NEW APPROACHES TO ECONOMIC CHALLENGES

Seminar, 21 October 2014

SKILLS AND WAGE INEQUALITY:

Evidence from PIAAC

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1. Introduction

Rising levels of inequality are a major concern in OECD countries, especially in the light of the recent economic crises and of the fact that growth prospects are currently mediocre (particularly for more advanced countries), even over a medium- to long-term horizon (OECD, 2014).

Human capital (individuals' endowments in terms of skills and knowledge) has long been recognized as a crucial factor determining the growth potential of the economy. The importance of human capital is not likely to diminish in future years, with economic growth increasingly driven by knowledge and skills.

As well as influencing levels of growth, human capital may also have a relation with economic inequality. The relationship is complicated and difficult to evaluate. An increase in the share of highly-educated individuals may initially increase earnings inequality, but this process is likely to stop at some point, if it also causes a decrease in the share of low-educated workers. Furthermore, large shifts in the skill composition of the workforce are likely to change the returns to skills, by changing the relative supply of workers with certain skills. Such general equilibrium effects depend on the degree of substitutability between different types of workers (Katz and Murphy, 1992; Card and Lemieux, 2001), and can be further influenced by possible changes in the relative demand for skills (Leuven, Oosterbeek and van Ophem, 2004). A more dispersed distribution of skills can lead to a more dispersed distribution of earnings, to the extent that people are paid according to their productivity (and to the extent that skills do increase productivity). However, the link between skills and earnings inequality is much more complex than it appears at first sight. The returns to skill or education can differ at different parts of the skill distribution. Indeed, a widely shared explanation for the observed increase in earning inequality is that technological change has been skill-biased, causing a larger increase in the returns to education in the upper part of the skill distribution. At the same time, the link between skills (or productivity) and earnings is mediated by a wide number of labour market institutions, the most prominent in this context being minimum wages, the degree of unionization, and the rules governing wage bargaining (Blau and Khan, 1996).

The Survey of Adult Skills (PIAAC) offers a unique opportunity to analyse the joint distribution of labour income (as measured by wages[1]), educational attainments, and literacy and numeracy proficiency.

This paper tries to investigate these issues in some depth, building on previous work by Blau and Khan (2005), Fournier and Koske (2012), Oecd (2013), and Van Damme (2014), among others.

First, the paper describes in detail how skills are distributed in the countries participating in the Survey, analysing both the overall distribution and the dispersion within different socio-demographic groups, as defined in particular by age and educational attainment.

Second, the paper shifts the focus to wages, analysing their distribution along the same dimensions, and putting it in relationship with the distribution of skills.

[1] The fact that the Survey only measures wages does not constitute a big limitation, given that the much of the rise in inequality observed in the past decade can be traced back to a widening in the dispersion of labor income. On the other hand, recent research by Greenwood et al. (2014) highlights the importance of moving the analysis at the household level, something that is not possible to do with the PIAAC data.

Third, the effect of skills on earnings is analysed along the entire distribution of earnings, by making use of unconditional quantile regression techniques (Firpo et al., 2009).

Finally, a decomposition exercise is performed (Blinder, 1973; Oaxaca, 1973; Firpo et al., 2011), trying to assess how much of the cross-country differences in the degree of wage inequalities can be accounted for by differences in the distribution of skills. By doing this, we update and extend previous work by Blau and Khan (2005) and Fournier and Koske (2012).

2. The distribution of skills

This section performs a detailed analysis of the distribution of skills in the countries that participated in the Survey of Adult Skills. Coherently with most of the recent literature on wage inequality, this paper will mainly take as a measure of inequality the spread of the distribution, and in particular the difference between the top and the bottom deciles of the distribution (i.e. between the 90th and the 10th percentile). As this indicator ignores information about the middle part of the distribution (as well as information above the top and below the bottom deciles), it is also useful to look at other differentials in order to gauge the extent of inequalities at different parts of the distribution. To this end, we will also look at the distance between the 50th and the 10th percentile and between the 90th and the 50th percentile.[2]

Tables 1 and 2 present the three percentile differences for each country, both for Literacy and Numeracy skills. Countries are sorted by the distance between the top and the bottom decile. As an additional summary measure of inequality, we also report the coefficient of variation, which is defined as the ratio between the standard deviation and the mean: unlike the variance, it is a standardized index that can be used to compare distributions characterized by different means.

Overall, slightly greater inequality is evident in the distribution of numeracy skills than of literacy skills. In all countries, and for both skills, inequality appears to be higher in the lower part of the distribution. The distance between the 50th and the 10th percentile ratio is always larger than between the 90th and the 10th percentile.[3]

[2] The Gini index is perhaps the most commonly used measure of income and wealth inequality. As the coefficient of variation, the Gini is also silent about what happens at different parts of the distribution (and is particularly sensitive to inequalities in the middle part of the distribution. The choice to focus on percentile differences is consistent with most of the recent literature on income inequality.

[3] Interestingly, there is instead a wide consensus that the recent increase in wage inequality is mainly due to an increase in dispersion in the upper tail of the distribution (Autor, Katz and Kearney, 2008).

Table 1

Inequality indices – Numeracy Skills				
Country	**CV**	**90th-10th**	**90th-50th**	**50th-10th**
Australia	0.21	136.59	62.33	74.26
Austria	0.18	121.24	55.95	65.30
Canada	0.21	138.28	62.61	75.67
Czech Republic	0.16	110.94	50.90	60.03
Denmark	0.18	126.10	57.47	68.63
Estonia	0.17	113.92	53.46	60.45
Finland	0.18	127.65	59.21	68.44
France	0.22	141.80	62.39	79.41
Germany	0.20	133.09	59.10	73.99
Ireland	0.21	129.33	59.28	70.05
Italy	0.20	126.26	59.87	66.39
Japan	0.15	110.05	50.89	59.17
Korea	0.17	114.60	51.31	63.29
Netherlands	0.18	125.11	53.97	71.14
Norway	0.19	131.77	57.90	73.88
Poland	0.20	127.86	59.20	68.66
Slovak Republic	0.17	117.16	51.03	66.12
Spain	0.21	129.61	57.08	72.53
Sweden	0.20	132.84	58.74	74.10
United States	0.23	144.84	66.66	78.18
Sub-national entities				
Flanders (Belgium)	0.18	127.84	57.13	70.71
England/N. Ireland (UK)	0.21	137.71	64.38	73.33
OECD Average	**0.20**	**130.99**	**59.20**	**71.79**

The ranking of countries in terms of skill inequality is largely consistent across each of the three indicators. The correlation of the different indicators, both across and within proficiency domains is well above 80 per cent. The United States, France, and Canada are the countries with the most unequal distribution of skills, while Japan, Korea, the Slovak Republic and the Czech Republic are characterized by low levels of inequality. Partial exceptions are the Netherlands, with a relatively low inequality in the upper half of the distribution of both literacy and numeracy skills when compared to the bottom half, and Italy (for which the reverse holds, especially in the case of literacy skills).

Table 2

Inequality indices – Literacy Skills				
Country	**CV**	**90th-10th**	**90th-50th**	**50th-10th**
Australia	0.18	122.28	55.04	67.24
Austria	0.16	110.10	50.51	59.60
Canada	0.18	125.56	56.20	69.36
Czech Republic	0.15	102.34	47.06	55.28
Denmark	0.18	116.25	49.88	66.38
Estonia	0.16	111.84	50.99	60.85
Finland	0.18	123.49	55.16	68.33
France	0.19	123.94	54.03	69.91
Germany	0.18	121.56	54.40	67.16
Ireland	0.18	115.71	52.14	63.57
Italy	0.18	113.74	53.68	60.05
Japan	0.13	99.78	44.06	55.72
Korea	0.15	103.81	46.31	57.49
Netherlands	0.17	121.61	51.88	69.73
Norway	0.17	115.30	49.98	65.32
Poland	0.18	120.92	55.11	65.81
Slovak Republic	0.15	99.37	42.89	56.49
Spain	0.19	123.52	55.30	68.22
Sweden	0.18	122.24	52.86	69.38
United States	0.18	126.13	57.14	68.99
Sub-national entities				
Flanders (Belgium)	0.17	119.07	51.11	67.96
England/N. Ireland (UK)	0.18	123.45	57.03	66.41
OECD Average	**0.18**	**119.41**	**53.29**	**66.12**

Overall, significant cross-country differences in the degree of skills inequality exist. This can be seen clearly in Figure 1, which depicts the distribution of numeracy skills for the countries with highest (United States and France) and the lowest (Japan and Czech Republic) distance between the top and the bottom decile, as well as the average distribution across all OECD countries.

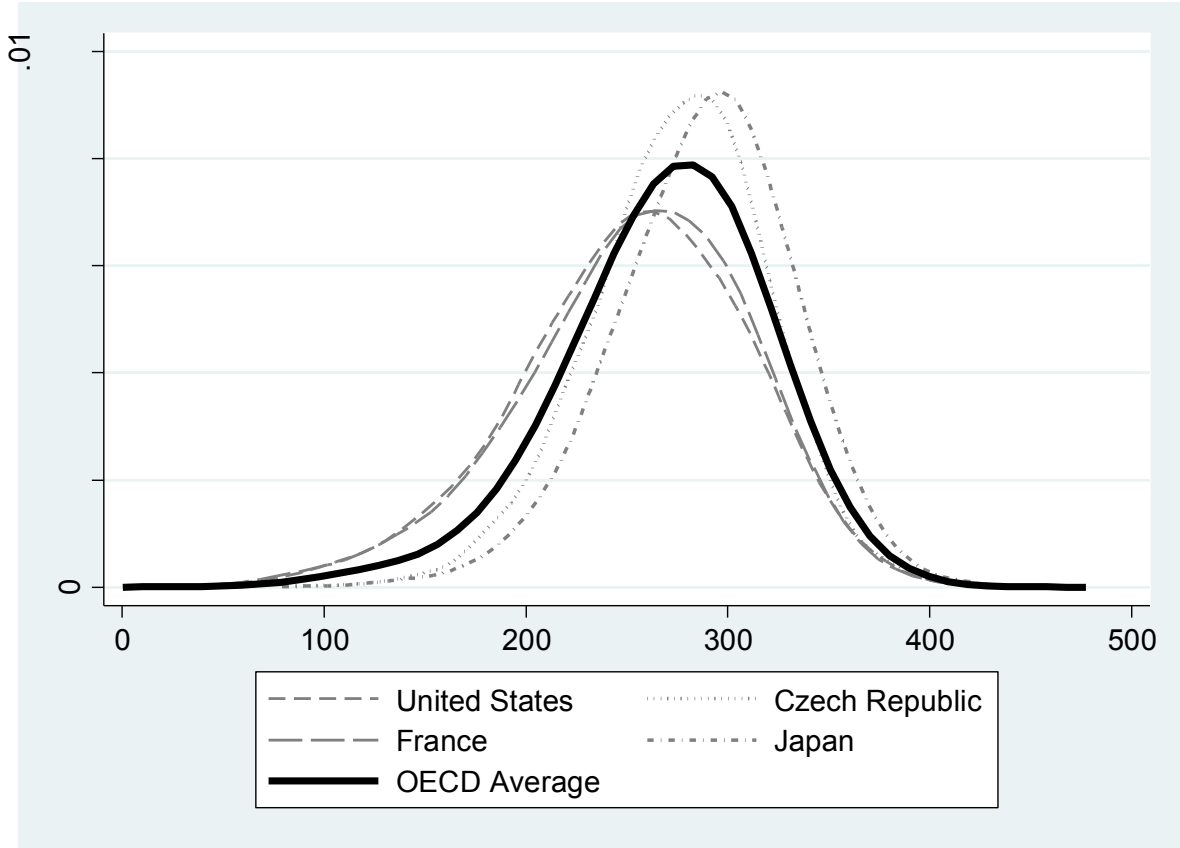

Figure 1

An important follow-up question is whether there is any relationship between within-country skills inequality and average skill level, as measured by the Survey of Adult Skills.

Figure 2 plots average scores versus the distance between the 90th and the 10th percentile of the distribution of numeracy and literacy scores for countries participating in PIAAC. The correlation between the *level* and the *dispersion* of skill is negative, in particular for numeracy proficiency. Such relationship can appear less strong than what Freeman, Machin and Viarengo (2010, 2011) found using data from assessments of school students in fourth and eighth grade (TIMMS) and students aged 15 years (PISA). However, in those papers the percentile difference is divided by the median, a fact that may introduce a mechanical correlation with the level of proficiency. When we do the same, the correlation coefficients do become much higher.

Figure 2

While the within-country dispersion of skills captures inequality at a given point in time, a related issue is the one of inter-generational mobility, i.e. the extent to which family background (in terms of parental income or education) plays a role in determining adult socio-economic outcomes. Inter-generational mobility can be interpreted as (in)equality of opportunities. Low levels of inter-generational mobility can cause current levels of inequality to perpetuate (or even increase) over time; more importantly, inequality of opportunities may make current level of inequality less socially acceptable.

The Survey of Adult Skills, by containing information on parents' educational attainments, allows the estimation of the "parental education gradient", through a regression of test scores on dummies for the highest qualification attained by parents.[4]

Figure 3 shows a *positive* correlation between the parental education gradient and the cross-sectional measure of inequality, suggesting that the two dimensions of inequality (the "cross-sectional" and the "inter-generational") are positively related.

[4] The regression also control for gender and a quadratic term in age. Only native-born are included in the estimation sample. The parental education gradient displayed in the figure is the coefficient associated to a dummy variable equal to one if the highest level of parent's educational attainment is a tertiary degree. The omitted category is lower-than-secondary attainment.

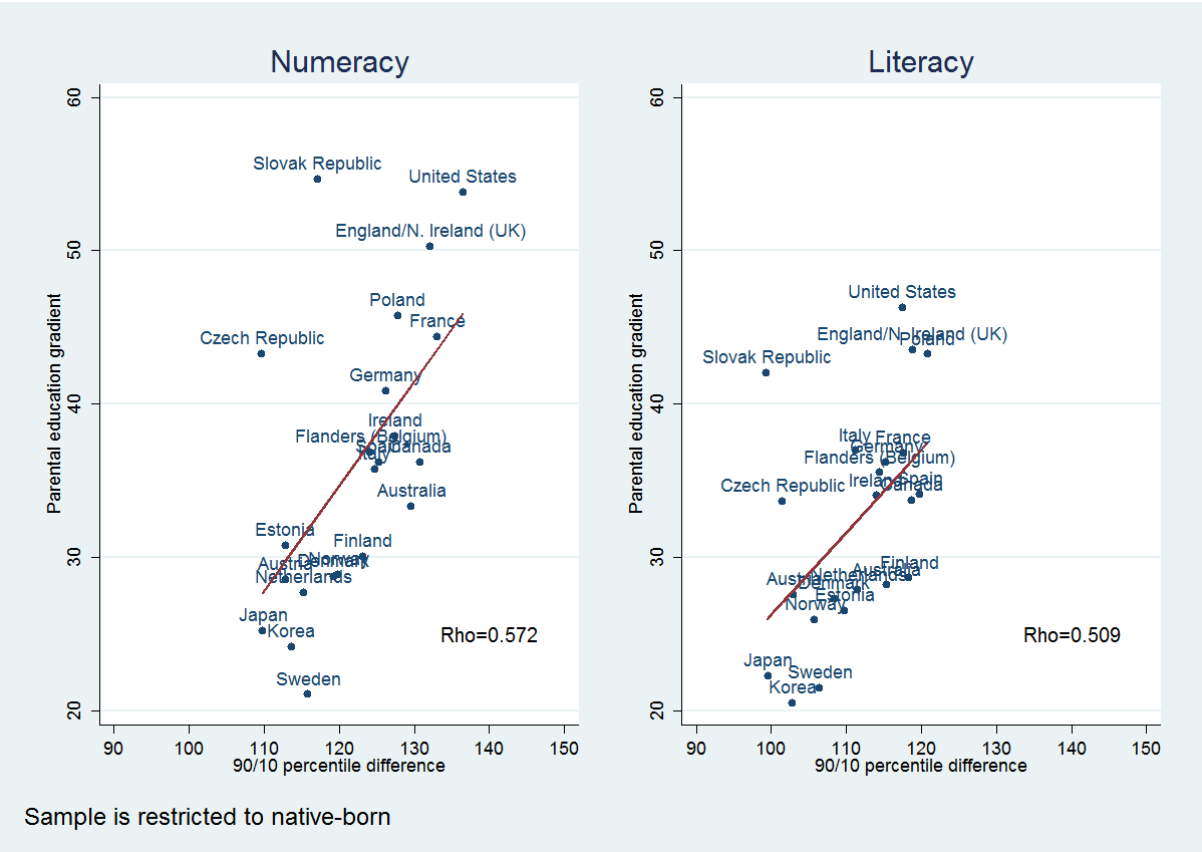

Figure 3

3. The distribution of (labour) earnings

The main purpose of this paper is the joint analysis of inequality in skills and earnings. In this section we present a brief description of wage inequality in the countries that participated in the Survey of Adult Skills. The collection of information on wages is a distinct feature of PIAAC that allows analysis of the link between skills and economic outcomes using individual data collected in a consistent and comparable way across different countries.[5]

It should be noted that PIAAC collects information only regarding earnings in the form of wages and salaries and self-employment rather than earnings from all sources. This does not constitute a major limitation to the above analysis, given that the much of the rise in inequality observed in the past decade can be traced back to a widening in the dispersion of labor income (OECD, 2014). In addition, Gini indices of earnings inequality for different population subgroups (from full-time employee, to the entire working age population, assigning zero income to the inactive and the unemployed) are highly correlated (Fournier, Koske and Wanner, 2012), although the reference population can make a difference in some countries, particularly those with a higher incidence of part-time workers.[6] The information collected in PIAAC refers to gross (pre-tax) earnings. This can potentially bias the cross-

[5] Other datasets, like the Luxembourg Income Study, or the European Labor Force Survey, are a collection of national dataset, harmonized *ex-post*. Fournier and Koske (2012) work with eight different household survey data, the largest of which (the EU-SILC) contains data on 21 EU member countries.

[6] A similar point is made by Brandolini and Viviano (2014), who extend the definition of the employment rate to account for differences in work intensity.

country comparison of wage dispersion, to the extent that different countries differ in the degree of progressivity of their tax system. However, the use of pre-tax income is standard in the literature, not only in studies that focus on a single country (Katz and Murphy, 1992; Autor, Katz and Kearney, 2008; Kopczuk, Saez and Song, 2010; Piketty and Saez, 2003), but also in cross-country studies (Blau and Khan, 2005; Leuven, Oosterbeek and Van Ophem, 2004; Fournier and Koske, 2012; Card and Lemieux, 2001; Brandolini, Rosolia and Torrini, 2011; Alvaredo, Atkinson, Piketty and Saez, 2013). Indeed, the use of pre-tax earnings has the advantage of capturing inequality in how the market rewards certain characteristics, before the mediating effect of the tax system.

In the rest of the paper, we focus on hourly wages, restricting the analysis to employed individuals for whom we observe earnings. This choice is also justified by the fact that restricting the sample to individuals for which we observe wages does not change in a significant way the ranking of countries in terms of skill inequality (see the Appendix).

Figure 4 depicts the distribution of (log) hourly wages for the four countries for which the skills distribution is presented in Figure 1. As can be seen, the distribution of wages differs considerably from that of literacy and numeracy skills within countries. Japan, with the most compressed distribution of skill, has a distribution of wages not dissimilar from the one of the United States; on the other hand, the distribution of wages in France appear to be much more compressed, and similar (although shifted to the right) to the one of the Czech Republic.[7]

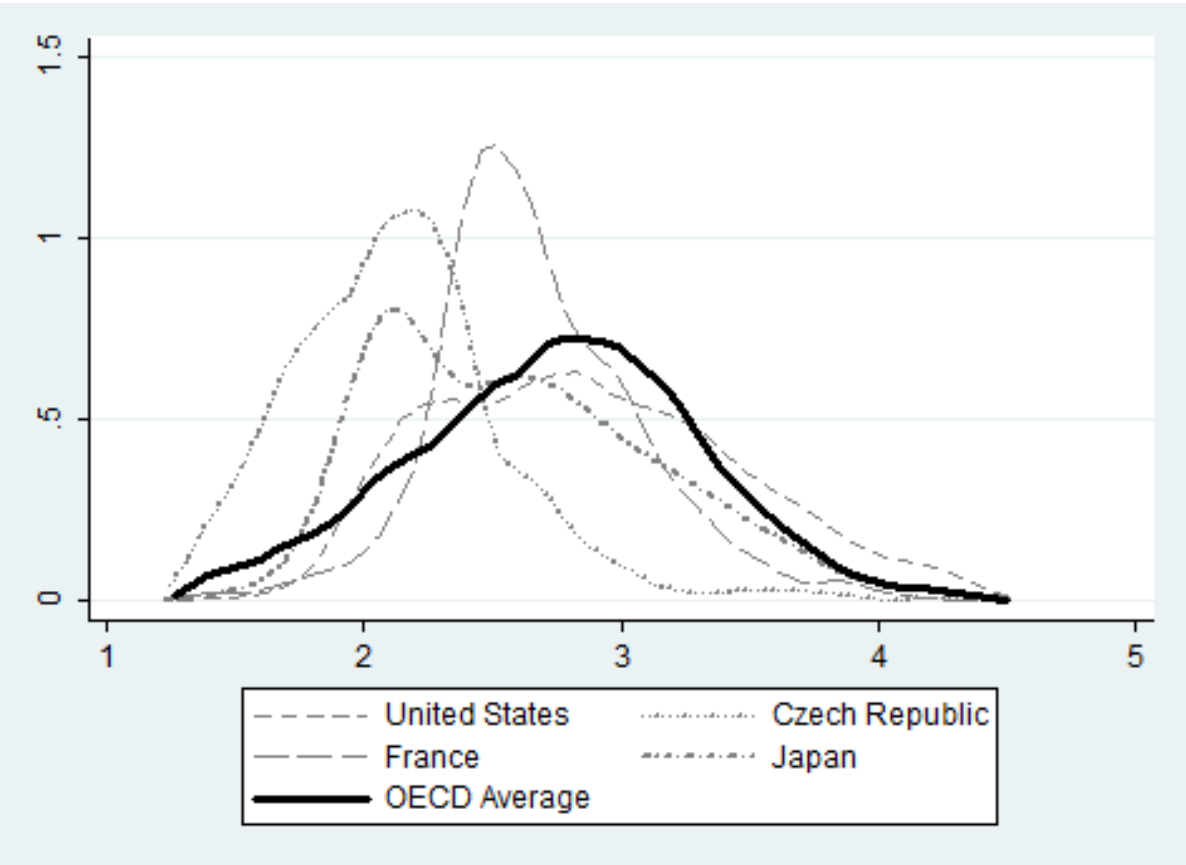

Figure 4

[7] The pattern is even more evident when looking at monthly wages.

The difference between Figure 1 and Figure 4 suggests that differences in workforce composition in terms of proficiency are not likely to play a major role in explaining cross-country differences in wage inequality. Probably, countries differ to a much greater extent along different dimensions, possibly related to institutional features that influence the way personal characteristics are rewarded in the labour market. Such issues will be discussed in more detail in Section 4.

Figure 5 plots the 90th/10th percentile ratio in hourly wages against the parental education gradient. The correlation is positive and strong. The strength of this relationship is stronger in the upper part of the wage distribution (the 90th/50th percentile ratio) than in the lower part of the distribution (the 50th/10th percentile ratio).[8] This finding is consistent with similar evidence provided in Corak (2013) and in Jerrim and Macmillan (2014).

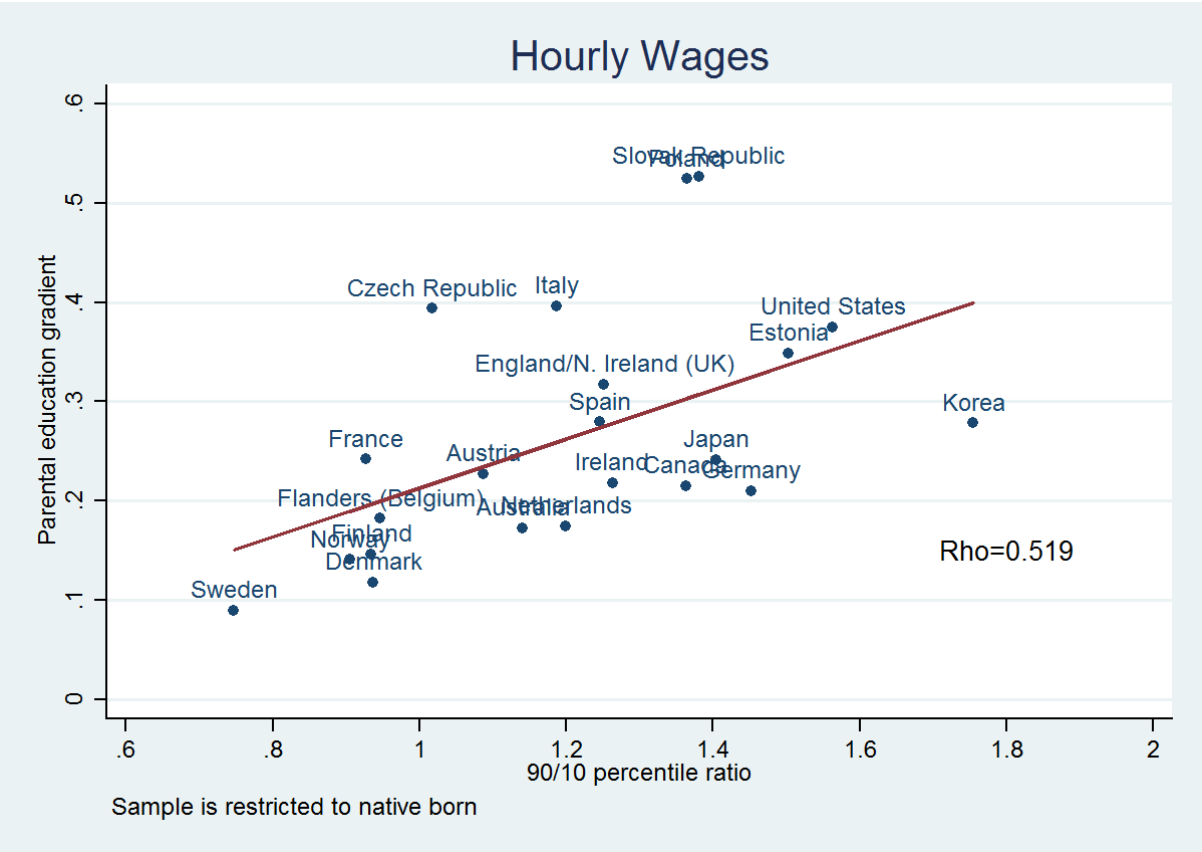

Figure 5

4. Comparing skills and wage dispersion

Previous sections have presented the main features of the distribution of skills and labour earnings in the countries participating in the Survey of Adult Skills. In the following sections, we jointly analyse these two dimensions of inequality. Following Hanushek, Schwerdt, Wiederhold and Woessmann (2013), we will take numeracy proficiency as our preferred measure of skills.

The first important finding is that the ranking of countries changes considerably when we look at the measures of skills and wage dispersion (Figure 9).

[8] The correlation coefficients are, respectively, 0.58 and 0.36.

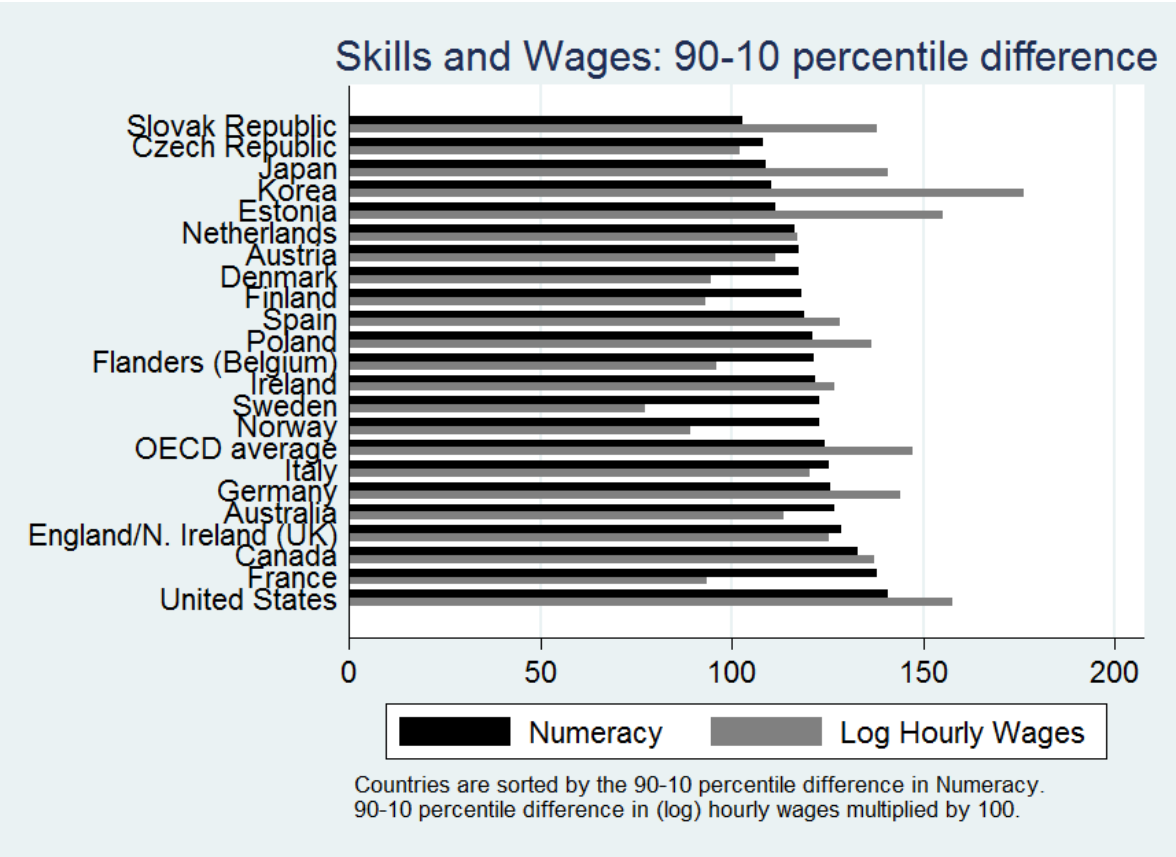

Figure 6

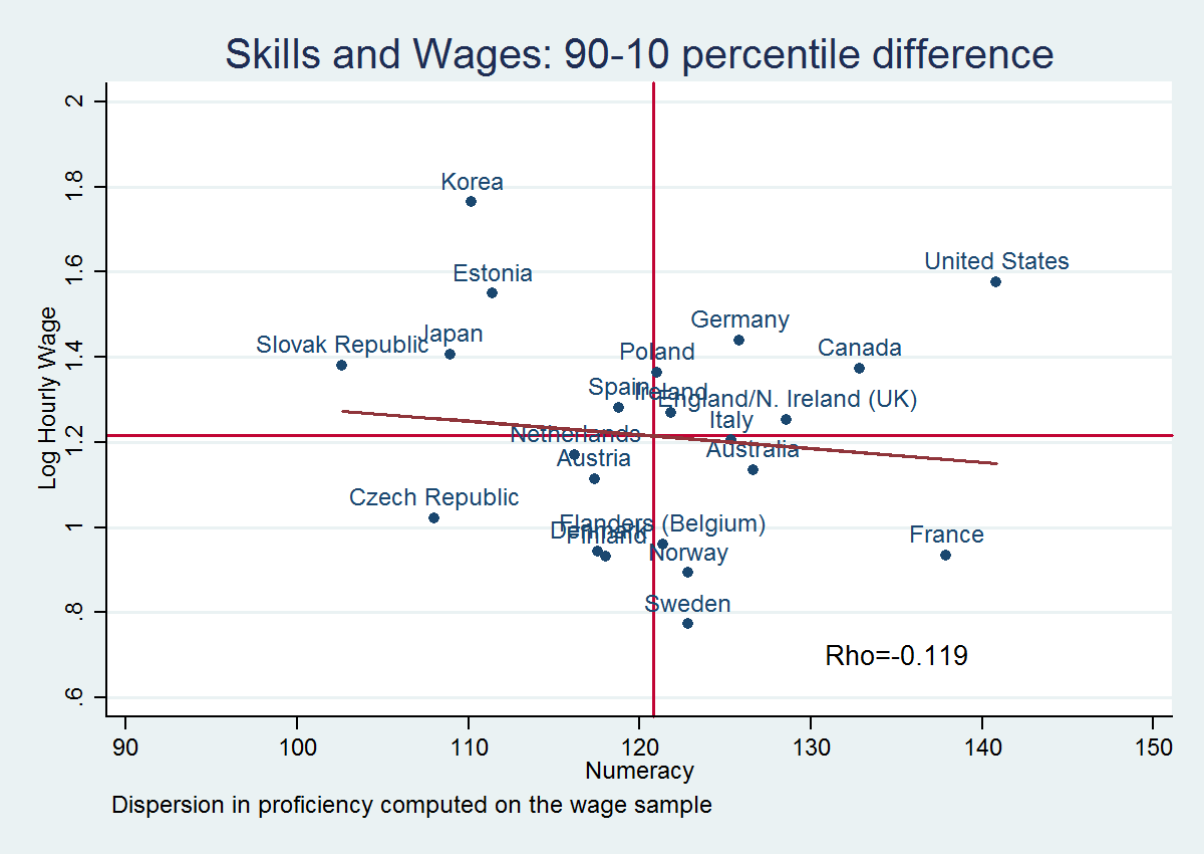

Figure 7

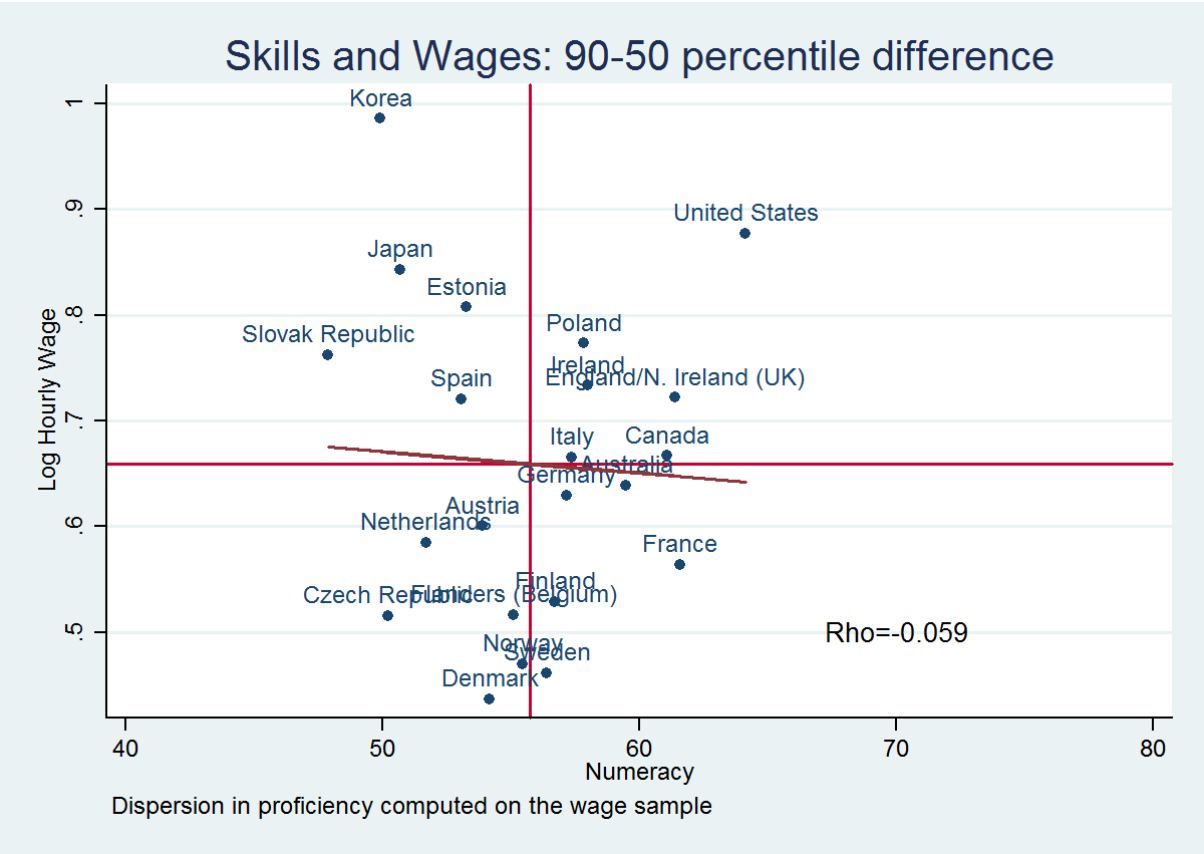

Figure 8

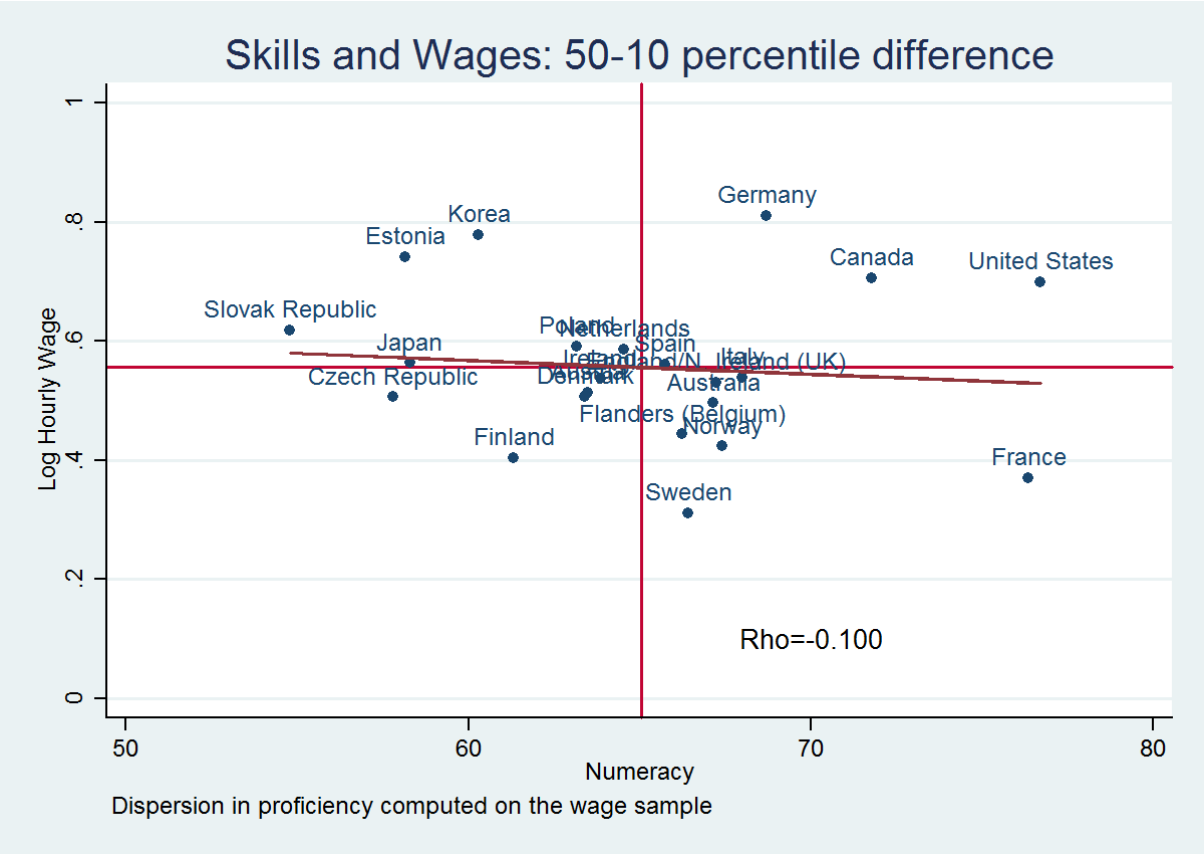

Figure 9

The same information is presented in the scatterplots in Figures 7-9. The correlation between the different indicators is small and always negative.

5. The distribution of skills and earnings within different groups

Overall inequality is the result of the interaction between within- and between-group dispersion. In this section we investigate the relationship of inequality in skills and wages to educational attainment and age.[9]

Figures 10 and 12 plot the 90th/10th percentile ratio for numeracy and hourly wages, respectively, across three different categories: people whose higher educational achievement is below an upper secondary degree, people with an upper secondary degree, and people with a tertiary degree.

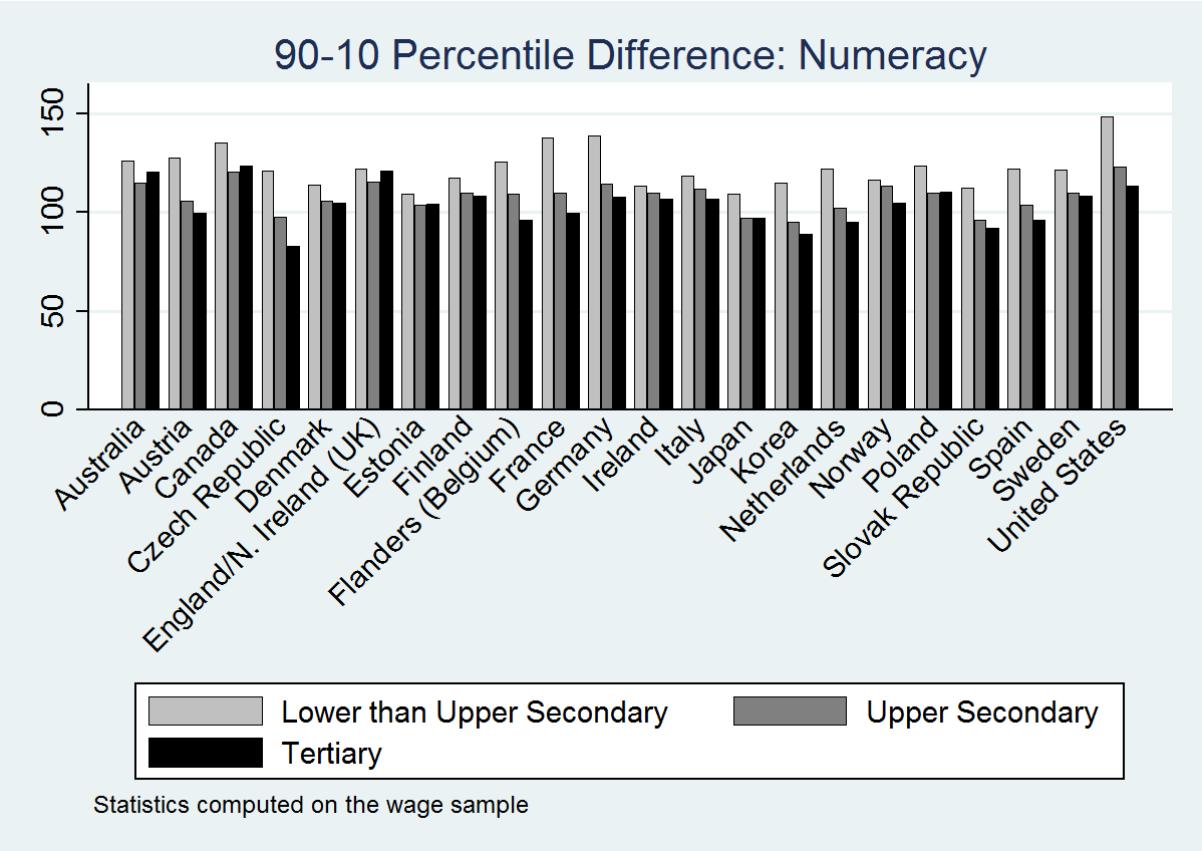

Figure 10

In almost all countries, a decline in the extent of skill dispersion is observed as educational attainment increases. The magnitude of the decline is similar across countries, although it is particularly pronounced in France, Germany and the United States.

Comparing the dispersion of skills in different groups across countries can also provide some evidence about the extent to which educational qualifications provide accurate signals of individual skills in different countries. Educational qualifications certify the existence of a wide range of skills, so that the evidence we provide can at most be suggestive. This is even truer for tertiary degrees,

[9] As noted above, to ensure comparability, the sample is restricted to employed individuals for which we observe hourly wages.

characterized by large variations in curricula. However, under the assumption that literacy and numeracy proficiency are valuable to employers (in that they contribute to labour productivity), the degree of skill dispersion among individuals with the same level of educational attainments is informative about the amount of uncertainty on employees' productivity employers are facing at the time of hiring (see Altonji and Pierret, 2001; Broecke, 2014).

In the following analysis, the sample is restricted to prime-age (25-44 years old) native-born individuals with at least an upper secondary degree on the basis that this group constitutes a reasonably homogeneous group that was educated in a similar educational system in the reasonably recent past. More importantly, in this age group individuals without a tertiary degree are unlikely to be still in education. Figure 11 shows that there are significant cross-country differences in skill dispersion by level of educational attainment. The distance between the countries with the greatest and the least dispersion in skills is of the same order of magnitude (20 to 30 points) as in the case of skill dispersion in the entire population (see table 1). An upper-secondary degree, for instance, appears to be a less precise signal of skills in the United States than in Japan, Korea or the Netherlands. Among tertiary-educated individuals, skill dispersion is particularly low in Korea, Austria, the Czech Republic, and the Netherlands, and is higher in Canada, Poland and the United States.

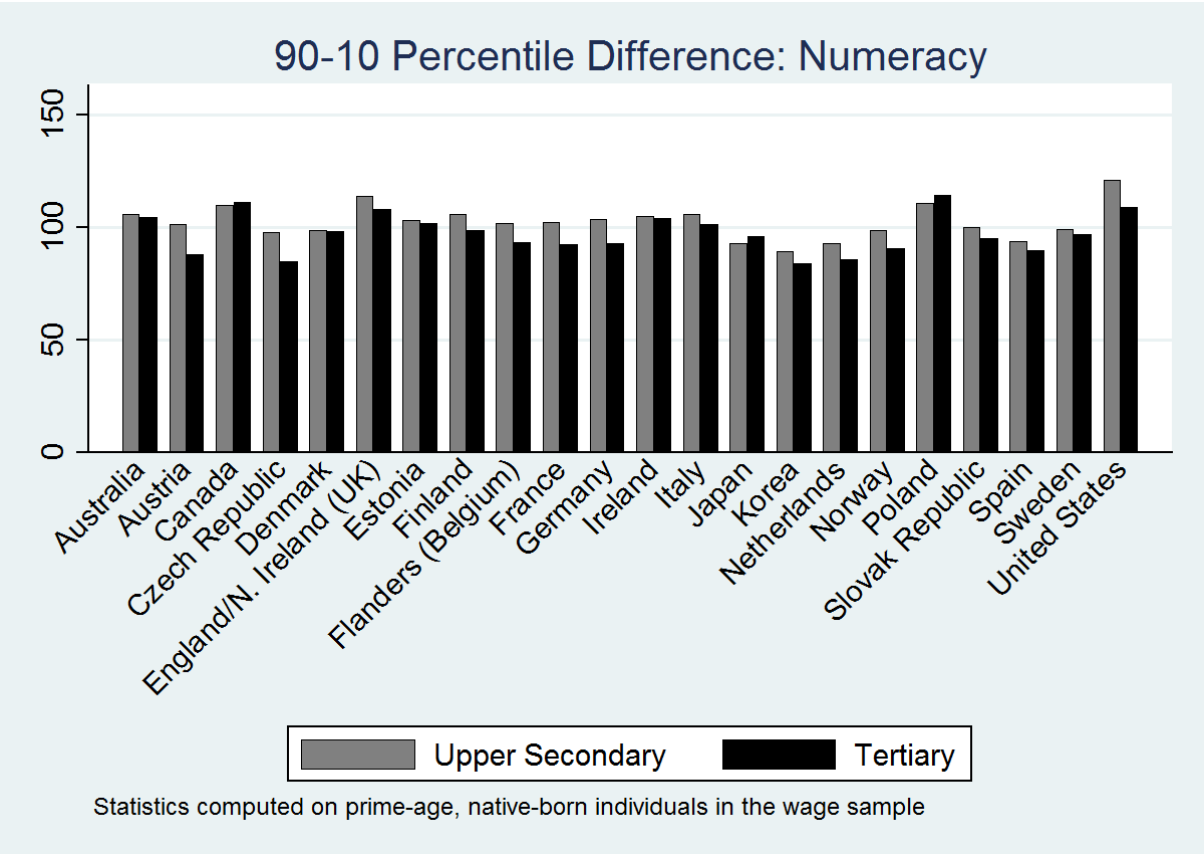

Figure 11

When we look at the dispersion of wages by level of educational attainment, the evidence is more mixed. Many countries do not display appreciable differences in earnings inequality across groups of people with different levels of educational attainment. In a few countries (for example, Austria, Denmark, Germany, and the Netherlands) earnings are more dispersed among the least educated.

However, in many others (most notably in the UK, Ireland, Japan, Poland, the Slovak Republic, and the United States), the reverse holds.

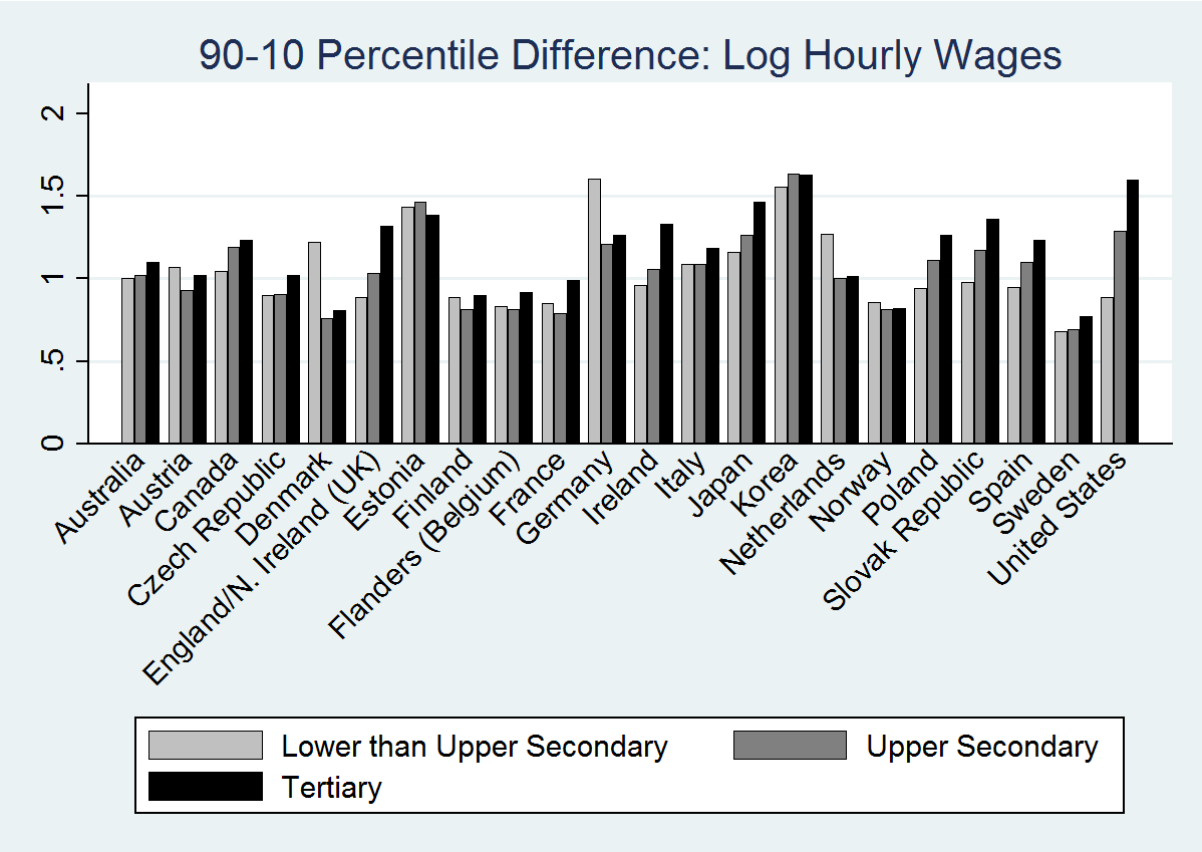

Figure 12

Next, we move to the analysis by different age classes. OECD (2013) showed that skills generally decline with age; furthermore, by combining information from previous Skills Surveys, it disentangled age and cohort effects, providing evidence that the loss of skills can indeed be attributable to ageing. In what follows we do not attempt to disentangle age and cohort effects, and limit ourselves to analyse skills and wage inequality (defined both in terms of dispersion at a given point in time and as the impact of parental background) within different age groups.

As can be seen in figure 13, in most countries skills are more dispersed among older than younger individuals (with the notable exception of Italy). However, in many countries the differences across age groups are very small, and, in some cases, almost non-existent (e.g. Australia, Austria, Norway and Poland). Part of the explanation lies in the fact that we are looking at the (selected) wage sample. In the full sample, differences in wage dispersion across age groups are indeed more pronounced, as shown in Figure 14.

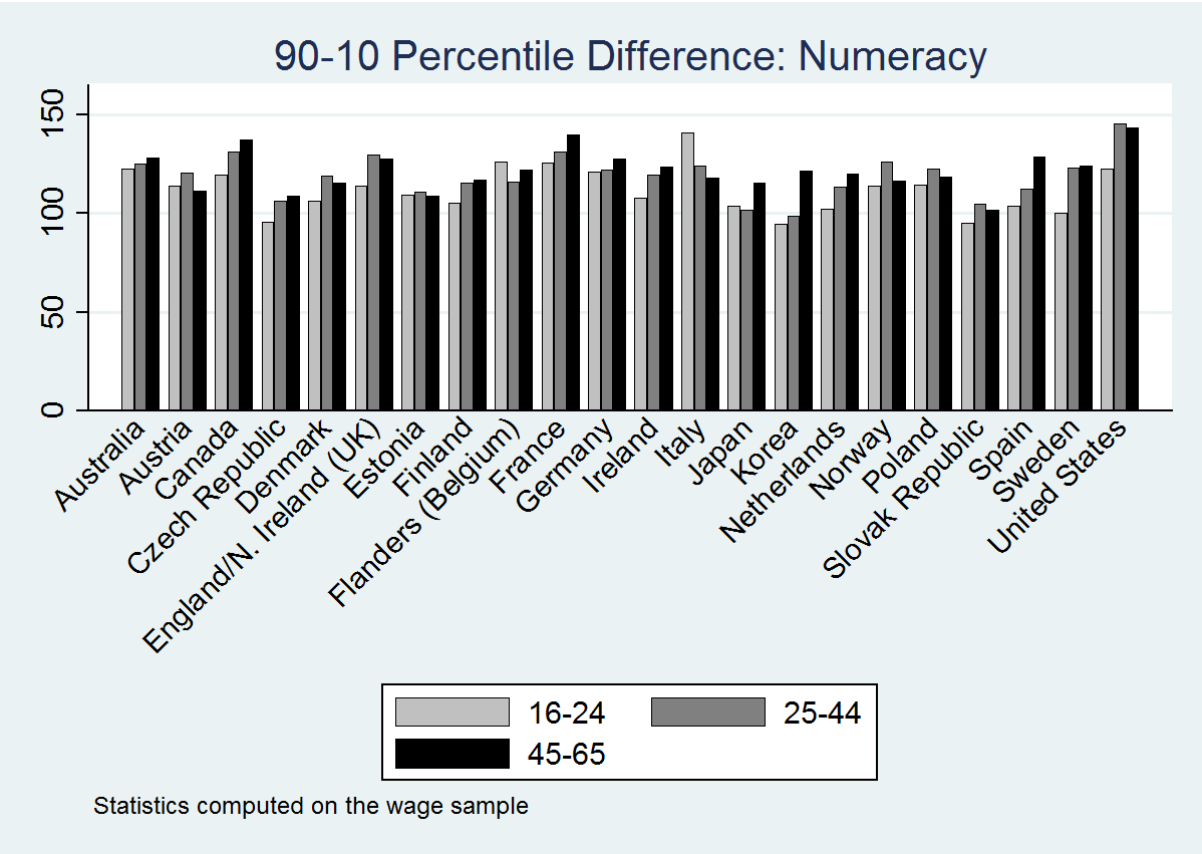

Figure 13

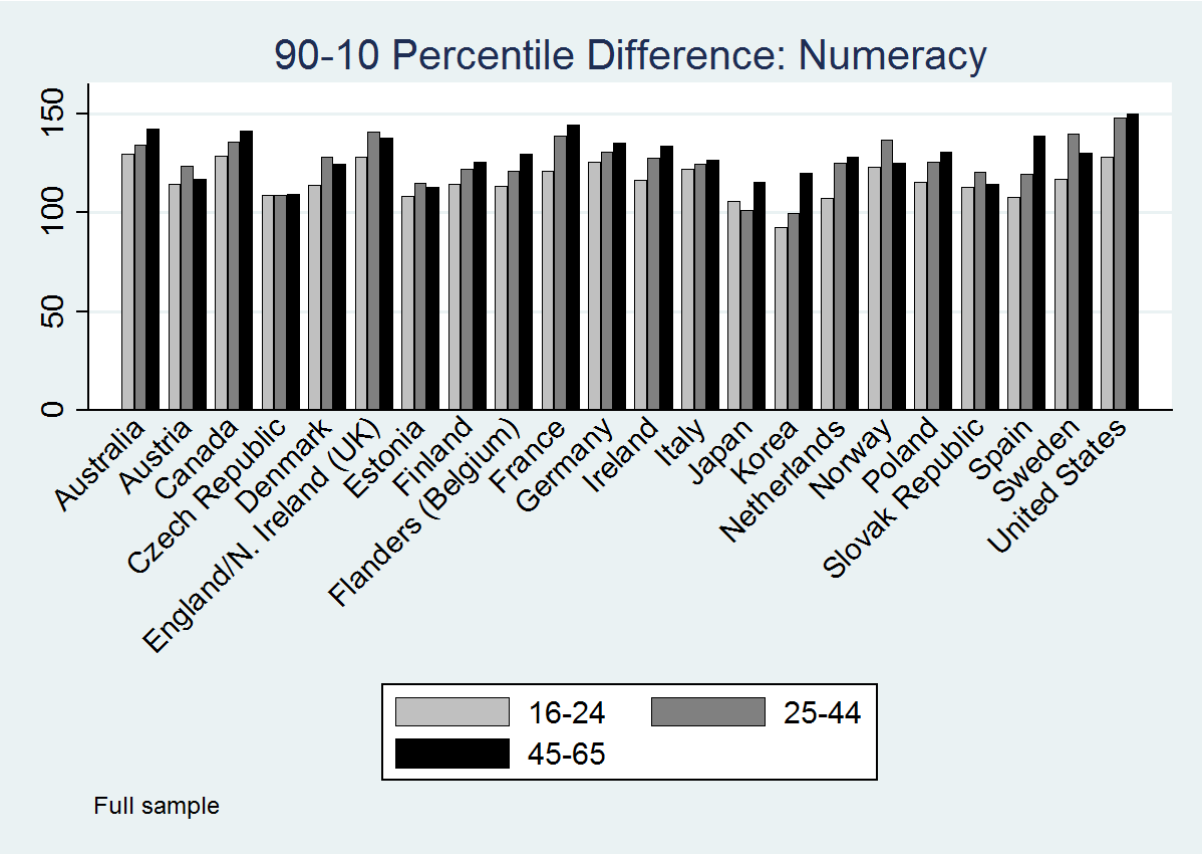

Figure 14

Also when we look at wages we see that, on average, dispersion increases with age. This is particularly true in Canada, the United Kingdom, Italy, Japan, Spain, and the United States. The relationship is much less strong in Nordic countries, most notably in Denmark, Norway and Sweden. The cross-country correlation between skills and wage dispersion is negative and declining with age (-0.28 amongst the youngest cohort, -0.13 amongst the prime-age individuals, and essentially zero in the oldest age group).

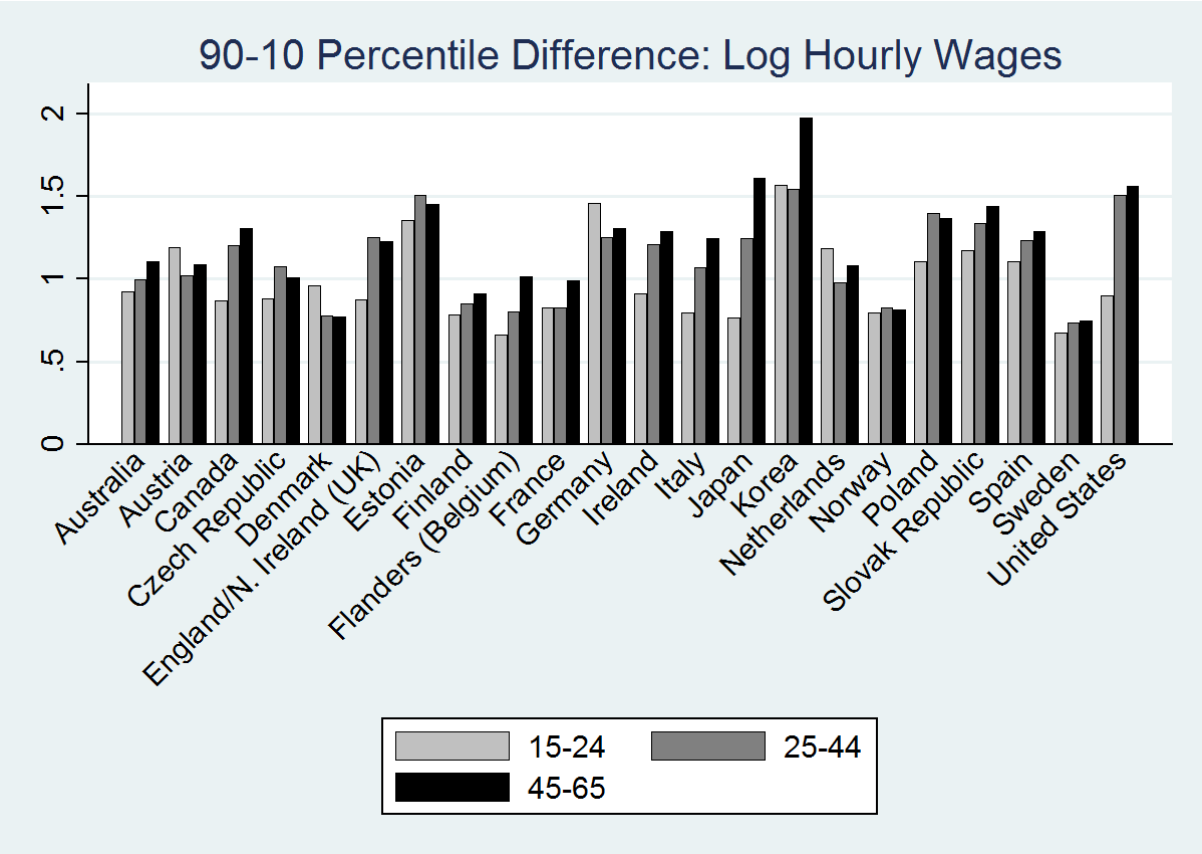

Figure 15

Finally, we can look at how the impact of family background (measured, as usual, with the parental education gradient) changes across different age groups/generations. In this analysis, we use a slightly different categorization of age groups than was used in the previous analyses, largely because the estimation of the parental education gradient on wages of the very young can be misleading, due to the issue of selection into the labour market.[10] In the next graphs, we analyse four age groups (25-34, 35-44, 45-54 and 55-65 year olds). The sample is restricted to adults aged at least 25 years, to exclude individuals still in education.

Figures 16 and 17 show considerable variation between countries in the direction and strength of the relationship of parental background to numeracy proficiency and to hourly wages by age.

[10] Recall that the parental education gradient is captured by a dummy for whether parents have tertiary education, which means we are looking at quite high socio-economic backgrounds.

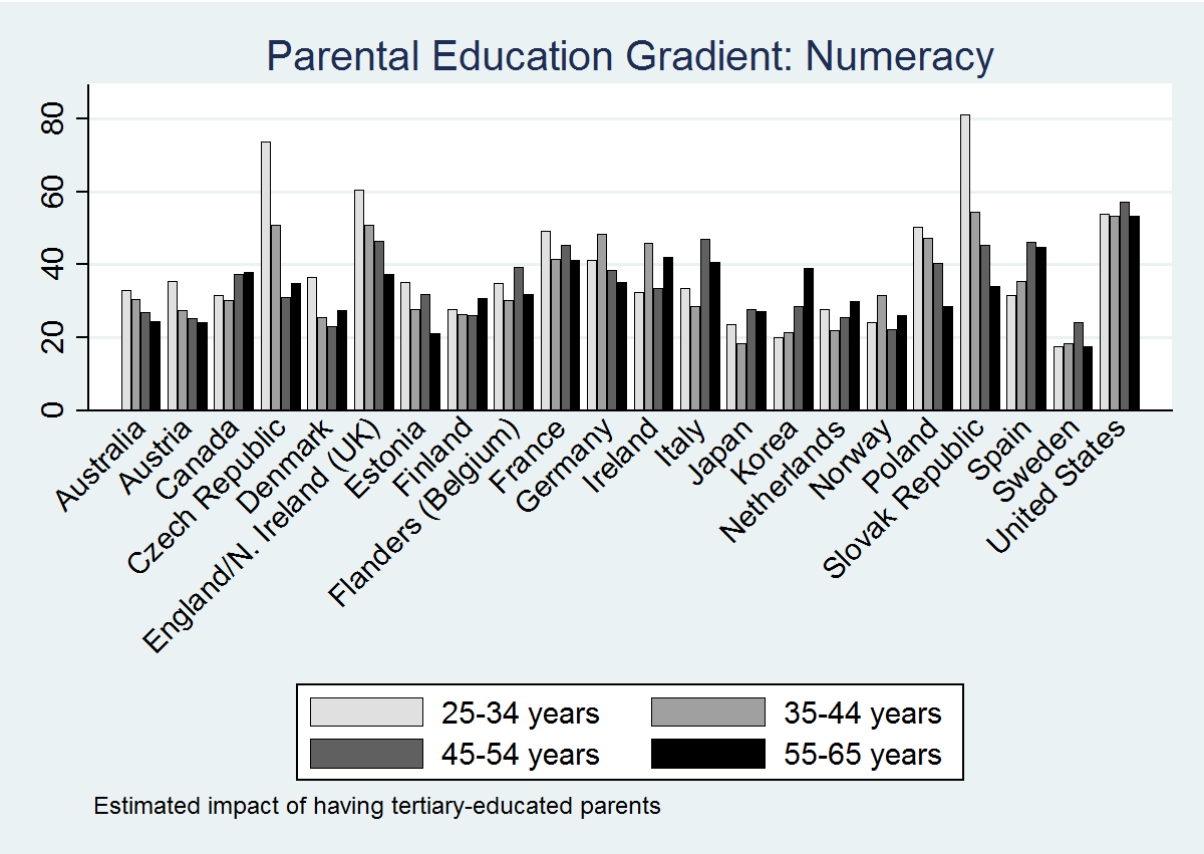

Figure 16

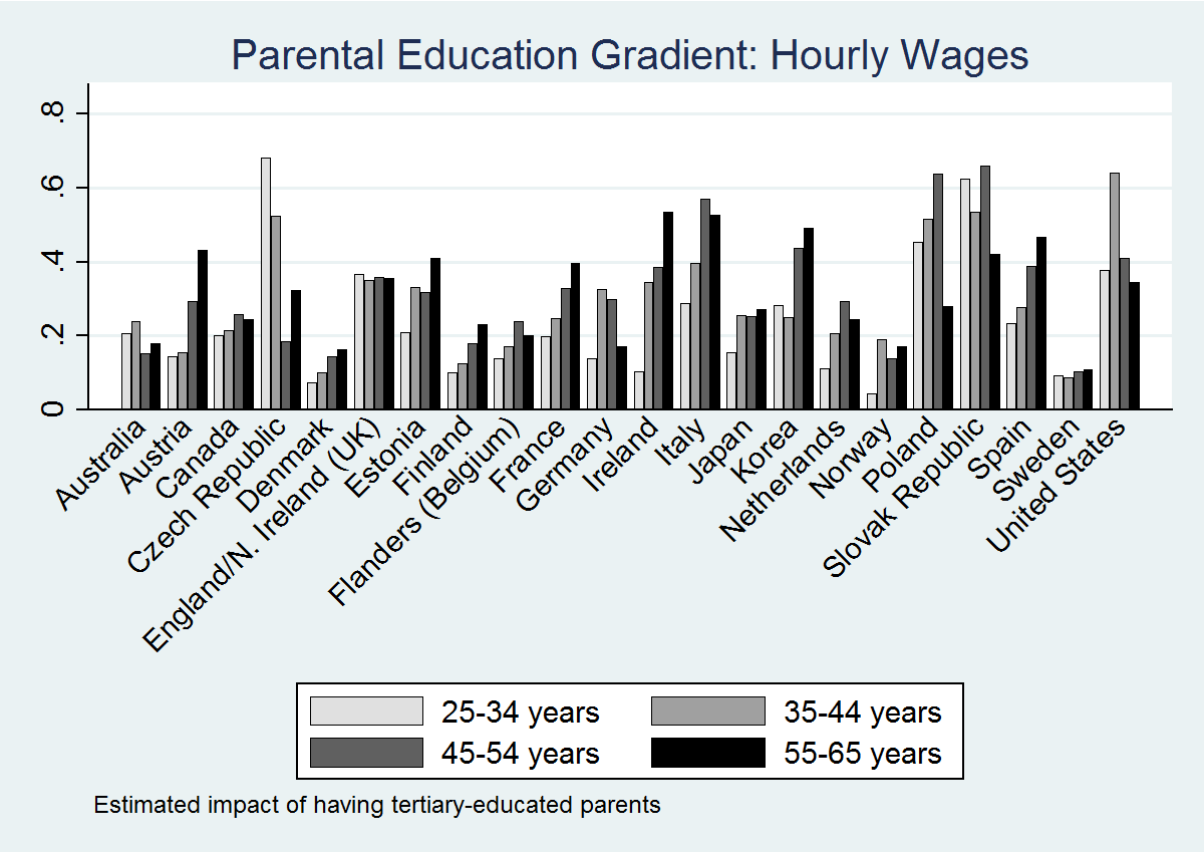

Figure 17

In both cases, pattern over the age profile is quite mixed. Over time, the impact of parental background appears to have has changed significantly, but in different ways in different countries. In countries such as Spain, Italy and Korea, parental background seems to matter much more for the older cohorts than for the youngest in the case of both numeracy skills and wages. In France, Denmark and the Netherlands this conclusion holds only for wages. There is no country in which the impact of parental background on wages appears to decline with age. When looking at skills, on the contrary, parental background seems to matter much more for the youngest than for the oldest generations in countries such as the Czech Republic, the UK, Poland and the Slovak Republic.

Interestingly, the cross-country correlation coefficient between the parental gradient on skills and the parental gradient on wages appears to decline in age: it is .84 for 25-34 years old, .78 for 35-44 years old, .65 for 45-54 years old, and .54 for 55-65 years old.

6. The drivers of earnings inequality: an analysis based on unconditional quantile regressions

In this section we analyse the drivers of labour earnings inequality as measured in the Survey of Adult Skills, focusing on the role played by education and proficiency, and thus extending previous work by Fournier and Koske (2012).

In OECD (2013), both years of education and (literacy) proficiency were estimated to have independent and sizeable effects on (average) wages. Overall, the effect of years of education was found to be larger than that of proficiency. Countries with higher wage inequality were also generally found to have higher returns to proficiency and education. The returns to proficiency are generally larger for the most educated individuals, a finding that is generally thought to be (partly) responsible for the increase in wage inequality at the very top of the earnings distribution observed in recent years.

Standard OLS regressions deliver the estimated effect of the regressors of interest on the *average* value of the dependent variable (earnings, in this case) and, for this reason, are not the most appropriate method to analyse the impact of a given variable on earning inequality. Unconditional quantile regressions (Firpo, Fortin and Lemieux, 2009) allow estimating the impact of a small locational shift in the distribution of a variable of interest on the entire (unconditional) distribution of the dependent variable.[11]

In this way, it is possible to estimate the returns to proficiency and education at different parts of the distribution of earnings, which in turn allows to analyse the impact of a certain variable on wage inequality: in fact, if the estimated effect is larger at the top decile than at the lowest decile, a

[11] Traditional quantile regression (Koenker and Basset, 1978) is *conditional*, because it allows the estimated return to a given characteristic to vary according to the *conditional* quantile of an individual, which can be thought of as the individual's position in a virtual distribution in which everybody else has the same observed characteristics (e.g., the conditional earning quantile of a man with tertiary education is defined as his position among the distribution of earnings of tertiary educated males).

marginal increase in the regressor of interest will tend to increase inequality, as measured by the decile ratio.[12]

For each country in the sample, as well as for the pooled sample of OECD countries, we estimated nineteen different unconditional quantile regressions, covering all percentiles from the 5th to the 95th (in steps of five). In each run, (log) hourly wages are regressed on age, age squared, tenure, a set of dummies for gender, marital status and place of birth, years of education and numeracy proficiency; standard errors are bootstrapped. As an alternative specification, years of education were replaced with dummies for secondary and tertiary attainment (lower-than-secondary being the excluded category).[13]

Figure 18 shows the estimated percentage effects (together with 95% confidence intervals) of a one standard-deviation increase in numeracy and years of education on different quantiles of the distribution of log hourly wages for the pooled sample of OECD countries (Figures 25-46 in the Appendix presents similar pictures for all countries in the sample).

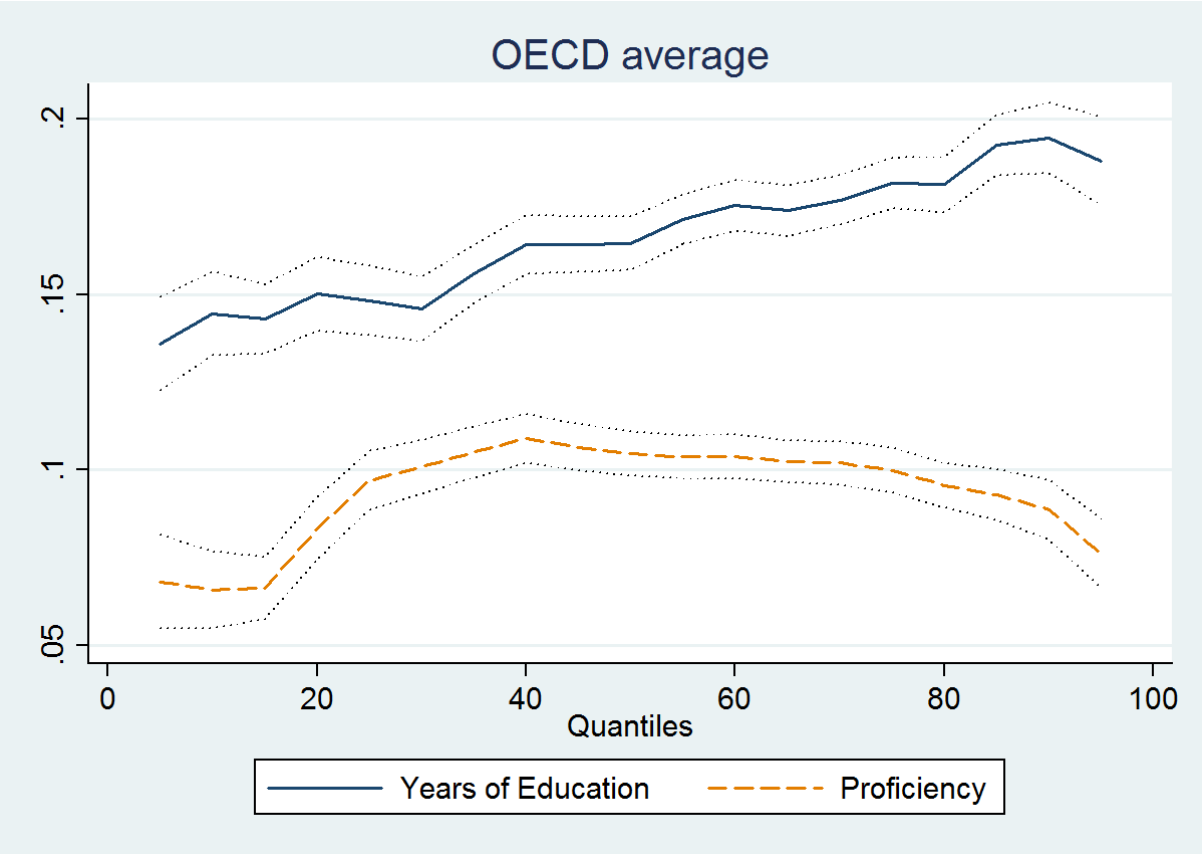

Figure 18

[12] A similar analysis is performed by Fournier and Koske (2012) on a dataset built from different household surveys. Other than including direct measures of skills, the advantage of PIAAC lays in the possibility of using a single dataset to perform the analysis, ensuring greater consistency and comparability. See also Brandolini, Rosolia and Torrini (2011), who analyse the distribution of labour earnings in the EU-SILC data.

[13] We adopt here a very simple and "minimal" specification of the earnings function. Hanushek et al. (2013) show that the estimated returns to skills in a simple specification are robust to the inclusion of alternative sets of control variables, like parental education.

Returns to education appear to be larger than returns to skills along the entire distribution of wages.[14] The gap is particularly pronounced at the top percentiles, mainly because the returns to skills flatten out above the median. Such differences in the profile of returns are likely to be due to the fact that PIAAC measures general skills, which at the top end of the wage distribution are relatively less important than the specialized knowledge acquired through formal education at tertiary level. As shown in figures 25-46 in the Appendix, a number of countries have a profile of returns to education almost as flat as the one of returns to skills (most notably in Germany, the Netherlands, Denmark and Sweden). Figure 19, displays the distribution (mean effect, 25th and 75th percentile) of the estimated percentage effects across countries, showing large cross-country variations.

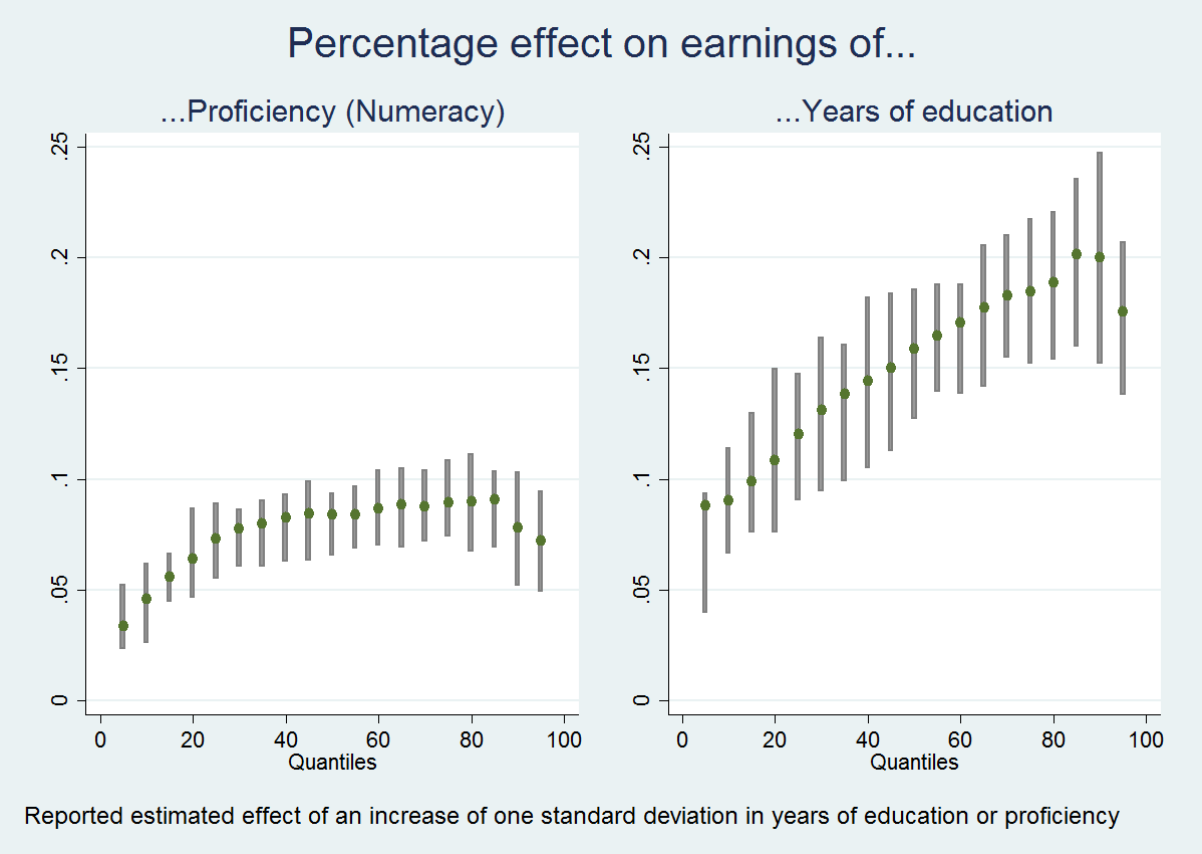

Figure 19

In an alternative specification, years of education is replaced with a set of dummies for different levels of educational attainment (the omitted category being individuals below secondary education). In this way, we can assess the effect on increasing, respectively, the share of secondary-educated versus tertiary-educated individuals. The estimated effects on inequality are substantially different, as displayed in Figure 20. Increasing the share of individuals with secondary attainment is

[14] More precisely, an increase by one standard deviation in years of education has a larger effect than an increase by one standard deviation in proficiency. However, the metric of the two measures is obviously very different, so that such kind of comparisons should be interpreted with a bit of caution.

associated with higher increases at the bottom, rather than at the top, of the distribution of earnings, while the reverse is true for the share of tertiary educated individuals.

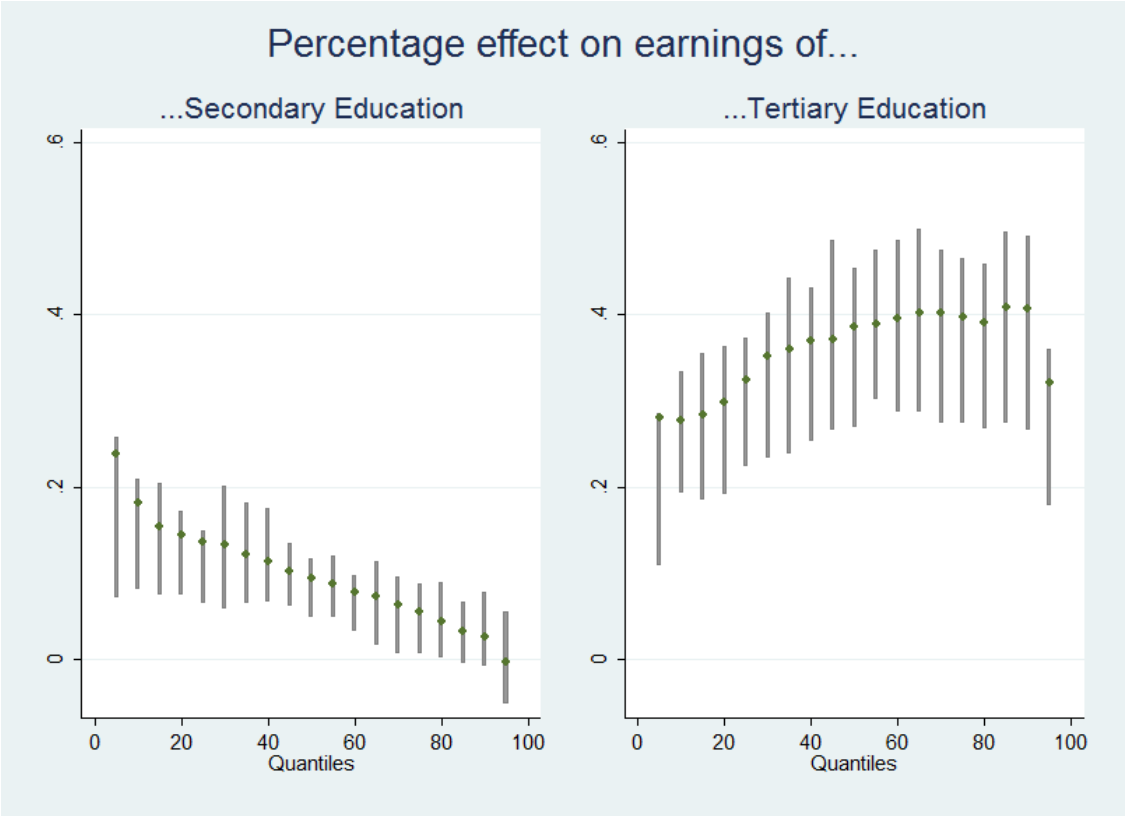

Figure 20

Figure 21 lend further support to the idea that increase in years of education generally have larger impacts on inequality than do have increases in numeracy proficiency. The figure shows, for each country, the estimated effects at the 90th and at the 10th percentile, together with the 45° line. Countries above the line are immediately identified as countries with higher returns at the top than at the bottom of the distribution. In the case of years of education, the effect at the 90th percentile is always greater than at the 10th. In the case of proficiency, the reverse holds in a number of countries, most notably Italy, Spain and Korea. Furthermore, the differences in returns to education between the 90th and the 10th percentiles appear to be much more dispersed than differences in returns to skills, a point on which we will return in Section 4.

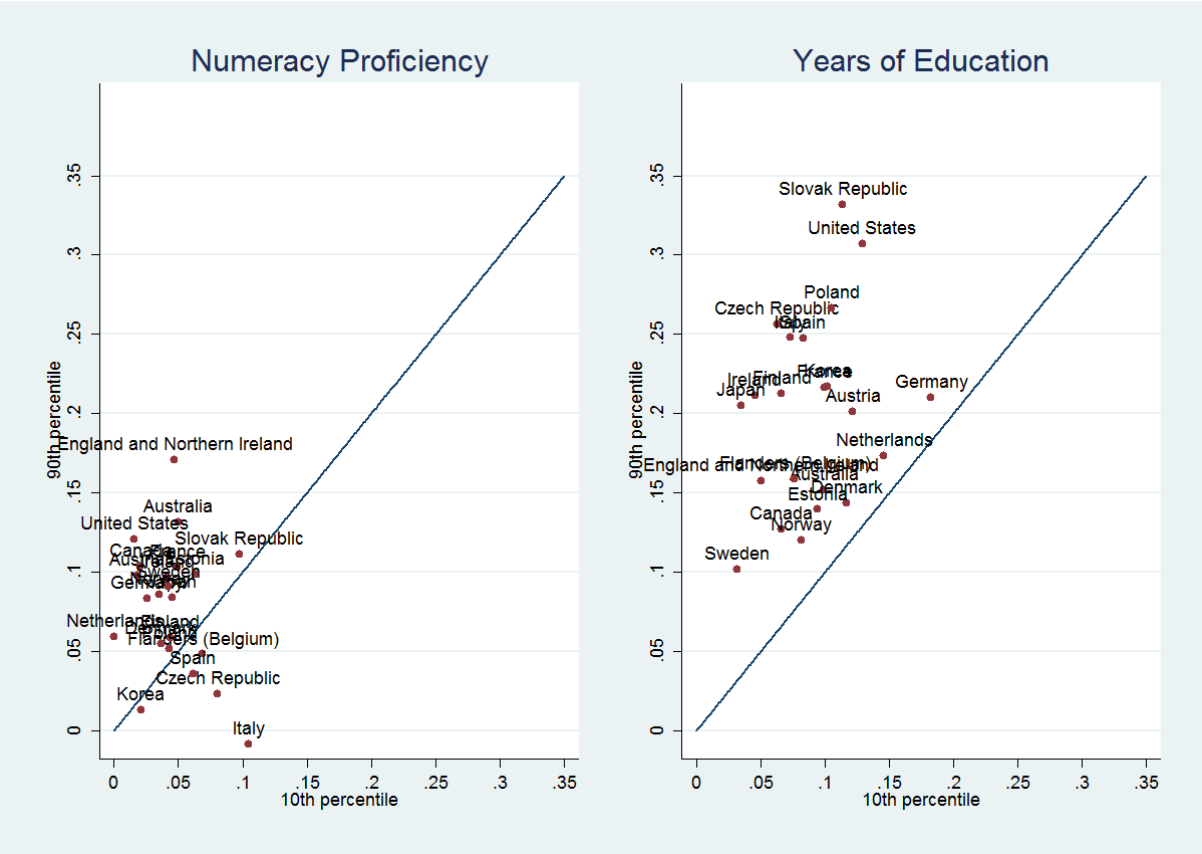

Figure 21

7. Decomposing Cross-Country Differences in Wage Inequality

In this section cross-country differences in earnings inequality are decomposed with the objective of quantifying the relative contribution of differences in the (observable) characteristics of the underlying population (*composition effect*) and of differences in the economic returns of the same characteristics (*wage structure effect*). In order to perform such exercise, we extend the standard Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973), commonly employed to decompose differences in the *mean*, to analyse differences in the *quantiles* of the variable of interest.[15]

Although widely used, this technique has some important limitations. The most relevant is that it follows, intrinsically, a partial equilibrium approach. The counterfactual question the Oaxaca-Blinder decomposition answers is: what would the observed gap have been if (a) the two countries were equal in terms of the distribution of observable characteristics, but only differed in terms of returns, or (b) the two countries had the same structure of returns, but differed in terms of characteristics of the population? These questions implicitly assume that changing the *quantity* of a variable (e.g., the share of highly skilled individual) has no effect on its *price* (the returns to skill).

[15] Different techniques have been proposed to estimate the counterfactual distribution of wages (and then perform the decomposition exercise). Motivated by the dramatic rise in wage inequality observed in the United States, Jun, Murphy and Pierce (1993) and Di Nardo, Fortin and Lemieux (1996) were the first to propose ways to decompose wage densities. Machado and Mata (2005) proposed a different approach based on quantile regressions.

Such exercises are useful for quantifying the contribution of various factors to a difference (or a change) in outcomes in an accounting sense, thus providing useful indications of particular hypothesis or explanations.[16]

Firpo, Fortin and Lemieux (2011) show how unconditional quantile regressions (the same tool that we used in the previous section) can be used to perform a *detailed* decomposition of quantile differences, allowing to assess the relative contribution of each of the regressor included in the model.[17]

In the following we will decompose the cross-country differences in wage inequality (measured by the $90^{th}/10^{th,}$ $90^{th}/50^{th}$ and $50^{th}/10^{th}$ percentile ratios), taking the United States as the reference country. The reason for this choice is twofold: (i) the United States are characterized by the highest levels of wage and skill inequality among the countries that participated in PIAAC; (ii) such choice allows a more direct comparison of our results with the ones in Fournier and Koske (2012) and Blau and Khan (2005).

More formally, the composition effect is computed, at each percentile (the 90th, the 50th and the 10th) as the difference between the United States and the country of interest in the observed value of each covariate (such as numeracy, years of education, and so on), evaluated at the coefficient associated to that covariate in a RIF-regression restricted to the country of interest. Therefore the contribution of each covariate to the gap in the percentile ratio between the United States and the country of interest two factors results from the interplay of two factors:

i) the difference (with respect to the United States) in the mean value of the variable;

ii) the country-specific return to that particular variable at that particular quantile.

The wage structure effect, instead, is computed as the difference in the estimated returns between the country of interest and the United States, taking as reference the United States value of the variable.[18]

A quick look at the table can help in understanding the exercise. The first column of each table presents the raw gap in the percentile ratio between the United States and the country of interest. All values are *positive*, indicating that wage inequality is larger in the United States than in all other countries (with the exception of Korea and, for the $50^{th}/10^{th}$ percentile ratio, Germany). The fourth and the seventh columns report the estimated composition and wage structure effects, i.e. the relative contribution of differences in the characteristics of the population (total composition effect) and of differences in rates of returns (total wage structure effect). By construction, the two total effects sum up to the observed raw gap (up to rounding). To make a concrete example, the $90^{th}/10^{th}$

[16] See Firpo, Fortin and Lemieux (2011) for a discussion of identification restrictions in Oaxaca-Blinder decompositions.

[17] Following Firpo, Fortin and Lemieux (2011), we first estimate the RIF, by computing the sample quantile and estimating the density at that point with kernel methods. Then, we regress the RIF on the usual vector of covariates (age, age squared, female dummy, native-born dummy, numeracy and years of education) and compute the standard Oaxaca-Blinder decomposition.

[18] The choice of which reference to take for the coefficients or the quantity effect is, of course, arbitrary, and many other possibilities have been proposed in the literature. Our results are overall robust to this particular choice.

percentile ration in Sweden (the country with the lowest level of wage inequality, and thus with the higher differential with respect to the United States) is 0.873 points lower than in the United States: 0.020 points are accounted for by the composition effect, and the remaining 0.852 are accounted for by the wage structure effect.

Such effects can be further decomposed to highlight the relative contribution of the variables of interest. By construction, the sum of the contribution of each variable of the model delivers the total composition or wage structure effect.[19] In the second, third, fifth and sixth column of the tables we report the contribution of two such variables, namely years of education and numeracy skills.

The signs of the contribution effects are worth discussing in order to better understand how the decomposition works. In table 3, the composition effects associated with numeracy skills are generally negative, indicating that in most countries wage inequality would decrease (and thus the gap with the United States would be even larger) if the distribution of skills was the same as that observed in the United States, keeping constant the country-specific return. This may seem puzzling at first sight, given that the United States is the country with the widest skill dispersion. Two effects are at play here. First, in most countries average proficiency in numeracy at the 90th and at the 10th percentiles is higher than in the United States. Consequently, imposing the levels of proficiency observed in the United States on other countries would imply a decline in earnings at that particular percentile. This effect, however, is mediated by the country-specific returns to skill at each percentile. In virtually all countries, returns to skills are higher at the 90th than at the 10th percentile. Such difference in returns is large enough to make the effect at the 90th percentile larger than at the 10th percentile, so that the resulting difference is still negative. In the Czech Republic the composition effect associated to numeracy is positive, precisely because in that country the returns to proficiency are larger at the bottom than at the top of the distribution (fig. 28). Italy is another country with higher returns to skills at the bottom than at the top of the distribution (Fig. 37), but it is also one of the few countries (together with Spain) in which the 90th percentile of the skill distribution is *below* the US-level. The pattern is almost reversed in table 4, with many coefficients being positive. The reason lies in the fact that, in many countries, the returns to skills flatten out considerably above the median. This can be clearly seen in the case of the Netherlands (fig. 40): the shape of the curve of returns to proficiency is such that returns are higher at the 90th than at the 10th percentile, but are even higher at the median, because of the slight decline that takes place after the 70th percentile. Table 5 (that looks at the ratio of the 50th to the 10th percentile) looks much more like table 3 (that looks at the ratio of the 90th to the 10th percentile), because the returns to skills are higher at the median than at the 10th percentile in most countries (again, with the notable exception of the Czech Republic).

In the case of educational attainment, the picture is almost completely reversed. Most countries have *lower* levels of education than the United States. Thus, imposing the US levels of educational attainment generally increases wages at the percentiles of interest. The resulting effect on wage dispersion is generally positive because returns to education are larger at the top than at the bottom of the distribution in virtually all countries. In Ireland (but the same holds for Australia) the composition effect is negative because Irish workers are on average more educated than their

[19] The contribution of the constant shows up only in the wage structure effect, that is also by construction "contamined" by differences in unobservables.

United States counterparts at both end of the distribution: given the structure of the returns to education, if Ireland had the same distribution of education as the United States, it would experience a decline at the top end of the distribution larger than at the bottom end, which would result in lower inequality. However, the opposite is true for the vast majority of countries, where workers are generally less educated than their United States counterparts, especially at the top end of the distribution. In Italy, for example, workers in the top decile of the distribution have on average 2.3 years of education *less* than United States workers at similar levels of earnings, and a similar gap is present for workers belonging to the bottom decile. Given that returns to education are higher at the top than at the bottom of the distribution, if Italy had the same distribution of education as the United States, wages would increase more at the top than at the bottom of the distribution. In other words, differences in the distribution of education help to explain the higher wage dispersion observed in the United States.

Such composition effects, however, are generally quite small (even smaller than the ones estimated by Blau and Khan (2005) and Fournier and Koske (2012), although it is difficult to make precise comparisons because of differences in the methodology used). In most countries, they account for at most 15% of the gap in wage dispersion. Differences in the distribution of educational attainment seem to play a greater role than differences in skills endowment

Table 3

Country	Gap	Composition Effect			Wage Structure Effect		
	$90^{th}/10^{th}$	*Education*	*Numeracy*	Total	*Education*	*Numeracy*	Total
Australia	0.507	*-0.022*	*-0.023*	-0.074	*0.459*	*0.060*	0.581
Austria	0.536	*0.046*	*-0.030*	0.054	*0.381*	*0.029*	0.482
Canada	0.275	*0.007*	*-0.017*	-0.022	*0.427*	*0.065*	0.297
Czech R.	0.624	*0.035*	*0.024*	0.068	*-0.268*	*0.844*	0.556
Denmark	0.701	*0.009*	*-0.009*	0.016	*0.628*	*0.377*	0.685
England/UK	0.392	*0.028*	*-0.032*	0.001	*0.131*	*-0.162*	0.391
Estonia	0.117	*0.020*	*-0.013*	0.009	*0.543*	*0.276*	0.109
Finland	0.713	*0.041*	*-0.011*	0.061	*0.051*	*0.386*	0.652
Belgium	0.684	*0.028*	*0.010*	0.111	*0.321*	*0.585*	0.572
France	0.715	*0.066*	*0.000*	0.086	*0.312*	*0.232*	0.629
Germany	0.218	*0.001*	*-0.018*	0.019	*0.662*	*0.191*	0.199
Ireland	0.381	*-0.098*	*-0.004*	-0.088	*-0.058*	*0.168*	0.469
Italy	0.441	*0.114*	*-0.013*	0.156	*0.130*	*1.076*	0.285
Japan	0.247	*0.038*	*-0.030*	0.010	*-0.235*	*0.233*	0.237
Korea	-0.121	*0.019*	*0.001*	0.164	*0.199*	*0.519*	-0.286
Netherlands	0.475	*0.004*	*-0.034*	-0.027	*0.602*	*0.143*	0.502
Norway	0.743	*-0.008*	*-0.023*	-0.028	*0.591*	*0.240*	0.771
Poland	0.285	*0.019*	*-0.001*	-0.065	*0.027*	*0.435*	0.350
Slovak Rep.	0.263	*0.011*	*-0.007*	-0.004	*-0.366*	*0.402*	0.268
Spain	0.366	*0.072*	*-0.002*	0.084	*0.116*	*0.620*	0.282
Sweden	0.873	*0.036*	*-0.024*	0.020	*0.382*	*0.241*	0.852

Table 4

Country	Gap 90th/50th	Composition Effect			Wage Structure Effect		
		Education	*Numeracy*	Total	*Education*	*Numeracy*	Total
Australia	0.269	*-0.010*	*-0.012*	-0.030	*0.132*	*-0.375*	0.299
Austria	0.308	*0.039*	*-0.006*	0.068	*-0.051*	*-0.254*	0.239
Canada	0.244	*-0.005*	*0.005*	-0.010	*0.561*	*-0.036*	0.254
Czech R.	0.394	*0.022*	*0.006*	0.015	*-0.389*	*-0.074*	0.378
Denmark	0.471	*0.017*	*-0.002*	0.018	*0.010*	*-0.190*	0.453
England/UK	0.195	*-0.002*	*-0.003*	-0.002	*0.323*	*-0.223*	0.197
Estonia	0.094	*-0.018*	*0.000*	-0.024	*0.482*	*-0.163*	0.118
Finland	0.378	*0.022*	*0.004*	0.041	*-0.105*	*-0.130*	0.337
Belgium	0.390	*0.019*	*0.012*	0.073	*-0.024*	*-0.046*	0.317
France	0.346	*0.051*	*0.000*	0.072	*-0.076*	*-0.334*	0.274
Germany	0.276	*0.001*	*0.003*	0.040	*0.123*	*-0.124*	0.235
Ireland	0.176	*-0.017*	*-0.000*	-0.003	*0.135*	*-0.191*	0.179
Italy	0.240	*0.063*	*-0.005*	0.115	*-0.080*	*0.047*	0.124
Japan	0.065	*0.015*	*0.006*	0.039	*-0.117*	*-0.120*	0.026
Korea	-0.080	*0.000*	*0.008*	0.116	*0.259*	*0.152*	-0.196
Netherlands	0.323	*0.005*	*0.023*	0.036	*0.045*	*0.059*	0.287
Norway	0.428	*-0.003*	*-0.003*	-0.003	*0.203*	*-0.194*	0.432
Poland	0.136	*-0.002*	*0.002*	-0.129	*0.349*	*-0.074*	0.264
Slovak Rep.	0.145	*0.006*	*-0.012*	-0.028	*-0.320*	*-0.292*	0.173
Spain	0.187	*0.011*	*-0.003*	0.037	*0.177*	*0.072*	0.149
Sweden	0.446	*0.023*	*-0.018*	0.007	*0.027*	*-0.340*	0.439

Table 5

Country	Gap 50th/10th	Composition Effect			Wage Structure Effect		
		Education	*Numeracy*	Total	*Education*	*Numeracy*	Total
Australia	0.238	*-0.011*	*-0.012*	-0.044	*0.328*	*0.435*	0.282
Austria	0.229	*0.007*	*-0.024*	-0.014	*0.432*	*0.284*	0.243
Canada	0.030	*0.012*	*-0.022*	-0.013	*-0.134*	*0.100*	0.043
Czech R.	0.231	*0.012*	*0.018*	0.053	*0.120*	*0.918*	0.177
Denmark	0.230	*-0.008*	*-0.007*	-0.001	*0.617*	*0.567*	0.231
England/UK	0.196	*0.031*	*-0.029*	0.003	*- 0.192*	*0.061*	0.194
Estonia	0.023	*0.039*	*-0.013*	0.033	*0.061*	*0.439*	-0.009
Finland	0.335	*0.020*	*-0.015*	0.020	*0.155*	*0.516*	0.315
Belgium	0.293	*0.009*	*-0.001*	0.038	*0.346*	*0.631*	0.255
France	0.369	*0.014*	*0.000*	0.014	*0.395*	*0.567*	0.355
Germany	-0.057	*-0.000*	*-0.021*	-0.021	*0.539*	*0.315*	-0.036
Ireland	0.205	*-0.081*	*-0.004*	-0.084	*-0.193*	*0.359*	0.289
Italy	0.201	*0.051*	*-0.009*	0.041	*0.209*	*1.029*	0.161
Japan	0.182	*0.023*	*-0.035*	-0.029	*-0.119*	*0.353*	0.211
Korea	-0.041	*0.018*	*-0.007*	0.048	*-0.059*	*0.367*	-0.089
Netherlands	0.151	*-0.001*	*-0.057*	-0.063	*0.557*	*0.084*	0.214
Norway	0.315	*-0.004*	*-0.020*	-0.024	*0.388*	*0.434*	0.339
Poland	0.149	*0.021*	*-0.003*	0.063	*0.509*	*-0.542*	0.086
Slovak Rep.	0.118	*0.005*	*0.005*	0.023	*-0.046*	*0.695*	0.095
Spain	0.180	*0.061*	*0.001*	0.047	*-0.061*	*0.549*	0.133
Sweden	0.427	*0.013*	*-0.006*	0.014	*0.355*	*0.581*	0.413

The wage structure effect, on the other hand, appears to be much more relevant. In the majority of countries, a significant role is played by differences in the rates of returns to education. These alone are able to explain between 30% (in Spain) and 90% (in Denmark) of the difference in wage dispersion. Differences in returns to skills also play a major role in many countries in explaining the gap with the United States, particularly in the bottom half of the distribution (where in most cases "over-explain" differences in dispersion). However, returns to numeracy skills are not able to explain differences in wage dispersion in the upper part of the distribution, where estimated effects have the "wrong" signs.[20]

To sum up, cross-country differences in wage inequality appear to be mainly explained by differences in the structure of returns to observable characteristics. Moreover, differences in returns to education appear to have a greater impact than differences in returns to skills. These findings are consistent with previous work that examined differences in wage inequality across countries (Blau and Khan, 2005; Fournier and Koske, 2012). Returns to education are also found to be an important role in explaining the rise in earnings inequality (see Autor, 2014).

It is beyond the scope of this paper to provide explanations for differences in returns to education or proficiency. Two types of explanation are commonly proposed in the literature. The first emphasises relative supply and demand for skills: characteristics in lower (net) supply get higher rewards. The second, emphasises the role played by labour market institutions such as minimum wages, the degree of unionization and the rules governing wage bargaining. By affecting the extent to which different individual characteristics are remunerated in the labour market, such features of the labour market in different countries may have a considerable impact on the distribution of earnings. In a cross-country setting, support for the role of demand and supply is provided by Leuven at al. (2004). In terms of the role of institutions, Fournier, Koske and Wanner (2012) identified a number of structural policies able to provide a "double dividend", in the sense that they are likely to foster growth without causing a rise in inequality. These include policies that facilitate the accumulation of human capital and make it less dependent on socio-economic background and policies that reduce labour market dualism and promote the labour market integration of immigrants and women.

The analysis conducted here suggests that educational attainment, through both a composition and a wage structure effect, plays a much more prominent role than numeracy proficiency in accounting for cross-country differences in wage dispersion.

8. Conclusion

In this paper we have analysed the relationship between dispersion in proficiency and wages, drawing on information from the Survey of Adult Skills (PIAAC).

In the first place, a negative correlation is found between the average level of proficiency and its degree of dispersion, a finding common to other international surveys conducted in a school context.

Second, both skills and wage dispersion differ a great deal across countries, but the relationship between the two does not appear to be particularly strong. The correlation coefficients between

[20] Italy, the Netherlands and Spain are an exception. In these countries, however, the magnitude of the contribution is quite small.

different measures of skills and wage inequality are, in fact, negative, although quite close to zero. At the same time, a strong positive correlation (for both proficiency and wages) is found between the extent of inequality in both the distribution of proficiency and wages and the strength of the parental education gradient, suggesting that in more unequal countries adult outcomes are more influenced by family background. This is a concerning finding. The strength of the parental education gradient differs widely across age groups, but to a differing extent in different countries. Unfortunately, the cross-sectional nature of PIAAC does not allow us to draw strong conclusion about the evolution *over time* of such gradient.

Proficiency in literacy and numeracy tends to be more dispersed among older adults and less dispersed among individuals with higher levels of educational attainment. In the case of wages, no clear pattern emerges, neither in respect of wages or proficiency.

Third, to investigate the determinants of inequality in labour earnings, we ran a series of unconditional quantile regressions, in order to assess the impact of different variables at different quantiles of the wage distributions. Consistent with previous findings, increasing years of education tend to increase inequality because the returns to education are much higher at the top than at the bottom of the distribution. When we look at the share of individuals with a given level of attainment (instead of looking at years of education), we find that such inequality-enhancing effect of education is present only when the increase in education takes place through a rise in the share of tertiary-educated individuals. The returns to proficiency, by contrast, are smaller, and tend to flatten out above the median, which implies that an increase in the average level of proficiency does not lead to higher overall wage dispersion.

Finally, we performed a decomposition exercise in order to assess the relative contribution of differences in observable characteristics (composition effect) versus differences in the rates of returns to those characteristics (wage structure effect) in explaining cross-country differences in wage dispersion. Overall, the wage structure effect largely dominates. Consistent with previous findings in the literature, differences in the way personal characteristics are rewarded in the labour market account for a large share of the observed cross-country differences in wage dispersion. Differences in completed years of education and in returns to education, much more than differences in skill endowments and returns, seem to play a prominent role in this respect.

It is beyond the purpose of this paper to directly assess the relative role of institutions versus market forces in explaining wage inequality. However, the fact that, even after controlling for direct measures of proficiency, the returns to formal education continue to play a very prominent role, suggests that labour market institutions are a crucial factor in explaining the observed international differences in earnings inequality by affecting the way in which certain characteristics are rewarded.

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Appendix

A1 – ROBUSTNESS – Focus on Wage Sample

In this brief section we provide evidence supporting our choice to restrict the sample to wage earners. The following graphs compare the three percentile ratios (for numeracy) computed on the entire sample with the ones computed on the subsample of wage earners. Figures 22-24 show that the values of the different percentile ratios computed for the full sample or for the subsample of wage earners are highly correlated; in particular, the country ranking is virtually unchanged. [21] Most of the differences are due to changes in inequality in the bottom part of the distribution (the $50^{th}/10^{th}$ percentile ratio). The correlation coefficient is equal to 0.93 for the 90-10 difference, to 0.97 for the 90-50 difference, and to 0.87 for the 50-10 difference.

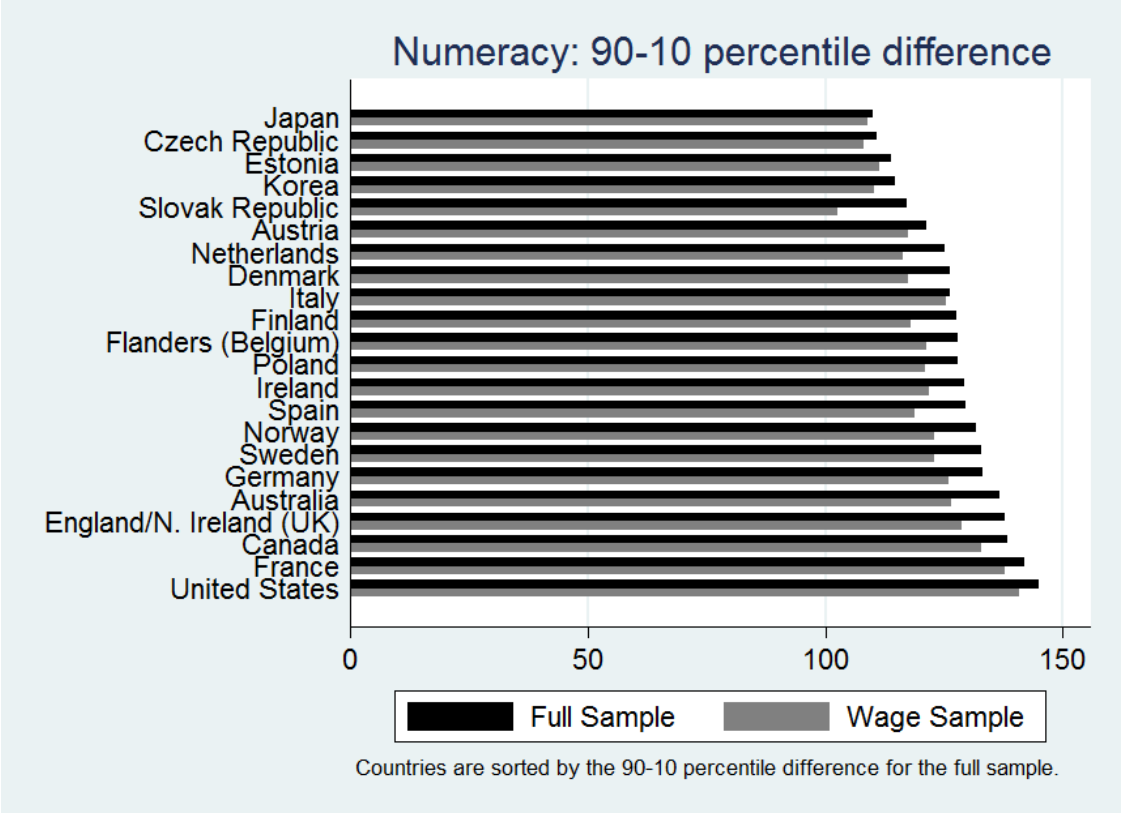
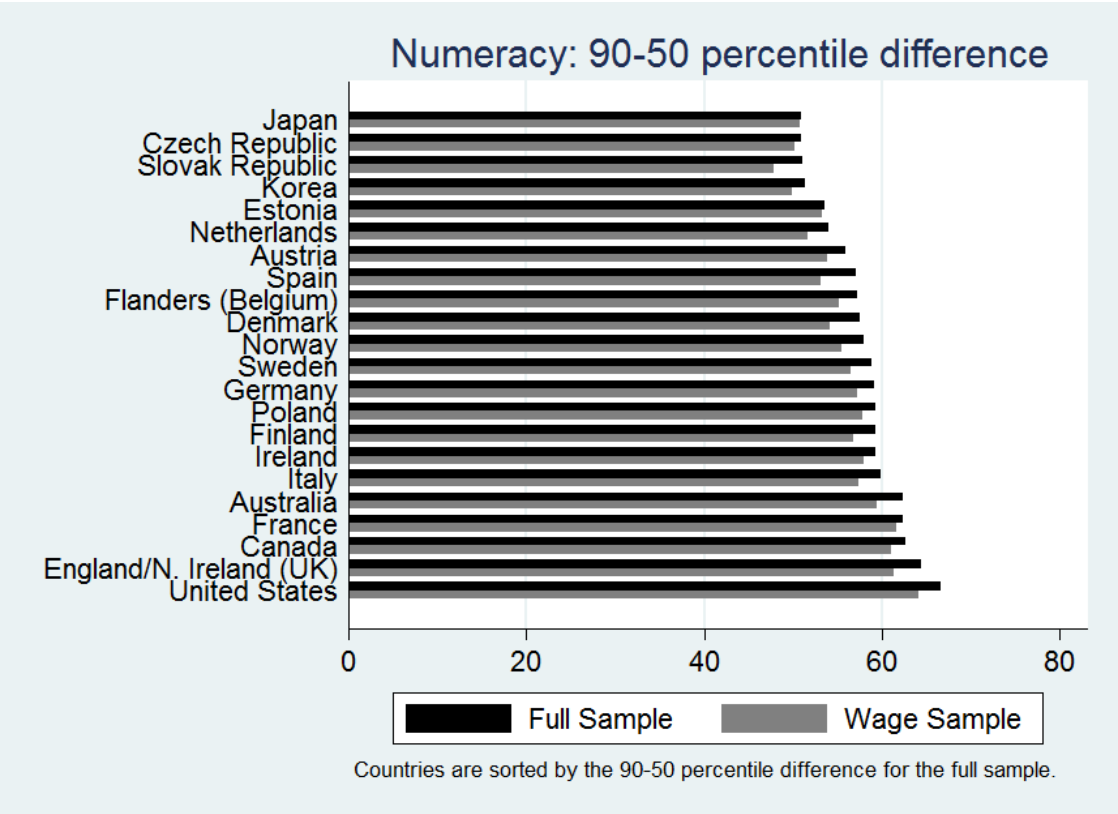


Figure 22

[21] Countries are sorted by the percentile ratio for the full sample.



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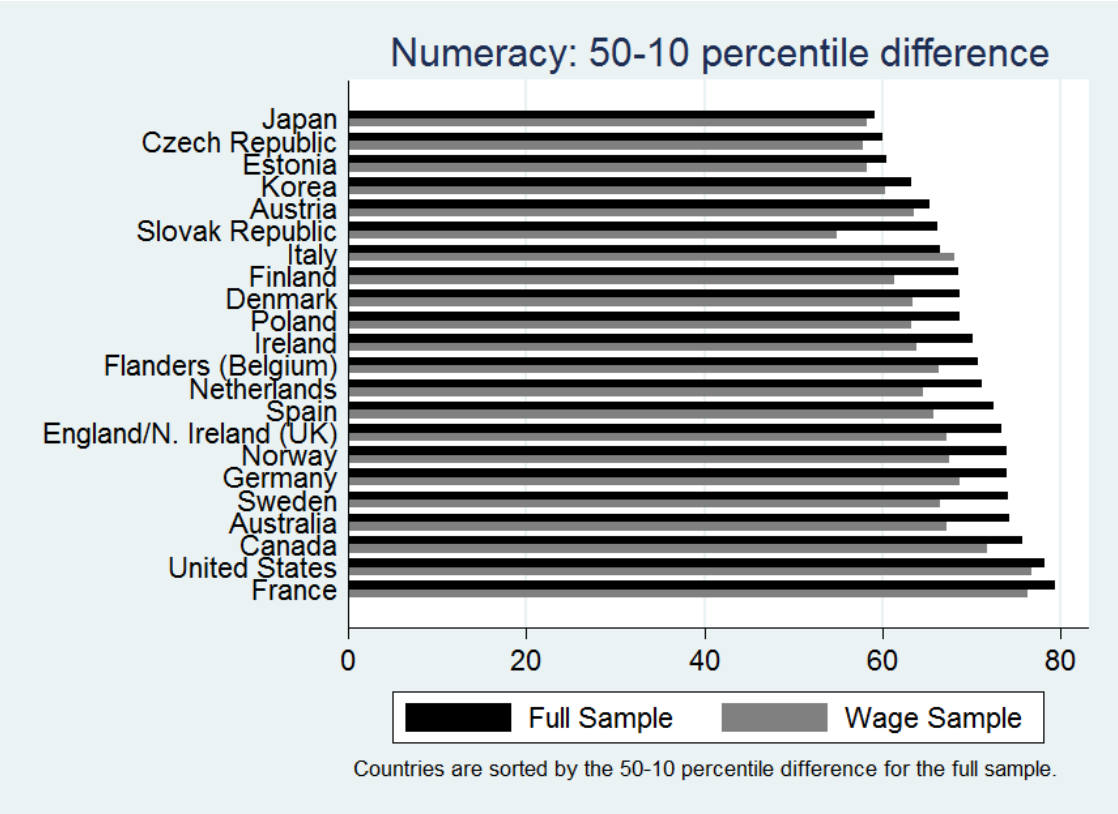
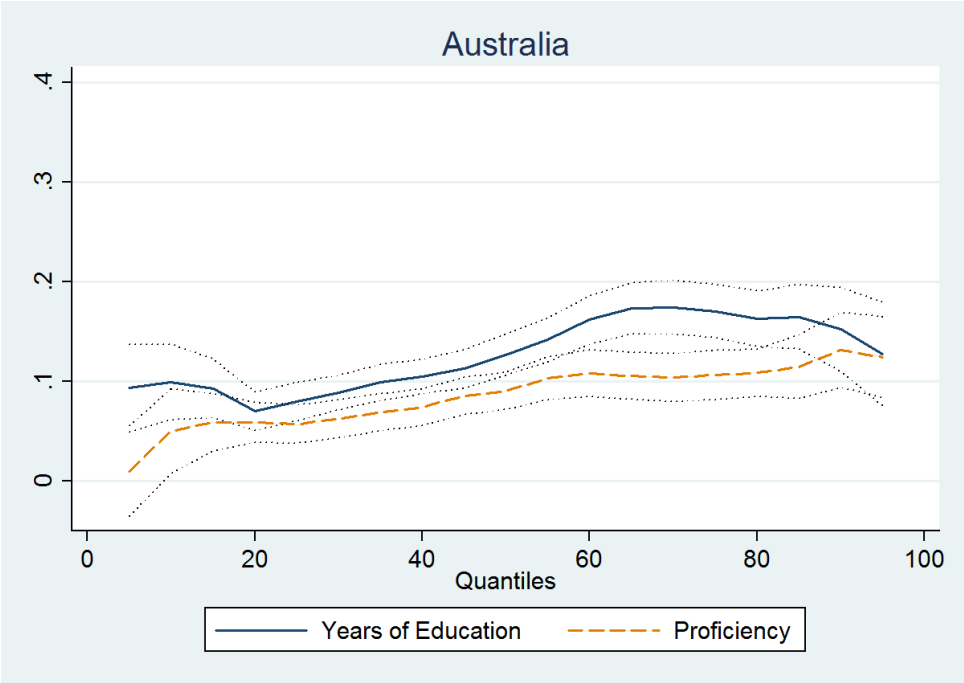


Figure 24

A2 – RETURNS TO SKILLS AND EDUCATIONS AT DIFFERENT QUANTILES – COUNTRY GRAPHS



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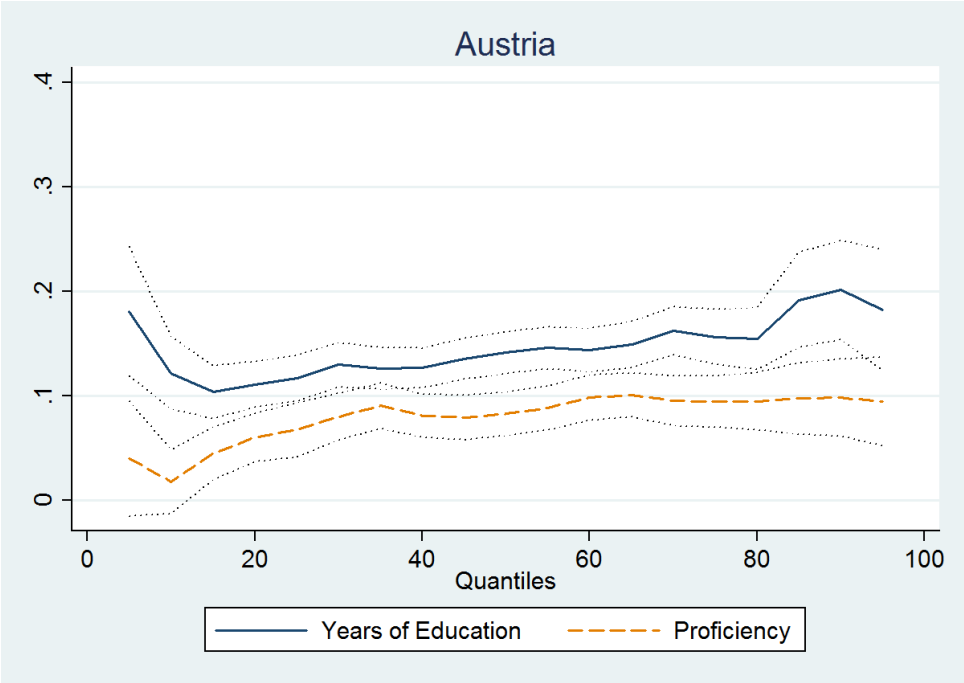

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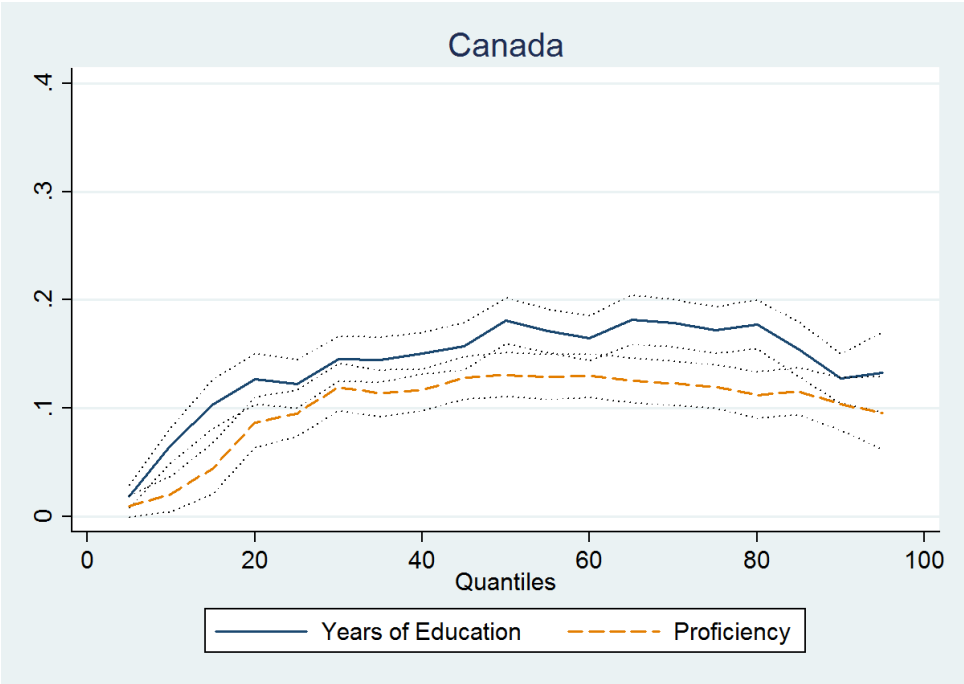

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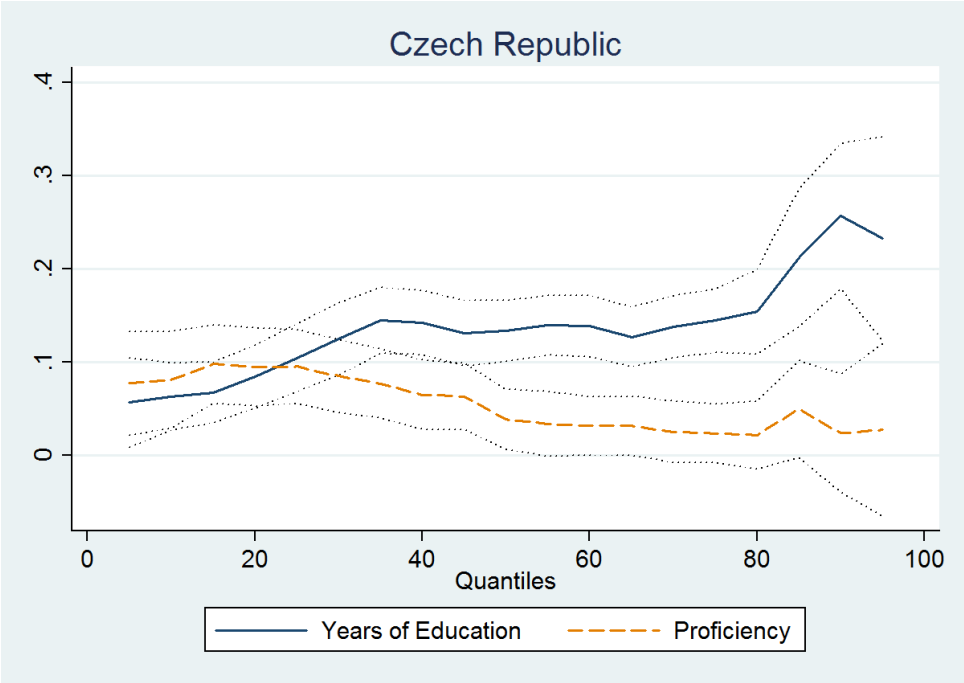

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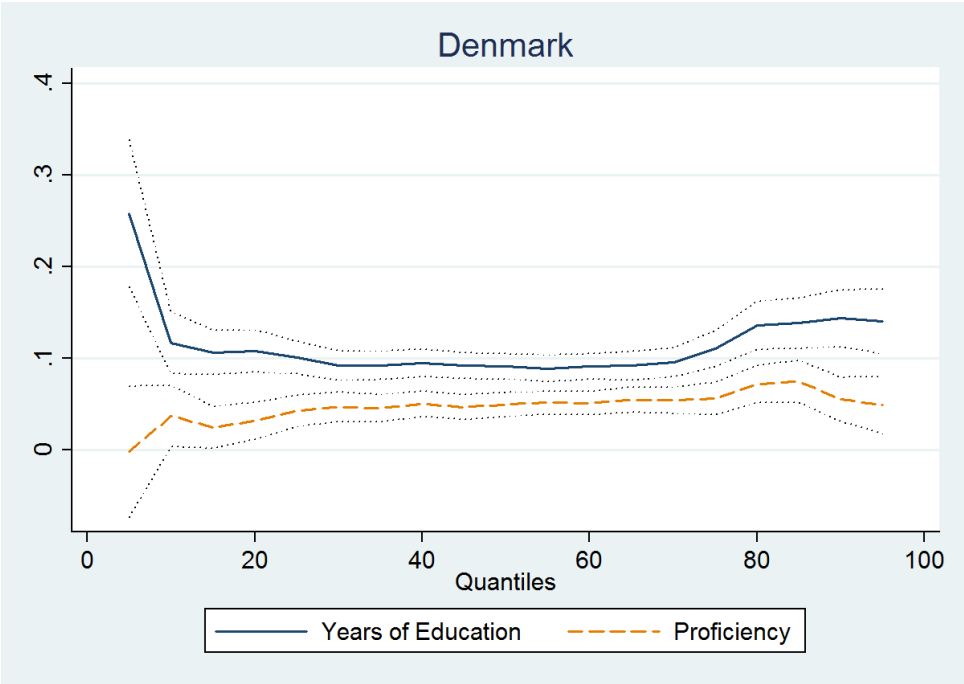

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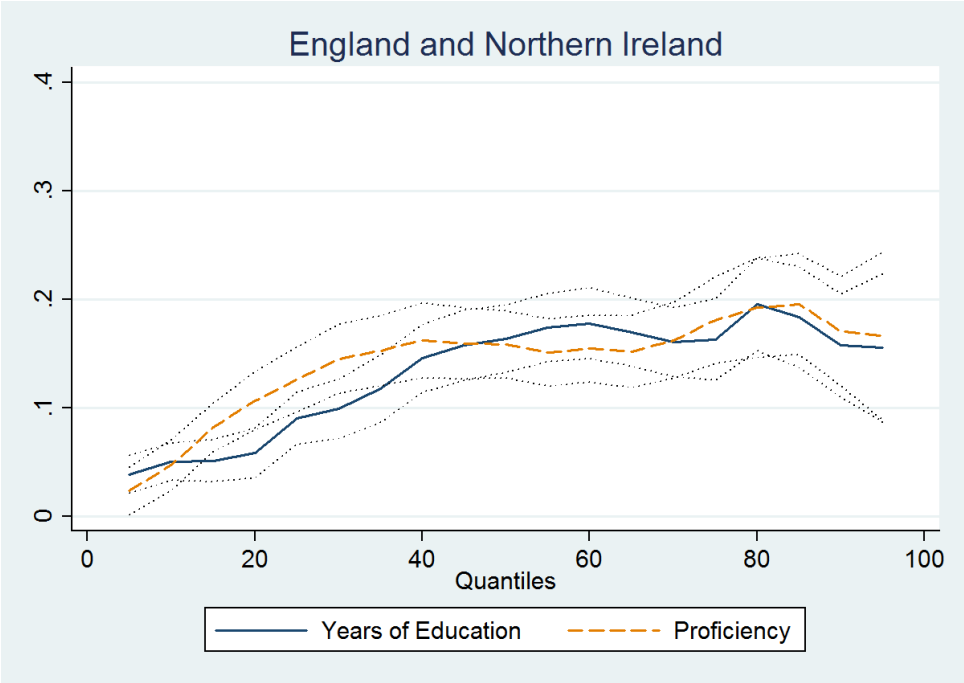

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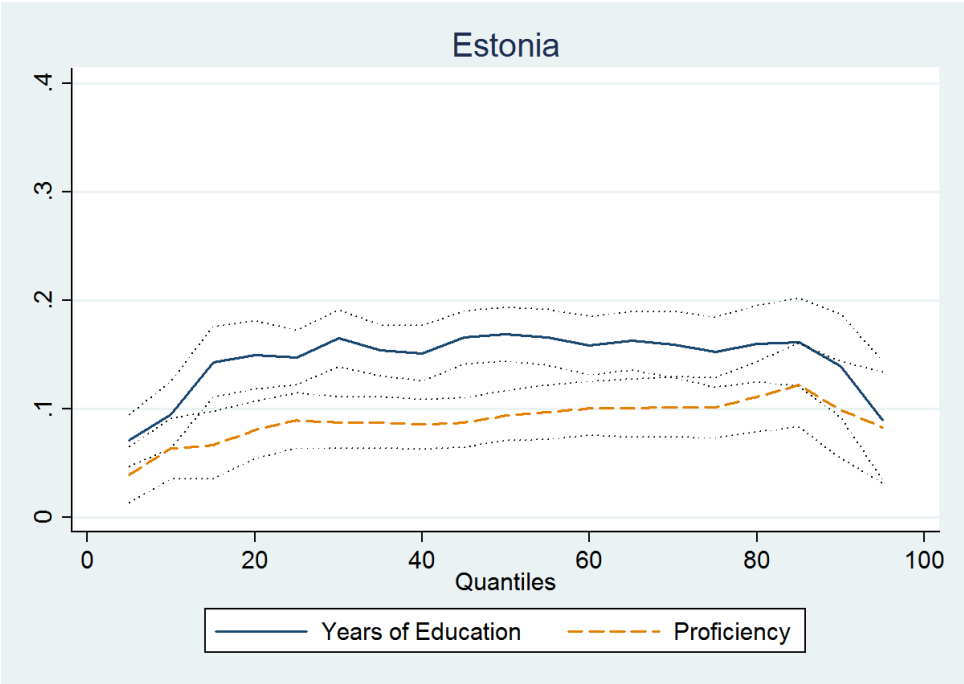

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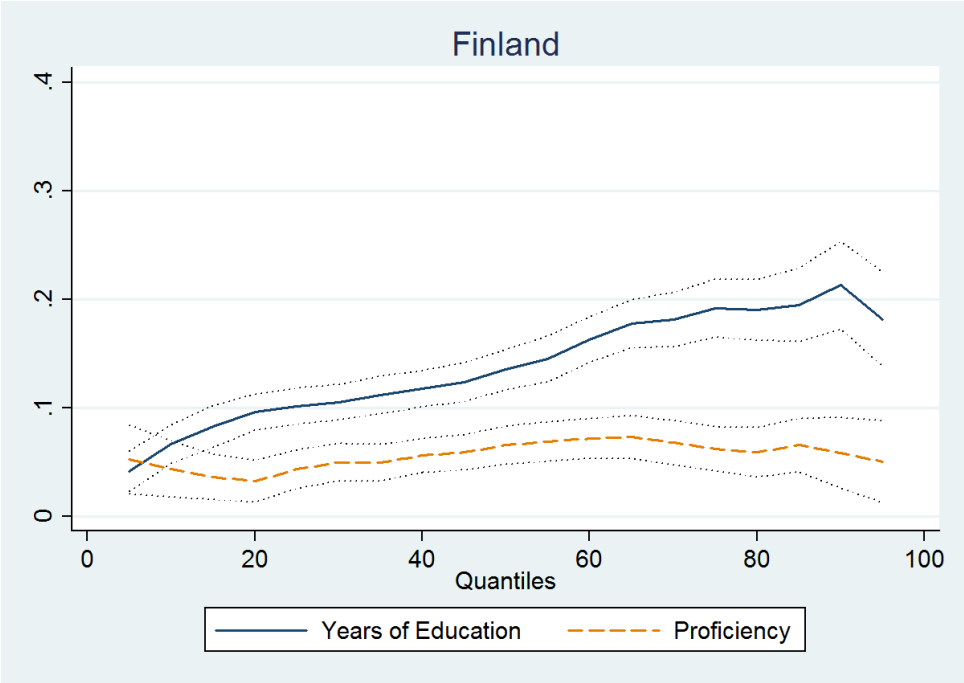

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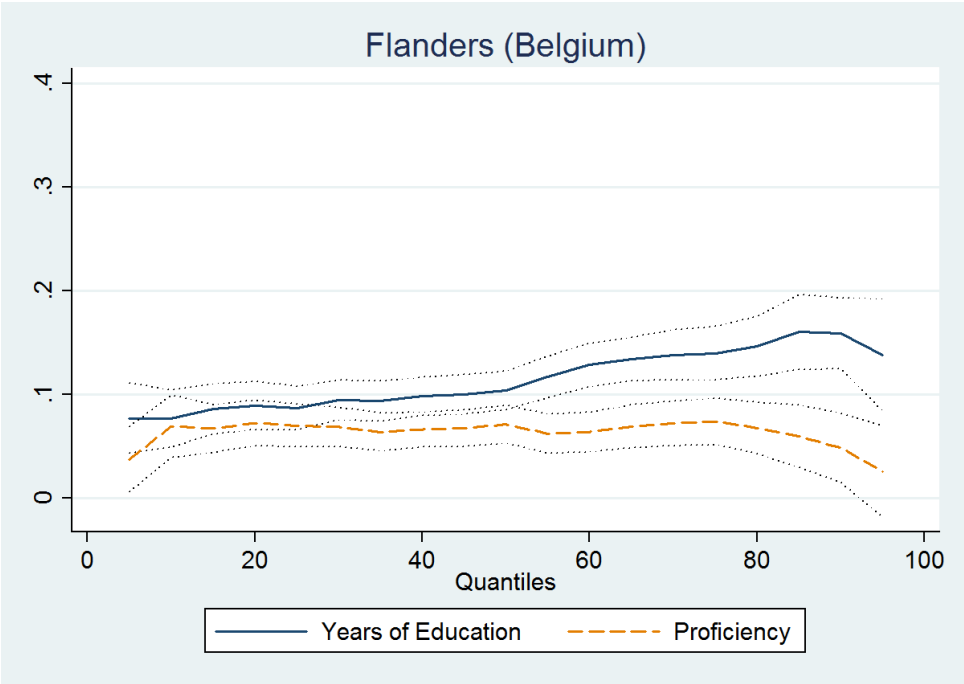
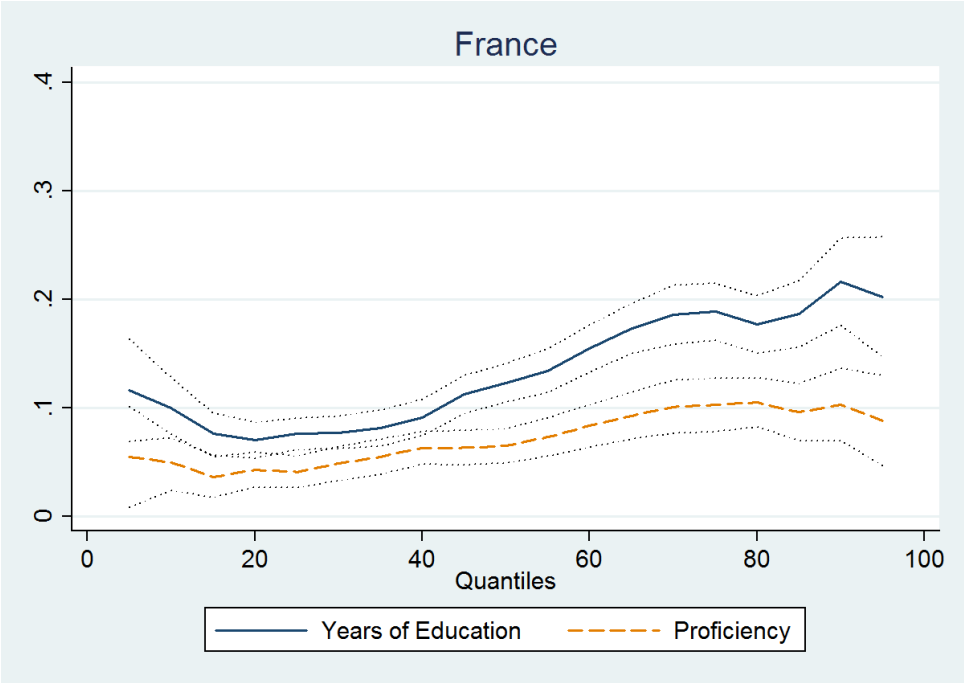


Figure 33



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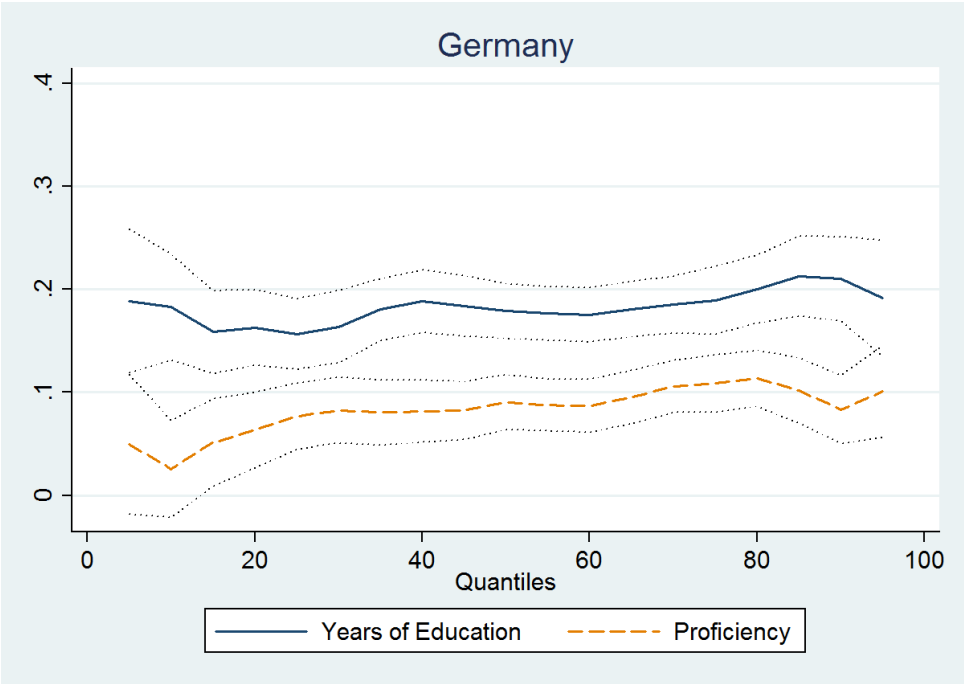

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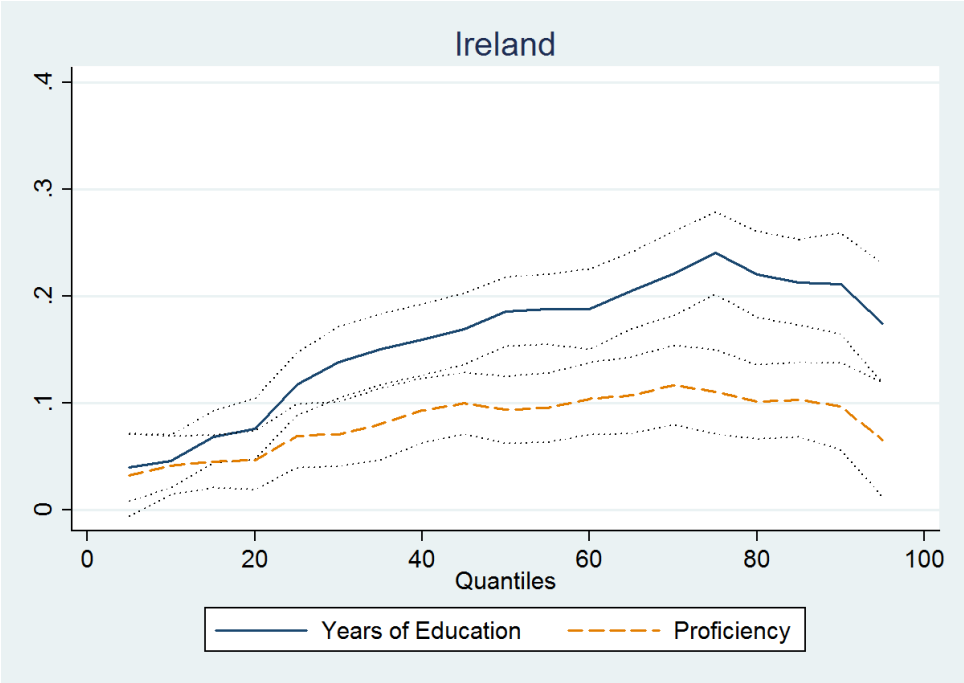

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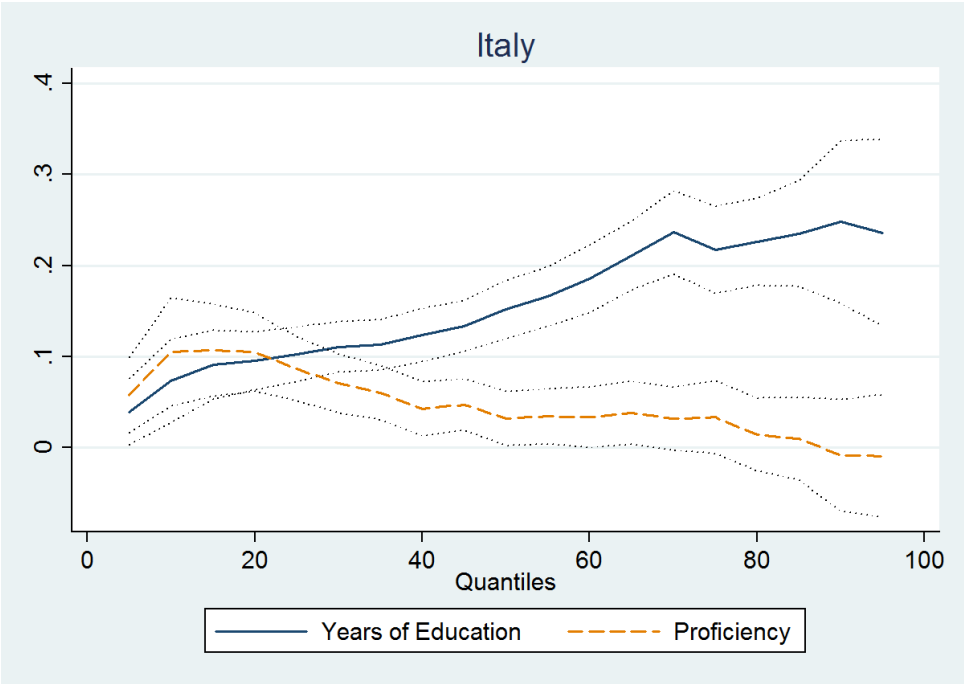

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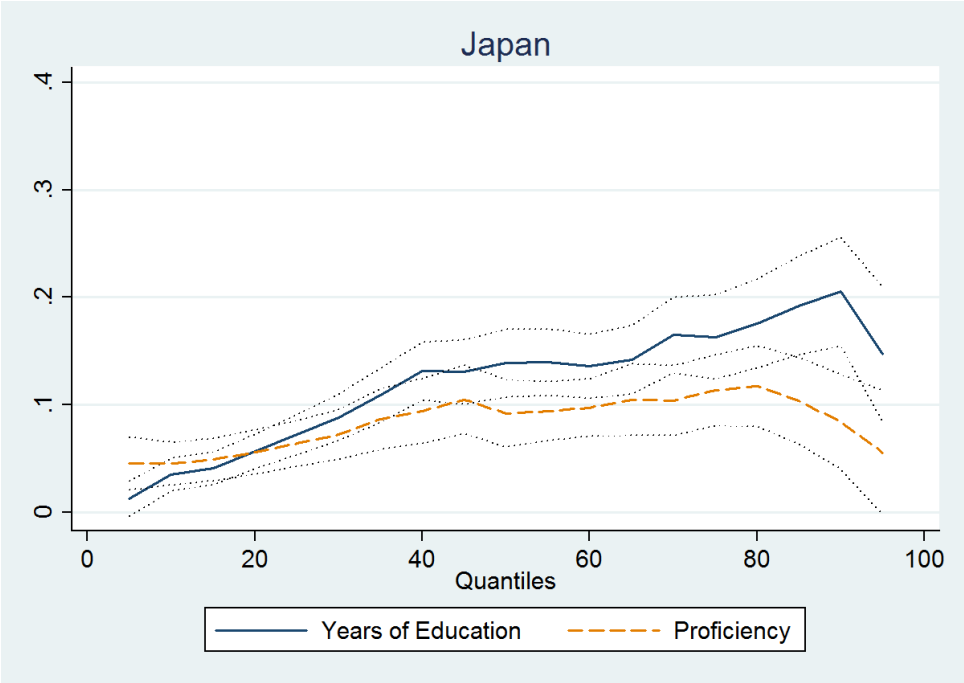

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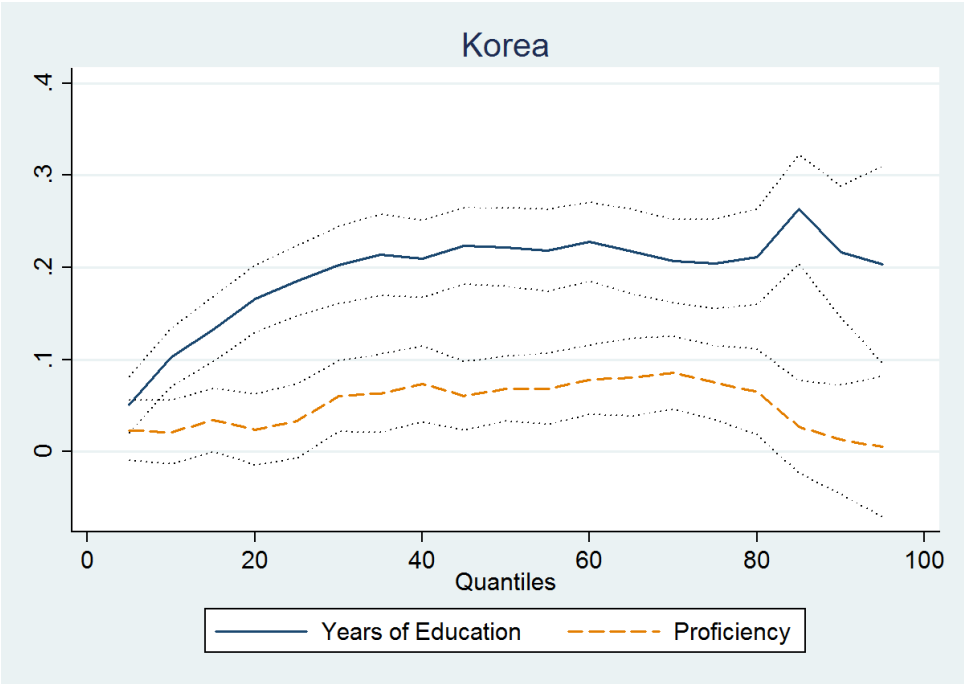

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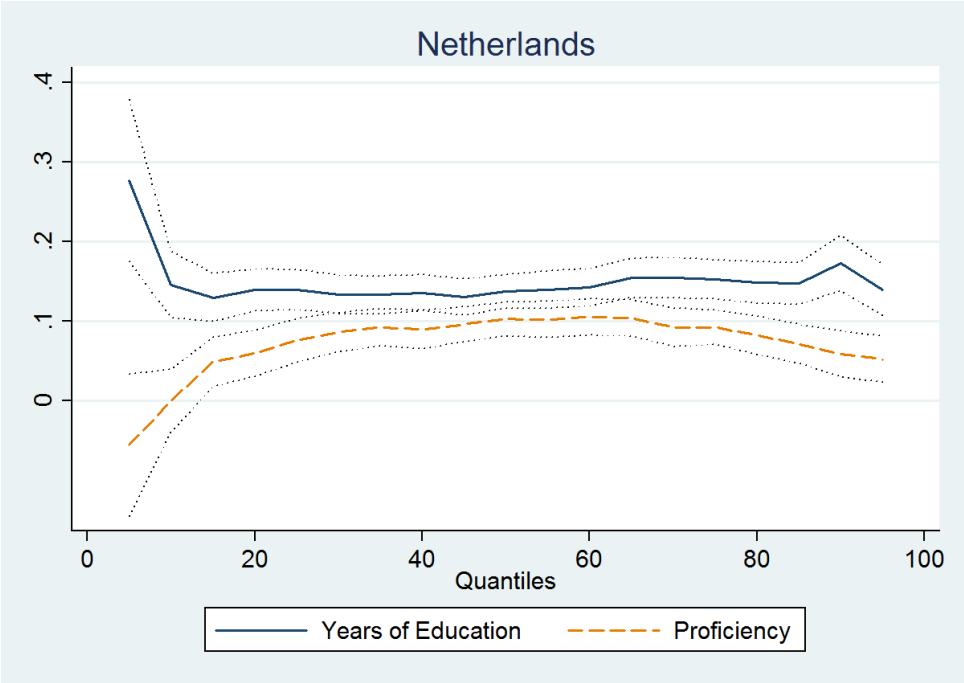

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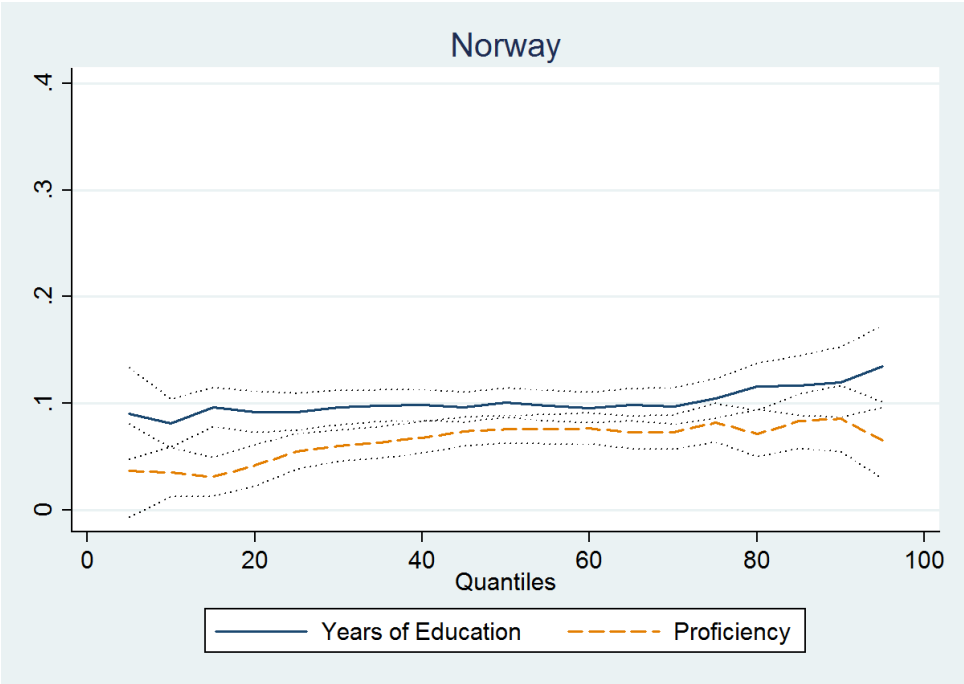

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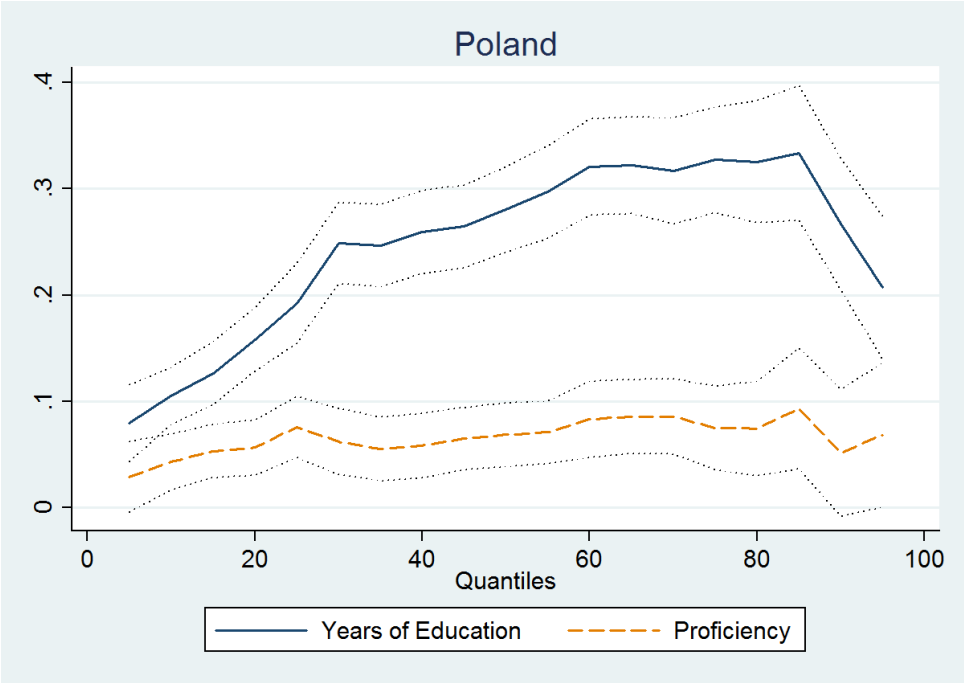

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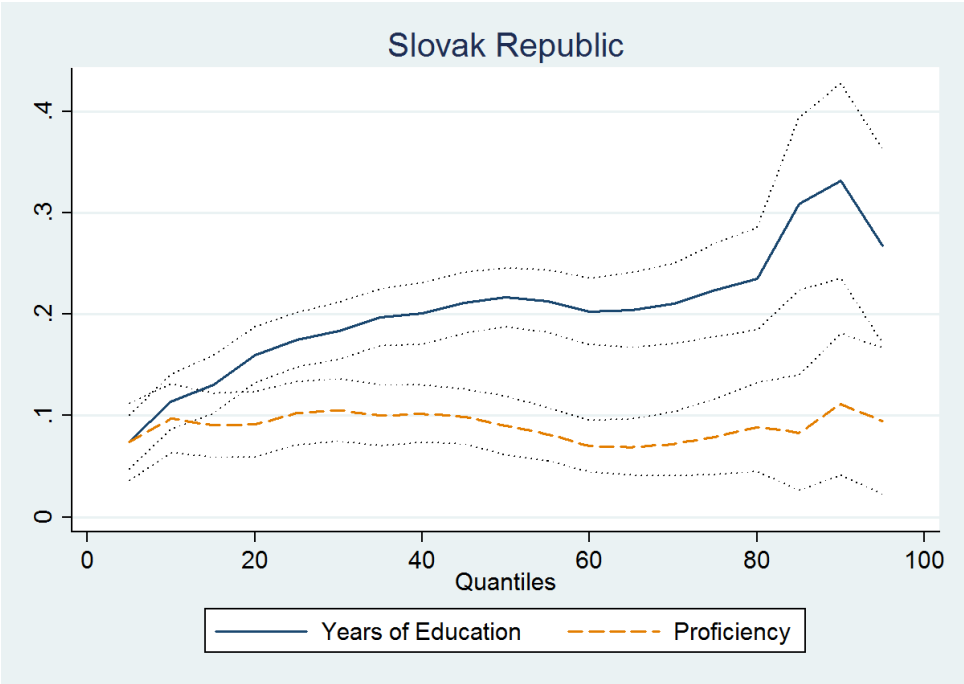

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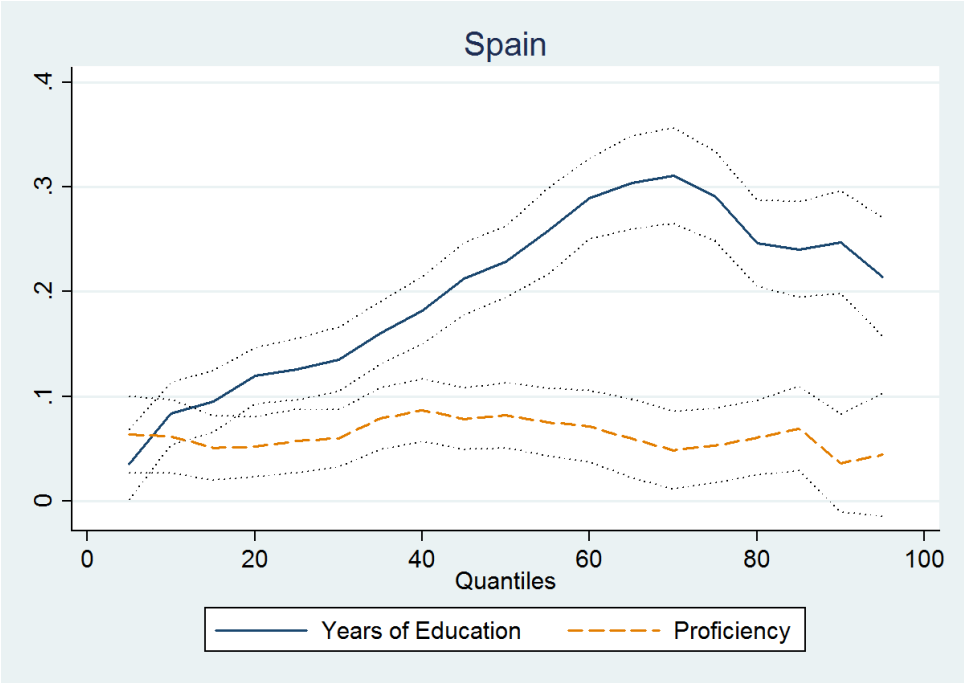

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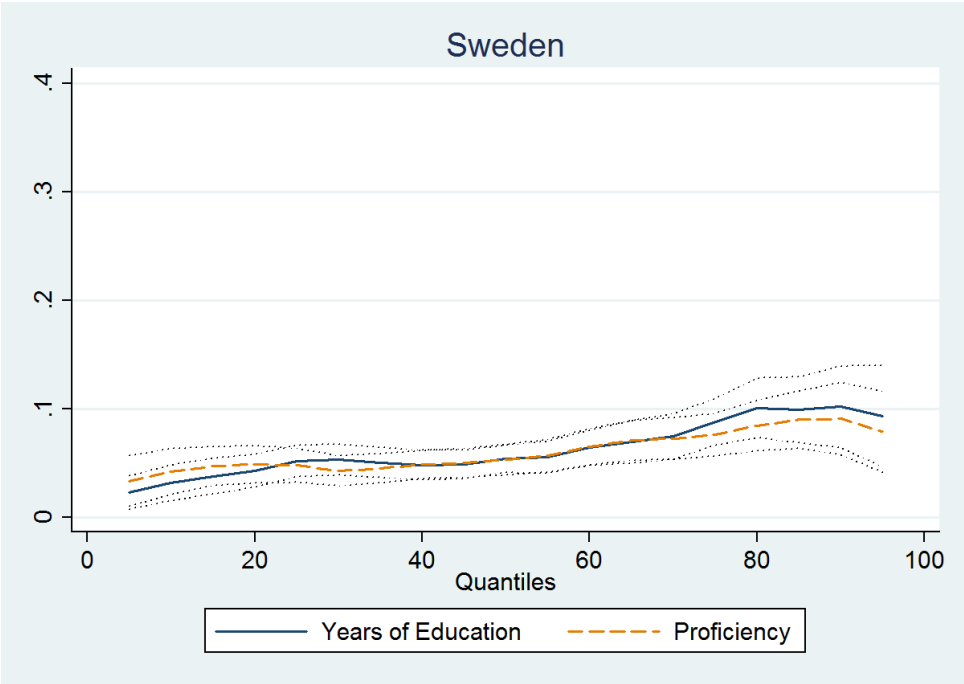

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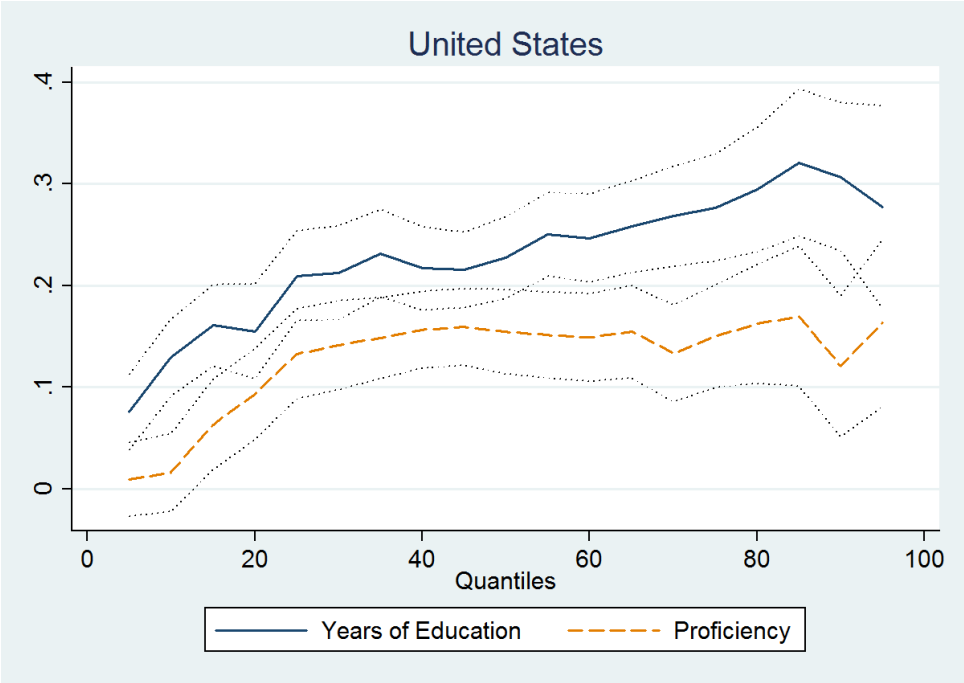

Figure 46

OECD INITIATIVE ON NEW APPROACHES TO ECONOMIC CHALLENGES

The OECD initiative on "New Approaches to Economic Challenges" (NAEC) is an organisation-wide reflection process on the causes of the crisis and the lessons for policy. It was launched at the 2012 OECD Ministerial Council Meeting (MCM) with the objective to catalyse a process of continuous improvement of the organisation's analytical frameworks and advice.

www.oecd.org/naec

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BETTER POLICIES FOR BETTER LIVES