

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

Lorenzo Cappellari (Catholic University of Milan and IZA)
Paolo Castelnovo (University of Milan)
Daniele Checchi (University of Milan and IZA)
Marco Leonardi (University of Milan and IZA)

June 2015

Preliminary and incomplete version

Abstract

We use OECD-PIAAC data to estimate the earnings effects of education and numeracy skills. Our identification strategy is based instrumental variables exploiting 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 education raises earnings by almost 20 percentage points (p.p.) –corresponding to a 6 p.p. per year of education—which compares with a 11 p.p. return to an equivalent increase in numeracy skills. Also, most of the endogeneity of skills appears to reflect the endogeneity in education, suggesting that it is the same set of unobservables that favours human capital accumulation in both dimensions. OLS estimates underestimate returns to human capital, consistent with the idea that educational reforms favour the human capital acquisition of able children from disadvantaged parental background. When we look at the effects at the tails of the earnings distribution, we show that while skills compress earnings from the bottom and are therefore inequality-reducing, returns to education are inequality-enhancing as their effects is concentrated in the top quartile of the earnings distribution.

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

^{*}Financial support from the Italian Ministry of Education (PRIN n. prot. 2010T8XAXB) is gratefully acknowledged. We thank Marco Paccagnella for helpful discussions.

1. Introduction

Two major hypotheses have been advanced to explain cross-country differences in wage inequality. One is related to relative skill demand and supply, either in a two-group labour force (the so called *canonical model* – see Katz and Murphy 1992) or in the more recent approach based on the separation between tasks, skills and jobs, explaining current trends of polarisation (Acemoglu and Autor 2011). A second line of research attributes international differences in wage inequality to differences in labour market institutions (a recent review in Salverda and Checchi 2015). In this view high minimum wages, employment protection and labour unions are responsible for wage compression in the top of the distribution and the relatively higher wages of low skilled workers in continental Europe.

In an often cited paper, Blau and Kahn (1996) claimed that there is no evidence that supply and demand can explain any of the cross-country differences in the relative earnings of the less-skilled. Therefore labour market institutions (in particular, labour unions and wage centralization) were better predictors of cross-country wage inequality than supply and demand indices constructed using education (for supply) and industrial and occupational composition (for demand).

This literature has gradually evolved in the direction of better defining the notion of skills. First of all recognizing that “skills” does not simply mean “years of education”, especially when direct measure of cognitive skills are available from specific surveys (IALS, ALL, PIAAC). Secondly institutional dimensions have been extended beyond labour market institutions to include educational dimensions that affect directly the accumulation and the distribution of schooling. Examples of the first line of research are Freeman and Schettkat (2001), Green and Riddell (2003), Leuven et al. (2004), and more recently Paccagnella (2015). Examples of the second line of research can be found in Bedard and Ferrall (2003) and more recently in Brunello et al. (2010).

Leuven et al. (2004) show that actually using measures of cognitive skills rather than formal education alone, one can go a much longer way in explaining inequality with supply and demand. They draw on the International Adult Literacy Survey (IALS), which was designed to provide

internationally comparable measures of cognitive skills across 20 advanced countries. Since then there are a number of other papers that use these data for related exercises, including Blau and Kahn (2005) and Freeman and Devroye (2001). More recently the same exercise has been done in Paccagnella (2015) using PIAAC data. He shows that a measure of numerical proficiency can explain part of the differences in inequality across countries, although years of formal schooling can explain more in a decomposition framework.

In this paper we also use PIAAC data providing a more systematic treatment of educational variables in the generation of wages. 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.

We take advantage of the approaches already existing in the literature. For example Brunello et al. (2010) instrument years of schooling with compulsory schooling reforms and show that changes in the educational policy of a country affect the accumulation of human capital and thus wage inequality. Hanushek et al. (2015) consider the potential endogeneity of skills using compulsory school laws at state level in the US subsample of PIAAC. Other authors (Paccagnella 2015) have used PIAAC data to measure the effect of cognitive skills on earnings inequality estimating coefficients at various quantiles of the wage distribution. However he has taken competences as purely exogenous, while in the present paper we instrument skills with measures of institutional changes in education quality.

The main unresolved issue in this paper is the potential endogeneity of skills, since more talented individuals may possess higher level of competences (as well as achieve higher educational attainments) while obtaining higher earnings. In the absence of credible instruments, it is hard to accept a causal interpretation of the results. In addition, competences are typically measured at the very same time when information on earnings is collected. Ideally, one would require a dataset where competences were predetermined with respect to schooling, which in turn were

predetermined with respect to the transition to the labour market. Unfortunately, these datasets do exist in a few countries where longitudinal datasets were started several decades ago (US, UK, Sweden), but they are hardly usable in a cross-country perspective. In the present paper we move some steps ahead in disentangling these effects.

We regress monthly labour income on years of education and skills and we use as instruments three reforms: compulsory schooling reforms as in Brunello et al., an index measure of reforms of autonomy and financial resources. These two last index of reforms were introduced in Checchi et al. (2013) and we are the first to use them as instruments of skills.

We find that the OLS coefficient of education is higher in magnitude than the coefficient of skills but it is more likely to be affected by endogeneity because IV estimates of education are much larger than OLS. However education absorbs all the relevant sources of endogeneity of skills because if we exclude education from the model, the OLS estimates increase substantially and IV estimates become twice as large as the OLS. These results suggest that the endogeneity of skills is essentially coming from the same unobservables determining educational attainment, for example ability.

We further investigate the effect of the two dimensions of human capital (education and skills) on inequality. The dependent variable is a position dummy for earnings in the bottom or top quartiles and skills are inequality-reducing because more skills imply a *high* reduction in the probability of being at the bottom of the wage distribution and a *low* increase in the probability of being at the top. On the contrary, the effect of education is significant only at the top of the wage distribution and is therefore inequality-increasing.

1. Literature review

Since the review by Card (2001), the literature on returns to education has moved in various direction. On one side the search of a causal impact of schooling on earnings has prompted the search for various sources of exogenous variations, from compulsory schooling legislation to

accessibility of schools. While most of the models interpret the role of instrument as an average effect (ATT), some papers study the effect on specific population subgroups. For example Brunello et al. (2010) have shown that changes in compulsory education legislation affect the potential beneficiaries with different intensity, leading to a wage inequality reduction (due to an implicit substitutability of ability and schooling). Stephens and Yang (2014) question the standard identification strategies based on year of birth, and extend the outcome variables.

Other papers have left aside the potential endogeneity of schooling and have pointed out that returns to schooling are heterogeneous in the population. After Buchinsky (1994) had shown that returns to education are higher in the US at the higher quantiles of the conditional distribution of wages, Harmon et al. (2003) replicated the result for the UK, confirming that the returns to schooling are higher for those at the top of the wage distribution: as a consequence, other things constant any exogenous push to increase education would produce an increase in wage inequality. Martins and Pereira (2004) show that returns are higher for the more skilled individuals, conditional on their observable characteristics. They interpret this result as evidence of self-selection (based on ability) and/or differences in quality of schools attended.

A third 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 raise productivity in the labour market. However, as soon as measures of cognitive abilities became available, several authors have started questioning whether these abilities should be included as complementary measures of earning potential. The large majority of these works exploited data from the IALS (International Adult Literacy Survey).¹

Barone and Van De Werfhost (2001) estimate a skill-augmented wage model, where earnings depend on education, skills and other observables, and they find that a large fraction of the

¹ IALS is a survey collecting information on adult literacy in representative samples for some OECD countries, implemented in different years - 1994, 1996, 1998 - for different countries 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>.

education effect is cognitive (from 32 to 63%, depending on the country. In the same vein, using the Canadian file of the same survey, Green and Riddell (2003) estimate a linear polynomial version of a Mincerian equation, showing that the impact of literacy on earnings does not vary across quantiles of the earnings distribution, while the interaction of schooling and literacy is statistically insignificant. They interpret this as a signal that competences provide an autonomous contribution to observed inequality, conditional on identical school attainment. In the same vein, Denny et al. (2004) estimate a skill-augmented Mincerian regression across a large number of countries, showing that including measures of skills lowers the return to schooling in many countries by 1-2%.

Both Leuven et al. (2004) and Blau and Kahn (2005) include cognitive skills when modelling earnings inequality, though reaching 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 part in explaining higher U.S. wage inequality², but the residual wage inequality in the US is primarily attributed to the more decentralized structure of wage bargaining rather than to market forces. Similar conclusions were already achieved by Freeman and Schettkat (2001) 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, they show that US is characterised by greater inequality in competences than Germany, which is reflected into greater inequality in earnings, and they attribute this difference to both the educational system (the German apprenticeship system would raise the bottom of the competence distribution) and the bargaining structure (Germany is characterised by stronger union movement than US). Eventually Hanushek and Zhang (2009) estimate a skill-augmented Mincerean regression finding out that considerable part of the estimated return to schooling in a standard Mincerean regression is due to the classical ability bias (the more able get

² 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.”

more schooling). They also show that cognitive skills play an important direct role in determining individuals' earnings, yielding the highest return in the US labour market.

The Adult Literacy and Lifeskills Survey (ALL)³ was meant to represent a second round of the IALS project, but was quickly superseded by the PIAAC project promoted by the OECD.⁴ Hanusheck et al (2015) provide estimates of the labour market return of cognitive skills for 23 countries, using the new PIAAC data. They find that focusing on early-career earnings leads to underestimating the lifetime returns to skills by about one quarter; on average, a one-standard-deviation increase in numeracy skills is associated with an 18% wage increase among prime-age workers. However, there is considerable heterogeneity across countries, which they try to explain using some labour market institutions (but the limited number of countries prevents a convincing identification of these effects). While taking both schooling and skills as exogenous, Paccagnella (2015) studies the heterogeneity of returns along the wage distribution, finding that returns to education are higher at the top than at the bottom of the distribution, while the profile of returns to competences being rather flat.

3. Data

Our analysis is based on two main data sources. The first one is the Program for the International Assessment of Adult Competencies (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 and 2012 in 24 countries (22 OECD member countries and 2 partner countries), obtaining information about around 166.000 adults (aged 16-65)

³ For details see <https://nces.ed.gov/surveys/all/>. It 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).

⁴ The PIAAC (Programme for the International Assessment of Adult competences) is the first survey conducted in 2012 that collects information on educational career, work history and social life participation in representative sample of the population comprised between 16 and 65. In 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/>.

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 allowed 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 environments⁵. 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). 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”*. Problem solving in technology-rich environments is defined as *“using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks”*.

All of the three skills categories are measured on a 500-point scale. Following Hanushek et al. (2015) our preferred model focuses on numeracy skills only, which is likely to be most comparable across countries. We compute the average across ten plausible values for this test score and we standardize it to have within-country mean of zero and standard deviation of one. As wage measure we employ the gross monthly earnings of both employees and self-employed workers.⁶

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 a large set of policy measures affecting the institutional set-up that characterize compulsory and post-compulsory education, from pre-primary to tertiary education. Specifically, in the present paper we focus our attention on three areas of intervention. First we consider *education expansions*; reforms implemented in this area typically aim at improving individuals' educational outcomes (measured in their work by completed years of school achieved). They include measures which affect: a) the duration of compulsory

⁵ The assessment of problem solving and of reading components was optional and administered by respectively 20 and 21 countries out of 24.

⁶ In the Public Use File earnings data for Austria, Germany and Sweden are reported in deciles only.

education; b) the age of first tracking; c) the presence of national standardized tests for the school career advancement of pupils; d) the expansion of university access (like the open access from vocational high schools and the geographical expansion of universities).

Secondly we look at *school autonomy and accountability*. Policy interventions in this area aim at supporting the decentralization of decision-making power and school accountability and are intended to enhance the efficiency of the educational system's organization. They include reforms which: a) promote school evaluation (carrying out independent external inspection and evaluation, introducing national standardized tests for measuring the performance of schools, creating structures for the steering and evaluation of the educational system, etc.); b) increase autonomy in the school management and decision-making processes; c) increase teachers' degree of autonomy in primary and secondary education.

Finally we consider *university financial support*. The measures implemented in this area aim at increasing the equality of opportunity and relaxing the liquidity constraints that may prevent children from poorer households to attend tertiary education. They include reforms which: a) increase the financial support through grants; b) change the dimension of the loan component to the grant component; c) affect the interest rate charged to loans.

Reforms are either measured in levels (like tracking age and the beginning/leaving age and duration of compulsory education) or as an index, taking value of zero/one in the absence/presence of a specific intervention (like the presence of national standardized tests for career advancement and for measuring school performance). 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.

Following Braga et al. (2013) we reject the idea of being able to fully characterize a national educational system by means of level indicators and therefore we combine level measures with temporal variations associated with the occurrence of educational reforms in a specific country/year. Specifically, we construct three reform indices corresponding to the three areas of

intervention described above, which we will use as instruments for individuals' cognitive skill and schooling levels. In such a way we can exploit both cross-country and temporal variations of government reforming activities in the educational areas, which are assumed to be exogenous to the achievements in the population.⁷ In order to construct these indices, all the reform variables are normalized between countries in a 0-1 interval and then indices are created as the average of the single components.

Matching the two datasets, we can implement our identification strategy, which relies on temporal and geographical variations in the institutional arrangement controlling for time and country fixed-effect. In order to match PIAAC individuals to reforms that have potentially hit them during their educational careers, we assume that individuals are initially affected by education expansion reforms at age 10, by autonomy and accountability reforms at age 6 and by university financial support reforms at age 18. Country fixed-effect are taken into account using country dummies, while time fixed-effect are accounted for by means of cohort dummies with a five-year range, from age 16 to age 65.

This merger forces us to drop non-European countries for which reforms data were not available, and we are left with a sample of 13 countries, including Austria, Belgium (Flanders), Denmark, Finland, France Germany, Great Britain, Ireland, Italy, Netherlands, Norway, Spain and Sweden, for a total of 61.103 observations. For Austria, Germany and Sweden we replace decile dummies in the public use file of PIAAC with data on actual earnings obtained from EU-SILC 2012 dataset.⁸ Exploiting this data source, we compute the median income for each deciles of the earning distribution and we impute this income value to the individuals in the PIAAC sample, according to the income decile they belong to.

Table 1 provides summary statistics for our sample. After dropping observations with missing values in the earning variable, sample sizes range from 747 in Austria to 4570 in Great Britain. The

⁷ Braga et al. (2013) provide direct test for the exogeneity of these reform variables.

⁸ It is a survey collected every year by Eurostat on Statistics on Income and living conditions (see http://ec.europa.eu/eurostat/statistics-explained/index.php/Living_conditions).

highest log-earnings values are recorded in Austria, Belgium (Flanders), Denmark, Germany and Norway, while the lowest in Spain, Italy and France. The highest earning variability is in Ireland and Netherlands, while most of the countries (Austria, Belgium, Germany, Finland, France, Italy, and Sweden) display similar standard deviations (about 0.7). Figure 1 provides Kernel density estimates of the earning distributions in the countries for which continuous income variables are available in PIAAC.

Individuals in our sample achieve an average numeracy test score higher than 290 (out of 500) in Austria, Germany, Finland and Sweden, between 280 and 290 in Belgium (Flanders) Denmark, Netherlands and Norway, lower than 280 in all the other countries, with Spain and Italy recording the poorest performance. Substantial variation across countries is evident also in average years of schooling, which range from more than 16 in Austria and Germany to 12.08 in Spain and 11.46 in Italy. Figures 2 and 3 provide respectively the distribution of numeracy skills and average years of schooling achieved.

The mean of respondents' age ranges from less than 39 in Great Britain and Ireland to more than 43 in Germany. The share of male individuals is usually between 51 and 54%, with the only exceptions of Italy (59.9%) and Germany (56.9%). Employees represent about 90% of the work force in most of the countries (Belgium, Denmark, Spain, Finland, France, Great Britain, Netherlands, Norway and Sweden), while Italy and Austria are the countries with the highest share of self-employed workers. Finally, Sweden and Norway are by far the countries with the highest share of non-native respondents, followed by Ireland, Italy and Denmark. On the opposite, Austria, Belgium (Flanders) and Finland display the lowest percentage of foreign born respondents.

In Figure 4 we provide a preliminary descriptive analysis of the relationship between log-earnings and numeracy skills: a positive association becomes visible, albeit not very pronounced. However, looking at the average value of the numeracy skills' score across the deciles of the earning distribution in Table 2 we can clearly see that skills significantly increase moving from the bottom to the top of the earning distribution.

4. Empirical strategy

We model the earnings effects of education (e) and skills (s). Our data cover 13 countries (indexed by c) and T birth cohorts (indexed by t). Our main model of interest is the following:

$$y_{ict} = \beta' x_{ict} + \gamma^e e_{ict} + \gamma^s s_{ict} + \mu_c + \mu_t + \varepsilon_{ict} \quad (1)$$

where y is an earnings measure which can be either log net earnings or a positional dummy for earnings below the first quartile or above the third quartile in the country specific distribution of earnings. In the latter case, the model allows investigating the effects of education and skills at the tails of the distribution, yielding insights on the effects on wage inequality. The vector of regressors x is a vector of controls for sex, age and its square, weekly hours of work, type of job (employee or self-employed) and being foreign-born, 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).

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

$$E(e_{ict}\varepsilon_{ict}) = E(s_{ict}\varepsilon_{ict}) = 0 \quad (2)$$

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 through an instrumental variable (IV) strategy. We exploit the variation generated by educational reforms whose implementation varies across birth cohorts within a country. A detailed description of the reforms is provided in the Data section. To summarise, these

reforms may be grouped into three broad categories. Expansionary reforms (R^E) are educational reforms which enhanced educational access, such as school leaving age reforms. We see these reforms mainly as a shifter of educational attainment. Autonomy and accountability reforms (R^A), instead, are reforms affecting the degree of autonomy within the educational system, such as changes of hiring and compensation policies for teaching personnel (reforms increasing autonomy in school management and decision-making processes; reforms introducing national standardized tests for measuring performance of schools, reforms creating structures for the steering and evaluation of the educational system, etc.), and we see these reforms as mainly affecting the effectiveness of workers skills. Finally, financial reforms (R^F) refer to changes that affected the financing of the educational system, impacting on both educational levels and skills acquisition. These reforms are summarised by three indices that capture the evolution of educational expansion and educational autonomy within countries and across cohorts. Note that these reforms do vary only at the cohort-by-country level and therefore might not generate enough power on individual level data; this is why we add extra variation using the interactions between the reforms and parental background (b). Clearly this requires these interactions to be excludable from the earnings equation. While we can not set up a formal test of this hypothesis, informal checks that included (non-interacted) parental background in the earnings equation showed that while the extra regressor was statistically significant, parameter estimates were not affected by its inclusion.

Using these reforms we estimate the following first stage regressions

$$e_{ict} = \delta'_e x_{ict} + \sum_{r \in \{E,A,F\}} (\pi_e^r R_{ct}^r + \lambda_e^r R_{ct}^r b_{ict}) + \theta_c + \theta_t + u_{ict} \quad (3)$$

$$s_{ict} = \delta'_s x_{ict} + \sum_{r \in \{E,A,F\}} (\pi_s^r R_{ct}^r + \lambda_s^r R_{ct}^r b_{ict}) + \eta_c + \eta_t + v_{ict} \quad (4)$$

where the π s and the λ s parameterise the effects of reforms and their interactions with parental background (respectively) on education and skills, while remaining terms are the first stage

equivalents for controls, fixed effects and white noise errors that already appear in the earnings equation. The IV estimator for the earnings effects of education and skills is derived from the following model

$$y_{ict} = \beta' x_{ict} + \gamma^e \hat{e}_{ict} + \gamma^s \hat{s}_{ict} + \mu_c + \mu_t + \varepsilon_{ict} \quad (5)$$

where “hats” denote predictions from the first stage regressions.

5. Results

In Table 3 we report estimates of the earnings model focusing on net monthly income from labour as the dependent variable. For some of the countries of interest (Austria, Germany and Sweden) PIAAC does not report information on the continuous earnings variable but only the earnings decile. For these countries we approximate the earnings variable imputing the decile mid-point using information from external sources. In the Table we report results obtained for both the sample with (13 countries) and without (10 countries) imputations, which show that the imputation procedure and the inclusion of three extra countries has no big impact on the estimates.

We use standardised indicators for skills and years of education so that estimated coefficients can be interpreted in the standard deviation metric. The overall standard deviation of years of education is roughly 3, so that division of the coefficient on education by 3 returns the magnitude of the per year earnings return to education.

Focussing our attention on the OLS results from the larger sample, we see that education exerts a more pronounced earnings impact compared with skills; while one standard deviation increase in skills is associated with a 10 percent point (p.p.) increase in monthly earnings, the corresponding impact from education is 13 p.p. and the difference between the two effects is statistically significant. The latter effect corresponds to an approximately 4.3 p.p. yearly return to education.

Moving to the IV estimates, we find that while the estimated coefficient on skills is only mildly affected, there is a noticeable increase in the estimated effect of education, which now is 19 p.p. for a standard deviation increase, or 6.3 p.p. per year. The fact that OLS estimates of returns to education are downwardly biased is suggestive of educational reforms helping high ability individuals obtaining education; presumably these are individuals with disadvantaged parental background.

In Table 4 we investigate to what extent education acts as a mediating factor for the impact of skills on earnings. We have seen in Table 2 that there is heterogeneity in the extent to which endogeneity issues bias parameter estimates of skills and education, estimation of the latter being the most exposed to the bias. Is this because the two processes are completely orthogonal to one another and the (unobserved) determinants of skills accumulation have nothing to do with educational ones? Or is it the case that the two processes are—at least to some extent—generated by the same unobservables and controlling for education absorbs all the relevant sources of endogeneity in skills? We try to shed light on this asymmetry by considering the same model as before but conditioning in turn on each dimension of human capital in isolation from the other one, and we focus on the larger sample. Results suggests that indeed educational heterogeneities are reflected in the distribution of skills. When we exclude education from the model, not only the OLS estimates increase substantially (the coefficient almost doubles compared with the model of Table 3) but also instrumentation has now a sizeable impact, the IV estimates being twice as large as the OLS. This suggests that there is indeed a relevant endogeneity issue to be taken into account when estimating the earnings returns to skills, but this endogeneity is essentially coming from the same unobservables determining educational attainment, say ability. In the right panel of the table we see that also estimates of the educational coefficient react to the exclusions of skills from the model, although to a lesser extent. Overall the evidence suggests that education is a key ingredient in the acquisition of skills, so that controlling for education in the earnings equation essentially eliminates skills endogeneity.

In Table 5 we consider the effects of human capital at the tails of the national earnings distribution by using as dependent variables positional dummies for earnings in the bottom or top quartiles. Skills have a positive earnings effect on both tails, resulting in a reduction in the probability of being at the bottom and an increase in the probability of being at the top. The IV estimator affects essentially only the effect at the bottom and the direction of the bias is the one already noticed in the model for average earnings: after instrumentation, the effects is stronger which suggests that the instruments acts on high ability individuals by favouring their acquisition of skills. This reduces the likelihood of low pay. A similar interpretation goes with the effect of education at the top. The one piece of evidence that does not conform with our interpretation of the instrument is the effect of education at the bottom, where we observe the evaporation of the effect which is typical in the presence of unobserved ability bias. Among low paid, and presumably low educated, workers, selection due to unobserved ability prevails on selection coming from credit constraints excluding high ability individuals from the acquisition of education for higher levels of education. Overall, the effect of education is operating only at the top and is therefore inequality-increasing, opposite to the effects of skills which is inequality reducing.

To be concluded

References

- Acemoglu, Daron and David Autor. 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. in O.Ashenfelter and D.Card (eds), *Handbook of labor economics*, volume 4, Part B, pages 1043-1171
- Barone, Carlo and Van de Werfhorst, Herman G. 2011. Education, Cognitive Skills and Earnings in Comparative Perspective. *International Sociology*, 26(4) 483–502.
- Becker, Gary. 1964. *Human capital*. The University of Chicago Press
- Bedard, Kelly and Christopher Ferrall. 2003. Wage and test score dispersion: some international evidence. *Economics of Education Review* 22: 31–43
- Blau, Francine and Kahn, Lawrence. 2005. Do cognitive test scores explain higher US wage inequality. *Review of Economics and Statistics*, 87(1): 184-193.
- Blau, Francine D. and Lawrence M. Kahn. 1996 .International Differences in Male Wage Inequality: Institutions versus Market Forces. *Journal of Political Economy* vol.104, pages 791-837
- Braga M., Checchi D. and Meschi E. 2013. Institutional Reforms and Educational Attainment in Europe: A long run perspective. *Economic Policy* 73: 45-100
- Brunello, Giorgio, Margherita Fort and Guglielmo Weber. 2009. Changes in Compulsory Schooling, Education and the Distribution of Wages in Europe. *Economic Journal*, , vol. 119(536), pages 516-539
- Buchinsky, M. 1994. Changes in the US wage structure 1963–1987: an application of quantile regression. *Econometrica*, vol. 62(2), pages 405–58
- Card, David. 2001. Estimating the return to schooling: progress on some persistent econometric problems. *Econometrica*, vol. 69(5), pp. 1127–60.
- Checchi, D. and H.van den Werfhorst. 2014. Educational Policies and Income Inequality. IZA Discussion Paper n.8222, 2014

- Denny, Kevin and Colm Harmon and Vincent O'Sullivan, 2004. Education, earnings and skills: a multi-country comparison. IFS Working Papers W04/08, Institute for Fiscal Studies.
- Devroye, Dan and Richard B. Freeman. 2001. Does Inequality in Skills Explain Inequality in Earnings Across Advanced Countries?. NBER Working Papers 8140
- Freeman, Richard and Ronald Schettkat. 2001. Skill Compression, Wage Differentials and Employment: Germany vs. the US. *Oxford Economic Papers*, 53:3, pages 582-603..
- Green, D. and Riddell, W. 2003. Literacy and earnings: an investigation of the interaction of cognitive and unobserved skills in earnings generation. *Labour Economics* 10(2): 165-84.
- Hanushek Eric A. and Lei Zhang. 2009. Quality-Consistent Estimates of International Schooling and Skill Gradients. *Journal of Human Capital*, vol. 3(2), pages 107-143.
- Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold and Woessmann, Ludger. 2013. Returns to Skills around the World: Evidence from PIAAC. *European Economic Review*, vol. 73(C), pages 103-130.
- Harmon, Colm and Hogan, Vincent and Walker, Ian. 2003. Dispersion in the economic return to schooling. *Labour Economics*, vol. 10(2), pages 205-214, April.
- Katz, Lawrence and Kevin Murphy. 1992. Changes in Relative Wages: Supply and Demand Factors. *Quarterly Journal of Economics*, vol.CVII, pages 35-78
- Leuven, Edwin, Hessel Oosterbeek and Hans van Ophem. 2004. Explaining international differences in male skill wage differentials by differences in demand and supply of skill. *Economic Journal*, vol. 114(495), pages 466-486.
- Martins, Pedro S. and Pedro T. Pereira. 2004. Does education reduce wage inequality? Quantile regression evidence from 16 countries. *Labour Economics* 11: 355-371
- OECD. 2013. *Skills Outlook: first results from the Survey of Adult Skills*. Paris
- Paccagnella, Marco. 2015. Skills and Wage Inequality: Evidence from PIAAC. mimeo

Salverda, Wiemer and Daniele Checchi. 2015. Labour-market institutions and the dispersion of wage earnings. in A. Atkinson and F. Bourguignon (eds). *Handbook of income distribution*, vol.2B, North Holland, pages 1535-1728

Stephens, Melvin Jr. and Dou-Yan Yang. 2014. Compulsory education and the benefits of schooling. *American Economic Review*, 104 (6) page 1777–1792

Table 1: Summary Statistics

	AUT	BEL	DEU	DNK	ESP	FIN	FRA	GB	IRL	ITA	NLD	NOR	SWE
Log of monthly earnings in PPP	8.07 (0.68)	8.04 (0.68)	7.98 (0.70)	7.99 (0.92)	7.60 (0.75)	7.89 (0.71)	7.65 (0.70)	7.74 (0.93)	7.78 (1.13)	7.63 (0.73)	7.70 (1.26)	8.03 (0.86)	7.76 (0.70)
Years of schooling	16.07 (1.57)	13.08 (2.57)	16.43 (1.98)	13.08 (2.69)	12.41 (4.03)	13.14 (2.99)	12.08 (3.36)	13.46 (2.29)	15.32 (2.99)	11.46 (3.89)	13.63 (2.58)	14.43 (2.53)	12.60 (2.46)
Numeracy skills score	311.19 (34.26)	287.82 (44.91)	304.89 (38.67)	288.06 (46.65)	259.04 (44.26)	293.47 (43.57)	264.52 (50.32)	277.10 (46.02)	266.27 (45.59)	256.76 (44.64)	289.98 (43.02)	287.55 (47.92)	290.31 (45.93)
Age	41.59 (10.46)	41.34 (11.14)	43.96 (10.87)	40.49 (12.98)	40.18 (10.63)	41.24 (12.52)	40.43 (11.54)	38.34 (12.41)	38.71 (11.92)	40.74 (10.43)	39.30 (12.85)	39.64 (13.05)	41.05 (12.72)
Males	54.1%	53.4%	56.9%	53.7%	53.6%	50.2%	51.5%	53.7%	51.2%	59.9%	53.9%	52.6%	54.0%
Weekly hours worked	39.96 (12.57)	37.68 (11.04)	39.36 (12.64)	35.33 (12.01)	37.72 (12.01)	37.12 (10.34)	36.68 (9.89)	36.04 (13.09)	34.98 (13.09)	37.95 (11.24)	32.10 (13.23)	35.12 (11.57)	38.05 (10.33)
Employees	85.0%	92.4%	86.7%	92.5%	90.8%	91.4%	92.9%	88.1%	87.5%	83.3%	89.2%	93.7%	92.1%
Foreign born/foreign language	4.6%	3.1%	7.0%	8.4%	4.3%	1.9%	5.9%	9.0%	10.3%	9.4%	7.0%	11.5%	12.4%
N	747	2965	1331	4516	2622	3222	3848	4570	3070	2164	3346	3482	2845

* Std. Deviations in brackets

Table 2 - Average numeracy skills by earning decile

Decile	Mean	Std. Dev.
Lowest	268.92	49.66
2 nd decile	260.29	48.27
3 rd decile	262.46	47.28
4 th decile	267.48	45.14
5 th decile	274.52	43.91
6 th decile	280.54	42.50
7 th decile	287.98	41.54
8 th decile	293.99	41.46
9 th decile	303.26	39.63
Highest decile	310.16	39.09

Table 3: Earnings effects of skills and years of education

	10 countries		13 countries	
	OLS	IV	OLS	IV
Num_skills_std	0.095*** (0.008)	0.093* (0.052)	0.103*** (0.007)	0.119** (0.048)
YS_std	0.162*** (0.007)	0.225*** (0.046)	0.138*** (0.008)	0.194*** (0.044)
1 st stage F-stats:				
Num_skills_std		197.65		204.89
YS_std		185.26		157.52
Cragg-Donald F-stat		46.57		41.09
N	32517	32517	37313	37313

Note: all regressions weighted with survey weights and use standardised skills and years of education. Cluster robust standard errors in parentheses account for correlated observations by country and birth year. *, **, *** denotes statistical significance at the 10, 5 and 1 percent level of confidence. Controls include a gender dummy, age and its square, weekly hours of work, a foreign born indicator, country and birth cohort fixed effects.

Table 4: Earnings effects of skills and years of education

	OLS	IV	OLS	IV
Num_skills_std	0.159*** (0.007)	0.317*** (0.026)		
YS_std			0.175*** (0.009)	0.288*** (0.020)

Note: all regressions weighted with survey weights and use standardised skills and years of education. Cluster robust standard errors in parentheses account for correlated observations by country and birth year. *, **, *** denotes statistical significance at the 10, 5 and 1 percent level of confidence. Controls include a gender dummy, age and its square, weekly hours of work, a foreign born indicator, country and birth cohort fixed effects. N=37313

Table 5: Effects at the tail of the earnings distribution

	P<0.25		P>0.75	
	OLS	IV	OLS	IV
Num_skills-std	-0.049*** (0.004)	-0.123*** (0.031)	0.079*** (0.005)	0.067*** (0.030)
YS_std	-0.049*** (0.004)	-0.004 (0.025)	0.086*** (0.005)	0.159*** (0.027)

Note: all regressions weighted with survey weights and use standardised skills and years of education. Cluster robust standard errors in parentheses account for correlated observations by country and birth year. *, **, *** denotes statistical significance at the 10, 5 and 1 percent level of confidence. Controls include a gender dummy, age and its square, weekly hours of work, a foreign born indicator, country and birth cohort fixed effects. N=37313

Figure 1: Kernel density estimate of earning distributions

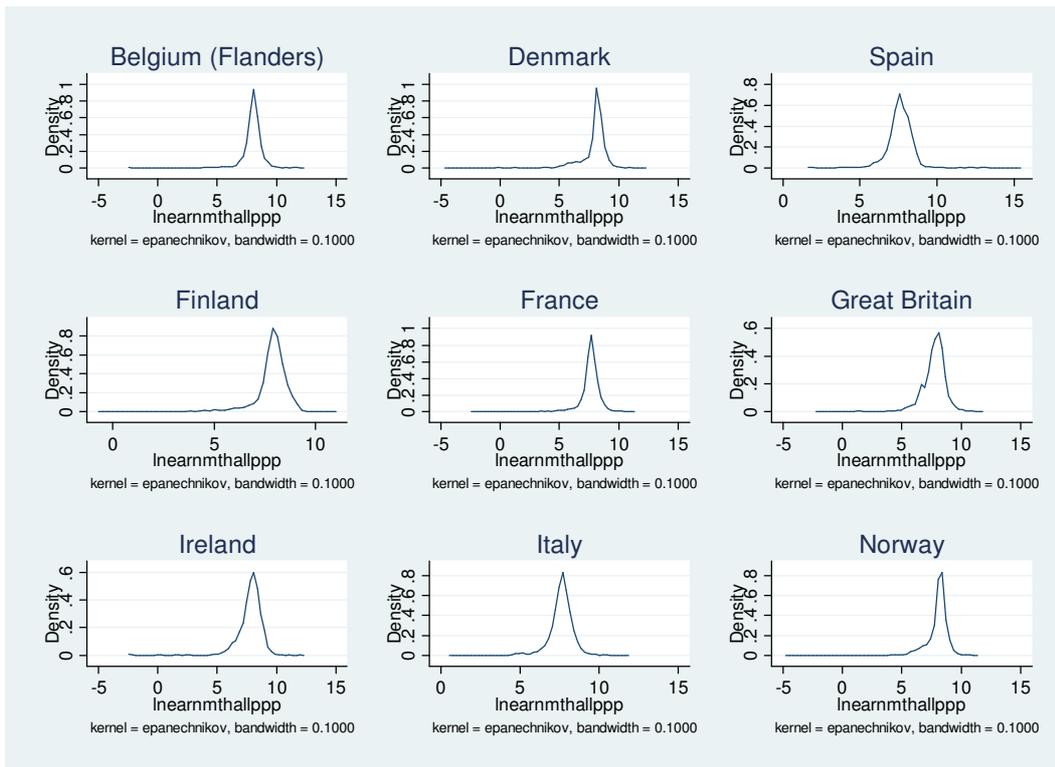


Figure 2: Kernel density estimate of numeracy skills distributions

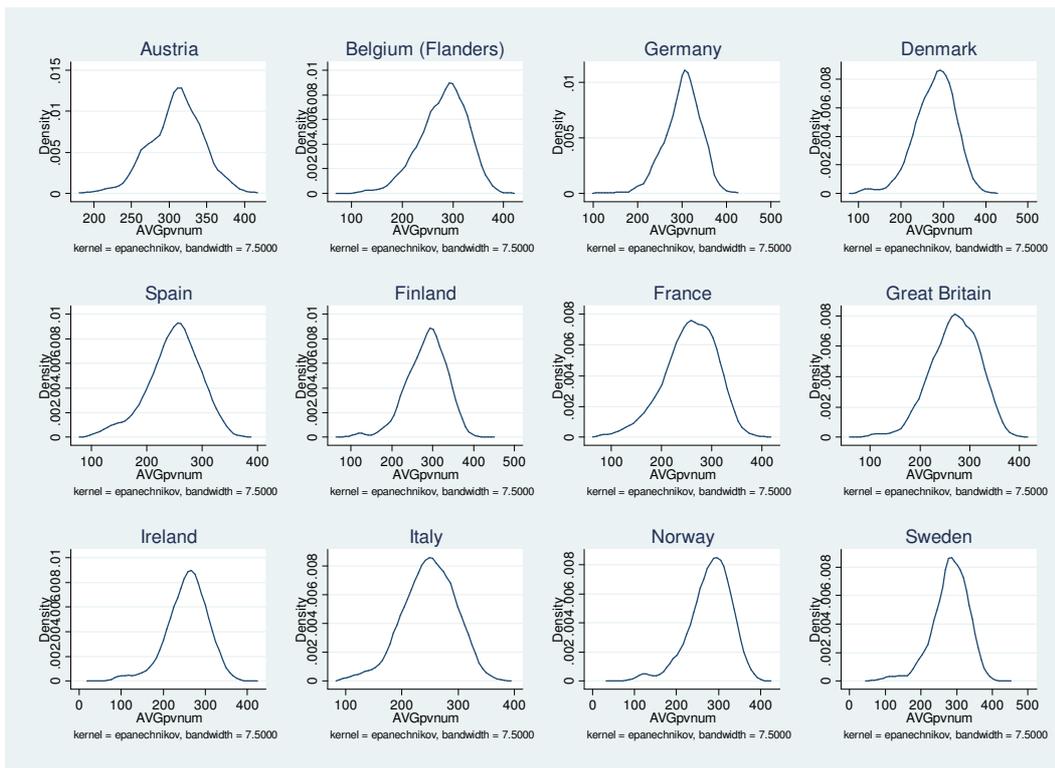


Figure 3: Distribution of educational attainment (in years of schooling)

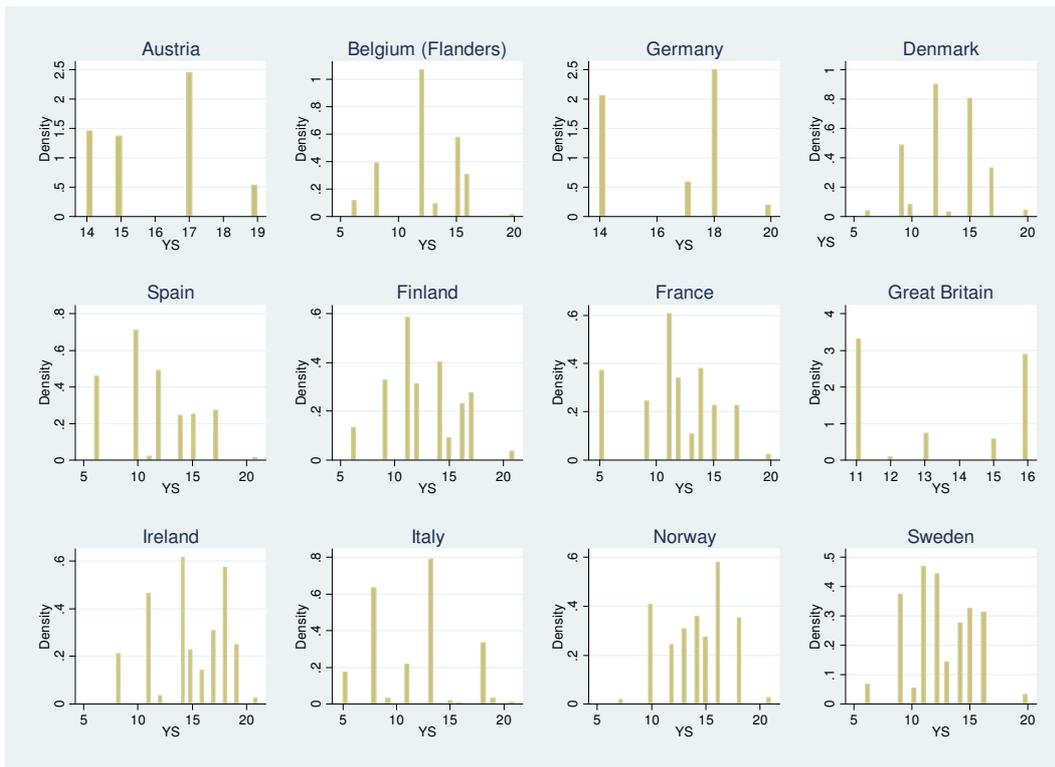


Figure 4: Relationship between earnings and cognitive skills

