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This paper investigates how much of the difference in wage distributions is related to differences in skill distributions and whether a compressed wage distribution is associated with high unemployment across core OECD countries. Some countries that have more compressed (dispersed) wage structures simultaneously have more compressed (dispersed) skill structures as well, and according to many economists, variations in skill inequality can explain variations in wage inequality across different countries. Firstly, this paper examines the relationship between skill compression and wage compression; secondly, wage compression is linked to labor market outcomes in terms of employment. Compressed wage structure (usually caused by labor market institutions) is often seen as a cause for high unemployment in the low-skill sector. Does the wage compression hypothesis hold? Based on the PIAAC survey of adult skills for seventeen OECD countries, this paper seeks to shed light on these two important topics.

JEL Code: J31, J24, E24

Keywords: wage distribution, earnings, skill distribution, employment

1. Introduction

The variation in wage inequality across developed countries has puzzled economists for many years, and different theoretical explanations and empirical evidence have been presented on this issue. Some economists argue that these differences can be explained by supply and demand factors, whereas others emphasize the influence of wage-setting institutions on the wage structure. Consistent with the first theory, the variations in wage inequality across different countries can be explained by variations in skill inequalities. Countries that have more compressed (dispersed) wage structures simultaneously have more compressed (dispersed) skill structures as well (Nickell and Bell, 1996[1]; Leuven *et al.*, 2004). According to neoclassical theory, supply and demand factors and skill-biased technical change (SBTC) are responsible for the increase in wage inequality in the past decades (Katz and Murphy, 1992; Juhn et al 1993; Katz and Autor, 1999), and market forces play a more significant role in explaining cross-national differences in wage inequality and return to skill than institutional factors (Gottschalk and Joyce, 1999). Since the Anglo-Saxon countries had simultaneously higher wage and skill inequalities compared to continental and Nordic Europe, this was taken as proof of the theory. According to this theory, wage inequality is related to skill inequality, and cross-country differences in skill distribution explain cross-country differences in wage distribution. The reasoning behind this theory is that increase in inequality leads to higher return to skills, which in turn increases motivation to invest in skill formation (Heckman *et al.,* 1998; Welch, 1999). This theory, however, fails to explain high educational attainment in Nordic countries, which exhibit among the lowest rates of wage inequality when compared to other developed countries.

Another set of explanations for variation in wage dispersion is based on the variation in wage-setting institutions. Economists who are in favor of this hypothesis stress the importance of decreasing real minimum wages and unions in order to explain the widening wage gap (Freeman, 1991; Freeman and Katz, 1994; Blau and Khan, 1996; Bach *et al.,* 2007). A similar conclusion comes from Dew-Becker and Gordon (2005, 2008), who, in addition to these explanations, identify peer-group behavior as responsible for increasing wage dispersion at the top of the distribution in the US. Card and DiNardo (2002) reach similar conclusions and also criticize the skill-biased technical change argument as being unable to account for gender and racial wage inequalities and differences in return to education. This set of explanations

[1] In his paper, however, skills are measured by years of schooling and not by competency test scores

will not be thoroughly discussed in this paper. The first question this paper attempts to answer is whether there is enough evidence for the skill compression hypothesis. How much cross-country variation in wage distribution is related to variation in skill distributions?

The second question this paper tries to answer looks at the relationship between wage inequality and employment. According to neoclassical theory, differences in wage dispersion are often credited as an important explanation for differences in unemployment rates. Whereas dispersed wage structure can contribute to employment creation, wage compression (usually assumed by labor market institutions) can cause unemployment (Siebert, 1997; Heckman and Jacobs, 2010). Due to the skill-biased technical change, relative demand for low-skilled workers in developed countries exhibited a decline. At the same time, wage compression and excessively high wages at the low end of the wage distribution cut low-skilled workers out of employment. By comparing the distribution of wages and employment in Germany and the US, Siebert (1997) concludes that the relevant policy recommendation to increase employment in Germany at the low end is to allow for dispersed wage structure (higher wage inequality). After first examining the relationship between skill compression and wage compression, wage compression is linked to labor market outcomes in terms of employment. Can cross-country differences in employment be explained by cross-country differences in wage inequality?

A certain body of literature deals with these issues, and this paper can be seen as its extension. Freeman and Schettkat (2001) examine the wage compression hypothesis based on the differences between the US and Germany regarding employment. They find that skill compression can only partly explain wage compression. However, the wage compression hypothesis cannot explain the US-German difference in employment. Devroye and Freeman (2001) study the relationship between distribution of earnings and distribution of skills and find that skill inequality explains only 7% of wage inequality. Within-skill-group inequality plays a larger role than inequality between skill groups; this contradicts the theory. Paccagnela (2014) investigates the relationship between skill inequality and wage inequality based on PIAAC data and finds no strong relationship between the two. Hanushek *et al.* (2014) examined return to skills based on the PIAAC data set and find significant heterogeneity between the countries. Returns to skills (associated with a one-standard-deviation increase in measured numeracy test scores) vary between 12-15 percent in Nordic countries and 28 percent in the United States. This is explained by higher union density, stricter employment protection, and a larger public sector in the Nordic countries.

This paper shares the most similarities with the work of Freeman and Schettkat (2001), Freeman and Devroye (2001) and Paccagnela (2014). In contrast to the first two studies that were based on the international literacy survey in the '90s (International Adult Literacy Survey - IALS), a more recent data set is used, with a larger number of countries and larger sample sizes. It is interesting and important to check whether the results based on the IALS survey can be confirmed by using the Program for International Assessment of Adult Competencies (PIAAC). In addition to Paccagnela (2014), who also uses PIAAC to analyze skill and wage inequality, in this paper the analysis is extended by covering the link to employment as well.

This paper is organized as follows. In section two, the data set and data adjustments are presented in more detail. This section is followed by an empirical analysis in sections three, four and five. Firstly, the relationship between skill inequality and wage inequality is examined in order to reveal if variation in wage inequality across OECD countries is associated with the variation in skill inequality and how much of wage inequality is attributable to skill inequality. In section six, dispersion of wages within skill levels is investigated. Section seven analyses wage compression hypothesis and its effect on employment. Finally, section eight concludes.

2. Data Description

This analysis is based on the PIAAC data set that was collected between 2011 and 2012 and initiated by the OECD. PIAAC is a unique data set that provides numerous opportunities for research, because it comprises the survey data on various indicators of skill competencies, earnings, demographic, socio-economic, and other information internationally comparable across OECD countries. Since countries' sample sizes are bigger than in previous similar data sets (around 5,000 observations per country), such a sample facilitates more comprehensive analysis and better investigation of different sub-groups. People were questioned on the basis of 1.5-2 hours interview, which was performed by a specially trained interviewer (tests were done either on computer or on paper). The adult competency skills are measured by literacy, numeracy, and problem-solving in technology-rich environments[2] that are central for good performance in the labor market. That is why the skills tested in the survey should be a good proxy for the skills needed in the workplace. According to the test score results, six different proficiency levels are created. The pooled dataset used in this paper contains national representative samples of around 120,000 observations based on representative working age population (16-65) from 17 different highly developed core OECD countries. Countries included in the dataset are Austria, Belgium[3] (Flanders), Canada, Denmark, Finland, France, Germany[4], Ireland, Italy, Japan, Korea, Netherlands, Norway, Spain, Sweden, Great Britain (England and Northern Ireland), and the United States.

The definition of the PIAAC literacy test is as follows, "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." Numeracy assessment is defined as the ability to access, use, interpret, and communicate mathematical information and ideas and to engage in and manage mathematical demands of a range of situations in adult life. Finally, problem solving accounts for "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks" (OECD, 2013:59).

The correlation coefficient between different test results is slightly lower than in previous test surveys (ALL or IALS) but is still highly positive. The correlation coefficient between numeracy and literacy scores is the highest and equal to 0.89, followed by the correlation coefficient between literacy scores and problem-solving skills (0.79). The smallest correlation coefficient is found between numeracy scores and problem-solving scores in technology-rich environments (0.75). In this analysis, numeracy test scores are used as a measure of skill test results, which is standard in this literature, but more in-depth analysis actually showed that the same results are confirmed when literacy test scores are used.[5] Furthermore, the bottom and top 1% of the wage distribution are excluded from the analysis, due to the probable measurement errors and large outliers[6]. After these abovementioned data adjustments have

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[2] Problem solving is not measured in France, Italy, and Spain.

[3] Belgium is represented by its subunit Flanders. It is the most developed part of the country, with the lowest unemployment rate, and it cannot be considered as a representative for the whole country. It is important to keep this in mind when interpreting the study results.

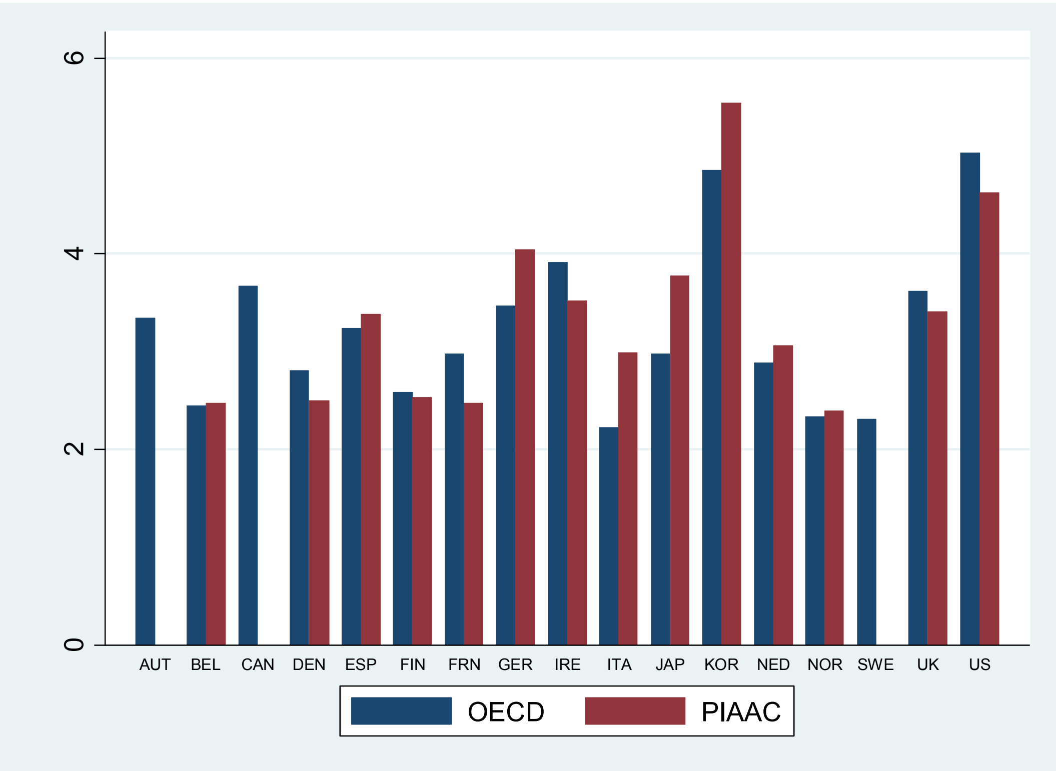
[4] For Germany and the United States, we obtained a Scientific-use file. For Austria, Canada, and Sweden information about continuous earnings is not available.

[5] These are available on request.

[6] The total number of observations in the pooled data set drops from 120,000 to 46,363, mainly due to the fact that there is no wage data for some countries and there is also missing data on wages in some other countries.

been performed, it is vital to compare the wage data from the micro data set – the PIAAC survey with the macro data from the OECD database. Figure 1 displays wage inequality taken from both databases and apart from a couple of outliers (Korea, Japan, Italy, and Germany have higher wage inequality; France and the US have lower wage inequality in the PIAAC survey comparative to the OECD database[7]), and micro data seems to correspond well to the aggregate macro data. According to both data sources, ranking of the countries in terms of inequality is almost unaffected. If D9/D5 and D5/D1 are observed, deviations between the datasets are even smaller.

Figure 1: Wage inequality (D9/D1) for 17 OECD countries, only employed persons



Source: OECD Earnings database and PIAAC.

[7] OECD Earnings Database collects data on gross earnings of full-time dependent employees which are usually taken from household surveys.

3. Skill Distribution

According to the OECD database, in the past 30 years, wage inequality has been on the rise in almost all of the OECD countries (see Jovicic and Schettkat, 2013). On one hand, the increase in inequality has been criticized by many economists; on the other hand, many others have justified this development as a result of the rise in skill inequality (see introduction). In order to get a better insight on the relationship between wage inequality and skill inequality, a deeper look into the data set is necessary. Table 1 presents the mean, median, standard deviation, and coefficient of variation of numeracy scores in 17 OECD countries. If all people are included, independent of their employment status, Anglo-Saxon countries together with France and Spain have the highest dispersion of skills, whereas Japan and Korea have the lowest inequality of skills. In terms of employed persons, the countries with the highest skill inequality among employed workers are the United States, France, and Italy (followed by Canada, the United Kingdom, and Ireland). Japan, Finland, and the Netherlands (followed by Korea, Denmark, and Belgium) have the lowest coefficient of variation of numeracy test results. There seems to be a significant cross-country difference in skill inequality.

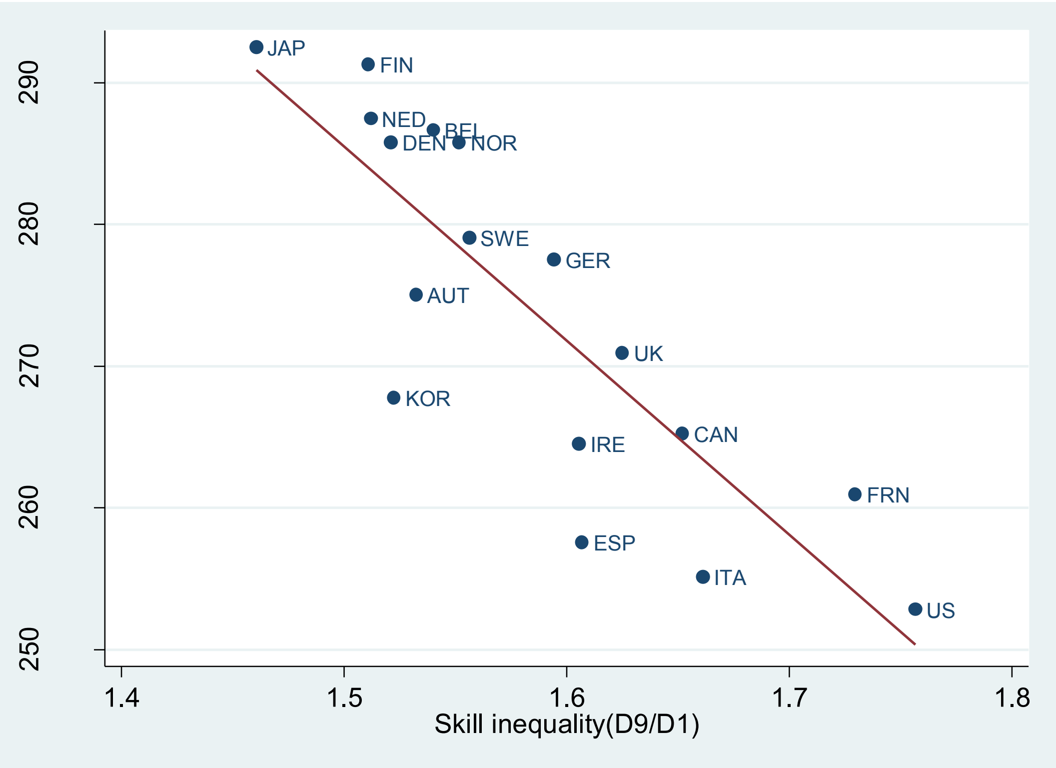
Another very important conclusion can be drawn from this table. Countries with the highest skill inequality exhibit the lowest average scores. Figure 2 presents the relationship between skill inequality and average skill scores. The relationship is negative and highly statistically significant, which means that countries with higher skill inequality exhibit lower average skill scores, whereas the countries with lower skill inequality perform better in terms of average skill scores (mean). This result is in line with the results of Freeman *et al.* (2011), who find an inverse relation between the within-country dispersion of scores and the average level of scores by country, based on the two waves of PISA mathematics tests (2000 and 2009) for 42 countries. Moreover, they observe that countries that have high test performance have better results at the bottom of the distribution. If the median is observed instead of the mean, the conclusion is the same. In every country, the median is only slightly higher than the mean; the difference between the two measures ranges between a maximum five points and a minimum two points (the distribution of skills is just slightly skewed to the left). This leaves the ranking of the countries according to their average results unaffected if the median is used (instead of the mean).

Table 1: Mean, median, standard deviation, and coefficient of variation of numeracy scores for all and employed persons

	All persons				Employed			
Country	mean	median	st dev.	var.coef	mean	median	st dev.	var.coef.
Canada	265.2	269.6	55.60	0.21	271.6	275.0	52.77	0.19
Denmark	278.2	282.0	51.23	0.18	285.7	288.9	47.63	0.17
Finland	282.2	285.8	52.21	0.18	291.3	293.2	47.63	0.16
France	254.1	259.1	56.17	0.22	260.9	265.1	54.42	0.21
Germany	271.7	275.9	53.07	0.20	277.5	280.4	49.71	0.18
Ireland	255.5	259.5	53.66	0.21	264.5	267.0	49.91	0.19
Italy	247.1	249.2	49.99	0.20	255.1	258.0	49.9	0.20
Japan	288.1	290.8	43.98	0.15	292.5	294.7	43.44	0.15
Austria	275.0	278.2	49.29	0.18	279.7	282.8	47.53	0.17
Korea	263.3	267.1	45.64	0.17	267.8	271.1	44.2	0.17
Netherlands	280.3	285.8	51.07	0.18	287.4	291.7	46.99	0.16
Flanders (Belgium)	280.3	284.4	50.59	0.18	286.6	290.2	48.42	0.17
Norway	278.3	283.5	54.21	0.19	285.8	289.9	50.55	0.18
Spain	245.8	250.3	51.32	0.21	257.5	261.3	47.58	0.18
Sweden	279.0	284.0	54.87	0.20	287.2	290.4	50.26	0.17
England/N. Ireland (UK)	261.7	264.9	54.88	0.21	270.9	273.3	51.6	0.19
United States	252.8	256.0	57.03	0.23	260.0	264.0	55.95	0.23

Source: Calculations based on PIAAC.

Figure 2: Relationship between skill inequality and average numeracy score results (mean), employed persons



Source: Calculations based on PIAAC.

In order to develop a better understanding of the cause of the difference in average score results, one must examine the share of people within different skill levels. Skill levels are defined according to test scores and divided into six different groups. People with the highest scores are assigned to group levels 5 and 4, whereas levels 0 and 1 are the groups with lowest numeracy scores.[8] Table 2 provides an answer to the previous question – the countries with the highest skill inequalities have the highest proportion of workers in the lowest skill group (below level 1 and at level 1) – Italy, the United States, France, and Spain. Japan, the Netherlands, and Finland (followed by Denmark and Belgium) have the lowest percentage of least-skilled workers. These countries, however, also have slightly higher percentage of people in the highest skill group[9]. According to the PIAAC survey, the difference in average skill results between the countries comes from both percentage shares of low- and high-skilled employees among the whole employed population – countries with the highest test performance simply have more high-skilled workers and less low-skilled workers than the low performance countries. That is the main reason their score results are comparatively high.

Table 2: Share of population in 6 different skill levels, employed persons

	Level 0+1	Level 2	Level 3	Level 4+5
Country	%	%	%	%
Canada	18.76	32.00	34.84	14.39
Denmark	10.12	28.67	42.11	19.11
Finland	8.18	27.28	41.46	23.08
France	24.31	33.57	31.73	10.4
Germany	14.93	31.59	37.51	15.98
Ireland	20	37.63	32.66	9.71
Italy	26.55	37.59	29.61	6.24
Japan	6.84	26.03	45.35	21.78
Austria	12.11	32.20	40.11	15.57
Korea	16.08	38.52	37.60	7.79
Netherlands	9.63	27.26	43.34	19.77
Flanders (Belgium)	10.62	27.57	41.36	20.45
Norway	11.03	27.41	40.93	20.63
Spain	23.07	39.75	31.40	5.77
Sweden	10.84	26.97	40.34	21.86
England/N. Ireland (UK)	18.79	33.41	33.82	13.99
United States	25.41	33.43	30.47	10.69

Source: Calculations based on PIAAC.

[8] Skill levels are defined according to numeracy score results in the following way: L0<176; L1= 176-226; L2=226-276; L3=276-326; L4=326-376; L5>376 points.

[9] Share of population in skill groups L0 and L5 is very low and not representative; that is why they are observed together with groups L1 and L4.

With the aim of performing a more detailed and careful analysis, it is noteworthy to determine if there are differences in performance between different subgroups as well. Table 3 displays average scores according to different gender, immigration, and age cohorts. The difference between men and women seems to be only marginal. On average, men have slightly higher proficiency scores than women, but this is true for every country. Since women acquire on average slightly higher average years of schooling (apart from Korea and Japan), this result is somewhat surprising. However, since women often demonstrate poorer scores in the quantitative tests, comparing additionally the literacy test results shows that there is no difference at all in the test performance (both cohorts have average literacy scores of 278 points). On the other hand, immigrants have much lower results than non-immigrants – around 35 points less on average. The biggest reason for this is the fact that the test was done in the countries' national languages; immigrants are disadvantaged comparatively to the non-immigrants and often experience difficulty with the foreign language. This may suggest underestimation of their proficiency skills. The only two countries where the difference is moderately small are Ireland and Canada. Canada is a large immigration country where immigration and integration policies probably play a big role and contribute to higher language proficiency of immigrants. When age cohorts are compared, the difference is only marginal in almost all groups, aside from the oldest age group. People in the older age cohorts have lower results on average, probably due to the fact that older people tend to forget and experience decline in skills after age forty-five, but especially after the age of fifty, according to Table 3. In most countries, the lowest age group also tends to have slightly lower proficiency scores than the age groups from 25-45. What stands out is that, in Denmark, Italy, and the US, these age cohorts have similar results to the oldest age cohorts, which is particularly alarming (especially in the US and Italy, since they also have very low scores). One reason for this (and comparatively lower young age cohort results in general) could be that the education systems alone do not produce relevant work-related skills and that the quality of schooling and the standard of education system are deteriorating.

Table 3: Mean of numeracy scores in different gender, immigrant and age groups, employed persons

Country	Men	Women	Non-immigrant	Immigrant	Age (16-24)	Age (25-34)	Age (35-44)	Age (45-54)	Age (55-65)
Canada	277.32	265.33	275.95	262.5	.	.	.	.	.
Denmark	289.96	281.55	289.43	254.26	276.87	290.96	295.59	283.4	275.58
Finland	297.04	285.93	293.95	235.79	289.11	306.47	296.51	288.9	270.07
France	265	256.85	267.24	226.17	260.97	276.59	268.15	251.24	237.58
Germany	283.59	270.89	282.62	255.51	277.74	284.96	286.12	271.59	264.14
Ireland	270.05	259.66	265.4	261.01	262.43	271.13	270.8	257.91	243.34
Italy	255.82	254.19	258.65	222.72	232.03	265.66	257.54	252.8	240.83
Japan	298.07	285.35	292.56	266.98	282.61	301.13	299.47	295.66	275.15
Austria	285.77	273.26	285.14	254.9	.	.	.	.	.
Korea	271.16	263.21	268.57	213.5	274.72	281.17	274	253.78	240.47
Netherlands	294.13	280.31	291.8	255.46	287.44	298.73	292.58	282.48	268.82
Flanders	292.75	280.17	290.08	247.65	278.4	298.8	290.91	282.82	268.42
Norway	292.16	279.36	291.67	246.83	277.99	289.73	295.24	286.3	272.43
Spain	263.63	250.8	261.33	230.15	258.98	262.94	264.37	253.4	234.01
Sweden	292.2	281.69	294.12	255.36	286.57	297.08	293.2	282.35	276.34
UK	276.96	264.64	275.51	249.84	263.29	279.51	278.94	264.14	261.01
US	265.71	253.79	265.64	235.46	249.81	260.34	257.48	250.39	247.07
Average	**280.67**	**269.82**	**279.39**	**245.53**	**272.08**	**286.06**	**283.10**	**271.91**	**259.16**

Source: Calculations based on PIAAC.

Table 3 reveals some differences between various cohorts, thus it is reasonable to see whether they also have effect on average scores and dispersion of numeracy scores. Cohorts that showed significantly lower average results were immigrants, followed by the oldest age group and women. Whereas the share of women and the share of the oldest age group are comparable across countries, there is a significant variation in the share of immigrants across countries, and this probably affects the average score results[10]. Some countries that have a high share of immigrants in the sample (big immigration countries) tend to have lower average scores. These low results in Canada, the US, the UK, and Ireland can be partly explained by the higher share of immigrants whose skills are underestimated due to the language difficulties. When immigrants are excluded from the sample, the average results tend to be higher in these countries, but the coefficient of variation is slightly reduced as well. This is true for every country, but the reduction is the highest in the US. The United States has the highest dispersion of skills, but this phenomenon can be partly explained by the lower score of immigrants. That is why, in the regression analysis that follows in the next chapter, there is always a control that accounts for immigration status.

[10] Share of immigrants varies between 1.4% in Korea and 32% in Canada

3.1 Skills and Schooling

Certainly the most widely used measure of skill in human capital literature is years of schooling. Years of schooling are easy to measure, and they are easily available for researchers. For a long time, this was probably the only measure of skills, since international comparative surveys of skills were first done in the '90s. However, many difficulties arise when it comes to the comparability of this data. When years of schooling is used in the analysis, this must be based on the assumption that one year of schooling has the same effect on human capital formation in every country, which is difficult to confirm. There are many differences between different schooling systems around the world, and this data is not a perfect proxy for human capital. International skill proficiency surveys are thus becoming more and more popular, since their comparability might be better. However, in order to develop a more comprehensive view on the relationship between skill dispersion and wage dispersion, in addition to measuring skills by proficiency score results, years of schooling are also included in the analysis.

According to the estimates, there is a positive but weak correlation between proficiency test scores and schooling – correlation coefficient for the entire PIAAC sample is 0.44 (correlation coefficient varies between 0.36 and 0.60 for individual countries; see Table 5). The fact that schooling and proficiency skills are positively correlated is expected, since higher education produces better skills and, at the same time, better-skilled individuals acquire more schooling. However, the rather small size of the coefficient is somewhat surprising[11]. It seems that there is to some degree a weaker link between scores and schooling, and this result cannot be explained by different cohort effects. One explanation for this factor could be that schooling is related to unmeasured competencies and unobserved non-cognitive skill. However, in order to examine this relationship more thoroughly, one must regress skills on schooling by using the following equation:

$$(1)\ skills_i = \alpha 0 + \Sigma\, \alpha 1_i\, schooling_i + \Sigma\, \alpha 2_i\, experience_i + \Sigma\, \alpha 3_i\, experience2_i + \Sigma\, \alpha 4_i\, gender_i + \Sigma\, \alpha 5_i\, immigrant_i + u_i$$

[11] Additional analysis shows that there is no difference in the correlation coefficient between gender, age, and (non-) immigrant cohorts. The correlation coefficient in all the subgroups varies between 0.41 and 0.48 in the pooled sample.

According to Table 4, one additional year of schooling increases test score results by 7.30 points on average in the core OECD countries. The return to schooling is 10.56 points in the United States, 8.62 in France, and 8.42 points in Germany. The smallest increase in numeracy test results by additional year of schooling is observed in Italy (5.54), Spain (5.91), and Korea (5.92). In the United States and France, and Germany, skills are much more strongly related to years of schooling, which means that, in these countries, people profit from schooling the most in terms of acquiring job-related cognitive skills.[12] France and the US have at the same time very high skill inequality, which corresponds perfectly to skill compression hypothesis. However, the same cannot be concluded for Germany, Italy and Spain. Italy and Spain, have very low return to schooling, but they do not exhibit high skill compression, as the theory would suggest. Germany has very high return to schooling, but its skill dispersion is only moderate in comparison to the other countries. Cross-country data does not seem to fit the theory.

Table 4: Regression of skills on schooling*

Country	Schooling	Controls	Cons	R^2
Denmark	7.20 (0.32)	x	220.93	0.25
Finland	6.28 (0.34)	x	249.38	0.31
France	8.64 (0.27)	x	185.03	0.41
Germany	8.62 (0.38)	x	195.63	0.30
Ireland	7.35 (0.51)	x	175.66	0.22
Italy	5.54 (0.41)	x	204.23	0.24
Japan	7.65 (0.34)	x	198.13	0.26
Korea	5.92 (0.36)	x	208.26	0.32
Netherlands	6.91 (0.34)	x	228.85	0.29
Norway	7.62 (0.37)	x	207.36	0.29
Spain	5.91 (0.33)	x	216.21	0.34
Sweden	8.13 (0.36)	x	225.20	0.28
US	10.56(0.32)	x	157.97	0.37
Belgium	8.53 (0.39)	x	208.68	0.33
UK	7.83 (0.53)	x	194.80	0.20
Pooled	**7.30 (0.10)**	x	**208.45**	**0.29**

Source: Calculations based on PIAAC.

Note: * standard errors are in parentheses. Controls are experience, experience^2, gender, and immigration status.

[12] At the same time, these are the countries with the highest correlation between skills and schooling (see Table 6), comparative to the other countries. This explains partly their higher return to schooling.

4. Skill Inequality and Wage Inequality

In addition to presenting some descriptive statistics on skill distribution, it is essential to examine the distribution of wages. Apart from the individual skill scores, the PIAAC data set provides information on hourly wages[13] of employed persons. This allows the comparison of the two. Table 5 shows dispersion of score results, wages, and years of schooling measured by the coefficient of variation. This data already shows that there is no clear pattern across countries, and that it is hardly possible to claim that wage dispersion is related to skill dispersion. Countries with the highest dispersions of test scores are the United States, France, Canada, and the United Kingdom, whereas the countries with the lowest dispersions are Japan, the Netherlands, and Finland. If wage inequality is observed, countries with the highest wage dispersions are Korea, Japan, and the United States, and the countries with the lowest wage dispersions are Belgium, Norway, Denmark, and Finland. If there was a strong link between skill dispersion and wage dispersion, the data would be expected to show that the countries with the highest skill dispersions exhibit the highest wage dispersion and vice versa; this is not always the case here. Additional analysis also shows that there is no significant difference when wage inequality between different cohorts is observed. In all the cohorts (men, women, immigrants, non-immigrants, different age cohorts), the countries with the highest wage dispersions are still Korea, Japan, and the US, and the countries with the lowest wage dispersions are Belgium and Scandinavian countries (ranking of the countries remains intact).[14] Dispersion of years of schooling is slightly higher than the dispersion of test scores in every country. The only three countries that have relatively high dispersion of schooling are Italy, France, and Spain; countries with the lowest skill dispersion measured by schooling are the UK, Norway, and Germany.

Apart from the distribution of scores, schooling, and wages, Table 5 reports correlation coefficients between these variables. The correlation coefficient between wages and scores is positive but ranges between 0.14 and 0.37 only. This could be additional proof that cross-country variation in scores is not strongly associated with cross-country variation in wages.

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[13] Wage and salary earners could choose among reporting their earnings per hour, day, week, two weeks, month or year, or by piece rate. There was also an option for respondents to report their earnings in broad categories which was especially attractive for those who knew only roughly how much they earn. These novelties improved the data quality and willingness to report earnings (for more details, see OECD, 2013).

[14] In the pooled sample, coefficient of variation does not seem to vary between men, women, immigrants, and non-immigrants. However, wage dispersion is the highest in the youngest and oldest age cohort, and it is decreasing with the decrease of the age in the rest of the groups. The same is true for D9/D5 and D5/D1. Additionally, D5/D1 is slightly higher for men and immigrants than for women and non-immigrants.

Although the variable of years of schooling performs a bit better (its correlation to wages is higher and ranges between 0.24 and 0.51), it can hardly confirm the skill compression hypothesis. Possible explanation for why there is a stronger link between schooling and wages (than between scores and wages) could be that either unmeasured competencies are related to schooling or schooling increases wages through signaling effect – employer assumes that more schooling is positively correlated with having advanced abilities. It could be that schooling has a large effect on wages, without having a large effect on skills measured by proficiency test scores.

Table 5: Coefficient of variation of average numeracy scores, hourly wages and years of schooling, and their correlation coefficient, employed persons

	Coefficient of variation			Correlation coefficient		
Country	Scores	Wages	Schooling	Scores-Wages	Scores-Schooling	Wages-Schooling
Canada	0.19		0.21		0.42*	
Denmark	0.17	0.38	0.20	0.31*	0.39*	0.46*
Finland	0.16	0.38	0.22	0.31*	0.43*	0.46*
France	0.21	0.43	0.29	0.33*	0.60*	0.37*
Germany	0.18	0.52	0.18	0.33*	0.46*	0.51*
Ireland	0.19	0.55	0.19	0.33*	0.47*	0.36*
Italy	0.20	0.53	0.33	0.23*	0.41*	0.34*
Japan	0.15	0.69	0.18	0.26*	0.46*	0.29*
Austria	0.17		0.22		0.43*	
Korea	0.17	0.84	0.23	0.14*	0.52*	0.24*
Netherlands	0.16	0.46	0.19	0.27*	0.40*	0.45*
Belgium	0.17	0.37	0.20	0.32*	0.49*	0.39*
Norway	0.18	0.37	0.17	0.31*	0.37*	0.42*
Spain	0.18	0.53	0.28	0.34*	0.51*	0.46*
Sweden	0.17		0.21		0.39*	
United Kingdom	0.19	0.61	0.17	0.36*	0.36*	0.36*
United States	0.23	0.67	0.23	0.37*	0.55*	0.47*

Source: Calculations based on PIAAC.

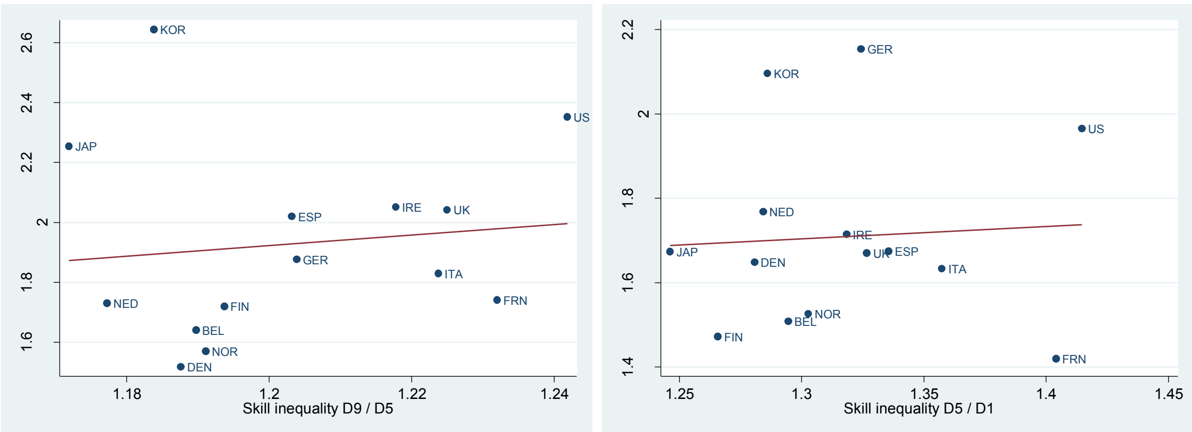
Note: * represents 1% significance level

In order to conclude the discussion on skill and wage dispersion and get a more comprehensive description of their relationship, in addition to coefficient of variation, other measures of inequality are introduced. Regardless whether the relationship between skill inequality and wage inequality is measured by decile ratios – D9/D5, D5/D1 and coefficient of variation – the relationship is not statistically significant (see Figure 3). Correlation coefficients[15] are 0.12, 0.09, and 0.03, respectively. Skill inequality is not correlated with wage inequality, and this is why variation in skill inequality cannot explain variation in wage inequality across 17 OECD countries. Decile ratios reveal additional evidence against skill compression hypothesis. Since wage inequality is the highest and fluctuates the most at the top of the wage distribution (D9/D5 is higher than D5/D1), it is expected that the same is true for skill inequality. However, Figure 3 (Panel A) shows that the opposite is the case. The highest skill inequality and the highest variability in the skill inequality are at the bottom. In every country, skill inequality at the bottom of the distribution is higher than at the top, whereas the opposite holds for wage inequality (the only outlier is Germany, where wage inequality at the bottom seem to be higher than at the top of the distribution).

The same is true if years of schooling are used as a measure of skill. The relationship between coefficient of variation of wages and years of schooling is flat – there is no significant relationship between the two. Correlation coefficient is low: 0.02. It does not hold that the countries with higher skill dispersion (either measured by proficiency scores or years of schooling) have higher wage dispersion and vice versa, as the lower panel of Figure 3 suggests. Countries with similar skill inequality differ significantly in terms of wage inequality. Skill compression hypothesis cannot be confirmed based on the cross-country analysis.

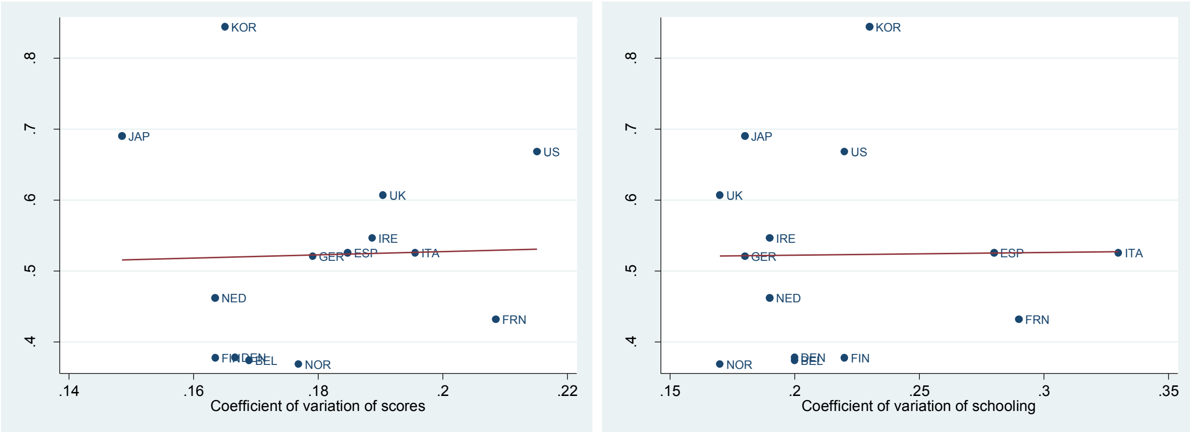
Figure 3: Relationship between skill inequality and wage inequality, employed persons

A: D5/D1, and D9/D5 ratios of wages and numeracy test scores, employed persons



[15] Wage and skill inequality measured by D9/D1, Gini coefficient, and Theil index also show that there is no strong relation. Their correlation coefficients are 0.09, 0.05, and 0.02, respectively.

B: Coefficient of variation of wages, skills, and schooling, employed persons



Source: Calculations based on PIAAC.

5. The Contribution of Skill Inequality to Wage Inequality

5.1 Mincer Equations

The diagrams presented in the previous section seem to oppose the skill compression hypothesis: there seems to be no significant relationship between skill and wage inequality. As descriptive statistics and simple graphs may be misrepresentative because they depend on a small number of data points, we analyze the relationship more carefully by using regression analysis. If wages can be explained by skills, pooled regression based on 17 OECD countries ought to show it. The biggest improvement in comparison to previous analysis is that it is possible to control for various factors (other than skills) that affect the wages. In this body of literature, Jacob Mincer (1958; 1974) was the pioneer in defining earnings as a function of schooling and experience in the log-linear form. The Mincer earnings equation proved to be a big empirical success in labor market economics, and the model is still a good specification for estimating the relationships between schooling, experience, and earnings relatively accurately (see Lemieux, 2006). The empirical model that is to be estimated in this paper is based on Mincer earnings equation and has the following principal form:

$$(2)\ \ln wage_i = \alpha 0 + \Sigma\, \alpha 1_i\, skill\ (schooling)_i + \Sigma\, \alpha 2_i\, experience_i + \Sigma\, \alpha 3_i\, experience2_i + \Sigma\, \alpha 4_i\, gender_i + \Sigma\, \alpha 5_i\, immigrant_i + u_i$$

Where ln wage is the natural logarithm of hourly wage, skill is numeracy test scores or years of schooling (or both), experience is defined as years of labor market experience, gender is a gender indicator, immigrant is related to immigration status, and *ui* is a stochastic error.

Table 6 reports regressions of log wage on indicators of scores and schooling by controlling for gender, experience, experience squared, and immigrant status (see Equation 1). Model 1 shows that the results vary significantly across countries. In some countries, an increase in scores brings more gain in terms of wages than in other countries. An increase of 100 points in numeracy score points increases the average wage by 30 percent in the pooled sample across countries. The highest coefficients are in the US, the UK, Germany, and Spain, and the lowest are in Norway, Italy and Denmark. If one interpreted these results by saying that skills affect wages significantly in the US (coefficient=0.48), one needs to be able to explain why the coefficient is only 0.21 in the case of Norway. Differences in dispersion of skills explain the differences in dispersion of earnings only partly. Model 2 shows that the coefficient of years of schooling on wages is the highest in the US (11 percent), Germany (10 percent) and the UK, Korea, and the Netherlands (9 percent), whereas the lowest is in Italy, France, and Scandinavia (6 percent). On average, one extra year of schooling is accompanied by 7 percent greater earnings. Once we add both numeracy scores and years of schooling to the model, both coefficients are significant, although the size of the score coefficient drops significantly (from 0.30 to 0.15 in the pooled regression). This is due to the fact that skills and schooling are correlated (0.45 on average). However, big variation across countries is evident here as well; whereas in most of the countries coefficient drops for around half, in the UK, Ireland, and Norway, it drops less. In this model, the coefficient of years of schooling remains stable at 7 percent on average. The 1 percent fall is observed in all countries, except for the UK and the US, where the drop is equal to 2 percent. These findings are similar to those of Hanushek *et al.* (2014).

Why does return to skills vary so much across countries? Once controlled for all factors, skills affect wages differently in different countries and return to skills varies. Although the fact that the coefficients are the highest in the first model could lead to the conclusion that the skill compression hypothesis holds, this notion is rejected. Especially in the model where both skills and years of schooling are included, the coefficient for skills drops by half. It might be that schooling affects wages independently from skills (possibly through the signaling effect). However, it all leads to the conclusion that there must be something else (in addition to cognitive scores and schooling) that affects wage structure significantly and affects wage inequality as well.

Table 6: Regression of log wages on scores and schooling, employed persons[16]

Model	Model 1			Model 2			Model 3			
Country	Scores	Contr.	R^2	Schooling	Contr.	R^2	Scores	Schooling	Contr.	R^2
Denmark	0.22 (0.01)	X	0.34	0.06 (0.00)	X	0.44	0.09(0.01)	0.06(0.00)	X	0.45
Finland	0.24 (0.01)	X	0.25	0.06 (0.00)	X	0.38	0.11(0.01)	0.06(0.00)	X	0.40
France	0.30 (0.01)	X	0.23	0.06 (0.00)	X	0.32	0.14(0.01)	0.05(0.00)	X	0.34
Germany	0.39 (0.02)	X	0.28	0.10 (0.00)	X	0.37	0.18(0.02)	0.09(0.00)	X	0.39
Ireland	0.34 (0.02)	X	0.23	0.08 (0.00)	X	0.29	0.20(0.02)	0.07(0.00)	X	0.32
Italy	0.22 (0.02)	X	0.14	0.06 (0.00)	X	0.26	0.08(0.02)	0.05(0.00)	X	0.27
Japan	0.34 (0.02)	X	0.29	0.07 (0.01)	X	0.31	0.22(0.02)	0.06(0.01)	X	0.33
Korea	0.31 (0.04)	X	0.13	0.09 (0.01)	X	0.20	0.13(0.04)	0.08(0.01)	X	0.20
Netherlands	0.30 (0.02)	X	0.34	0.09 (0.00)	X	0.47	0.13(0.02)	0.08(0.00)	X	0.48
Flanders (Belgium)	0.28 (0.01)	X	0.25	0.07 (0.00)	X	0.34	0.14(0.01)	0.06(0.00)	X	0.36
Norway	0.21 (0.01)	X	0.31	0.06 (0.00)	X	0.39	0.11(0.01)	0.05(0.00)	X	0.41
Spain	0.35 (0.03)	X	0.18	0.08 (0.00)	X	0.33	0.15(0.03)	0.07(0.00)	X	0.34
England/N. Ireland	0.40 (0.02)	X	0.29	0.09 (0.00)	X	0.29	0.30(0.02)	0.07(0.00)	X	0.36
United States	0.48(0.02)	X	0.28	0.11(0.00)	X	0.39	0.22(0.02)	0.09(0.00)	X	0.42
Pooled	**0.30 (0.01)**	**X**	**0.25**	**0.07 (0.00)**	**X**	**0.34**	**0.15(0.01)**	**0.07(0.00)**	**X**	**0.36**

Source: Calculations based on PIAAC

Note: Controls are related to experience, experience^2, gender and immigration status. Tables are available upon request.

5.2 Variance Decomposition

With the aim of confirming the findings and conclusions from the previous section, the variance decomposition approach from Devroye and Freeman (2001) is followed in order to see the dispersion of earnings the US would have if US workers had the distribution of skills of the Scandinavian countries and the other way around. For the purpose of this exercise, the results for the US and Finland are chosen, because these are the two extreme countries in the sample – countries with very high (low) wage and skill inequality. Distributions of wages and skills are more compressed in Finland. If the skill compression hypothesis was true, that would imply that Finland has lower wage dispersion due to the lower skill dispersion. That means as well that, if the US had the Finnish dispersion (lower) of skills, it would have lower wage dispersion as well. On the other hand, if Finland had the US skill dispersion (higher), this would increase its wage dispersion. In order to test for this, the following equations are used (see Devroye and Freeman 2001:8):

[16] For purpose of easier interpretation, numeracy test scores are divided by 100

(3) $\sigma 2ln\ wage_{US} = b^2_{US}\ \sigma^2_{FIN\ skills/all\ characteristics} + \sigma^2_{unexplained\ US}$

(4) $\sigma^2 ln\ wage_{FIN} = b^2_{FIN}\ \sigma^2_{US\ skills/all\ characteristics} + \sigma^2_{unexplained\ US}$

Where $\sigma^2 ln\ wage_i$ is the variance of log earnings, $\sigma^2_{skills/all\ characteristics}$ is the variance of skills or relevant characteristics[17], b^2 is the coefficient of skills/relevant characteristics, and σ^2 are the variances of those skills/characteristics. Table 7 displays the results of the variance decomposition approach. The initial actual difference in the standard deviation of ln wage dispersion is 0.228 points. If the US had the Finnish dispersion of scores, its standard deviation of wages would be 0.016 points less, and the initial difference would be only humbly reduced to 0.212. That means that the variation in skill inequality is able to explain only 7.09% of the initial difference in wage inequality. If Finland had the US's dispersion of scores, its standard deviation of ln wages would be only 0.008 points higher. It can be seen that the distribution of skills alone does not affect the distribution of log wages significantly. In the next step, we try to account for all of the relevant characteristics that affect wages and differ across these two countries. If the US had its own coefficients but the Finnish distribution of all relevant characteristics, its wage inequality would be reduced by 0.033 points, which corresponds to 14.54% of initial difference between these two countries. If Finland had the US's dispersion of characteristics, its wage dispersion would be 0.021 points higher (which explains only 9.15% of initial difference). Finally, the last exercise is performed in which change in standard deviation of log wages is predicted by assigning the countries their own distributions of characteristics but the coefficients from wage equation of the other country. According to equation four, instead of assigning Finnish skill dispersion to the US, we assign it the Finnish score coefficient. In this case, the US's wage inequality would be 0.028 points lower (in the case of skills only), or 0.084 points (when all characteristics are included). According to table 7, this change explains around 12% (37%) of the initial difference in wage inequality. In the case of Finland, the estimates are similar – around 17% and 42%. The difference in wage coefficients explains much more of its higher wage inequality comparatively to the skill inequality, and that means that, not skill compression, but the way skills are valued has more significance in explaining cross-country difference in wage dispersion. However, this explanation accounts for maximum 40% of the US-Finland difference in the wage dispersion.

[17] Relevant characteristics are skills, years of schooling, experience, experience^2, gender, and immigrant status.

Although Devroye and Freeman (2001) compared the US and EU (Sweden, Germany and the Netherlands) in the '90s, (and not the US and Finland), their results are comparable to these results. In their example, they showed that skill dispersion explains only a small part of wage dispersion – if the US had the EU dispersion of skills/characteristics, its wage inequality would be reduced, but only around 8% (6.6%) of the initial difference could be explained by this. The difference in coefficients could explain 37% of the initial difference in the wage dispersion. Almost 20 years later, by repeating the same analysis on the new data file, it can be confirmed that only a small percentage of the initial difference could be attributed to the skill hypothesis. To conclude, according to these and some other studies (see Paccagnella 2014[18]), the answer for cross-country variation in wage inequality should be sought for somewhere else and not exclusively in the variation of skill inequality. Some other factors play a bigger role in explaining wage inequalities, and some of the main alternative candidates are labor market institutions.

Table 7: Standard deviation of dispersion of log wages and its projected change

St.deviation of ln wage	United States	Finland
Actual	0.579	0.352
Change (Equation 3)	-0.016 (7.09%)	0.008 (3.51%)
Change (Equation 3)	-0.033 (14.54%)	0.021 (9.15%)
Change (Equation 4)	-0.028 (12.43%)	0.038 (16.62%)
Change (Equation 4)	-0.084 (36.92%)	0.094 (41.23%)

Source: Calculations based on PIAAC.

6. Dispersion within Skill Level

While it is often argued that high wage inequality fosters investment in human capital, Agell (1999) claimed that that could be true, but only if the wage dispersion is between education levels. However, if there is high wage dispersion within the same education level (which is often the case), wage dispersion serves as a discouragement for educational attainment. Based on similar logic, as among the most convincing evidence that the skill hypothesis does not hold, Freeman and Devroye (2001) used the tables that show that dispersion of wages is much higher within the skill levels than between the skill levels. If the skill compression hypothesis

[18] Paccagnella (2014) applied the Blinder-Oaxaca variance decomposition method on the same data set (PIAAC) and concluded that the wage structure effect (return to observable characteristics) is more important than the composition effect (observable characteristics) in order to explain the cross-country differences in wage dispersions. Differences in return to education can explain between 30% (in Spain) and 90% (in Denmark) of the difference in wage dispersion.

was true, the highest dispersion should be between different skill levels; within the skill levels there should barely be any significant dispersion. If skill determines the wages, people at the same skill level should earn similar wages. In their analysis based on the IALS data set and four OECD countries, this was not the case. We perform the same calculations based on the PIAAC data set. Table 8 records the coefficient of the variation of log wages by six defined score levels. The conclusion is the same – wage dispersion within skill levels differs significantly across countries. The highest dispersions of earnings are in Germany, Ireland, Spain, and the United States for every score level. The smallest dispersions are in Japan, Korea, Denmark, and Norway. Countries that have the highest wage dispersion in the lowest skill levels have on average comparatively higher wage dispersions for all skill levels and vice versa.

In the second part of Table 8, the same exercise is performed for six different schooling levels.[19] Schooling levels tell the same story. It is interesting to see how countries do not deviate at all in the coefficient of variation of wages. Countries that have among the highest within-skill level wage dispersion also have the highest within the education level dispersion of wages. The biggest variation is within different school levels and not between them, and it is astonishing how this pattern is repeated in every country and on every education level. Some other factor (other than skills and schooling) in these countries and their institutional settings must create these differences. Variation in skills cannot fully explain the variation in wages if the variation in wages is the highest among the same skill levels; that is what this data shows.

Table 8: Coefficient of variation of log wages by score level, employed persons

	SKILL LEVELS				EDUCATION LEVELS					
Country	L0+1	L2	L3	L4+5	L1	L2	L3	L4	L5	L6
Canada										
Denmark	0.08	0.08	0.08	0.07	0.10	0.06	0.06	0.05	0.07	0.06
Finland	0.15	0.10	0.12	0.12	0.13	0.11	0.11	0.11	0.11	0.10
France	0.14	0.14	0.14	0.15	0.15	0.13		0.13	0.15	0.13
Germany	0.23	0.23	0.21	0.20	0.28	0.19	0.17	0.16	0.18	0.15
Ireland	0.26	0.18	0.18	0.18	0.20	0.19	0.16	0.18	0.17	0.15
Italy	0.18	0.20	0.17	0.17	0.17	0.17	0.17	0.12	0.18	0.16
Japan	0.06	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.07
Austria										
Korea	0.07	0.07	0.07	0.07	0.07	0.07		0.06	0.06	0.06
Netherlands	0.15	0.16	0.17	0.17	0.20	0.15		0.11	0.13	0.13

[19] L1 – lower secondary or less; L2 – upper secondary; L3 – post-secondary, non-tertiary; L4 – tertiary professional; L5 – tertiary bachelor; L6 – tertiary master degree

Belgium	0.13	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.13	0.12
Norway	0.06	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06
Spain	0.21	0.21	0.21	0.19	0.19	0.20	0.20	0.20	0.18	0.17
Sweden										
UK	0.17	0.18	0.19	0.19	0.18	0.19	0.15	0.19		
US	0.18	0.18	0.19	0.19	0.16	0.18	0.17	0.17	0.18	0.16

Source: Calculations based on PIAAC.

7. Wage Compression and Unemployment

Since the variation in wage dispersion across countries cannot be fully explained by variation in skill dispersion, another set of explanations needs to be considered. Some economists stress the importance of variation in wage setting institutions across countries, for example minimum wages and unions (Freeman, 1991; Freeman and Katz, 1994; Blau and Khan, 1996), as the most plausible explanation for cross-country variation in wage dispersion. Before the link between wage dispersion and unemployment is explored, the focus is shortly shifted to the relationship between wage setting institutions and wage dispersion. Table 9 shows a clear pattern – there is a significant negative correlation between various wage bargaining institutions and wage inequality. Countries with higher union density and union membership, stronger and more coordinated wage bargaining institutions, and higher minimum wage display lower wage inequality and vice versa[20]. This is in line with other studies with the same findings based on the panel data analysis (Schettkat, 2003; Freeman, 2007; Salverda and Checchi, 2014). It is interesting to observe that the correlation coefficient between wage dispersion and various institutions is much higher than the correlation coefficient between wages and skills (see section 3). Regrettably, the PIAAC data set does not provide information on union membership of the employees, so more thorough analysis is not possible. However, this data set offers information on employment status which allows us to examine wage compression hypothesis.

[20] Detailed tables are available on request.

Table 9: Relationship between wage inequality and wage setting institutions, employed persons, 2011

Institutions/ Inequality	Minimum wage	Union density	Union membership	Bargaining coordination	Comprehensi-veness index[21]
COV	-0.65*	-0.78*	-0.63*	-0.84*	-0.78*
D9/D1	-0.70*	-0.85*	-0.61*	-0.71*	-0.62*
D9/D5	-0.72*	-0.71*	-0.61*	-0.86*	-0.76*
D5/D1	-0.43*	-0.67*	-0.38*	-0.37*	-0.32*
Gini	-0.66*	-0.87*	-0.69*	-0.78*	-0.72*

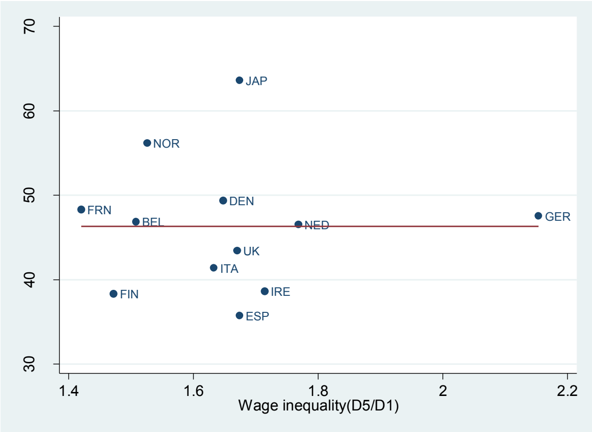
Source: Institutions from Schumpeter School International Comparative Institutions Database, for details see (Jovicic, 2015). Wage Inequality from PIAAC.

Note: * represents 1% significance level

As seen in the previous graph, minimum wages and wage setting institutions are negatively correlated with wage inequality. This is exactly why some economists (neoclassical school of thought) claim that strong institutions cause wage compression, which in turn causes high unemployment among the low skilled (Siebert, 1997; Heckman and Jacobs, 2010). Due to the skill-biased technical change, the relative demand for low-skilled workers declined in the past three decades. In countries with flexible labor markets (and weaker institutions), workers' wages dropped, but they remained employed. In countries with rigid markets, institutions prevented the wages of low-skilled workers from falling, and therefore these workers lost their jobs. In the first group of countries, an increase in wage inequality contributed to higher employment comparatively. If the wage compression hypothesis was true and differences in wage inequalities across countries can explain differences in employment, we expect to find a positive relationship between wage inequality in the low skill sector and employment to population rates among low-skilled workers. Figure 4 shows a slightly positive (although insignificant) relationship between D5/D1 wage ratio and e-pops in the lowest skill level. The diagram is considerably influenced by Korea and the US – the countries with the highest wage inequality (D5/D1) that simultaneously have a good performance in terms of employment. Korea is also an outlier in which wage dispersion is higher in this sample than in the OECD database (see Figure 1). If the US and Korea are excluded from the diagram, the regression line becomes horizontal.

[21] Comprehensiveness index corresponds to product of bargaining level and bargaining coverage (see Schettkat, 2003)

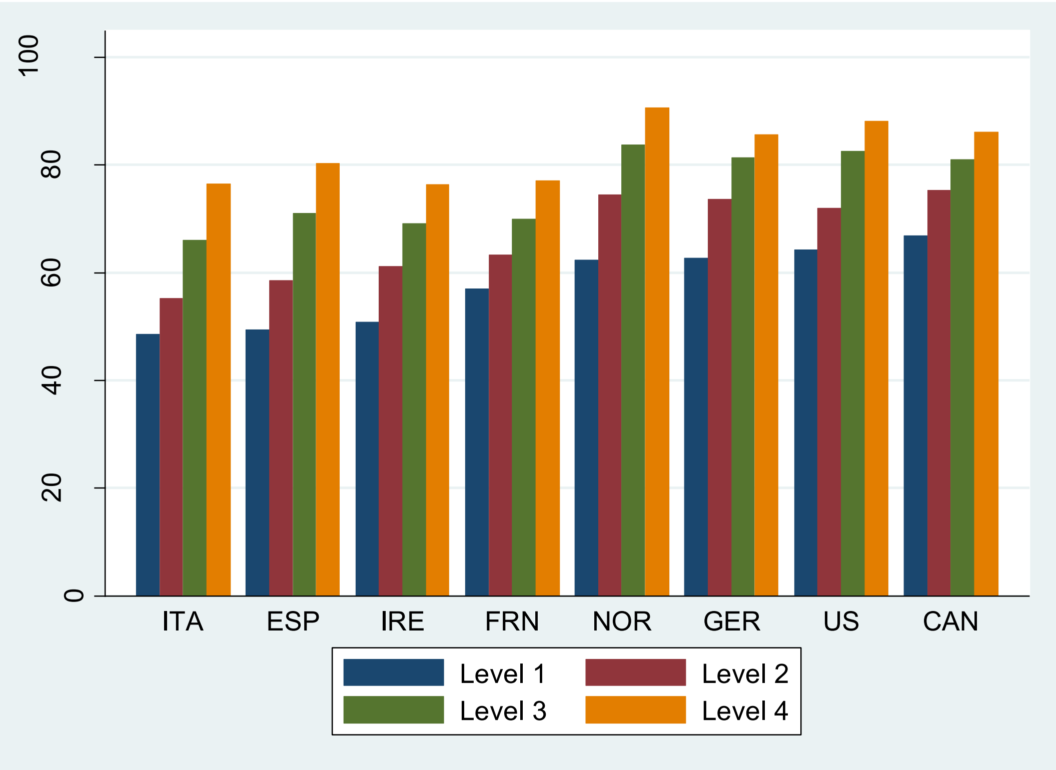
Figure 4: Wage inequality (D5/D1) and employment to population rate for the lowest skill level



Source: Calculations based on PIAAC.

Why do the US, Germany, Japan, Norway, and Korea do so well in terms of low-skill employment, whereas Italy, Spain, Ireland, and France are much less successful in job creation? Can this cross-country variation in employment be explained by cross-country variation in wage inequality? Figure 5 presents e-pops for four different skill levels for eight selected countries. Countries are selected according to the lowest (highest) proportion of employed persons in the low-skill group L1. Due to the better clarity of graphical representation skill groups, L0 and L5 are excluded; they have the smallest percentage of people, which makes them less representative than the other groups. However, the same results hold in these groups as well. The diagram displays a very clear pattern. Employment to population rates are highest in highly skilled level groups, as expected. Countries that have comparatively higher employment among low-skilled workers (Canada, the US, Germany, and Norway) also demonstrate higher employment in the other skill groups. Countries with the lowest employment among low-skilled workers (Italy, Spain, Ireland, and France) also have the lowest employment in other groups. When the wage inequality among these countries is observed, the picture becomes mixed, and there is no clear pattern. It rather seems more plausible that some countries are in general more successful in employment creation than the others. It is not the low-skill sector and excessively high wages at the bottom end that make the whole difference in the employment performance of the countries, but rather something else; e.g. economic policy making. The only two countries that do not follow this general pattern are Japan and Korea. They have one of the highest e-pops in the groups L0 and L1, whereas the share of the employed in other groups is significantly lower. Korea is actually a country with the highest D5/D1, which is in line with the wage compression hypothesis. As previously seen, this is rather an exception and not the rule.

Figure 5: Employment to population rate for four different skill levels, by country



Source: Calculations based on PIAAC.

Finally, in order to perform an additional check, the mean and median score results between the employed and unemployed across countries are compared. If the wage compression hypothesis was true, it would be expected that, in the countries with rigid labor markets and low inequality, the pool of unemployed consists mainly of low-skilled workers. At the same time, countries with flexible labor markets are expected to have much higher employment in the low-skilled sector[22] (and low-skilled should not be unemployed). Table 10 shows the mean, median, and standard deviation of numeracy skill scores by labor force status. Employed persons in the US, the UK, Spain, and Italy have lower average scores than the unemployed in Japan, Belgium, Finland, Denmark, Korea, and the Netherlands. Since the

[22] Analysis shows that there is no correlation between the relative deviation of scores between the employed and the unemployed and the wage dispersion in the low-skilled sector (D5/D1), which is not in line with wage compression hypothesis.

latter countries (apart from Japan and Korea) have at the same time more compressed wage structure, low-skilled people in these countries should be unemployed (because their wage is too high). Indeed, some of these less unequal countries do demonstrate low employment at the bottom. But these workers are not unskilled; their average score results are too high, as the data suggests. The data actually shows that the unemployed in these countries have higher average scores than the employed in some other countries. On the other hand, in the first group of countries, where wage flexibility is higher, the employment of low-skilled workers should be higher. However, the unemployed do have very low average skill scores, which is contradictory to the wage compression hypothesis. Furthermore, in Japan and Korea, there is almost no difference in the average score results between the employed and unemployed, which is again evidence against wage compression hypothesis. The average score results of people out of the labor force are comparable to those of the unemployed people with a minor variation in the number of score points in both directions.

Table 10: Mean and standard deviation of numeracy skill scores by labor force status

	Employed			Unemployed			Out-of-labor force		
Country	mean	median	sd	mean	median	sd	mean	median	sd
Canada	271.66	275.03	52.77	249.22	253.41	54.96	244.41	249.26	60.18
Denmark	285.54	288.93	48.64	265.43	268.74	50.13	256.54	258.59	53.32
Finland	289.70	291.94	48.45	271.21	275.33	56.99	263.58	268.26	56.19
France	261.14	265.48	54.22	244.86	248.02	53.51	241.27	247.33	58.27
Germany	278.43	282.07	49.97	248.43	248.90	49.07	251.74	255.49	58.35
Ireland	264.35	266.99	50.17	246.98	250.29	50.12	240.18	246.60	57.65
Italy	255.00	257.20	49.31	236.38	241.41	50.62	237.33	239.22	48.62
Japan	291.03	293.52	43.99	285.69	285.76	43.80	280.17	283.01	43.01
Austria	279.78	282.81	47.53	265.33	269.37	51.86	261.41	264.63	51.58
Korea	263.99	266.89	44.59	264.33	266.09	46.06	262.15	267.63	47.71
Netherlands	286.86	291.30	47.38	264.84	270.00	56.89	258.45	264.04	56.41
Belgium (Flanders)	287.18	290.62	48.64	278.17	277.92	49.09	263.51	268.61	51.53
Norway	285.05	289.47	51.31	256.80	262.47	55.71	252.44	258.59	57.47
Spain	256.24	259.84	47.77	234.72	238.83	50.43	229.33	236.39	53.53
Sweden	287.22	290.41	50.26	255.12	263.08	59.44	256.62	264.86	60.57
England/N. Ireland (UK)	269.80	272.30	51.69	236.61	238.70	55.69	244.25	246.64	57.51
United States	260.04	264.03	55.95	235.63	236.30	46.89	232.21	235.90	58.14

Source: Calculations based on PIAAC.

But then again, who are the employed, unemployed, and out-of-labor force? Are the subgroups of these three pools of people somehow different, and can they reveal important insights? Data shows[23] that on average there is no significant difference between gender

[23] All tables and graphs are available upon request.

cohorts – they are equally represented in both pools of the employed and unemployed. However, on average, the people out-of-labor force tend to have a higher percentage of women (60%), compared to only 40% men in this group. This share is even higher in Japan, Korea, Italy, the Netherlands, the US, and the UK, where women are more reluctant than men to participate in the labor market, possibly while they engage more in the household activities and parenthood and due to social norms. Only in the Scandinavian countries does there seem to be almost no gender difference in this regard. When it comes to immigration status, immigrants are only slightly more present in the pool of the unemployed compared to the pool of the employed and the out-of-labor force, relative to the non-immigrants. The main conclusion about the age cohorts is that unemployment is gradually decreasing with age across all countries. The pool of people out of the labor force is mainly represented by the lowest and highest age cohorts (age groups 1 and 5), and these two groups together account for around 60% of the out-of-labor force people on average.

The doubt of validity of the wage compression hypothesis was raised with some other earlier cross-country empirical work (Glyn *et al.*, 2006; Howell *et al.*, 2007, Jovicic and Schettkat, 2013), which found no evidence of a relation between wage compression (strong institutions) and unemployment. There is also a significant number of studies based on the micro data that could not explain the high European unemployment with institutional rigidity (Card *et al.*, 1996; Krueger, and Pischke, 1997). At the same time, some other economists were insisting on exploring the aggregate demand deficiency and macroeconomic policies as a potential explanation for the employment differences across countries (see Solow, 2008; Krugman, 2009; Wolf, 2014). However, this remained ignored, and the deregulation of institutions and austerity measures remained the main policy recommendations even today in Europe.

8. Conclusion

Based on the PIAAC adult skill survey, this paper examined the relationship between skill dispersion and wage dispersion and the relationship between wage compression and unemployment. Although both of these hypotheses have strong theoretical backgrounds, none of the hypotheses could be empirically verified based on this cross-country study.

Firstly, there is a large variation in wage dispersion across countries, but its correlation to variation in skill dispersion is rather weak. International differences in wage inequality cannot be explained by differences in skill inequalities. The variance decomposition approach based on the two antagonistic countries (the UK and Finland) showed that only minor percentage of their initial difference in wage inequality could be explained by skill inequality only. Instead, it seems plausible that the other set of explanations in terms of institutions have more power in explaining these differences. According to this analysis, the correlation between various measures of institutions and wage inequality is significantly higher than the correlation between skill inequality and wage inequality. However, in order to confirm this finding, a more detailed analysis is required.

Secondly, the international differences in employment in the low-skilled sector cannot be explained by differences in wage inequality – the wage compression hypothesis cannot be confirmed either. Relative employment performance of low-skilled workers is not worse in countries where the wage premium for skill is more rigid (lower wage inequality). Countries that do well in this sector in terms of employment perform well in general (in all the other groups as well), which is independent from the level of wage inequality.

This study is based on the previous work of Freeman and Devroye (2001) and Freeman and Schettkat (2001), who performed similar analysis based on the IALS literacy survey from 1998 and two (four) countries. These findings, based on the more recent literacy survey (PIAAC) and 17 OECD countries, are in line with their findings and confirm their results.

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