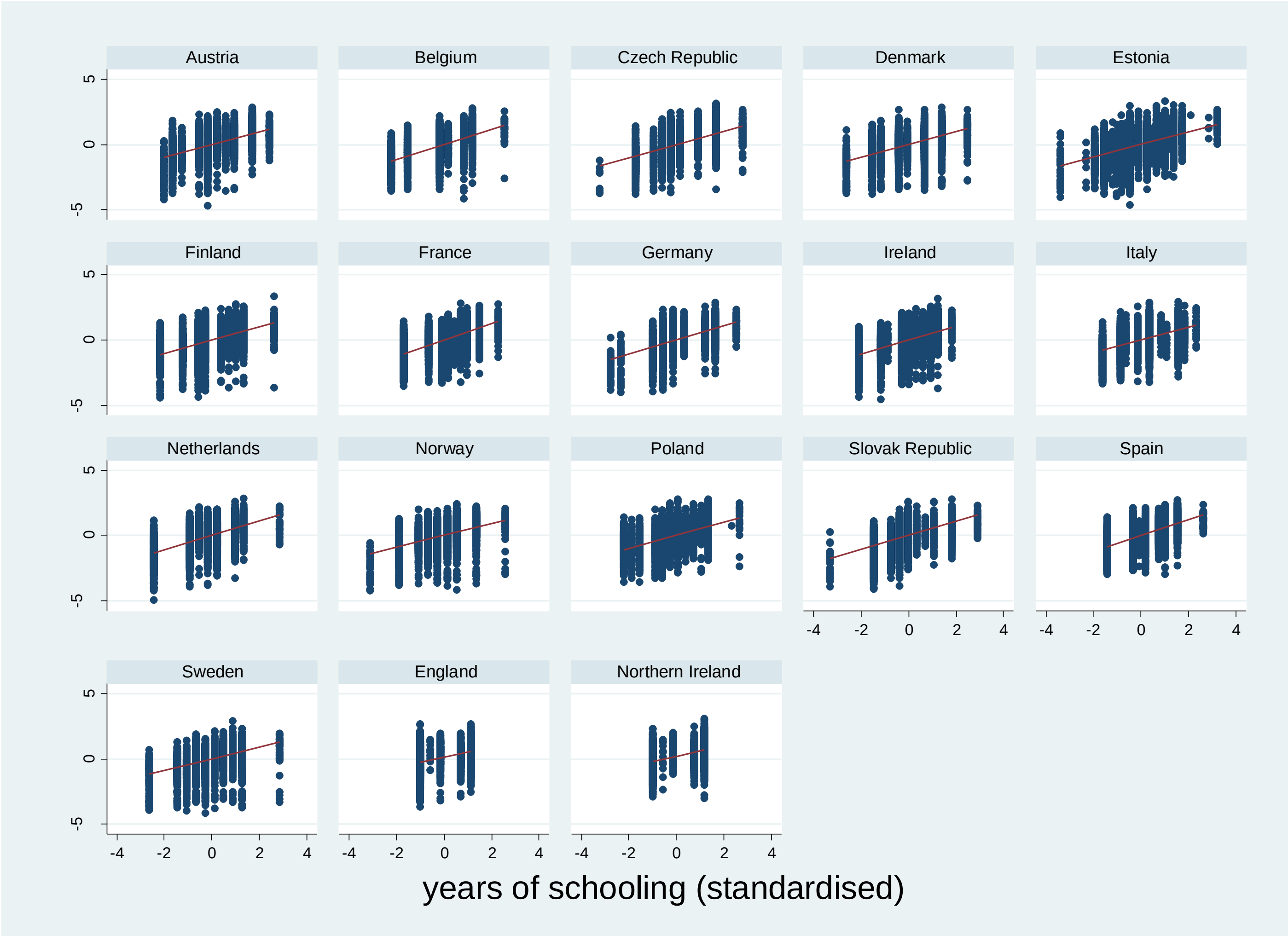
Reforms extending pre-primary schooling and/or expanding the access education (via raise in leaving age for compulsory education or in tracking age, removing barriers to university admissions) and/or increasing teacher qualifications exhibit positive correlation with average years of education in the population and negative one with inequality and intergenerational persistence. Let us <u>label these reforms as *inclusive*</u>.



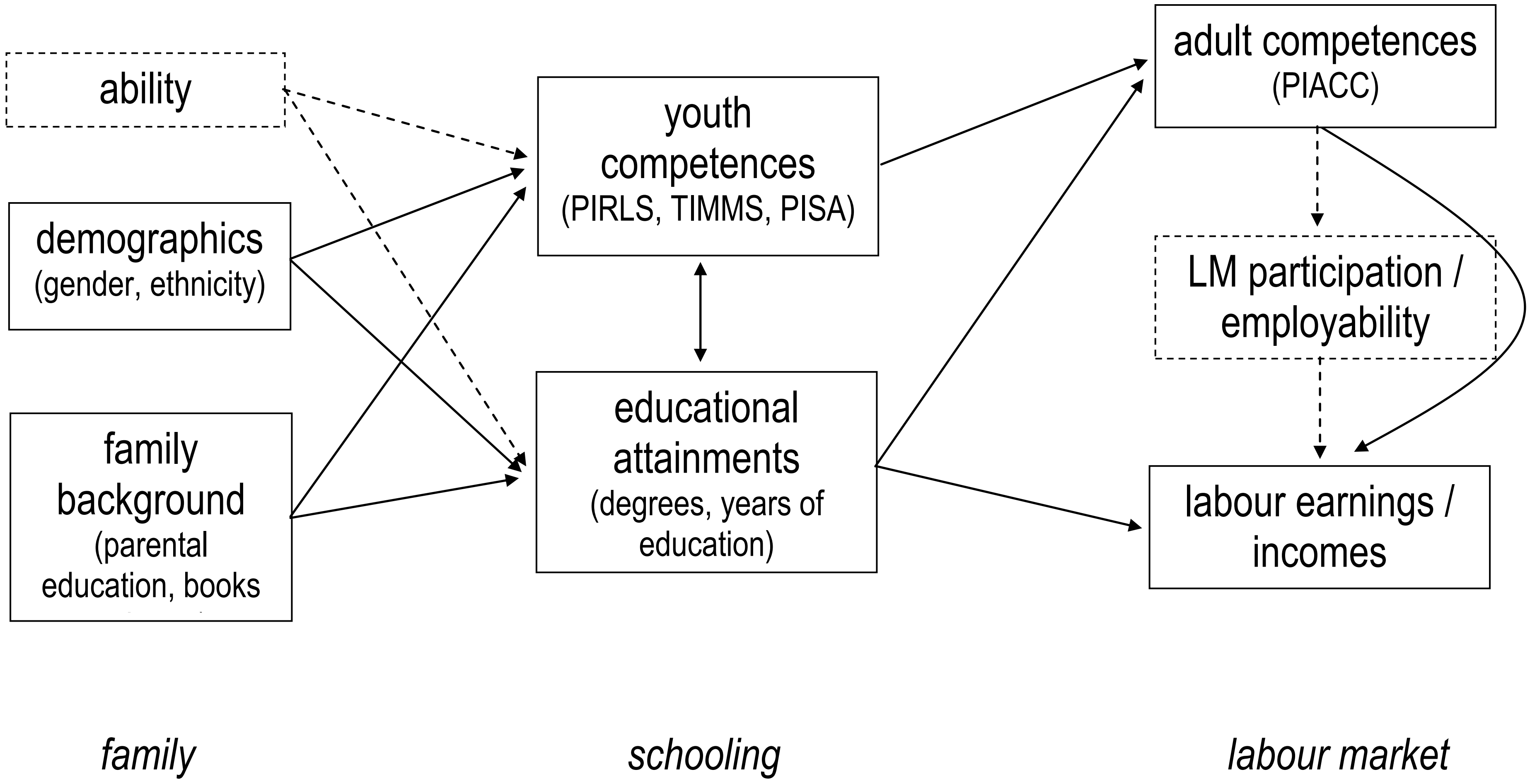
Reforms increasing school autonomy and accountability as well as university autonomy are also positively correlated with mean educational attainment, but also with inequality and persistence. Similar properties are also associated to reforms related to financial support to university students. Let’s identify these reforms as *selective*.



Human capital embodies both quantity (formal schooling, certification) and quality (competences) dimensions: raising one does not necessarily implies raising the other. The two are correlated but which is exogenous ?



Where should the policies attack educational inequalities ?



Eric A. Hanushek, Guido Schwerdt, Simon Wiederhold and Ludger Woessmann. 2013. Returns to Skills around the World: Evidence from PIAAC. IZA DP No. 7850

Table 4: Skills, Years of Schooling, and Earnings

	Pooled	Austria	Belgium	Canada	Cyprus	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Numeracy	.101***	.120***	.089***	.129***	.057***	.074***	.085***	.116***	.079***	.094***	.148***	.151***
	(.003)	(.010)	(.010)	(.008)	(.018)	(.020)	(.009)	(.014)	(.011)	(.009)	(.014)	(.021)
Yrs schooling	.059***	.058***	.045***	.057***	.082***	.045***	.043***	.055***	.057***	.041***	.064***	.060***
	(.001)	(.004)	(.004)	(.003)	(.007)	(.010)	(.003)	(.005)	(.003)	(.003)	(.005)	(.007)
Experience	.022***	.016**	.011*	.020***	.020**	.015*	.007*	.024***	.014***	.018***	.009	.030***
	(.001)	(.007)	(.006)	(.004)	(.008)	(.008)	(.004)	(.009)	(.005)	(.005)	(.008)	(.011)
Experience^2	−.032***	−.019	−.006	−.024***	−.002	−.029	−.006	−.069***	−.014	−.018*	−.004	−.040
	(.003)	(.013)	(.013)	(.008)	(.019)	(.019)	(.008)	(.020)	(.012)	(.010)	(.017)	(.024)
Female	−.176***	−.119***	−.050***	−.131***	−.193***	−.196***	−.116***	−.442***	−.205***	−.118***	−.125***	−.029
	(.005)	(.022)	(.017)	(.014)	(.034)	(.033)	(.013)	(.024)	(.015)	(.015)	(.024)	(.033)
R^2	.308	.370	.286	.303	.315	.262	.282	.310	.414	.331	.338	.286
Observations	34159	1115	1219	7155	938	1065	1875	1767	1478	1707	1296	1031

	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	U.S.
Numeracy	.057***	.114***	.102***	.111***	.082***	.071***	.086***	.104***	.089***	.173***	.138***
	(.016)	(.015)	(.015)	(.012)	(.008)	(.015)	(.018)	(.018)	(.010)	(.016)	(.022)
Yrs schooling	.046***	.067***	.076***	.063***	.042***	.090***	.084***	.066***	.026***	.061***	.081***
	(.004)	(.006)	(.005)	(.006)	(.003)	(.006)	(.006)	(.004)	(.004)	(.007)	(.007)
Experience	.011	.022***	.025***	.027***	.023***	.027***	.013	.021***	.017***	.009	.015*
	(.007)	(.007)	(.005)	(.006)	(.005)	(.007)	(.012)	(.007)	(.004)	(.009)	(.008)
Experience^2	.007	−.009	−.019	−.044***	−.042***	−.044**	−.023	−.024	−.028***	−.009	−.028*
	(.017)	(.018)	(.015)	(.014)	(.011)	(.017)	(.026)	(.015)	(.010)	(.019)	(.016)
Female	−.168***	−.308***	−.314***	−.022	−.137***	−.216***	−.282***	−.111***	−.109***	−.107***	−.228***
	(.026)	(.026)	(.028)	(.022)	(.014)	(.028)	(.027)	(.025)	(.014)	(.026)	(.032)
R^2	.278	.381	.438	.337	.297	.410	.323	.392	.252	.301	.420
Observations	1018	1322	1441	1013	1519	816	1198	1190	1316	1671	983

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54 (Canada includes part-time employees). Numeracy score standardized to std. dev. 1 within each country. Experience^2 divided by 1000. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2. Robust standard errors in parentheses. *Data source:* PIAAC.

Unfortunately we observe competences when adult, ignoring what may have occurred when people were young.

We would need more longitudinal datasets where we observe test scores when young, schooling experience, labour market transitions and competences when old.

Recall of past events does not solve the problem, since people tend to make their lives coherent when recalling.

Three exercises to explore the relative contribution of skills to inequality:
① distribution of skills in pupils matched to the wage distribution of the corresponding cohorts (joint with H.van der Werfhorst)
② PISA 2000 students matched to young PIAAC 2012 workers
③ PIAAC workers instrumenting skills and/or education (joint with M.Leonardi and L.Cappellari)

① Policies, Skills and Earnings: How Educational Inequality Affects Earnings Inequality (forthcoming in *Socio-Economic Review*)

We distinguish between quantity (typically measured by the years of schooling) and quality of educational attainments (measured by level of competences).

In particular, the educational endowment (call it human capital for simplicity) can be considered as made by two dimensions: *quantity* (years of education h) and *quality* (competences q).

Earnings y are assumed to be correlated with total human capital. Making the further assumption that quantity and quality interact in the production of human capital as imperfect substitutes, we may write

$$y = f(h,q),\; f'_h > 0,\; f'_q > 0,\; f''_{hq} \geq 0$$

As a consequence, inequality in earnings depends on the distribution of years of education and of competences, as well as their covariance.

Assuming a specific functional form of the log-linear family (like $y = Ah^{\alpha}q^{\beta}, \alpha < 1, \beta < 1$) when information about cognitive skills of the interviewee is available, it is then possible to estimate an augmented Mincerian wage function of the type

$$\log(y_{ij}) = a_j + \alpha_j \log(h_i) + \beta_j \log(q_i) + \varepsilon_{ij}$$

where i indicates the individual and j a specific labour market (typically a country/region).

This equation has been estimated by Blau and Kahn (2005) using micro-data from IALS. They claim that the greater dispersion of cognitive test scores in the United States plays a part in explaining higher U.S. wage inequality.

TABLE 2.—LOG WAGE EFFECTS OF A 1 STANDARD DEVIATION INCREASE IN TEST SCORE OR EDUCATION

	Men		Women	
	Test Score	Education	Test Score	Education
Canada	0.0900 (0.0175)	0.0884 (0.0194)	0.1615 (0.0224)	0.1497 (0.0271)
Denmark	0.0719 (0.0171)	0.1113 (0.0140)	0.0777 (0.0210)	0.1130 (0.0169)
Finland	0.0905 (0.0248)	0.0938 (0.0202)	0.0615 (0.0202)	0.1456 (0.0157)
Italy	0.0531 (0.0181)	0.1039 (0.0180)	0.0597 (0.0210)	0.1310 (0.0197)
Netherlands	0.1579 (0.0188)	0.0475 (0.0126)	0.1210 (0.0325)	0.0978 (0.0217)
Norway	0.0975 (0.0208)	0.0539 (0.0206)	0.0074 (0.0238)	0.1403 (0.0236)
Sweden	0.0734 (0.0173)	0.0603 (0.0155)	0.0321 (0.0164)	0.0990 (0.0145)
Switzerland	0.0785 (0.0216)	0.0634 (0.0247)	0.0899 (0.0273)	0.0683 (0.0292)
United States	0.1586 (0.0194)	0.1680 (0.0256)	0.1151 (0.0211)	0.2663 (0.0318)
Non-U.S. Average	0.0891	0.0778	0.0763	0.1181

Notes: Regressions include controls for test score, education, and age dummies; standard errors are in parentheses. A 1 standard deviation increase in education is 3.5805 years; a 1 standard deviation increase in test scores is 49.4907 points. Standard deviations are calculated on the pooled weighted male and female wage samples giving each country the same weight.

The estimated $\hat{\alpha}$ and $\hat{\beta}$ give us an idea of the relative contribution of quantity and quality of education in generating income inequality. They write "For example, a one standard deviation increase in test scores raises wages by 5.3 to 15.9 percent for men and 0.7 to 16.2 percent for women, while a one standard deviation increase in education raises wages by 4.8 to 16.8 percent for men and 6.8 to 26.6 percent for women."

Freeman and Schettkat (2001) follow a parallel approach when comparing US and Germany earnings inequality, by comparing the distribution of earnings at different points of the distribution of competences in the adult population using the same IALS survey.

The main problem of this research strategy is the potential endogeneity of the right-hand side regressors, since more talented individuals may possess higher level of competences as well as achieve higher educational attainments.

Ideally, one would require a dataset where competences are predetermined with respect to schooling, which in turn is predetermined with respect to the transition to the labour market. Unfortunately, these dataset do not yet exist, especially in a cross-country perspective.

A different approach has been followed by Bedard and Ferrall (2003), who study the correlation between the distribution of competences and the wage distribution of workers in the same age cohorts. They show that Lorenz curves for a cohort’s wages always lie above or on top of the cohort’s test score Lorenz curve. However, they ignore the mediating role played by schooling.

We pursue the alternative strategy of *country/cohort analysis, matching aggregate inequality measures of competences, schooling and earnings based on the birth year of the relevant cohort*.

This strategy has pros and cons:
⇨ pros are represented by the possibility of identifying causal effects of the human capital distribution onto the earnings distribution.
⇨ cons are working with aggregate data, which introduce potentially confounding factors, which are only partially cured by including country/year fixed effects. In addition, aggregate data dramatically reduces the degrees of freedom, incurring in small sample problems when estimating.

We start with a linearised version of previous equation, which reads

$$y_{ij} = a_j + \alpha_j h_i + \beta_j q_i + \boldsymbol{\gamma}'\mathbf{X}_{ij} + \varepsilon_{ij}$$

The inequality observed in the distribution of y will depend on the inequality in both quality q and quantity h of education, as well as on any other observable in the vector $\mathbf{X}_i$ (like age, gender, and ethnicity) or unobservable ε.

Given the non-zero correlation between education and other observables and unobservables, it is generally impossible to decompose observed earnings inequality into separated contributions of underlying factors.

Given the practical impossibility of estimating the structural relationship between the underlying distributions, we have resorted to the more modest strategy of studying the correlation among inequality measures, from which we can still deduce educational policy relevant propositions.

By indicating with $I(x)$ a generic inequality indicator, an equivalent of previous equation can be expressed as

$$I(y) = \delta_j + \alpha I(h) + \beta I(q) + \omega_j$$

where δ_j is a country/year fixed effect capturing any other sort of earnings inequality variation, while α and β measure the correlation between various dimensions of human capital (quantity and quality) to earnings (or income) inequality, providing a more reliable measure than previously obtained ones.

If h and/or q are measured well in advance with respect to y (in our case h is measured at the end of schooling by the maximal educational attainment, q is measured at the age of 14, while y is measured alternatively at the ages of 28, 44 and 59), one is tempted to provide a causal interpretation of statements like “a reduction in inequality in test scores is associated to a β-reduction in income inequality”

However, unobservable components at country level (like competitiveness, solidarity, ethnic fractionalisation and so on) may drive both dimension of inequality, leading to biased estimates of the relevant coefficients.

Accounting for this possibility, we have resorted to an instrumental variable strategy to estimate previous equation leading to

$$\begin{cases} I(h) = a_j + \mathbf{b}'_j \mathbf{Z}_j + e_j \\ I(q) = c_j + \mathbf{d}'_j \mathbf{Z}_j + g_j \\ I(y) = \delta_j + \alpha \hat{I}(h) + \beta \hat{I}(q) + \omega_j \end{cases}$$

where the educational inequality measures are replaced by their projections obtained from a vector of (supposedly) exogenous variables pertaining reforms in the educational sectors affecting the relevant age cohorts.

We thus exploit both geographical and temporal variations in educational reforms by government to obtain unbiased estimates of the causal impact of educational inequality onto income inequality.

Data sources

Data on students' competences are obtained from three surveys on mathematical competences of 14-year-old students conducted in past decades (FIMS 1964 on students born in 1950, SIMS 1980-82 on students born in 1966 and TIMSS 1995 on students born in 1981).

Data on schooling and labour market outcomes of the same cohorts can be obtained from representative samples of the corresponding population at later stages.

Possibility of confusing cohorts and age effects (namely, older cohorts are characterised by higher level of competences and/or earnings inequality) is avoided by repeated observations of the same birth cohort at different ages (using both European Community Household Panel (ECHP) and European Union Statistics on Income and Living Conditions (EUSILC).)

SAMPLE CREATION

Matching rule

Birth year	Aged 14	Aged 28	Aged 43-44	Aged 59	matched cohorts/countries
1950	1964 (from FIMS: BE,FI,FR,DE,NL,UK)	1978 (data not available)	1994 (from ECHP1994: BE,FR,DE,NL,UK)	2009 (from SILC2009: BE,FI,FR,DE,NL,UK)	11
1966	1980 (from SIMS: (BE,FI,FR,HU,NL,SE,UK)	1994 (from ECHP1994: BE,FR,NL,UK)	2009 (from SILC2009: BE, FI,FR,HU,NL,SE,UK)		11
1981	1995 (from TIMS: AT,BE,CZ,DK,FR,DE, GR,HU,IE,IT,LV,NL,NO, PT,SK,SI,ES,SE,UK)	2009 (from SILC2009: AT,BE,CZ,DK,FR,DE, GR,HU,IE,IT,LV,NL,NO, PT,SK,SI,ES,SE,UK)			19

Overall we possess an unbalanced panel covering 20 countries with 82 observations (41 country/cohort $\times$ 2 genders).

Inequality in earnings and educational attainment

1st number: Gini index on gross total labour earnings of employed – 2nd number: Gini index on years of education (from maximal educational attainment) – 3rd number: Gini index on math test scores – 4th individuals with positive incomes 5th observations available in the sample

	birth year					birth year					birth year			
	1950	1966	1981	Total		1950	1966	1981	Total		1950	1966	1981	Total
Austria			0.32	0.32	Greece			0.31	0.31	Portugal			0.33	0.33
			0.1	0.1				0.11	0.11				0.15	0.15
			0.15	0.15				0.21	0.21				0.19	0.19
			134	134				168	168				106	106
			2	2				2	2				2	2
Belgium	0.32	0.25	0.21	0.27	Hungary		0.35	0.37	0.36	Slovak Republic			0.26	0.26
	0.15	0.12	0.1	0.13			0.09	0.09	0.09				0.08	0.08
	0.17	0.15	0.12	0.15			0.16	0.16	0.16				0.16	0.16
	202	282	136	620			266	234	500				198	198
	4	4	2	10			2	2	4				2	2
Czech Republic			0.3	0.3	Ireland			0.26	0.26	Slovenia			0.3	0.3
			0.08	0.08				0.1	0.1				0.08	0.08
			0.15	0.15				0.17	0.17				0.16	0.16
			188	188				85	85				420	420
			2	2				2	2				2	2
Denmark			0.3	0.3	Italy			0.33	0.33	Spain			0.31	0.31
			0.11	0.11				0.11	0.11				0.14	0.14
			0.16	0.16				0.2	0.2				0.18	0.18
			97	97				421	421				361	361
			2	2				2	2				2	2
Finland	0.37	0.35		0.36	Latvia			0.39	0.39	Sweden		0.23	0.28	0.25
	0.12	0.1		0.11				0.1	0.1			0.09	0.09	0.09
	0.21	0.22		0.21				0.18	0.18			0.22	0.16	0.19
	363	361		724				134	134			260	155	415
	2	2		4				2	2			2	2	4
France	0.41	0.33	0.26	0.35	Netherlands	0.32	0.28	0.22	0.28	United Kingdom	0.37	0.36	0.29	0.35
	0.17	0.12	0.1	0.14		0.12	0.11	0.1	0.11		0.14	0.13	0.09	0.13
	0.18	0.15	0.14	0.16		0.18	0.18	0.14	0.17		0.23	0.24	0.18	0.22
	456	545	246	1247		406	482	196	1084		387	554	130	1071
	4	4	2	10		4	4	2	10		4	4	2	10
Germany	0.35		0.36	0.35	Norway			0.3	0.3	Total	0.35	0.3	0.3	0.32
	0.12		0.09	0.11				0.11	0.11		0.14	0.11	0.1	0.11
	0.14		0.16	0.15				0.18	0.18		0.18	0.19	0.17	0.18
	638		185	823				107	107		2452	2750	3701	8903
	4		2	6				2	2		22	22	38	82

MEASUREMENT

Years of education: from ISCED attainment converted into legal duration by observing median values from question on time spent in school

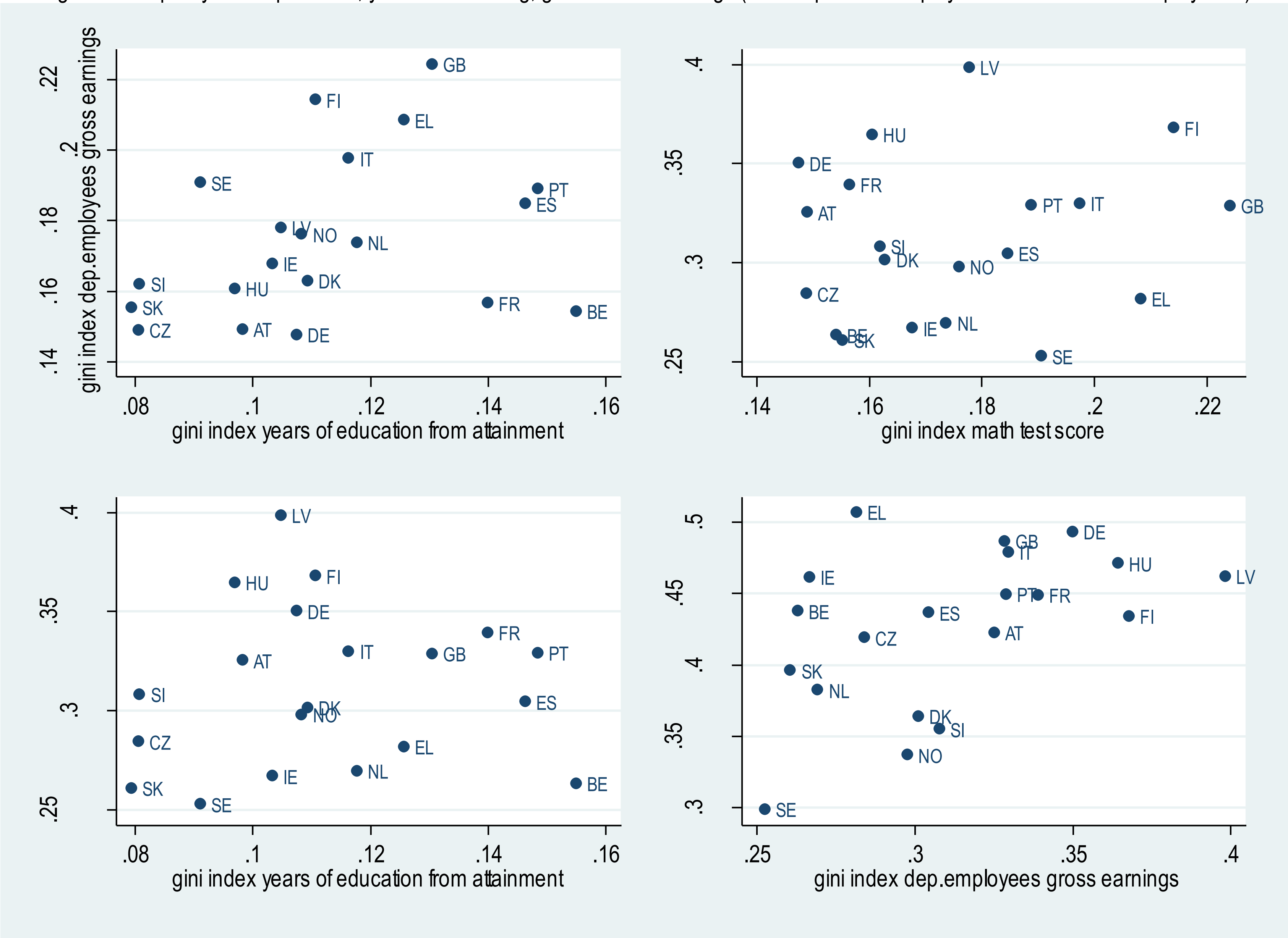
Test scores: number of correct answers to multiple-choice items in the math domain.

Labour earnings: sum of earnings from dependent employment (variable EARNINGS in ECHP or variable PY010G in SILC) and earnings from self-employment (variable SELFINCOME in ECHP or variable PY050G in SILC) - negative values converted into zeros. Net of taxes in ECHP, gross in SILC. Not employment individuals are retained into the analysis, since labour market participation is affected by education and competences.

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini index on dependent employment gross earnings (including non labour force with zero incomes)	82	0.466	0.110	0.254	0.721
Gini index on gross incomes (including self-employed and non labour force - negative incomes set to 0)	82	0.433	0.109	0.229	0.698
Gini index on years of education (computed from ISCED attainments)	82	0.120	0.032	0.072	0.243
Gini index on dependent employment gross earnings (only positive values - excluding unemployed with zero incomes)	82	0.310	0.061	0.193	0.452
Gini index on gross incomes (including self-employed but excluding non labour force - negative incomes set to 0)	82	0.316	0.061	0.209	0.472
Gini index on years of education (computed from ISCED attainments - only population with positive incomes)	82	0.115	0.029	0.074	0.216
Gini index on math test scores	82	0.175	0.031	0.124	0.244
age of individuals (when interviewed about occupational status)	82	37.04	11.40	28	59
reform on public pre-primary schooling	82	0.508	0.445	0	1
compulsory education (start age)	82	6.024	0.608	5	7
compulsory education (end age)	82	15.415	1.440	12	18
tracking age	82	13.476	2.263	10	16
introduction of standardised test	82	0.341	0.451	0	1
reform on school accountability	82	0.293	0.458	0	1
reform on school teacher autonomy	82	0.549	0.494	0	1
reform of university access	82	0.606	0.430	0	1

Figure 1: Inequality in competences, years of schooling, gross labour earnings (from dependent employment and from total employment)



- positive correlation between inequality in quantity and inequality in quality of education for the country/gender/cohort cell available
- both dimensions are also positively correlated with earnings inequality.
- the relationship between earnings inequality for dependent employees and for total employment is altered by the extent of self-employment, labour market participation (which is significantly varying across countries in accordance with gender), unemployment and early retirement (which are both computed at zero incomes).

Our general strategy is to regress earnings inequality measures onto corresponding inequality measures for years of schooling (proxy for quantity measured over the same population on which non negative/positive earnings are available) and for math test scores when the same cohort was 14-year-old (proxy for quality measure). All other potentially confounding factors are controlled by means of corresponding dummies (gender, birth year, age, country and survey).

INEQUALITY INDEX

In principle we do not have *a priori* about which is the most appropriate inequality measure to be used in the analysis, since each index captures different dimensions of the underlying distributions.

We propose three inequality measures, which are simply meant as descriptive correlation coefficients:
⇨ Gini concentration index and coefficient of variation exhibit statistically significant correlations, confirming that inequality in quantity and inequality in quality of human capital are positively associated with the observed earnings inequality (irrespective of whether we consider dependent employment incomes or total employment incomes).

Gross earnings and educational inequality - alternative inequality measures - OLS

	1	2	3	4	5	6
	Gini index		coefficient of variation		standard deviation of logs	
	dep.empl. earnings (gross)	total earnings (gross)	dep.empl. earnings (gross)	total earnings (gross)	dep.empl. earnings (gross)	total earnings (gross)
inequality in math test scores	0.899	0.683	1.282	1.100	0.464	0.325
	[0.241]***	[0.210]***	[0.388]***	[0.351]***	[0.506]	[0.409]
inequality in years of education (from isced attainments)	0.833	0.881	1.227	1.278	-0.263	0.197
	[0.258]***	[0.231]***	[0.366]***	[0.361]***	[0.835]	[0.747]
male component	-0.078	-0.107	-0.161	-0.213	-0.115	-0.105
	[0.017]***	[0.015]***	[0.046]***	[0.042]***	[0.049]**	[0.043]**
Observations	82	82	82	82	82	82
Countries	20	20	20	20	20	20
R-squared	0.58	0.64	0.51	0.56	0.18	0.21

Robust standard errors in brackets – constant, age, birth year and survey controls included
* significant at 10%; ** significant at 5%; *** significant at 1%

We have then decided to focus on the Gini index as our relevant measure of inequality, since a linear relationship seems to fit the data better.

In addition, the Gini index is a better measure for inequality when compared to the coefficient of variation, since it satisfies a preference for redistribution (Galton-Pigou principle).

Under more restrictive assumptions, we may also provide an interpretation of these coefficients. Let us assume that earnings are generated according to

$$y_{ij} = a_j + \alpha_j h_i + \beta_j q_i + \varepsilon_{ij}$$

which is a more restrictive version of previous equation since it ignores covariates. The Gini index for a generic country can be computed according to

$$Gini(y) = \frac{1}{2\mu_y} \sum_i \sum_k \left| y_i - y_k \right| =$$

$$= \frac{1}{2\mu_y} \sum_i \sum_k \left| \alpha(h_i - h_k) + \beta(q_i - q_k) + (\varepsilon_i - \varepsilon_k) \right|.$$

If you are available to accept that

① the rank correlation between quality and quantity is one (namely students with the highest level of competences also obtain the highest educational attainments – in symbols $h_i > h_k \ \ iff \ \ q_i > q_k$)

② the unexpected component in earnings is small relative to the predictable component (in symbols $a + \alpha h_i + \beta q_i > \varepsilon_i, \forall i$)

then we can express the earnings inequality as

$$Gini(y) = \alpha \frac{\mu_h}{\mu_y} Gini(h) + \beta \frac{\mu_q}{\mu_y} Gini(q) + residual.$$

Thus under quite restrictive assumption the estimated coefficients allow for retrieval of the structural coefficient of earning determination.

SPECIFICATIONS

Gross earnings and educational inequality – Gini indices – OLS country FE

	1	2	3	4	5	6	7	8	9	10
	dep.empl. earnings robust se	total earnings robust se	dep.empl. earnings clustered se	total earnings clustered se	dep.empl. earnings >0 clustered se	total earnings >0 clustered se	male dep.empl. earnings clustered	male total earnings clustered	female dep.empl. earnings clustered	female total earnings clustered
inequality in math test scores	1.631	1.716	1.631	1.716	**1.084**	**1.079**	1.152	1.615	1.386	1.517
	[0.555]***	[0.546]***	[0.815]*	[0.817]**	[0.508]**	[0.560]*	[1.493]	[1.431]	[1.729]	[1.836]
inequality in years of education (from isced attainments)	0.849	0.825	0.849	0.825	**0.570**	**0.519**	0.864	0.604	0.954	0.928
	[0.371]**	[0.354]**	[0.370]**	[0.377]**	[0.153]***	[0.194]**	[0.705]	[0.611]	[0.516]*	[0.600]
male component	-0.076	-0.103	-0.076	-0.103	-0.037	-0.033				
	[0.012]***	[0.012]***	[0.013]***	[0.012]***	[0.009]***	[0.010]***				
Observations	82	82	82	82	82	82	41	41	41	41
R-squared	0.84	0.85	0.84	0.85	0.77	0.74	0.88	0.87	0.88	0.86

col.1-2: robust standard errors in brackets - col.3-8: standard errors in brackets clustered by country - constant, country and year controls included – * significant at 10%; ** significant at 5%; *** significant at 1%

In terms of elasticities (measured at sample means), **earnings inequality measured by Gini concentration indices would exhibit an elasticity of 0.61-0.69 with respect to inequality in test scores and 0.21-0.22 with respect to inequality in years of education**.

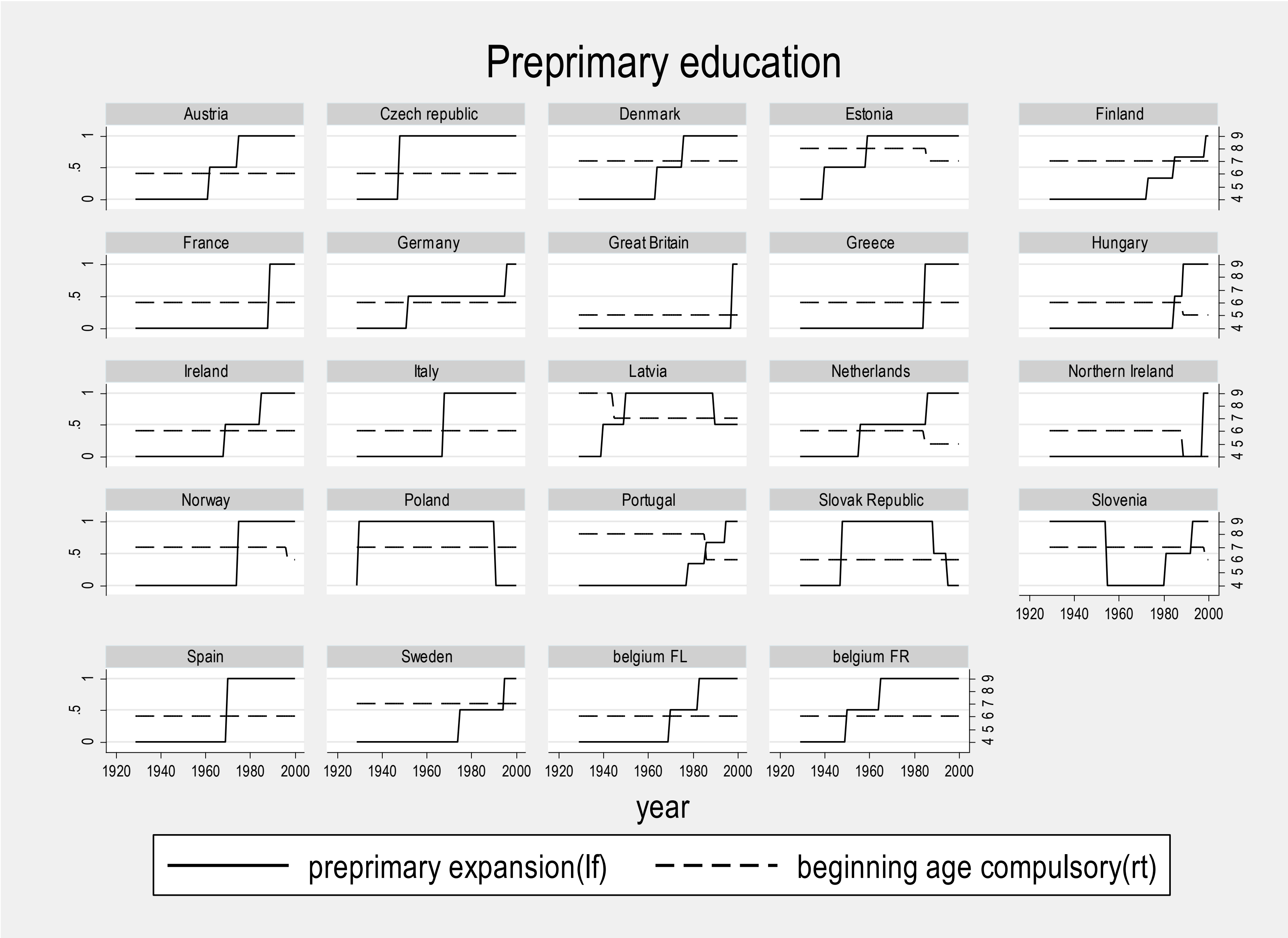
CAUSALITY VIA IV ESTIMATION

Despite the fact that schooling presumably ended before entrance in the labour market, and test scores were collected in years when the sampled population was 14-year-old, still we cannot claim that inequalities in quantity and quality of human capital are causing inequalities in income.

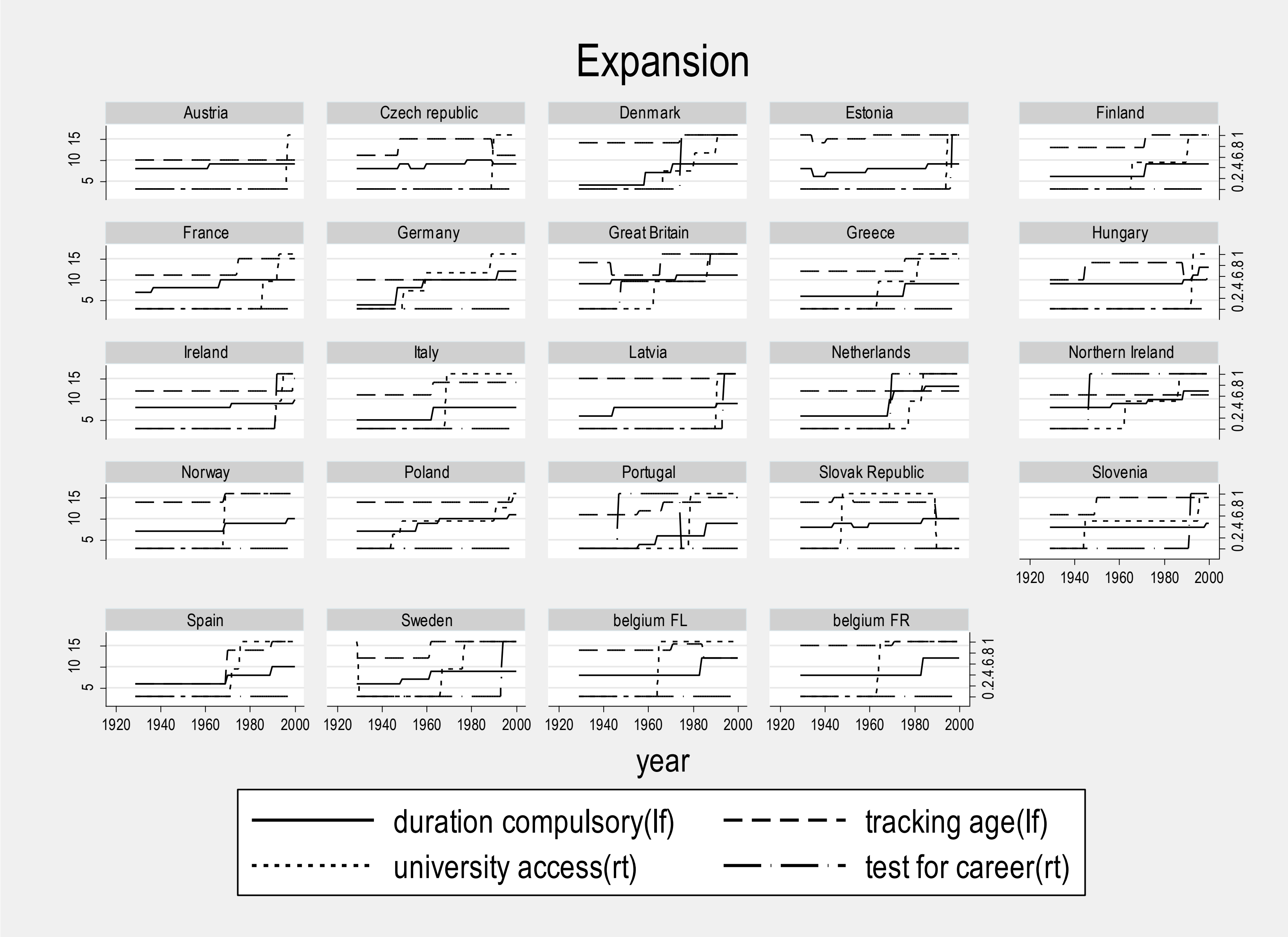
In order to strengthen the claim of causality, we resort to instrumental variable estimation, which has the additional advantage of allowing us the study of the impact of educational reforms on income inequality via their impact on inequality in quantity and quality of human capital.

Educational reforms provide evidence that schooling inequality may be affected by institutional design (Braga, Checchi and Meschi 2013).

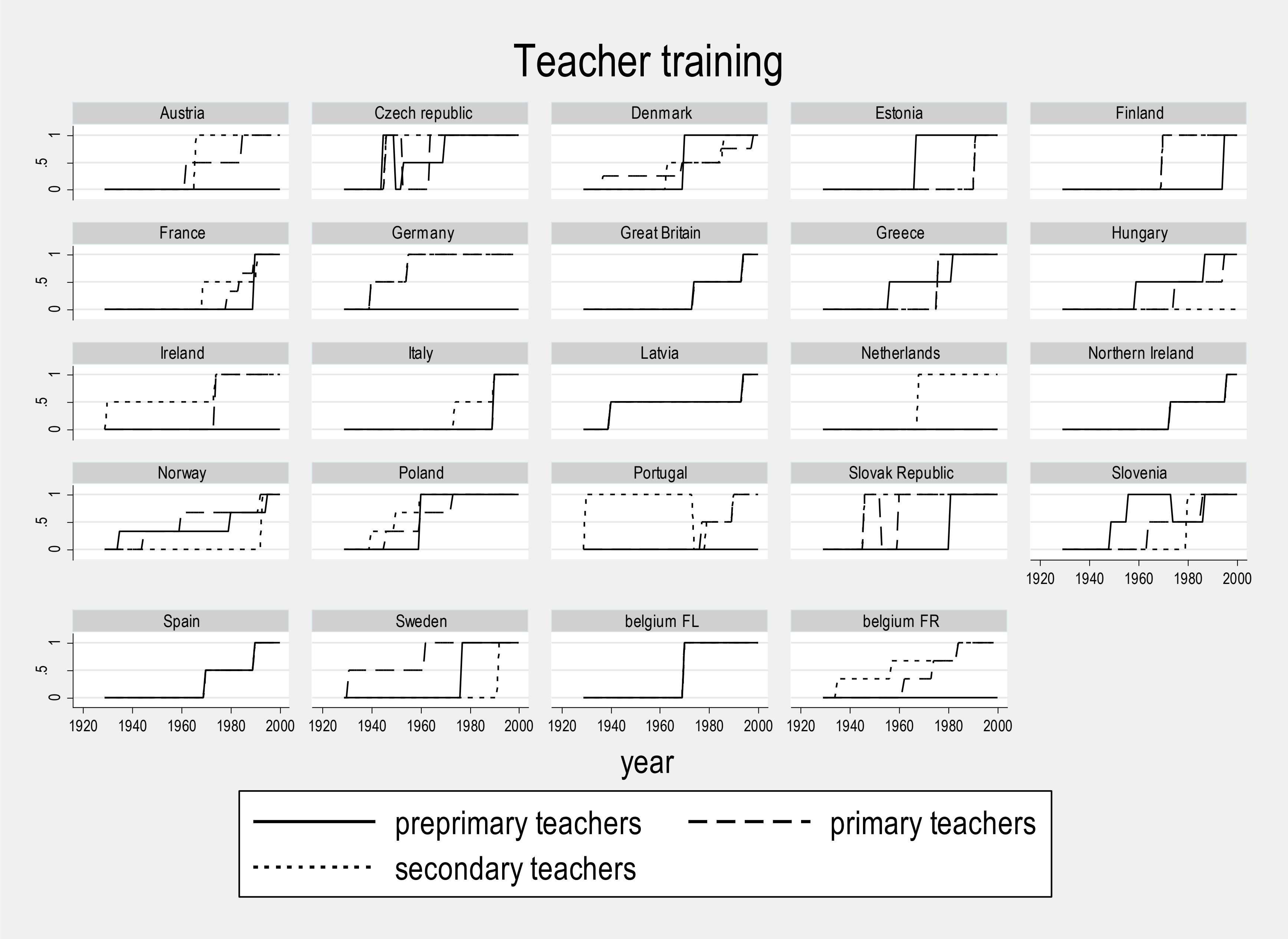
area of reform	expected impact on schooling inequality
pre-primary education	reduction (through increased educational attainment of students from disadvantaged background)
expansion of compulsory education	reduction (through increased educational attainment of students from disadvantaged background)
school tracking	ambiguous (vocational tracks have shorter duration, prevent academic enrolment but have lower drop-out rates)
school autonomy	ambiguous (adaptability to social environment, increased competition in presence of centralised control)
school accountability	increase (school differentiation, screening and sorting of students)
teacher qualification	ambiguous (better quality benefits students from poorer backgrounds but allows fro greater differentiation)
student financial support	reduction (increased enrolment of students from poorer backgrounds)
university autonomy and selectivity	increase (increased signalling value of tertiary education requires a more intensive selectivity in university admissions)



Preprimary education
Austria
Czech republic
Denmark
Estonia
Finland
France
Germany
Great Britain
Greece
Hungary
Ireland
Italy
Latvia
Netherlands
Northern Ireland
Norway
Poland
Portugal
Slovak Republic
Slovenia
Spain
Sweden
belgium FL
belgium FR
year
preprimary expansion(lf)
beginning age compulsory(rt)



Expansion
Austria
Czech republic
Denmark
Estonia
Finland
France
Germany
Great Britain
Greece
Hungary
Ireland
Italy
Latvia
Netherlands
Northern Ireland
Norway
Poland
Portugal
Slovak Republic
Slovenia
Spain
Sweden
belgium FL
belgium FR
5 10 15
0 .2 .4 .6 .8 1
1920 1940 1960 1980 2000
year
duration compulsory(lf)
tracking age(lf)
university access(rt)
test for career(rt)


Teacher training
Austria
Czech republic
Denmark
Estonia
Finland
France
Germany
Great Britain
Greece
Hungary
Ireland
Italy
Latvia
Netherlands
Northern Ireland
Norway
Poland
Portugal
Slovak Republic
Slovenia
Spain
Sweden
belgium FL
belgium FR
0
.5
1
1920
1940
1960
1980
2000
year
preprimary teachers
primary teachers
secondary teachers

Inequality and reforms - Gini indices – OLS and IV estimates with educational reforms as instruments

	1	2	3	4	5	6
	OLS		IV 2SLS		IV GMM	
	dep.empl. earnings	total earnings	dep.empl. earnings	total earnings	dep.empl. earnings	total earnings
inequality in math test scores	1.631	1.716	1.073	1.269	1.519	1.426
	[0.815]*	[0.817]**	[1.029]	[0.998]	[0.579]***	[0.690]**
inequality in years of education (from isced attainments)	0.849	0.825	1.277	1.544	0.73	1.314
	[0.370]**	[0.377]**	[1.261]	[1.272]	[0.843]	[0.916]
Observations	82	82	82	82	82	82
R-squared	0.84	0.85	0.84	0.83	0.83	0.84
			1st stage:		1st stage:	
			Gini math test	Gini yrs education	Gini math test	Gini yrs education
reform on public pre-primary schooling			-0.102	-0.096	-0.102	-0.096
			[0.020]***	[0.020]***	[0.021]***	[0.072]
compulsory education (start age)			-0.066	-0.075	-0.066	-0.075
			[0.012]***	[0.015]***	[0.017]***	[0.041]*
compulsory education (end age)			0.01	0.009	0.01	0.009
			[0.002]***	[0.002]***	[0.002]***	[0.005]*
tracking age			0.009	0.007	0.009	0.007
			[0.002]***	[0.002]***	[0.003]**	[0.055]
introduction of standardised test			-0.093	-0.074	-0.093	-0.074
			[0.015]***	[0.014]***	[0.018]***	[0.055]
reform on school accountability			0.015	0.051	0.015	0.051
			[0.027]	[0.024]*	[0.032]	[0.075]*
reform on school teacher autonomy			0.03	0.029	0.030	0.029
			[0.008]***	[0.009]***	[0.008]***	[0.018]
reform of university access			0.082	0.038	0.082	0.038
			[0.012]***	[0.011]***	[0.015]***	[0.037]
R-squared			0.94	0.77	0.94	0.77
F test 1st stage [p-value]			169.5[0.00]	1932.2[0.0]	29.29 [0.0]	1.08 [0.38]

Standard errors in brackets clustered by country [2sls] or robust against heteroscedasticity [gmm] –
* significant at 10%; ** significant at 5%; *** significant at 1% - constant, gender, age, country, survey and year controls included

First stage:

⇨ inequality in education (both years of education or test scores) is reduced in countries that expanded pre-primary education or postponed the beginning age for compulsory education, while the school leaving age seems to have a counterintuitive positive correlation.

⇨ Postponing the age at which students have to choose the secondary school track (wherever the educational system is stratified, like in Austria, Germany, Italy and the Netherlands) seem to increase both inequalities in schooling and test scores.

⇨ strengthening the standardisation of national educational systems through the introduction of student testing is associated to a reduction of inequality.

⇨ increasing schools/teachers and universities autonomy reinforce their potential competitiveness, at the expenses of increased educational inequality. Similar patterns are observed in the case of competence inequality

Second stage:

⇨ Using the predicted inequalities in quantity and quality of human capital as regressors for income inequality, we observe that their coefficients lose statistical significance in comparison with OLS, while rising in magnitude in the case of schooling inequality.

⇨ When compared to inequality in wages, the effects of educational inequalities on total earnings inequality tend to be more statistically significant. OLS estimates for test score inequality were upward biased, while the opposite situation occurs for schooling inequality, which now becomes more relevant.

In terms of elasticities, the two dimensions of educational inequalities get closer (0.57 for test score inequality and 0.36 for schooling inequality)

This table summarises our findings in two ways, either by computing the overall impact of educational reforms onto earnings inequality or by re-estimating a reduced form.

Table 1 – Reduced form multipliers computed from previous table: effects of policies on income inequality

	estimated from reduced form		computed from columns (5) and (6) of previous table	
	Gini index dependent employment earnings	Gini index on total labour earnings	Gini index dependent employment earnings	Gini index on total labour earnings
reform on public pre-primary schooling	-0.346	-0.407	-0.225	-0.272
	[0.078]***	[0.083]***		
compulsory education (start age)	-0.200	-0.226	-0.155	-0.193
	[0.053]***	[0.056]***		
compulsory education (end age)	0.001	0.008	0.022	0.026
	[0.007]	[0.008]		
tracking age	-0.007	-0.005	0.019	0.022
	[0.008]	[0.008]		
introduction of standardised test	-0.178	-0.232	-0.195	-0.230
	[0.076]**	[0.088]**		
reform on school accountability	0.176	0.232	0.060	0.088
	[0.099]*	[0.102]**		
reform on school teacher autonomy	0.100	0.125	0.067	0.081
	[0.031]***	[0.032]***		
reform of university access	0.077	0.104	0.152	0.167
	[0.052]	[0.055]*		
Observations	82	82		
R-squared	0.83	0.85		

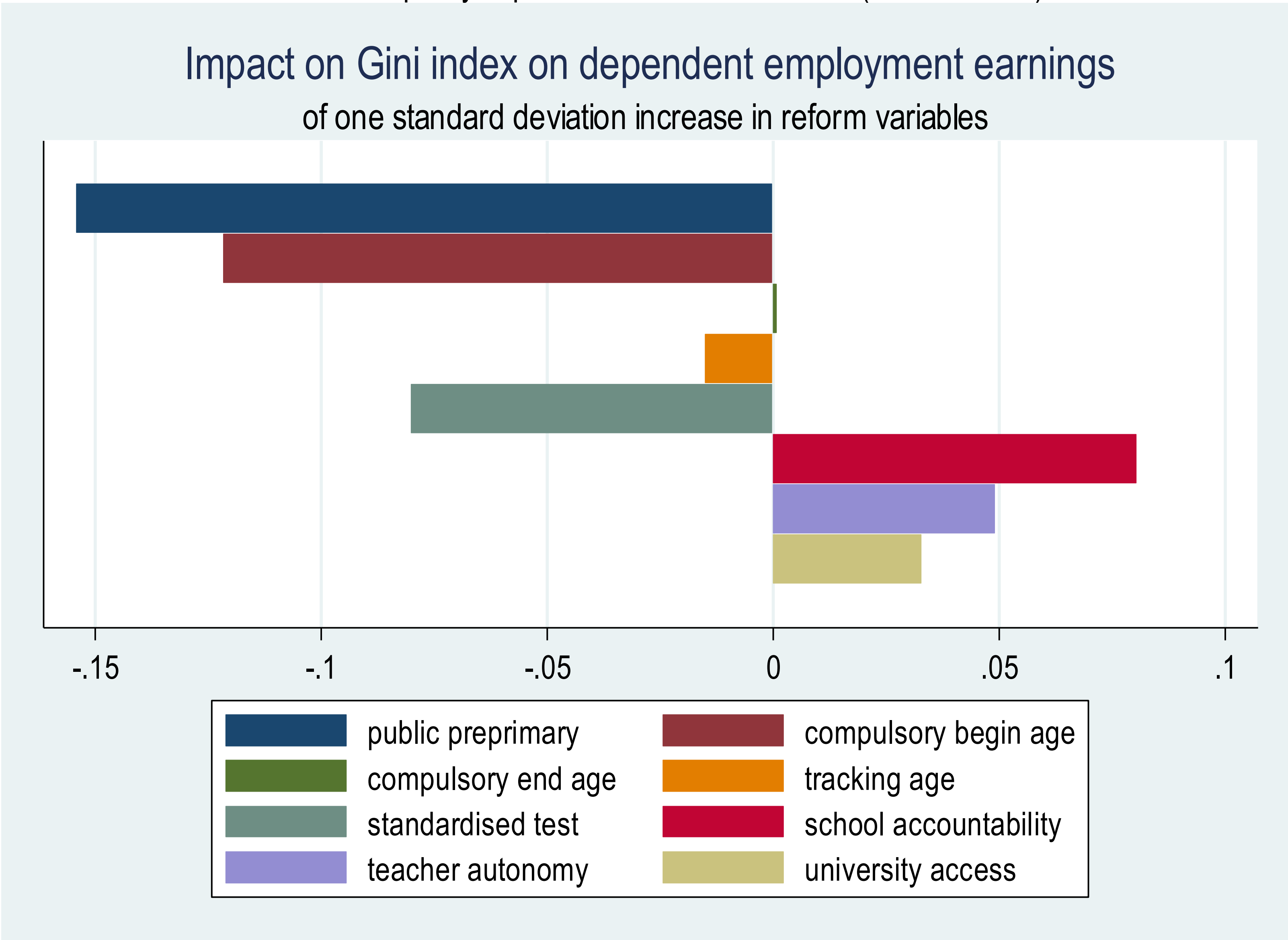
Most of these effects are consistent with previous literature:

① reinforcing early (pre)schooling, raising the beginning age for compulsory education, reinforcing educational standardisation by introducing standardised test scores, all reforms yield a reduction in income inequalities observed many years later in the labour market (INCLUSIVE reforms)

② On the contrary, increasing teachers' autonomy (in the selection of teaching contents), reinforcing school accountability and/or boosting university autonomy widen income differentials (SELECTIVE reforms)

③ According to the reduced form estimation, two additional reforms (increasing the years of education and delaying the tracking) come out statistically insignificant with respect to earnings inequalities.

Income inequality impact of educational reforms (reduced form)



② Can Educational policies today change income inequality tomorrow ? (joint with S.Iacus and G.Porro – still mimeo)

Main idea: (exact) individual matching between PISA 2000 and PIACC 2012.

PISA 2000 surveyed 65726 students born in 1985 in 21 countries which were later on surveyed in PIACC 2012. Birth year is absent in 5 countries of PIACC, therefore we rely on 5-year birth cohort (born between 1983 and 1987). As robustness check we may extend to neighbouring cohorts.

Individual characteristics that can be identically traced (or similarly aggregated) in both surveys are:
* gender
* foreign born
* highest parental education
* books at home

$(2\times2\times3\times4)$=48 types in each of 21 countries.

Distribution of population by background information – PISA 2000 and PIAAC 2012

individual characteristics (per cent points)	PISA 2000 (sample weights)	PIAAC 2012 Aged 25-29 (sample weights)	PIAAC 2012 Aged 20-34 (sample weights)
male	49.40	50.91	50.21
female	50.60	49.09	49.79
Either native-born or native-language at home	98.34	91.99	91.89
Foreign-born and foreign-language at home	1.66	8.01	8.11
both parents less than secondary completed	29.38	15.90	16.53
at least one parent with secondary degree	30.66	43.22	43.74
at least one parent with college degree	39.96	40.88	39.72
books at home (when 14 yrs old): 0-10	9.93	12.39	12.21
books at home (when 14 yrs old): 11-100	40.69	47.96	48.23
books at home (when 14 yrs old): 101-500	37.63	32.06	32.39
books at home (when 14 yrs old): >500	11.74	7.60	7.18

Pisa 2000 test score can be imputed to PIACC 2012 individuals following alternative strategies:

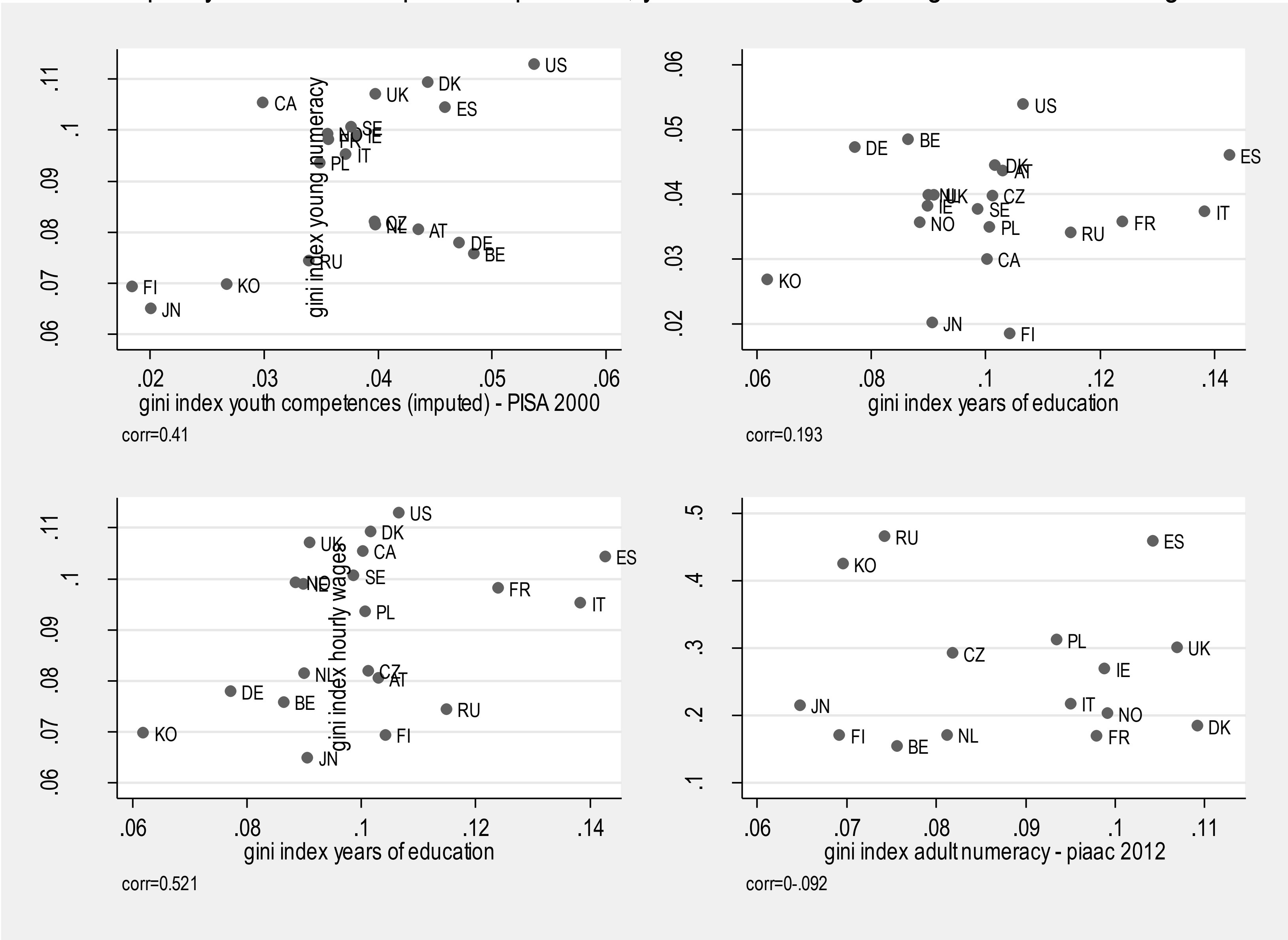
* using means (or median) by type
* estimating a DGP in PISA 2000 and replicating in PIACC 2012

Determinants of (log) earnings – population aged 25-29 - PIAAC 2012

	1	2	3		4	5	6
	OLS	OLS	OLS		oprobit	oprobit	oprobit
adult competences	0.001**		0.001***		0.005***		0.004***
	[0.000]		[0.000]		[0.001]		[0.000]
young competences (from		0.001	0.000			0.003***	0.002***
PISA cells' means)		[0.001]	[0.001]			[0.000]	[0.000]
Years of education	0.036***	0.041***	0.036***		0.099***	0.117***	0.093***
	[0.008]	[0.008]	[0.010]		[0.022]	[0.030]	[0.023]
female	-0.124***	-0.123***	-0.116**		-0.287***	-0.299***	-0.259***
	[0.035]	[0.038]	[0.039]		[0.068]	[0.049]	[0.062]
age	-0.203	-0.255	-0.248		0.769	0.586	0.651
	[0.580]	[0.599]	[0.596]		[0.691]	[0.692]	[0.718]
age²	0.004	0.005	0.005		-0.013	-0.01	-0.011
	[0.011]	[0.011]	[0.011]		[0.013]	[0.013]	[0.013]
Observations	5605	5485	5485		8345	8206	8206
Countries	15	15	15		20	20	20
R^2-Pseudo R^2	0.92	0.919	0.92		0.04	0.04	0.04

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1 errors clustered by country - weighted – country fixed effect included

Inequality in current and past competences, years of schooling and gross labour earnings



The strongest correlation is between inequality in schooling and inequality in current competences (south-west quadrant), because the latter are clearly cumulated following the permanence in school. However current competences are also correlated with competences when in school (north-west quadrant). But we have to remind that inequality in competences when young is an underestimate of actual inequality (since it comprises only the between-group component). This may explain its low correlation with schooling (south-west quadrant).

Inequality in education and earnings – population aged 25-29 and 20-65 - PIAAC 2012

	1	2	3		4	5	6
VARIABLES	Gini hourly wage decile	Gini hourly wage decile	Gini hourly wage decile		Gini hourly wage decile	Gini hourly wage decile	Gini hourly wage decile
	aged 25-29		*aged 20-65*				
Gini index years of education	0.487**	0.657***	0.484**		-0.209	-0.007	-0.209
	[0.227]	[0.212]	[0.230]		[0.177]	[0.175]	[0.177]
Gini index adult competences – PIAAC 2012	0.676**		0.716**		1.074***		0.981***
	[0.250]		[0.295]		[0.277]		[0.289]
Gini index youth competences (imputed) - PISA 2000		0.395	-0.139			1.025**	0.595
		[0.370]	[0.443]			[0.448]	[0.458]
female population share	0.033***	0.032***	0.033***		0.050***	0.046***	0.049***
	[0.007]	[0.008]	[0.008]		[0.004]	[0.004]	[0.004]
Observations	40	40	40		360	360	360
Countries	20	20	20		20	20	20
R^2	0.467	0.384	0.468		0.65	0.639	0.652

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1 - constant, country controls included – columns 4 to 6 also include birth cohort controls

Summing up:
⇨ educational attainment should incorporate schooling and achievements
⇨ both dimensions are endogenous, being correlated with parental background and unobservable abilities
⇨ educational reforms affect the distribution of both schooling and competences
⇨ not clear whether one dimension dominates the other
⇨ one would need to ascertain how competences are formed, and whether they are primitive measures (i.e. prior to schooling experience) → longitudinal surveys and/or administrative data can answer this question

③ Skilled or educated? Educational reforms, human capital and earnings (joint with L.Cappellari, M.Leonardi and P.Castelnovo – forthcoming in Research in labour economics)

Standard analysis of intergenerational mobility in educational attainment → increasing educational attainment reduces immobility (structural mobility) (PIAAC 2012-15 – 18 countries – subsample of employees) but makes it difficult to disentangle the contribution of education

CHILDREN OLDER THAN 44

highest parental education	child educational attainment: less than	secondary	post-seco	Total
less than secondary	29.00	40.37	30.63	100.00
secondary completed	10.09	45.04	44.87	100.00
post-secondary	4.47	22.82	72.72	100.00
Total	18.62	39.28	42.10	100.00

CHILDREN YOUNGER THAN 45

highest parental education	child educational attainment: less than	secondary	post-seco	Total
less than secondary	23.49	41.30	35.21	100.00
secondary completed	6.93	45.70	47.37	100.00
post-secondary	3.70	21.90	74.40	100.00
Total	10.37	37.91	51.72	100.00

But what underlies mobility ?

YEARS OF EDUCATION – ENTIRE SAMPLE

highest parental education	child educational attainment: less than	secondary	post-seco	Total
less than secondary	26.89	40.73	32.38	100.00
secondary completed	8.17	45.44	46.39	100.00
post-secondary	3.95	22.20	73.86	100.00
Total	14.17	38.54	47.29	100.00

NUMERACY ATTAINMENT (AND WITHIN-GROUP INEQUALITY)

highest parental education	child educational attainment: less than secondary	secondary completed	post-secondary
less than secondary	231.811	262.704	286.471
	(46.07)	(40.52)	(41.54)
secondary completed	247.880	273.172	297.233
	(45.59)	(38.60)	(39.14)
post-secondary	255.162	282.910	307.690
	(46.64)	(39.87)	(39.75)

Skills (proxied by numeracy) could play some role in promoting mobility

Basic educational production function

OLS Men - log hourly wage

	(1)	(2)	(3)
years of education (std)	0.176***		0.129***
	(0.007)		(0.006)
numeracy (std)		0.171***	0.112***
		(0.010)	(0.010)
Observations	22141	22309	22141
R^2	0.378	0.364	0.400

OLS Women - log hourly wage

	(1)	(2)	(3)
years of education (std)	0.208***		0.175***
	(0.006)		(0.007)
numeracy (std)		0.163***	0.095***
		(0.006)	(0.006)
Observations	23708	23893	23708
R-squared	0.377	0.335	0.393

Controls include foreign born, highest parental education, books at home when 14 years old, country fixed effect - residuals clustered by country×years of birth

Searching for family background variables to control for heterogeneity (books or parental education) ?

highest parental education	books at home 0-10	11-100	101-500	>500	Total
1	3,683	10,612	3,480	380	18,155
2	1,204	9,765	7,924	1,166	20,059
3	162	2,494	5,625	2,654	10,935
Total	5,049	22,871	17,029	4,200	49,149

Questions:

⇨ which are the relevant dimensions capturing available resources

* parental education correlated with (unobservable) ability, household income, networking in the labour market
* books correlated with parental education, family wealth, aspirations

⇨ do returns exhibit convex or concave patterns wrt family background ?

OLS Men - log hourly wage

	(1) books 0-10	(2) books 11-100	(3) books 10~500	(4) books >500
years of education (std)	0.111***	0.130***	0.133***	0.175***
	(0.016)	(0.009)	(0.011)	(0.021)
numeracy (std)	0.096***	0.118***	0.115***	0.131***
	(0.018)	(0.010)	(0.015)	(0.025)
Observations	2556	10750	7416	1720
R^2	0.355	0.388	0.371	0.404

OLS Women - log hourly wage

	(1) books 0-10	(2) books 11-100	(3) books 10~500	(4) books >500
years of education	0.114***	0.178***	0.189***	0.190***
	(0.021)	(0.009)	(0.011)	(0.021)
numeracy	0.078***	0.097***	0.102***	0.123***
	(0.021)	(0.010)	(0.011)	(0.027)
Observations	2201	10926	8649	2208
R^2	0.255	0.406	0.369	0.369

Controls include foreign born, highest parental education, country fixed effect - residuals clustered by country×years of birth

Convex wrt to books

OLS Men

	(1) pared<sec	(2) pared sec	(3) pared ter
years of education	0.122***	0.118***	0.157***
	(0.009)	(0.011)	(0.012)
numeracy	0.084***	0.140***	0.127***
	(0.010)	(0.015)	(0.016)
Observations	8191	8999	4951
R^2	0.377	0.409	0.348

OLS Women

	(1) pared<sec	(2) pared sec	(3) pared ter
years of education	0.159***	0.197***	0.159***
	(0.011)	(0.011)	(0.014)
numeracy	0.082***	0.093***	0.134***
	(0.010)	(0.010)	(0.013)
Observations	8624	9750	5334
R^2	0.352	0.428	0.302

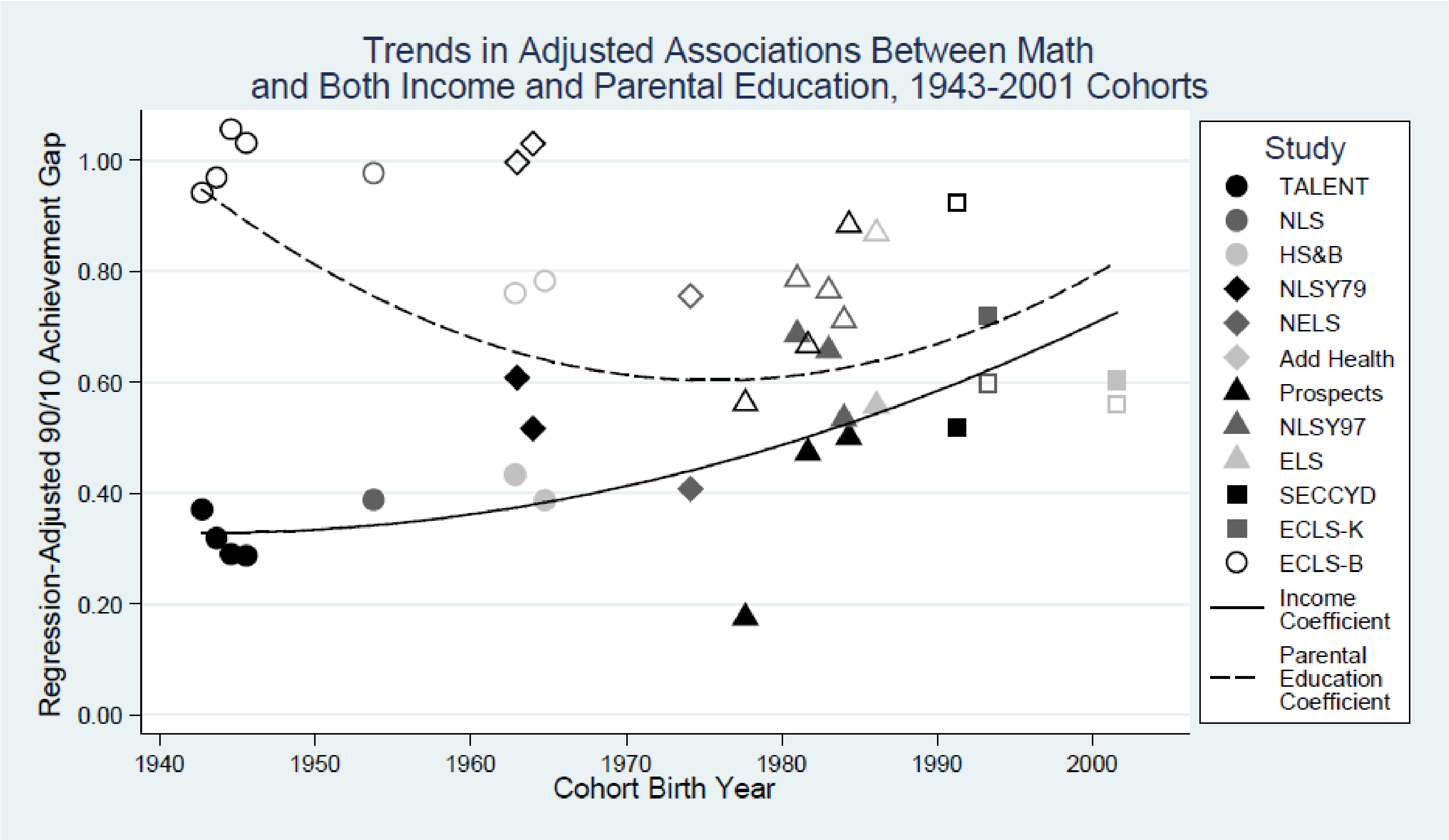
Controls include foreign born, books at home when 14 years old, country fixed effect - residuals clustered by country×years of birth

Some concavity wrt to parental education

If we observe concave patterns for parental education, we do expect increasing intergenerational mobility in education associated to increasing educational attainment of the population (using sociological jargon, structural mobility induce saturation in educational attainment of next generations). Thus more mobility implies greater equality of opportunity and less earnings inequality.

However, the literature suggests that returns to skills are increasingly convex (“convexification”). In such a case, developing skills in off-springs looks as a promising strategy to preserve social status. In such a case we could observe increasing intergenerational mobility in education (as well as increasing equality of opportunity) associated to increasing earnings inequality due to the increasing inequality in skills.

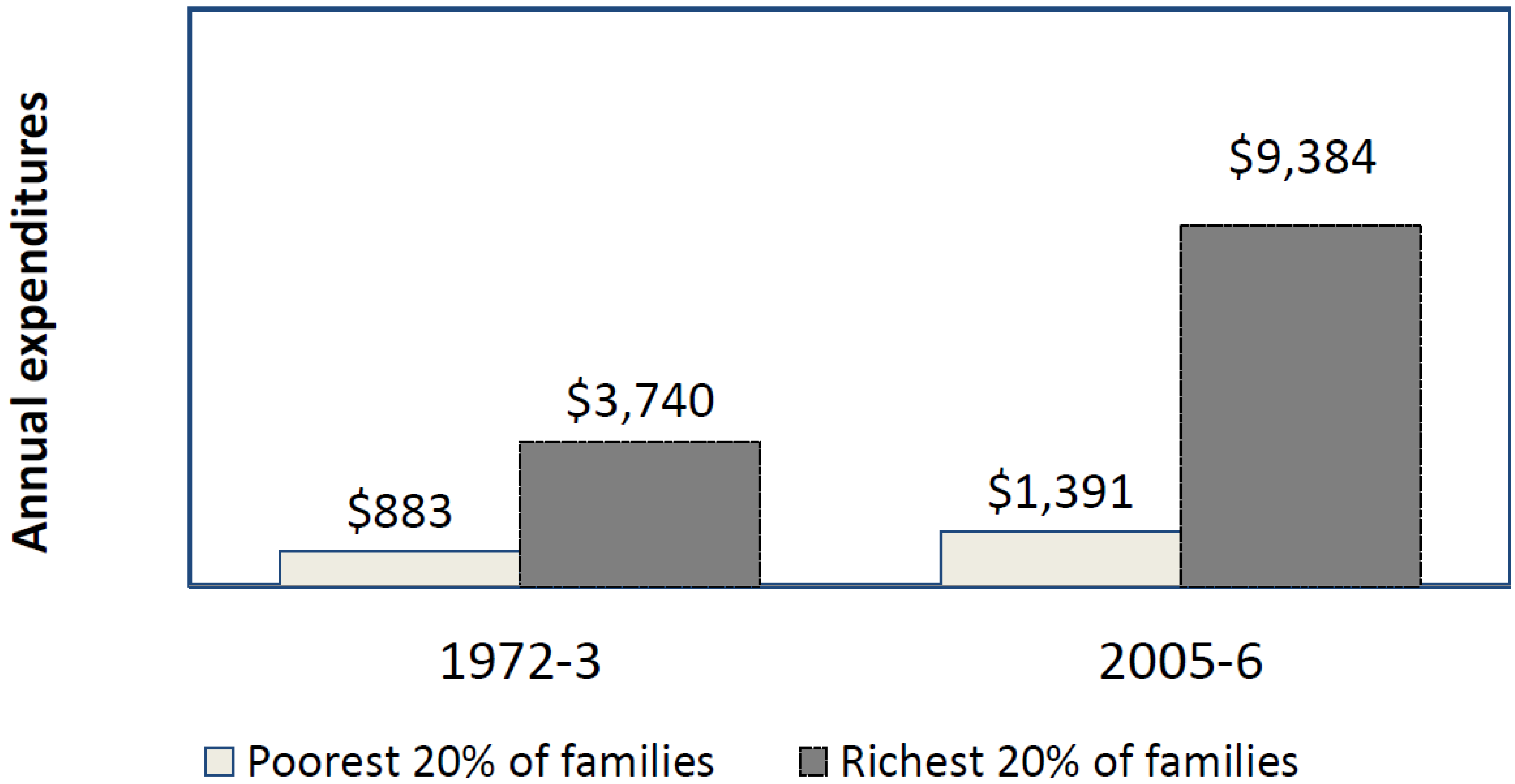
FIGURE 5.11 *Estimated Partial Associations Between Math Test Scores and Both Income and Parental Education, by Birth Cohort (1943 to 2001 Cohorts)*



Source: Author's compilation based on data from Project Talent (Flanagan et al. n.d.); NLS, HS&B, NELS, ELS, ECLS-K, ECLS-B (U.S. Department of Education, Center for Education Statistics 1999, 2000, 2001, 2004, 2009, 2010); Prospects (U.S. Department of Education 1995); NLSY79, NLSY97 (U.S. Bureau of Labor Statistics 1980, 1999); and SECCYD (National Institute of Child Health and Human Development 2010).
Note: Solid symbols represent regression-adjusted 90/10 income coefficients; hollow symbols represent regression-adjusted parental education coefficients. See note 12 for further details.

The economists Richard J. Murnane and Greg J. Duncan report that from 1972 to 2006 high-income families increased the amount they spent on enrichment activities for their children by 150 percent, while the spending of low-income families grew by 57 percent over the same time period. Likewise, the amount of time parents spend with their children has grown twice as fast since 1975 among college-educated parents as it has among less-educated parents.

Figure 6: Family enrichment expenditures on children



Authors' calculations based on data from the Consumer Expenditure Surveys. Amounts are in 2012$. Reprinted with permission from *Whither Opportunity*? 2011 © Russell Sage Foundation.

But… returns change over the life cycle:
⇨ formal education gets access to better jobs (returns do not decay)
⇨ skills decline with age (and returns follow an inverted U-shaped pattern)

OLS by age

	(1) 26-29	(2) 30-34	(3) 35-39	(4) 40-44
years of education	0.091***	0.136***	0.158***	0.152***
	(0.017)	(0.014)	(0.012)	(0.014)
numeracy	0.078***	0.089***	0.099***	0.124***
	(0.019)	(0.014)	(0.012)	(0.012)
Observations	5201	6484	6530	6820
R-squared	0.288	0.389	0.424	0.417

	(5) 45-49	(6) 50-54	(7) 55-59	(8) 60-64
years of education	0.176***	0.165***	0.159***	0.163***
	(0.010)	(0.018)	(0.011)	(0.017)
numeracy	0.126***	0.095***	0.098***	0.099***
	(0.018)	(0.013)	(0.012)	(0.021)
Observations	6780	6012	5263	2759
R-squared	0.417	0.450	0.449	0.343

Controls include gender, foreign born, highest parental education, books at home when 14 years old, country fixed effect - residuals clustered by country×years of birth

In order to get rid of (some) endogeneity we resort to educational reforms

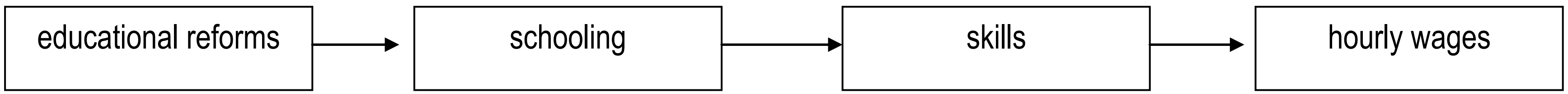
	(1) IV	(2) First Stage
	a. Men, years of schooling	
Years of schooling (standardized)	0.268***	
	(0.059)	
Reforms of primary teachers training		0.381***
		(0.047) [65.7]
Number of obs.	27717	
	b. Men, numerical skills	
Numerical skills (standardized)	-0.049	
	(0.184)	
Reforms of university access		0.105**
		(0.036) [8.5]
Number of obs.	27876	
	c. Women, years of schooling	
Years of schooling (standardized)	0.291**	
	(0.093)	
Reforms of primary teachers training		0.256***
		(0.043) [35.44]
Number of obs.	29056	
	d. Women, numerical skills	
Numerical skills (standardized)	0.266	
	(0.178)	
Reforms of university access		0.109***
		(0.031) [12.36]
Number of obs.	29237	

+,*, ** and *** indicate statistical significance at the 10, 5, 1 and 0.1 confidence level, respectively. The dependent variable is log gross hourly wage. Regression includes year of birth fixed effects and country fixed effects, plus controls for being foreign born, the highest parental educational attainment and the number of books at home when young. Robust standard errors in parentheses are clustered on year of birth by country cells. Regressions use survey weights. Numbers in square brackets are the F-test statistics of significance of the instruments in the first stage equation.

Recursive system estimates

	(1) Men	(2) Women
	a. Schooling equation	
Reforms of primary teachers training	0.379***	0.275***
	(0.046)	(0.039)
	b. Skills production function	
Years of schooling (standardized)	0.244***	0.071
	(0.072)	(0.114)
	c. Wage equation	
Numerical skills (standardized)	0.244***	0.156*
	(0.039)	(0.073)
Number of obs.	27717	29056

+,*, ** and *** indicate statistical significance at the 10, 5, 1 and 0.1 confidence level, respectively. The dependent variable is log gross hourly wage. Regression includes year of birth fixed effects and country fixed effects, plus controls for being foreign born, the highest parental educational attainment and the number of books at home when young. Robust standard errors in parentheses are clustered on year of birth by country cells. Regressions use survey weights.



Summing up:

⇨ educational attainment should incorporate schooling and achievements

⇨ both dimensions are endogenous, being correlated with parental background and unobservable abilities

⇨ educational reforms affect the distribution of both schooling and competences

⇨ not clear whether one dimension dominates the other

⇨ one would need to ascertain how competences are formed, and whether they are primitive measures (i.e. prior to schooling experience) → longitudinal surveys and/or administrative data can answer this question