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Skilled or educated?
Educational reforms, human capital and earnings*

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Abstract

We use OECD-PIAAC data to estimate the earnings effects of both years of education and of numerical skills. Our identification strategy exploits differential exposure to educational reforms across birth cohorts and countries. We find that education has the strongest earnings effect. A one standard deviation increase in years of education raises earnings by almost 22 percentage points (corresponding to a return to education above 7 percentage points), which compares with a lower percentage points return to an equivalent increase in numerical skills. Our results suggest that the same set of unobservables drives the accumulation of both formal years of education and numeracy skills. OLS estimates underestimate returns to human capital, consistently with the idea that educational reforms favour the human capital acquisition of abler children from disadvantaged parental backgrounds. When we consider numerical skills alone education reforms cannot identify any significant effect of skills on wages, however, when we jointly consider schooling and skills as endogenous factors in a recursive structure we find a significant role for skills in determining wages.

Keywords: Returns to human capital, cognitive skills, educational reforms, PIAAC
JEL code: I21, I24, I26, J24, J31

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1. Introduction

Since the reviews by Card (1995, 2001), the literature on returns to education has moved in various directions. On one side the search of a causal impact of schooling on earnings has prompted the investigation of various sources of exogenous variations, from compulsory schooling legislation to accessibility of schools. Particularly relevant for our purposes are those papers that use institutional reforms as instruments for schooling attainment exploiting variations across country/regions and years. For example Meghir and Palme (2005) consider a detracking reform (i.e. postponement of the age of initial tracking) occurred in Sweden, which was implemented gradually from Northern counties to Southern ones, over a period of 3 years. Brunello et al. (2009) show that changes in compulsory education legislation affect schooling and wages, in a cross-country perspective. Both Oreopoulos (2006) and Stephens and Yang (2014) use US cross-state changes in legislated compulsory education to identify a causal effect of schooling onto a number of outcomes (including wages, unemployment, and divorce).[1]

A second line of research has addressed the issue of the appropriate measure of human capital. Since Becker (1964) seminal work, years of schooling have always been considered the best proxy available for knowledge that raises productivity in the labour market. However, as soon as measures of cognitive abilities became available (in surveys such as the International Adult Literacy Survey, IALS, the Adult Literacy and Lifeskills Survey, ALL, and the Programme for the International Assessment of Adult Competences, PIAAC), several authors have started questioning whether these abilities should be included as complementary measures of earnings potential. The large majority of these works exploited data from IALS [2]; ALL was meant to represent a second

[1] Lofstrom and Tyler (2008) exploited exogenous changes in GED passing standards to estimate the signalling value of GED credentials.

[2] IALS is a survey collecting information on adult literacy in representative samples for different OECD countries, implemented in different years - 1994, 1996, 1998 - using a common questionnaire. The central element of the survey was the direct assessment of the literacy skills of respondents, but the background questionnaire also included detailed information on individual socio-demographic characteristics. For more information, see http://www.statcan.gc.ca/dli-ild/data-donnees/ftp/ials-eiaa-eng.htm). ALL was conducted in 10 countries (Italy, Norway, Switzerland, United States, Canada and Bermuda in 2003, and Hungary, Netherlands, Australia and New Zealand between 2006 and 2008); for details see https://nces.ed.gov/surveys/all/. PIAAC is the first survey that collects information on educational career, work history and social life participation in representative sample of the population comprised between 16 and 65. In

round of the IALS project, but was quickly superseded by the PIAAC project promoted by the OECD.

Barone and Van De Werfhost (2001) estimate a skill-augmented wage model and find that a large fraction of the education effect is attributable to cognitive skills (from 32 to 63%, depending on the country - see also Green and Riddell, 2003). In the same vein, Denny et al. (2004) show that the inclusion of measures of skills lowers the return to schooling in many countries by 1-2%. Hanushek and Zhang (2009) in a cross-country study show that cognitive skills play an important direct role in determining individuals' earnings, yielding the highest return in the US labour market. Eventually Hanushek et al. (2015) provide estimates of the labour market return of cognitive skills for 23 countries, using the new PIAAC data and finding considerable heterogeneity across countries.[3]

Some papers compare the effects of skills and institutions on wages. Well-known is the debate between Leuven et al. (2004) and Blau and Kahn (1996, 2005). Although both papers include cognitive skills when modelling earnings inequality, they reach different conclusions: the former article claims that demand and supply factors matter, despite a mediating role of skills; the latter claim that the greater dispersion of cognitive test scores in the United States plays a role in explaining higher U.S. wage inequality[4], but the residual wage inequality in the US is primarily attributed to the more decentralized structure of wage bargaining rather than to market forces. Freeman and Schettkat (2001) reach similar conclusions when comparing earnings inequality in the US and in Germany: the US is characterised by greater inequality in competences (skills) than Germany, therefore much of the differences in inequality can be attributed to both the educational system (the German apprenticeship system would raise the bottom of the competence distribution)

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addition the survey also measures the proficiency in literacy and numeracy through tests aiming to map "*…cognitive and non cognitive skills that individuals need for full participation in modern society*". See http://www.oecd.org/site/piaac/.

[3] See also Bedard and Farrell (2003), Salverda and Checchi (2014) and Paccagnella (2015) for work related more to inequality rather than average returns to education and skills.

[4] 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.*"

and the bargaining structure (Germany is characterised by more centralised wage bargaining led by stronger unions than in the US, thus compressing the top of the wage distribution).

In this paper, we put together these two lines of research: we take a broader view of education by comparing the effects both of years of schooling and of PIAAC test scores (a proxy of cognitive skills) on wages; concurrently we instrument skills and formal years of education using new measures of educational reforms that may directly affect the accumulation of schooling and skills. Differently from previous papers we do not compare the effects of skills and institutions; rather we exploit differential exposure to educational reforms across birth cohorts and countries to instrument skills with educational reforms. In this respect our paper differs from Hanushek et al. (2015) which consider the potential endogeneity of skills using compulsory school laws at state level only in the US subsample of PIAAC.

Both schooling and cognitive skills are potentially endogenous variables, since unobservable ability may affect educational choices as well as productivity in the labour market. On the other side, cognitive skills are also correlated with unobservable ability, but they also depend on schooling. The novelty of this paper is tackling the potential endogeneity of skills, since more talented individuals may possess higher level of skills (as well as achieve higher educational attainments) while obtaining higher earnings.

We regress hourly wages on years of education and skills and we use as instruments measures of educational reforms, namely teacher qualification requirements and regulations of access to universities, respectively. Both variables were originally proposed in Braga et al. (2013) and are based on inspecting national legislations in order to register changes that went either in the direction of rising the qualification requirements to become a teacher or in the direction of liberalising the access to universities (for example by lowering standard requirements, like graduating only from high schools). The assumption underlying the instrument use of reforms to primary teachers qualifications as instrument is that increases in the quality of primary education foster educational attainment later in life. Expansions of access to university education are used as instruments based on the view that more widespread access to higher education is conducive to the development of numerical skills in the labour force.

We start by estimating the wage effects of human capital using OLS regressions, which show that returns to schooling are higher than returns to numerical skills and that using both schooling and numerical skills in conjunction reduces the returns to each. We interpret the latter finding which as suggesting that to some extent the two measures belong to the same underlying process of income generation. Next we move to instrumenting one variable (schooling and skills) at the time. We show that while reforms of primary teachers hiring requirements perform well (in a first stage sense) as instruments for years of schooling, reforms of university access – our preferred instrument for numerical skills—are not powerful enough, particularly for men. The IV estimates of returns to schooling are larger than OLS ones, consistent with the view that educational reforms raise schooling attainment at the bottom of the educational distribution, where returns are the highest. On the other hand, we do not find any significant wage effect of numerical skills using IV, a likely consequence of using an underpowered instrument.

In the effort to jointly consider years of schooling and numeracy skills as endogenous determinants of wages, we adopt a multistage production function of skills (Cunha et al., 2010). We incorporate the skill production function into a recursive structure in which education depends on educational reforms, numerical skills depend on education, and wages depend on numerical skills. This is also consistent with the timing of the measurement of our variables in PIAAC: numeracy skills and wages are measured in adult life when formal education is already completed. When we assume this recursive structure (and differently form the zero effect that we get when instrumenting skills with university access reforms), we find – at least for men – that educational attainment has a sizeable impact on skill formation and, in turn, skills have a positive and sizeable effect on wages.

2. Data

Our analysis in based on two main data sources. The first one is PIAAC, which provides measures of the cognitive skills of adult individuals, while the second one is a dataset of institutional reforms affecting the national school system over the period 1929-2000 in 24 European countries, built by Braga et al. (2013).

PIAAC data have been collected between 2011 (1^{st} round) and 2014 (2^{nd} round) in 34 countries (29 OECD member countries and 5 partner countries), obtaining information about 216.250 adults (aged 16-65) residing in these States at the time of data collection, irrespective of their nationality, citizenship and language. Different countries used different sampling schemes, but post-sampling weighting allows matching the samples with the known population count.

PIAAC provides internationally comparable measures of individuals' competency level in literacy, numeracy and problem solving in technology-rich environments[5]. In PIAAC, literacy is defined as the ability of "*understanding, evaluating, using and engaging with written text to participate in society, to achieve one's goals and to develop one's knowledge and potential*" (OECD 2013), while numeracy is defined as "*the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life*". Following Hanushek et al. (2015) our preferred model focuses on numerical skills only, which is likely to be most comparable across countries. However, especially when considering the robustness of estimated gender differentials in schooling, competences and wages, we have also considered literacy as an alternative proxy for skills. As wage measure we employ the gross hourly wages of full-time employees, inclusive of bonus payments.

For the purpose of our analysis, we combine the data from PIAAC with the dataset of educational reforms built by Braga et al (2013), which collect information on policy measures affecting the institutional set-up that characterize the educational career of the residing population.

[5] The assessment of problem solving in technology-rich environment was optional and administered by 27 countries out of 32.

Specifically, in the present paper we focus our attention on *primary school teacher training*, a variable collecting information on reforms aimed at increasing teacher qualifications at primary level. These reforms are not very frequent in our sample and capture legislative intervention modifying the hiring procedures for primary school teachers, making them more selective in one respect or another. The second reform we concentrate on is the *expansion of university access*, like the open access from vocational high schools and the geographical expansion of universities. Also in this case the legislator attitudes went in the direction of opening university access during the second half of the last century, though there are a couple of reversals.

Reforms are measured as indices, taking value of zero/one in the absence/presence of a specific intervention; when legislators have repeatedly reformed a specific dimension over the sample period, step dummies are created, which are summed over the years and finally normalized to have a unitary range of variation. Figures 1 and 2 plot the within-country variation of these reform over cohorts, that represents the source of variation that we use for identification.

Following Braga et al. (2013) we reject the idea of being able to fully characterize an institutional setting like teacher hiring or student selective admissions. Nevertheless the constitutive dimensions of nation-specific educational institutions are controlled for by means of country fixed effects, as well as general trends in education expansion are accounted by birth year fixed effects. The remaining variability in the educational reform data accounts for single countries experiencing more/less reforming activities of their national governments (vis a vis other governments). For this reason we consider them as appropriate instruments for individuals' cognitive skill formation and schooling achievements.[6,]

Matching the two datasets, we can implement our identification strategy, which relies on temporal and geographical variations in the institutional arrangements controlling for time and

[6] One may question the presumed exogeneity of these reform variables, on the ground of reversed causality (governments were expanding university access under the pressure of students demanding more education). Braga et al. (2013) provide two answers to this objection: a direct test for the exogeneity of these reform variables (being unable to reject exogeneity), and an IV analysis, where educational reform variables are instrumented with political orientation of governments.

country fixed-effects. In order to match PIAAC individuals to reforms that have potentially hit them during their educational careers, we assume that individuals are potentially affected by the improved quality of primary school teachers at the start of the primary school, conventionally defined as ending at age 6. Thus if a country reformed teacher qualification requirements in 1970, the pupil affected by this reform are those born from 1964 onwards. Similarly, we match the reform of university access to students close to concluding compulsory secondary school, conventionally identified as the age of 15 year old. Since we are controlling for country and birth-year fixed effects, the exogenous variation hitting our individuals is the deviation from the pool of the other countries, acting as benchmark.

Since the reform dataset was compiled for European countries only, this merge forces us to drop non-European countries, leaving us with a sample of 20 countries (some of which are indeed large regions within a country), including Austria, Belgium (Flanders), Czech Republic, Denmark, Estonia, Finland, France, Germany, England and Northern Ireland, Greece, Ireland, Italy, Netherlands, Norway, Poland, Slovak Republic, Slovenia, Spain and Sweden, for a total of 57.012 observations.

Table 1 provides summary statistics for our sample. After dropping observations with missing values in the dependent employment earning variable, sample sizes range from 1236 in Greece to 4431 in Denmark. The highest hourly wages (corrected for purchasing power parity) are recorded in Denmark and Norway, while the lowest in Poland, Slovakia and Estonia. The highest earning inequality (as measured by the standard deviation of logs) is recorded in Germany, Estonia and Spain (standard deviation of log(wage) greater than 0.55), while the Nordic countries (Sweden, Finland, Norway and Denmark) exhibit the lowest one (standard deviation of log(wage) smaller than 0.40). Since in Table 1 we report statistics disaggregated by gender, we can analyse the gender gap by means of a simple graph (see Figure **3**). From this graph we gauge that hourly wages and alternative measures of human capital (schooling, numeracy and literacy) tend to move together, though competences (numeracy or literacy) display varying correlations with schooling and earnings.

Table 2 reports unconditional correlations among the relevant variables. One can notice that male wages are more strongly correlated with measures of skill than women ones, despite an almost equivalent correlation with formal schooling. In addition the two dimensions of competences are highly correlated (correlation coefficient equal to 0.89).

The hourly wage is approximately log-normal, as shown in Figure **4**. While years of schooling are skewed (with the distribution shifting to the right across birth cohorts), skills are also normally distributed, though around different country means. Average numeracy and literacy test score are highest in Northern Europe (Scandinavia plus the Netherlands and Belgium) and lowest among Mediterranean countries (Italy, Spain and Greece). Part of this country heterogeneity has to do with national histories of access to schooling, since equivalent country ranking emerges when considering average years of schooling.[7] However the relationship between the distribution of skills and the distribution of formal schooling is not linear: if we look at Figure **5** we notice that for any given level of attained education there is a significant variation in the level of skills (here we report numerical skills, but literacy exhibits a similar pattern). This should convince the reader that both schooling and competences have a potential explanatory power onto wages, which we are going to explore in a more formal way in the next section.

3. Empirical strategy

We model the earnings effects of human capital (h) as measured in terms of either returns to education (e) or to numerical skills (s). Our data cover 20 countries (indexed by c) and T birth cohorts (indexed by t). Our main model of interest is the following:

$$y_{ict} = \beta' x_{ict} + \gamma h_{ict} + \mu_c + \mu_t + \varepsilon_{ict} \qquad (1)$$

[7] Country differences would be enhanced if we were to consider the entire population, while here we are restricting to working one.

where y_{ict} is (log of) gross hourly earnings of individual i, i=1…N. The vector of regressors x_{ict} includes birth year fixed effects and controls for being foreign-born, parental education (the highest parental degree) and family background (number of books in the parental home), the μ's are fixed effects for countries and birth cohorts and ε is a white noise error term (we relax the iid assumption with cluster robust standard error at the country by cohort level). We conduct separate analysis by gender throughout.

Consistent estimation of returns to human capital hinges upon the assumption that each measure of human capital is exogenous in the wage equation, net of observables characteristics and country or cohort specific effects in earnings:

$$E\left[h_{ict}\varepsilon_{ict}\right] = 0; h = e, s \qquad (2)$$

There are reasons why these assumptions may fail: for example heterogeneous unobserved ability that is correlated with both human capital and earnings within cohort-country cells. We cope with this endogeneity issue using two strategies. The first strategy is based on an instrumental variable (IV) framework. We exploit the variation generated by educational reforms whose implementation varies across birth cohorts within a country, described in Section 2. Specifically, we look at changes in different educational institutions that may have differential impacts depending on the particular human capital measure considered. The database of educational reforms contains indicators on 29 distinct aspects of the educational system at different levels. Within these, we search for the two variables with the highest statistical power (F-statistic) in first stage regressions of the human capital indicators. For years of education, we select changes in the quality of primary education induced by the expansion of teacher qualification requirements. The underlying assumption is that increases in the quality of primary education foster educational attainment later in life. As instrument for numerical skills we select expansions of access to university education, with a view that more widespread access to higher education is conducive to the development of numerical skills in the labour force.

The first stage model of our IV set-up is the following:

$$h_{ict} = \delta' x_{ict} + \pi R_{ct} + \theta_c + \theta_t + u_{ict} \qquad (3)$$

where R_{ct} is the indicator for educational reforms, primary teachers training or university access depending upon human capital h being measured as years of schooling or numerical skills, respectively. Let the reduced form wage equation be given by:

$$y_{ict} = \beta' x_{ict} + \lambda R_{ct} + \mu_c + \mu_t + \varepsilon_{ict} \qquad (4)$$

then the IV estimate of the wage returns to human capital is given by the ratio of the reduced form effect over the first stage:

$$\gamma_{IV} = \frac{\lambda}{\pi} \qquad (5)$$

Our second strategy combines IV with a skill production function in the vein of Cunha et al. (2010).[8] According to this set-up, skills later in life are generated by inputs accumulated when young, in particular via educational investments. We specify a recursive model in which education depends on educational reforms, numerical skills depend on education, and wages depend on numerical skills. Within this structure, educational reforms act as instrument for educational attainment in the production function equation, while educational attainment acts as instrument for numerical skills in the wage equation. This provides the exclusion restriction under the assumption that the only way on which education affects wages is via human capital formation (for example ruling out signalling effects).

Assuming linearity, we can write the skill production function as follows:

$$s_{ict} = \eta' x_{ict} + \rho e_{ict} + \phi_c + \phi_t + \xi_{ict} \qquad (6)$$

where ρ parameterises the effect of years of schooling on numerical skills. Clearly, unobserved ability bias (akin to the one plaguing equation (1)) may complicate estimation of equation (6). We

[8] Cunha et al. (2010) estimate multistage production functions for children's cognitive and non-cognitive skills. They claim that skills are determined by parental environments and investments at different stages of childhood. Their focus is on the elasticity of substitution between investments in one period and stocks of skills in that period which shows the benefits of early investment in children. We focus instead on the different timing of measurement of the investment in education and of the numeracy skills in our data.

therefore use equation (3) setting h=e and using reforms of primary teacher training as R_{ct} as the exclusion restriction, providing a first stage equation for (6). In turn, equation (6) is the first stage of the following wage equation:

$$y_{ict} = \beta' x_{ict} + \gamma s_{ict} + \mu_c + \mu_t + \varepsilon_{ict} \qquad (7)$$

We assume joint normality of u_{ict}, ξ_{ict}, ε_{ict} and estimate equations (3), (6) and (7) jointly by Limited Information Maximum Likelihood (LIML).

4. Results

In Table 3 we report separately for men and women OLS estimates of the earnings model of equation (1) using gross hourly wages inclusive of bonus payments (measured in Purchasing Power Parity) as our dependent variable. Besides human capital indicators, the conditioning set includes year of birth fixed effects, country fixed effects, a foreign born indicator, an indicator for the highest educational attainment of the parents and the number of books at home when young. Regressions use survey weights and standard errors allow for repeated observations within year of birth by country cells, which is the level of variation of the educational reforms indicators that we use as instruments.

We use standardised indicators for skills and years of education so that estimated coefficients can be compared in the standard deviation metric. We standardise these variables relative to the within-country distribution. Still, to get an approximate idea of the extent to which standardised returns to education translate into the more conventional per-year returns to education, one can refer to the overall standard deviation of years of education, which is 2.9 for men and 2.8 for women; rescaling of the estimated coefficient on standardised years of education using these numbers returns the magnitude of the per-year earnings return to education.

For both men and women, OLS results point to substantial returns to human capital. Considering years of schooling in Column (1), one standard deviation increase in measured human capital corresponds to a 17.6 percent wage increase for men and 20.2 percent for women, or a return to one additional year of schooling of about 6 and 7 percentage points respectively. Returns to numerical skills are smaller for both men and women at 15.3 and 15 percent, respectively; see Column (2). When we use the two human capital indicators in conjunction in Column (3), returns to each are reduced, indicating that the two variables are not independent. Each variable retains some explanatory power in the wage equation, but it seems that returns to skills are the most sensitive to the joint inclusion, suggesting that their contribution to wage formation independently from education is limited.

We report results from the IV analysis in Table 4, which also includes the estimated coefficients on the instruments in the first stage equation. We instrument years of education exploiting changes in the quality of primary education induced by the expansion of teacher qualification requirements. As instrument for numerical skills we exploit expansions of access to university.

For men, reforms enhancing the qualification contents of primary teacher curricula exert a positive and statistically significant effect on schooling attainment. Reforms indicators are coded on a [0-1] scale, such as a unit increase in the variable represents a change from “no training at all” to “maximum training”. According to the estimates, such a [0-1] change increases schooling attainment by a third of a standard deviation, and the associated F-statistic (in square brackets) is well above the weak instruments threshold. The wage effect of schooling in this case is much larger compared with the OLS case (0.27 versus 0.17). Given that reforms in schooling institutions across cohorts can be assumed to be characterised by a high degree of compliance, the IV estimates can be given a Local Average Treatment Effects (LATE) interpretation, namely the effect of additional years of schooling for compliers, individuals whose schooling attainment was affected by the reform. That IV estimates be larger than OLS ones is a recurrent finding for instruments that increase schooling at the bottom of the educational distribution, where wage returns are the highest.

Our instrument induces a similar pattern in the estimates, suggesting that training of primary school teachers is mostly beneficial for the schooling attainment of the less educated.

Evidence from the IV estimation of the effects of numerical skills for males is less clear-cut, in particular because the instrument is not characterised by sufficient power. Indeed, a preliminary inspection of the reform database over a set of 29 alternative reforms indicators could not find one single indicator that was strong enough to operate as instrument for numerical skills for men in the sample under investigation. We therefore retained reform of university access as an instrument, both because it is anyway significant in affecting numerical skills of men and because for women it is characterised by sufficient power (see below). The lack of power of the instrument translates into a null effect of numerical skills on wages.

Considering the evidence for women, for each human capital indicator – and for each instrument – we find evidence that resembles the one of men. The instruments are significant and characterised by sufficient statistical power, and the instrumented returns to human capital are larger than their naïve OLS counterparts.

The evidence shown thus far indicates that to some extent years of education and numerical skills capture the same process of income generation, as suggested by the fact that when using the two human capital indicators in conjunction reduces their wage effects compared to models in which they enter separately in the conditioning set. This points to the facts that education and numerical skills are part of the same underlying process of production of human capital. Also, we have seen that while educational reforms perform well as instrumental variables for years of schooling, they sometimes do not have sufficient statistical power in the case of numerical skills, which may result in biased IV estimates.

We now combine these two observations and estimate the wage returns to human capital through a recursive system of equations. The idea is to exploit institutions as instruments only where they are the most powerful (i.e. on the educational indicator), and use education as instrument for skills via the skill production function of equation (6), which provides the exclusion restriction under the assumption that the only way on which education affects wages is via human capital formation. With this assumption we rule out the existence of mechanisms such as ability signalling via education. The other identifying restriction underlying the recursive system is that the only channel through which changes in primary school teachers' training affect numerical skills is via educational attainment.

Results from this exercise are reported in Table 5. For men, there is evidence of a significant causal chain from education to wages via skills. In particular, formal schooling has a sizeable impact on skill formation: one standard deviation increase in educational attainment translates into a quarter of a standard deviation increase in skills. In turn, skills have a positive and sizeable wage effect, which contrast with the evidence of no effect obtained when instrumenting skills directly with (insufficiently powerful) educational reforms. Evidence for women is radically different, in that education exerts no effect on numerical skills which, in turn, have little or no effect on wages. Considering that both education and skills have significant wage effects in the naïve OLS model for women, this evidence suggests that for them formal schooling matters as credential for entering the labour market, partly independent from their true level of competences (which consequently are less important in affecting their wage opportunities). This is confirmed when replacing numeracy with literacy (not reported but available from the authors), where in principle women enjoy an advantage over men: once again the return to skill for women is lower than for men, because formal education is partly independent from (and more relevant than) skills.

5. Concluding remarks

In this paper we have analysed the relationship between schooling, skills and earnings in PIAAC data. The evidence indicates that to some extent years of education and numerical skills capture the same process of income generation, as suggested by the fact that when using the two human capital indicators in conjunction reduces their wage effects compared to models in which they enter separately in the conditioning set. Education reforms work better as instruments for formal schooling rather than for numeracy skills; however, when we impose a recursive structure specification in the effort to jointly consider years of schooling and numeracy skills as endogenous determinants of wages, we find – at least for men – that educational attainment has a sizeable impact on skill formation and, in turn, skills have a positive and sizeable effect on wages.

The use of this structure where educational reforms affect formal schooling which in turn affects the accumulation of numeracy skills which determine wages is consistent with the characteristics of our data: PIAAC data measure skills and wages in adult life when formal schooling is already completed. Our paper remains silent about how skills and schooling interact in the human capital formation (namely whether they are complement, substitutes or independent), but this dataset is inappropriate to answer this type of question. A more appropriate dataset would contain information on skills before the start (or at least before the conclusion) of the schooling career. This is the objective of future research.

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Table 1: Summary Statistics

Country	sample size	% of female	age	sd age	men: hourly earnings PPP (median)	men: hourly earnings PPP (sd)	women: hourly earnings PPP (median)	women: hourly earnings PPP (sd)	men: years of schooling (mean)	men: years of schooling (sd)	women: years of schooling (mean)	women: years of schooling (sd)
Austria	2919	0.50	38.61	11.73	19.06	10.17	16.21	8.05	12.47	2.56	12.48	2.75
Belgium (FL)	2708	0.49	40.16	11.33	20.3	20.52	18.98	26.42	12.80	2.57	13.23	2.52
Czech republic	2581	0.52	38.55	12.49	8.75	4.72	7.21	4.27	13.62	2.62	13.64	2.66
Denmark	4431	0.51	43.40	13.31	23.97	10.03	22.37	8.21	13.08	2.75	13.41	2.64
Estonia	3930	0.58	41.11	12.49	9.52	6.94	6.76	4.89	12.09	2.68	12.94	2.49
Finland	3186	0.52	41.68	12.37	19.41	7.82	16.29	6.6	12.85	2.91	13.57	2.82
France	3399	0.50	41.09	11.50	14.96	7.38	13.26	6.62	11.97	3.41	12.40	3.34
Germany	3325	0.50	40.00	12.57	18.64	11.43	15.65	9.03	13.85	2.58	13.92	2.40
Great Britain	2424	0.58	39.52	11.99	18.43	13.47	14.83	9.83	13.45	2.33	13.52	2.33
Greece	1236	0.51	39.36	10.01	8.98	6.85	8.29	5.78	12.97	3.01	13.47	3.02
Ireland	2741	0.56	39.14	11.24	20.26	12.77	18.62	11.65	15.61	2.95	15.88	2.68
Italy	1801	0.47	41.50	10.19	14.64	9.35	13.98	9.17	11.73	3.60	13.13	3.71
Netherlands	3132	0.50	40.03	13.01	21.32	11.34	18.59	9.29	13.47	2.58	13.53	2.44
Northern Ireland	1780	0.62	38.28	11.67	16.16	12.33	14.18	10.09	13.41	2.28	13.58	2.29
Norway	3539	0.49	40.15	12.91	24.51	10.48	21.49	7.78	14.52	2.45	14.69	2.36
Poland	3864	0.44	31.09	11.66	6.97	5.24	6.18	5.27	12.59	2.59	14.07	2.53
Slovak Republic	2479	0.51	40.47	11.64	7.71	5.84	6.26	4.96	13.30	2.47	13.81	2.61
Slovenia	2211	0.50	41.20	10.03	8.48	5.34	8.16	4.56	10.63	1.88	11.23	1.81
Spain	2476	0.48	39.73	10.83	13.45	63.04	11.7	12.34	11.84	3.53	12.64	3.36
Sweden	2850	0.51	42.00	12.70	18.42	6.64	16.51	5.33	12.64	2.35	13.11	2.35
Total	57012	0.51	39.85	12.30	16.13	17.71	14.21	82.41	12.96	2.91	13.46	2.80

Table 1 (*continued*)

Country	sample size	men: numeracy (mean)	men: numeracy (sd)	women: numeracy (mean)	women: numeracy (sd)	men: literacy (mean)	men: literacy (sd)	women: literacy (mean)	women: literacy (sd)	wage: men/ women (median)	schooling: men/ women (mean)	numeracy: men/ women (mean)	literacy: men/ women (mean)
Austria	2919	287.14	45.95	277.56	41.57	276.05	41.11	276.12	38.22	1.18	1.00	1.11	1.00
Belgium (FL)	2708	294.08	45.74	281.96	42.05	283.39	42.82	283.05	39.64	1.07	0.97	1.09	1.00
Czech republic	2581	287.15	40.68	276.56	38.31	282.68	37.79	277.86	36.94	1.21	1.00	1.06	1.02
Denmark	4431	289.86	48.37	279.36	43.48	275.17	44.65	274.94	40.47	1.07	0.98	1.11	1.00
Estonia	3930	280.16	41.76	274.74	38.82	278.47	40.52	281.07	39	1.41	0.93	1.08	0.99
Finland	3186	301.43	42.20	288.47	40.26	299.59	40.35	300.15	39.52	1.19	0.95	1.05	1.00
France	3399	270.18	52.58	261.56	49.50	269.75	45.32	270.8	43.41	1.13	0.97	1.06	1.00
Germany	3325	287.82	45.58	275.96	43.79	279.42	42.25	277.92	40.56	1.19	0.99	1.04	1.01
Great Britain	2424	284.95	48.09	270.95	42.64	288.05	43.61	285.36	38.88	1.24	0.99	1.13	1.01
Greece	1236	260.74	42.72	261.45	41.97	254.44	41.14	262.15	40.68	1.08	0.96	1.02	0.97
Ireland	2741	274.63	48.22	262.15	42.56	278.41	43.77	275.98	38.88	1.09	0.98	1.13	1.01
Italy	1801	263.46	46.88	258.84	43.72	258.42	42.23	262.25	40.42	1.05	0.89	1.07	0.99
Netherlands	3132	295.37	43.09	281.62	39.84	293.68	41.55	291.24	39.25	1.15	1.00	1.08	1.01
Northern Ireland	1780	286.30	41.74	270.73	40.38	289.8	37.89	281.72	37.57	1.14	0.99	1.03	1.03
Norway	3539	295.20	47.84	282.39	43.46	287.19	42.49	285.54	38.99	1.14	0.99	1.10	1.01
Poland	3864	267.06	45.42	270.38	39.91	271.93	42.76	282.74	38.43	1.13	0.89	1.14	0.96
Slovak Republic	2479	282.88	39.67	285.43	35.30	277.63	33.76	280.98	31.45	1.23	0.96	1.12	0.99
Slovenia	2211	265.67	50.66	264.99	45.77	259.3	45.17	264.66	42.02	1.04	0.95	1.11	0.98
Spain	2476	262.01	45.94	250.14	44.23	262.37	44.6	257.68	43.51	1.15	0.94	1.04	1.02
Sweden	2850	296.90	49.00	285.12	44.31	291.18	44.53	290.22	40.66	1.12	0.96	1.11	1.00
Total	57012	282.76	47.54	274.15	43.24	278.62	43.64	279.39	40.65	1.14	0.96	1.10	1.00

Table 2 – Unconditional correlations among relevant variables (pooled sample – 57012 individuals)

	men (27842 obs)				women (29169 obs)			
	log hourly wage	years of schooling	numeracy	literacy	log hourly wage	years of schooling	numeracy	literacy
log hourly wage	1.00				1.00			
years of schooling	0.37	1.00			0.36	1.00		
numeracy	0.34	0.48	1.00		0.25	0.44	1.00	
literacy	0.28	0.46	0.90	1.00	0.23	0.43	0.89	1.00

Table 3 - OLS estimates

	(1)	(2)	(3)
		a. Men	
Year of schooling (standardized)	0.176***		0.137***
	(0.006)		(0.006)
Numerical skills (standardized)		0.153***	0.095***
		(0.007)	(0.007)
Number of obs.	27842	28002	27842
R^2	0.456	0.436	0.472
		b. Women	
Year of schooling (standardized)	0.202***		0.172***
	(0.005)		(0.006)
Numerical skills (standardized)		0.150***	0.086***
		(0.006)	(0.006)
Number of obs.	29169	29350	29169
R^2	0.459	0.412	0.473

+,*, ** 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.

Table 4 - IV estimates

	(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.

Table 5 - 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.

Figure 1 – The reforming activity with respect to primary school teachers

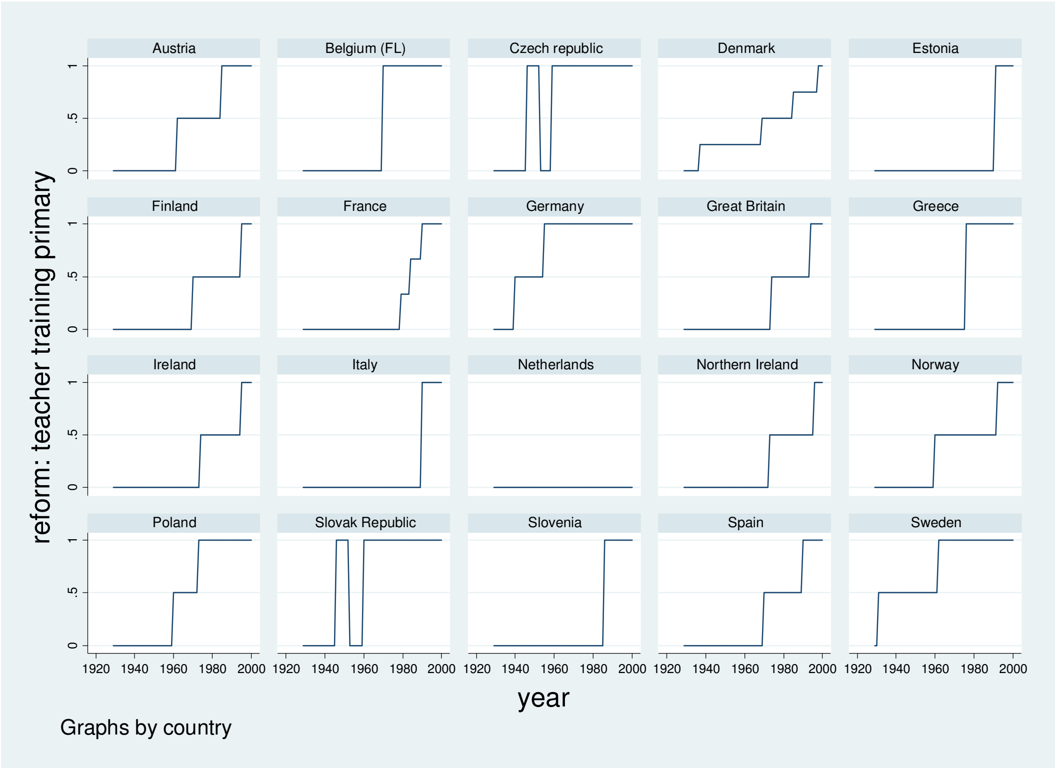


Figure 2 – The reforming activity in admission to universities

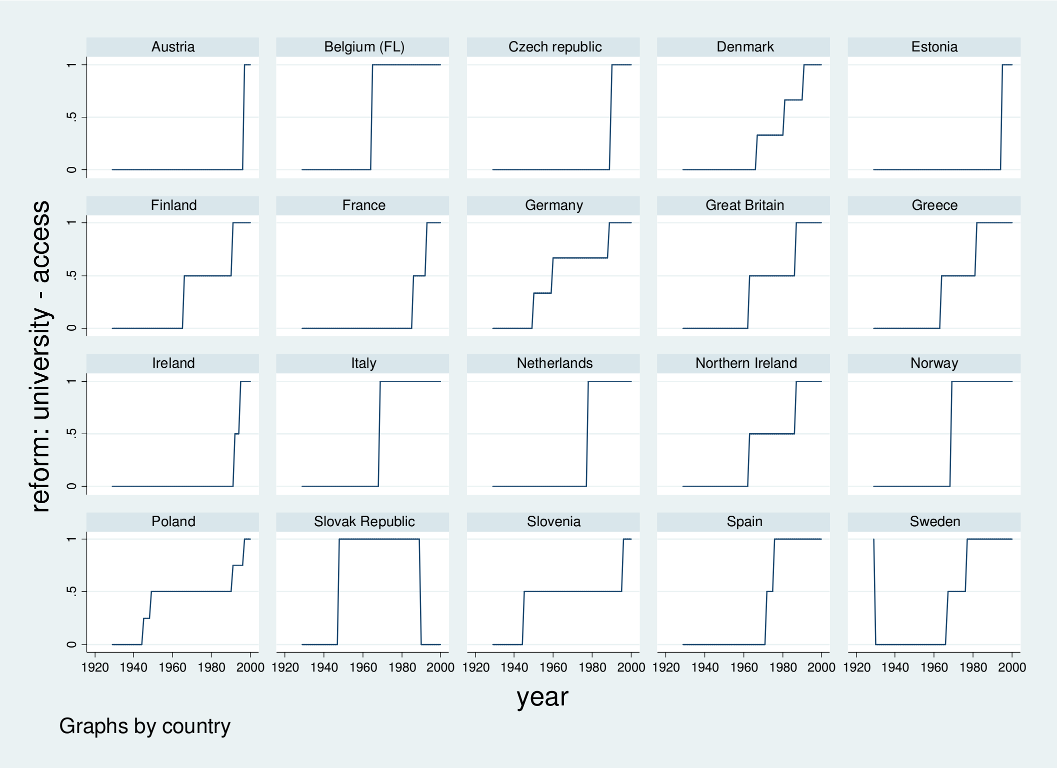


Figure 3 – Gender differentials

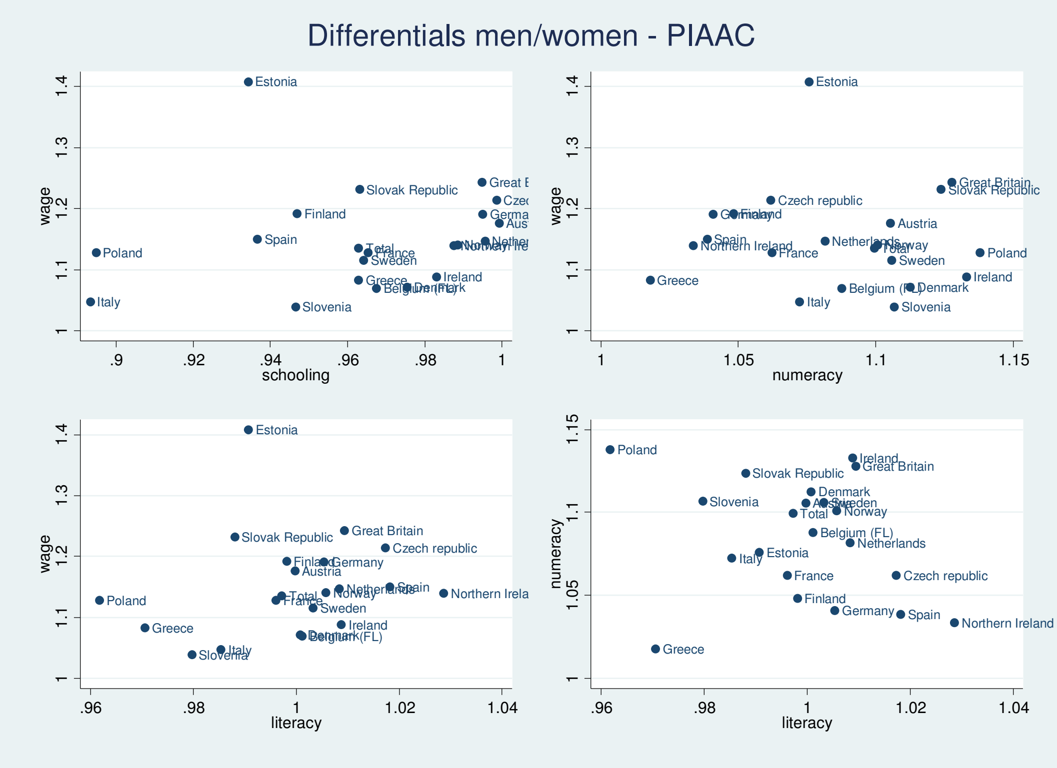


Figure 4 – Distribution of hourly wages - PIAAC 2011-2014

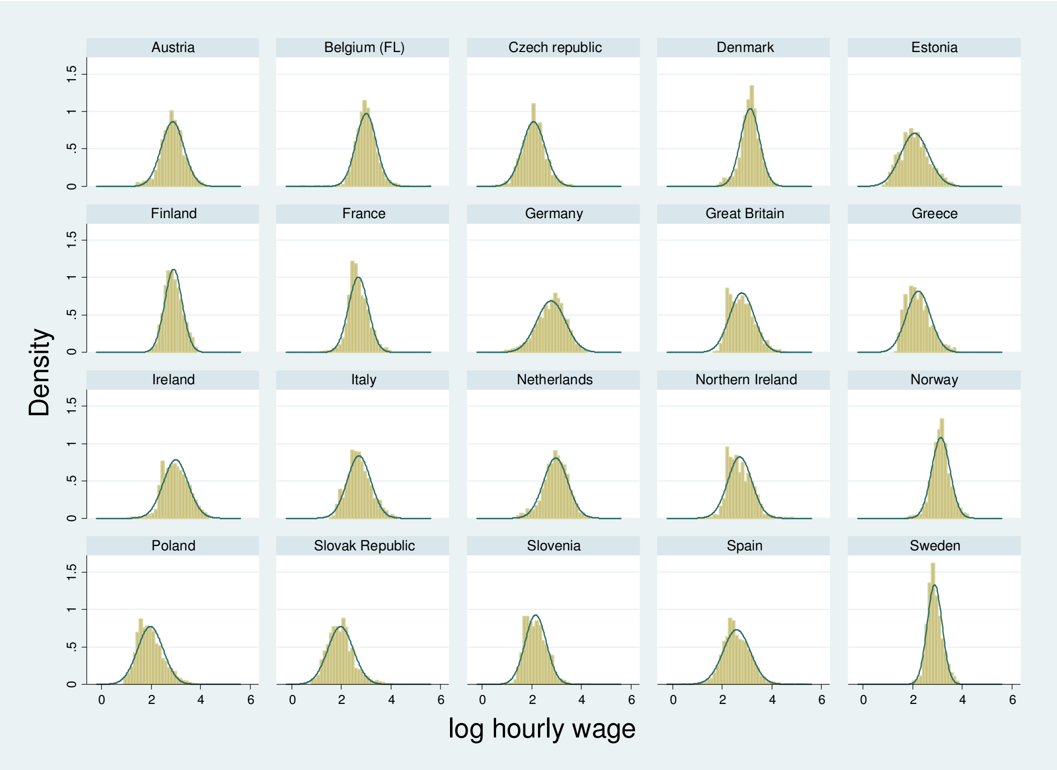
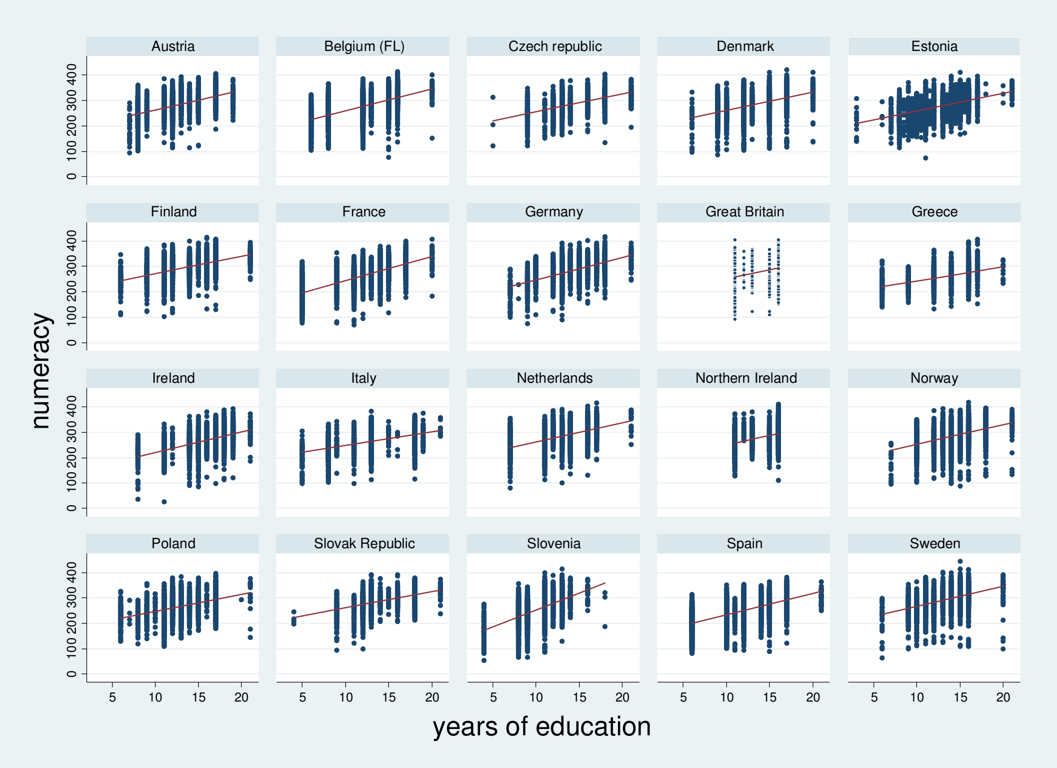


Figure 5 – Competences and skills - PIAAC 2011-2014



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