Wage inequality and cognitive skills: Re-opening the debate

Stijn Broecke (OECD), Glenda Quintini (OECD) and Marieke Vandeweyer (KU Leuven)[1]

Abstract. Inequality in the United States is high by international standards, and keeps rising. This is likely to bring significant social as well as economic costs, including lower growth. In this paper, we use the Survey of Adult Skills (PIAAC) to revisit the debate on the relative importance of skills in explaining international differences in wage inequality. While simple decomposition exercises suggest that skills only play a minor role, demand and supply analysis indicates that the relatively low supply of, but high demand for, high-skilled workers in the United States compared to other countries could explain 29% of the higher top-end wage inequality observed in the United States.

1. Background and objectives

In the late 1990s / early 2000s, a brief debate raged on the importance of cognitive skills in explaining international differences in wage inequality – a debate which was never really settled. On the one hand, Blau and Kahn (1996), Devroye and Freeman (2001) and Blau and Kahn (2005) argued that differences in cognitive skills played a relatively minor role in explaining differences in wage inequality between the United States and other advanced economies while, on the other hand, Leuven, Oosterbeek and van Ophem (2004) (LOV, 2004 henceforth) claimed that around one third of the variation in relative wages between skill groups across countries could be explained by differences in the net supply of skills.

While these papers used different methodologies and, in fact, addressed slightly different issues (wage inequality versus skills wage premia), what was really at stake was the role of the market (demand and supply) as an explanation for differences in the returns to skill versus an alternative explanation that attributes skill prices to differences in institutional set-ups, like the minimum wage and unionization. This mirrors a wider debate in the economic literature that has pitched the market (including the role of technological change and international trade) against institutions in explaining wage dispersion. As argued by Salverda and Checchi (2014), this literature really consists of two separate strands that, despite not being mutually exclusive, have developed in parallel with very little interaction between the two.

Since the publication of these papers, the debate on the importance of cognitive skills in explaining international differences in wage inequality has been left largely untouched. During this period, however, inequality has continued to rise. In the United States, the P90/P10 earnings ratio rose from 3.75 in 1975 to 4.59 in 1995 and to 5.22 in 2012.[2] At the same time, a growing body of evidence has demonstrated that inequality has high social costs (Krueger, 2012; Pickett and Wilkinson, 2011; Stiglitz, 2012), and there also appears to be a growing consensus that inequality may be bad for economic growth (Ostry, Berg and Tsangarides, 2014; Cingano, 2014).

Recently, with the availability of new data (the Survey of Adult Skills – PIAAC[3]), researchers have started looking again at the relationship between cognitive skills and wage inequality. Using decomposition methods identical or similar to Blau and Kahn (2005), Paccagnella (2015) and Pena (2015) also find that

[1] We are grateful for useful comments from the editors and Frank Levy on an earlier draft of this paper. This work should not be reported as representing the official views of the OECD or its member countries. The opinions expressed and remaining errors are those of the authors.
[2] These figures are taken from the OECD earnings database and are estimated using gross usual weekly earnings of full-time workers aged 16 from the Current Population Survey.
[3] PIAAC stands for the Programme for the International Assessment of Adult Competencies.

skills contribute very little to international differences in wage inequality, and that skills prices play a far more important role. From this, these authors conclude that differences in inequality must be driven primarily by differences in institutions – a view echoed by another recent paper (Jovicic, 2015). However, neither of these studies considers the early criticisms made by LOV (2004) of the Blau and Kahn (2005) work. In particular, LOV (2004) argued that skills prices will not only reflect institutional set-ups but also basic market forces, and that the decomposition approach taken by Blau and Kahn (2005) ignores important dynamic aspects of the relationship between skills supply and demand that determine both the returns to skill, and wage inequality.

In this paper, we re-consider both sides of the argument, and conclude that the new wave of studies based on the PIAAC data (Jovecic, 2015; Paccagnella, 2015; Pena, 2015) may have been too quick in dismissing the importance of cognitive skills in explaining international differences in wage inequality. First, we simulate alternative wage distributions for the United States using the methods proposed by DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010) to see what would happen to wage inequality in the United States if it had: (i) the skills endowments; and (ii) the skills prices of other PIAAC countries. Consistent with the aforementioned studies, this exercise leads us to conclude: (i) that differences in skills endowments cannot explain much of the higher wage inequality observed in the United States; and (ii) that higher skills prices in the United States account for a much larger share (nearly one third on average) of the difference in wage inequality.

However, as argued by LOV (2004), this price effect will not just reflect differences in institutions. Indeed, the higher price of skill in the United States will reflect at least two factors: (i) differences in institutions; but also (ii) differences in the relative supply of, and demand for, skills. To evaluate the importance of the latter, we follow LOV (2004) and use Katz and Murphy's (1992) demand and supply model to study the relationship between the net supply of skills, on the one hand, and wage inequality, on the other. While tentative, this analysis shows that market forces do indeed matter, and that differences in the relative net supply of high- versus medium-skilled workers can account for 29% of the higher P90/P50 wage ratio in the United States (although the net supply of skills explains little of the higher wage inequality at the bottom of the wage distribution). We show that these findings are robust to the inclusion of labor market institutions in the set of control variables of the regression.

We also explore the extent to which higher wage inequality in the United States might be compensated for by relatively higher employment rates among the low-skilled. Contrary to this "wage compression" hypothesis, and consistent with findings from Freeman and Schettkat (2001) and Jovicic (2015), we find that the employment (unemployment) rates of the low-skilled are not much higher (lower) in the United States relative to those of the high-skilled than they are in other countries. We also find that the ratio between the average skills levels of the employed and the unemployed is quite high in the United States which, once again, is inconsistent with the idea that higher wage inequality is the price paid for better employment outcomes for the low-skilled.

The next section of this paper describes the PIAAC data we use in our analysis, and provides a descriptive overview of wage inequality, skills endowments and prices in the 22 OECD countries included in our sample. Section 3 introduces the method we employ for analyzing international differences in wage inequality and presents the results obtained. Section 4 covers the demand and supply analysis and Section 5 tests the robustness of these findings to the inclusion of labor market institutions. Section 6 explores the wage compression hypothesis, while Section 7 concludes and offers some pointers for future research.

2. Data

The data collected by the OECD's 2012 Survey of Adult Skills (PIAAC) offers an unparalleled opportunity to investigate the relationship between cognitive skills and wage inequality. The survey directly assessed the proficiency of around 166 000 adults (aged 16-65) from 24 countries[4] in literacy, numeracy and problem solving in technology-rich environments. In addition, the survey collected information on individuals' skills use in the workplace, as well as on their labor market status, wages, education, experience, and a range of demographic characteristics. The achieved samples range from around 4 500 in Sweden to nearly 27 300 in Canada. In this paper, the focus is on the 22 OECD countries in the sample (i.e. excluding the Russian Federation and Cyprus).

The direct assessment of cognitive skills in PIAAC represents a significant improvement over the more traditional skills proxies (such as years of education, qualification levels and experience) used in many other surveys and research. Such direct measures are particularly important when doing international comparisons because a year of education, for example, will mean something very different from one country to another, partly because there are important differences in the quality of educational systems between countries. By contrast, the PIAAC assessments were deliberatly designed to provide reliable measures of skills proficiency that can be compared across countries, languages and cultures. There is also a growing body of research which has highlighted the importance of cognitive skill in determining a range of labor market outcomes, including employment and wages (e.g. OECD, 2014, Hanushek et al. 2015).

It is important to point out that cognitive skills are not the same as the task-based definition of skill emerging from the literature on routine-biased technological change (see, for example: Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006; Autor and Dorn, 2013). While cognitive skills can be seen as characteristics of the worker, and reflect his or her education, personal background, as well as a number of other factors, tasks focus on the content of occupations. There is not necessarily a one-to-one mapping between the two, and any worker with a particular skills set can perform a variety of tasks. In addition, the set of tasks performed by a worker can change in response to changes in the labor market which are driven by technological progress, globalization and other such trends.

The two skills concepts are nonetheless closely related. According to the routine-biased technological change hypothesis, routine tasks (i.e. those that can easily be automated) are disappearing (and with it the demand for routine skills), while the demand for non-routine tasks and skills is rising. The concept of non-routine skills encompasses a wide array of skills, but cognitive skills (or "key information-processing skills" as they are sometimes referred to) form an essential part of them. These skills provide a fundamental basis for the development of other, higher-order skills, and are necessary in a broad range of contexts, including work. The close relationship between the two concepts is borne out by the data: just as there has been an increase in employment in non-routine occupations, there has been growth in the share of employment in occupations associated with the highest levels of key information-processing skills (OECD, 2013).

It is also important to point out that cognitive skills are assessed in PIAAC by focusing on the ability of individuals to perform certain tasks. For example, numeracy skills in PIAAC are defined as the ability to

[4] 22 OECD countries/regions: Australia, Austria, Canada, the Czech Republic, Denmark, Estonia, Finland, Flanders (Belgium), France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States; one region; as well as two non-OECD countries: Cyprus and the Russian Federation.

"access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life". To this end, numeracy involves managing a situation or solving a problem in a real context, by responding to mathematical content/information/ideas represented in multiple ways" (OECD, 2013). Literacy and problem solving in technology-rich environments are assessed in a similar way.

Finally, while PIAAC collected information on three different cognitive skills, only numeracy skills will be used in the present paper. This is because the three measures are highly correlated and the conclusions reached do not depend on the choice of measure.

A second strength of the present paper is its ability to draw on detailed (and continuous) wage data for the 22 OECD countries/regions that are covered by PIAAC. In contrast, LOV (2004) could use only 15 (out of 20) countries that participated in the International Adult Literacy Survey (IALS – a predecessor of PIAAC), because wage information was only available in quintiles for the other 5 countries. Similarly, Blau and Kahn (2005) cite wage data restrictions as a primary reason for focusing on just 9 of the advanced countries included in IALS, while Devroye and Freeman (2001) use 11. Even among the 15 countries covered by LOV (2004), wage data were only available in 20 intervals for 3 of them (Germany, the Netherlands and Switzerland), while it was impossible to calculate hourly wages in the case of Sweden. Finally, the more recent research using PIAAC data also suffers from similar problems.. In the data used by Pena (2015), for example, continuous wage data is missing for five of the countries (including the United States), while Jovecic (2015) does not have access to continuous wage data for Austria, Canada and Sweden.

Table 1 offers some basic descriptive statistics on the number of observations in PIAAC with valid wage observations, as well as on the level and dispersion of both skills and wages. The table shows that the United States combines one of the lowest levels of skill (only Spain and Italy do worse) with the highest skill dispersion (both at the top and at the bottom of the distribution). Gross hourly wages (which are expressed in PPP corrected USD) are among the highest in the United States (although they are higher still in Ireland, Flanders, Denmark and Norway). Wage inequality in the United States (as measured by the P90/P10 wage ratio) is second only to Korea, and is particularly high at the top of the distribution. In contrast, Canada, Estonia, Korea and Germany all have P50/P10 wage ratios higher than that observed in the United States. Figure 1 shows the full skill and wage distributions of the United States in comparison to the PIAAC average. The shapes and positions of these curves confirm the higher skills and wage inequality in the United States, as well as the lower average skill level of the employed population.

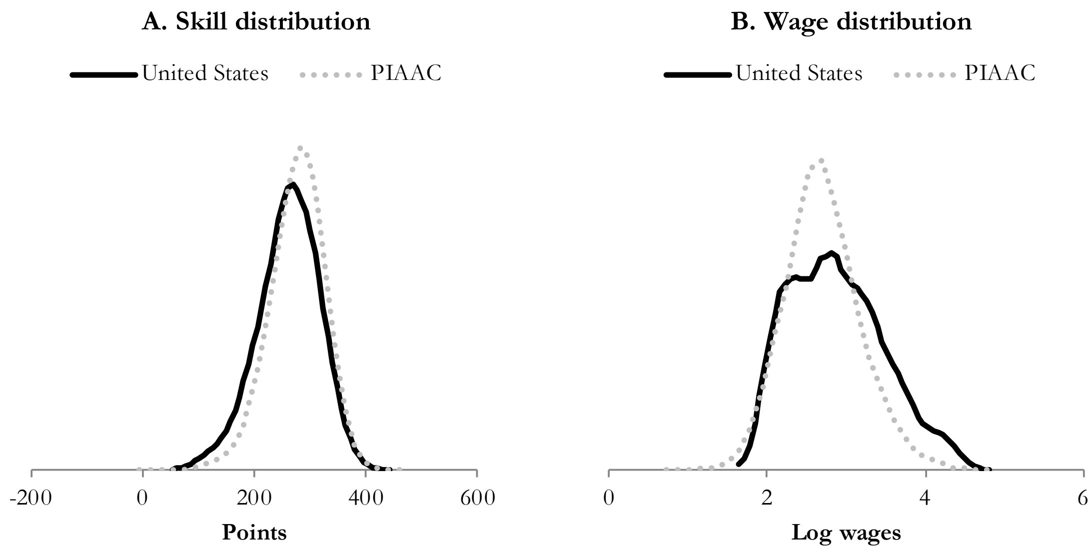
To conclude this section, Figure 2 shows the results of a simple Mincer-type regression of log wages on skills, experience and experience squared, and confirms that the higher return to skill in the United States might be one of the key reasons why wage inequality is so much higher. Indeed, among the 22 countries shown in Figure 2, the United States is the country with the highest return to skill (more than twice as high as in Sweden and Denmark). As will be argued throughout this paper, this higher return to skill in the United States will reflect a combination of differences in: (i) the demand for and supply of skill; and (ii) labor market institutions, policies and practices.

Table 1. Descriptive statistics: Skills and wages by country

	N	Skill				Wages			
		Mean	P90/P10	P90/P50	P50/P10	Mean	P90/P10	P90/P50	P50/P10
Australia	4371	276	1.60	1.21	1.32	18.90	3.14	1.90	1.65
Austria	2943	279	1.54	1.19	1.29	19.06	3.05	1.83	1.67
Canada	16116	271	1.66	1.22	1.35	20.37	3.94	1.94	2.03
Czech Republic	2630	279	1.49	1.18	1.26	8.96	2.88	1.68	1.71
Denmark	4448	286	1.52	1.19	1.28	23.84	2.58	1.55	1.66
England/N. Ireland (UK)	4801	271	1.63	1.23	1.33	18.40	3.53	2.07	1.71
Estonia	3972	277	1.51	1.19	1.26	9.64	4.71	2.24	2.10
Finland	3251	292	1.51	1.19	1.26	19.30	2.54	1.70	1.50
Flanders (B)	2736	287	1.54	1.19	1.30	22.23	2.61	1.67	1.56
France	3696	261	1.73	1.23	1.40	15.58	2.56	1.77	1.45
Germany	3382	278	1.60	1.20	1.33	18.82	4.22	1.88	2.25
Ireland	2784	265	1.61	1.22	1.32	21.57	3.57	2.08	1.71
Italy	1815	255	1.66	1.22	1.36	16.14	3.42	1.99	1.72
Japan	3262	292	1.46	1.17	1.25	16.09	4.08	2.32	1.76
Korea	3097	268	1.52	1.18	1.29	17.84	5.83	2.68	2.18
Netherlands	3162	287	1.51	1.18	1.28	21.47	3.24	1.79	1.81
Norway	3553	286	1.55	1.19	1.30	24.32	2.44	1.60	1.52
Poland	3908	267	1.59	1.22	1.31	9.27	3.89	2.15	1.81
Slovak Republic	2505	285	1.44	1.17	1.24	8.90	4.01	2.15	1.87
Spain	2456	258	1.61	1.20	1.34	14.96	3.60	2.05	1.75
Sweden	2888	287	1.55	1.19	1.30	18.68	2.18	1.59	1.37
United States	2793	261	1.75	1.24	1.41	21.52	4.81	2.40	2.01

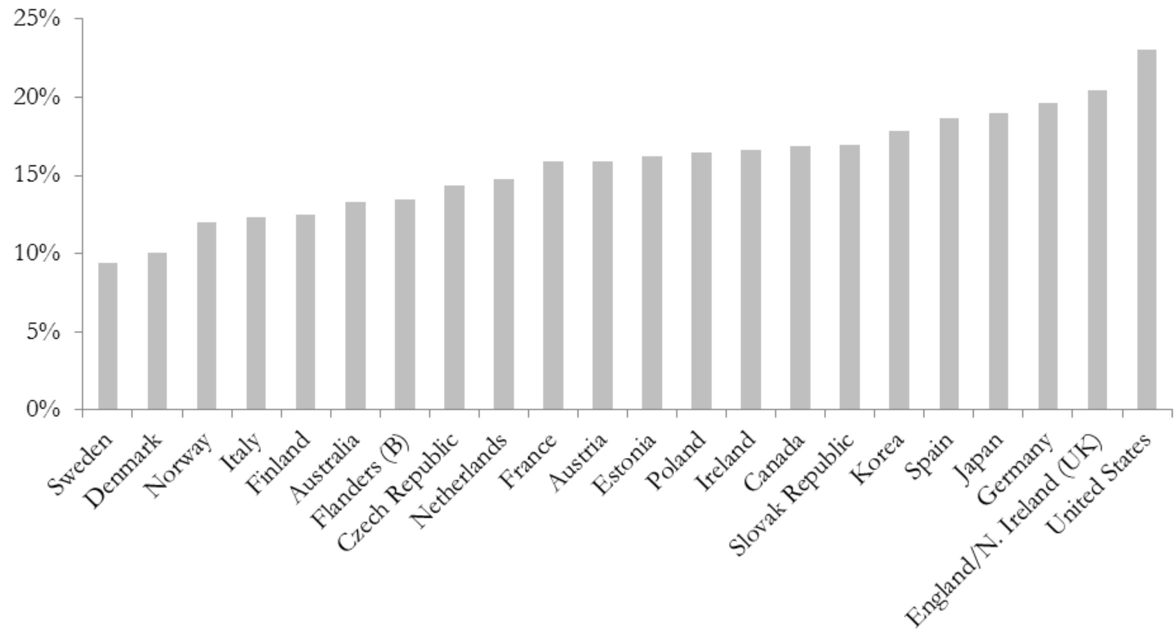
Notes: Skills refer to proficiency in numeracy and are expressed in score points (1=minimum and 500=maximum).Wage data are trimmed, by country, at the top and bottom percentiles. Wages are hourly, include bonuses and are expressed in PPP corrected USD.

Figure 1. Skills and wage distributions, United States and PIAAC average



Notes: Obtained by Kernel density estimation.

Figure 2. The return to skill, United States and other PIAAC countries



Notes: The figure shows the coefficient on skill from a regression of log hourly wages (including bonuses) for wage and salary earners (in PPP corrected USD) on standardized numeracy scores and a quartic of experience.

3. The role of skills and skills prices

In this section, we estimate the extent to which higher wage inequality in the United States is associated with differences in: (i) skills endowments; and (ii) skills prices. Our method differs from those used in the previous research on wage inequality and cognitive skills, and brings a number of improvements. Both Devroye and Freeman (2001) and Jovecic (2015) use a simple variance decomposition method, which cannot account for the full distributional aspects of both wages and skills. Blau and Kahn (2005) and Pena (2015) use the Juhn, Murphy and Pierce (1993) decomposition – but this method has become the subject of a number of criticisms over time (Yun, 2009; Suen, 1997; Fortin, Lemieux and Firpo, 2010).[5] Finally, Paccagnella (2015) resorts to unconditional quantile regressions (Fortin, Lemieux and Firpo 2010), but his application of the method only allows an analysis of the effect of overall, average skill levels (and not the entire skills distribution) on wage inequality. Instead, we draw on DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010) and simulate counterfactual wage distributions using reweighting techniques. As will be shown below, an important attraction of this method lies in its simplicity and the visual inspection of alternative wage distributions that it permits.

While we believe that our approach offers some improvement over previous methods used in the literature, the conclusions we reach in this section are essentially the same as those reached by other authors – i.e. that differences in skills endowments across countries can account for little of the difference in wage inequality, while differences in skills prices (or how skills are rewarded) appear to play a far more

[5] One of the main criticisms of the Juhn, Murphy and Pierce decomposition concerns the "residual imputation" step. In this step, the residuals of the base country are replaced with the similarly ranked residuals of the comparator country. However, a key assumption behind this approach is that these residuals (from a regression of wages on skills) are independent of skills, which is clearly unrealistic. For further detail, see Fortin, Lemieux and Firpo (2010).

important role. We begin this section by explaining our methodology in some more detail, and then present the results.

Simulating counterfactual wage distributions

To estimate the contributions of skills prices and skills endowments to higher wage inequality in the United States, we will estimate two sets of alternative wage distributions. In the first, we impose the skills distributions of the other PIAAC countries onto the United States (holding skills prices constant). In the second, we impose the skills prices of the other PIAAC countries onto the United States (this time holding skills endowments constant).

The effect of skill endowments

To see what would happen to wage inequality in the United States if it had the same skills distribution as the other PIAAC countries, we reweight the United States data to make the skills profile of its workforce resemble that of the comparator country. We then estimate the difference this makes to wage inequality. Intuitively, if the comparator country has more skilled workers, then the reweighting method will give more weight to skilled workers in the United States, while reducing the weight given to less-skilled ones. Because the other characteristics of the individuals are left unchanged (including their wages), this results in an alternative wage distribution. This alternative wage distribution can then be used to calculate standard measures of wage inequality that can be compared to those estimated on the original wage distribution. The difference between the two measures of wage inequality can be attributed to the difference in skills endowments.

More formally, assume one is interested in seeing what would happen to the wage distribution of the United States (*US*) if it had the same skills distribution as country *x*. Then, taking an individual *i* in the United States, the original sample weights $\omega_{i,US}$ for that individual are replaced by a counterfactual weight $\omega'_{i,US} = \omega_{i,US}\,\Psi_i$ where Ψ_i represents the reweighting factor. While DiNardo, Fortin and Lemieux (1996) suggest regression methods to compute the reweighting factor Ψ_i, the latter may be obtained more simply and non-parametrically if the data can be divided up in a finite number of cells (Lemieux, 2002). In the case of skills, this is indeed possible.

In practice, the procedure is implemented as follows. The data for the United States and the comparator country are divided into skill cells/intervals *s* of 5 points each,[6] and the shares of the total workforce employed in each cell, $\theta_{s,US}$ and $\theta_{s,x}$, are calculated. One can then reweight the United States data to approximate the skills distribution of the comparator country by simply using the following reweighting factor:

$$\Psi_i = \theta_{(s,x)}/\theta_{(s,US)}$$

The effect of skill prices

The price effect simulations are inspired by a method proposed by Lemieux (2002). Intuitively, we give individuals with a certain skill level in the United States the same return to skill as individuals with that skill level would obtain in country *x*. More formally: assuming that the data can be divided up in a finite number of cells (e.g. intervals *s* of 5 numeracy points each), then changes in skill prices can be simulated by comparing the mean of (log) wages of skill group *s* in the United States, $y_{s,US}$, with the mean of (log) wages in skill group *s* in country *x*, $y_{s,x}$. The new (log) wage for each individual *i* in the United States, $y'_{i,US}$,

[6] Except for individuals at the top (more than 355 points) and bottom (fewer than 180 points) of the distribution. These are put into two separate groups.

can then be calculated by adding the difference between country *x*'s average (log) wage for skill group *s* and the average (log) wage for skill group *s* in the United States:

$$y'_{i,US} = y_{i,US} + (y_{s,x} - y_{s,US})$$

Price and quantity effects may of course be applied simultaneously to obtain a joint effect on the wage distribution. The order in which these effects are calculated does not affect the outcome, since both are calculated within the same skill cell.

Figure 3 below illustrates the effect on the United States wage distribution of: (i) adopting the skills distribution of the average PIAAC country;[7] (ii) adopting the skills prices of the average PIAAC country; and (iii) adopting both the skills distribution and prices of the average PIAAC country simultaneously. As the figure shows, imposing the skills distribution of the average PIAAC country onto the United States would change the wage distribution somewhat, but would have relatively little effect on wage inequality (as indicated by the height of the distribution). Imposing skills prices of the average PIAAC country would, however, have a more important compressing effect on the wage distribution. Similarly, imposing both the skills distribution and prices of the average PIAAC country onto the United States would lead to a fall in wage inequality.

Figure 3. Simulating alternative wage distributions in the United States based on PIAAC skills endowments and prices

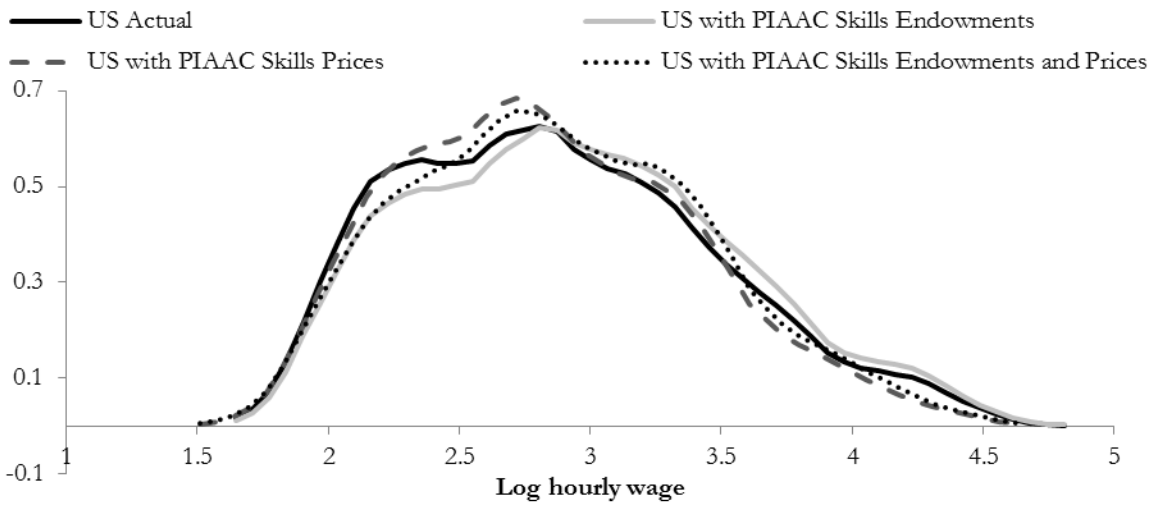


Table 2 contains the full set of results from our analysis.[8] The first set of columns shows the impact on wage inequality in the United States if it adopted the skills distribution of the comparator country. It essentially confirms the findings of earlier papers (e.g. Blau and Kahn, 2005) that the contribution of cognitive skills to explaining higher wage inequality in the United States is small. One difference is that the earlier analysis had found that the contribution of skills was positive (ranging from 3% to 13% on average), while Table 2 indicates that, in most cases, the contribution is actually negative – i.e. that the

[7] The average PIAAC country is constructed on the basis of all PIAAC observations. However, because countries with larger populations would have a greater weight and, therefore, a disproportionate influence on the distribution, the survey weights are rescaled so that the sum of each country's weights is equal to one. In essence, this is equivalent to taking an unweighted average across countries. In addition, because wage levels differ significantly across countries, they need to be adjusted before being combined into a single PIAAC distribution (which would otherwise be too wide). Wages are therefore demeaned by country, and all the analysis is carried out on these country-specific deviations from the mean.

[8] The full set of figures associated with these simulations can be found in Annex A.

P90/P10 wage ratio in the United States would increase if it had the skills distribution of the comparator country (the estimates suggest that it would be around 10% higher on average). Only if the United States had the skills distribution of France, Poland, Ireland, Italy and Spain would wage inequality fall.

While surprising, these results are consistent with the recent findings of Paccagnella (2015), who finds that average skills levels in the United States can account for -4%, on average, of the higher P90/P10 wage ratio in the United States (although the author controls for educational attainment in addition to skills, which will is likely to explain the lower estimate). Again, similar to Paccagnella (2015), Table 2 suggests that these negative effects are driven primarily by the P50/P10 wage ratio (i.e. the bottom of the wage distribution).[9] These counterintuitive results can be explained by the skills profile of wages in the United States, which is significantly steeper in the top half of the skills distribution. Because skills prices are held constant in the analysis, increasing the number of skilled workers in the United States mechanically results in higher wage inequality as the wages of those at the P50 of the wage distribution would increase faster than the wages of those at the P10.

The difference between our results and those of Blau and Kahn (2005) may be driven by the different methodology that we use. When we apply Blau and Kahn's (2005) methdology to the PIAAC data we still find that the contribution of skills is small and negative on average (-7.9%) – however this result is driven primarily be a large negative effect for Estonia.[10] Excluding this country, we find that the contribution of skills is still small, but positive (4.5% on average) – as in Blau and Kahn (2005). However, to confirm that this difference in results is truly driven by the difference in methodology, one would also want to run the experiment the other way around, and use our methodology on the IALS data. Unfortunately this was not possible because access to the detailed IALS wage data is restricted for the United States and we were unable to obtain access to these. One cannot rule out, therefore, that some of the difference between our results and those of Blau and Kahn (2005) is also driven by: (i) a real change over time in the role that skills play in explaining higher wage inequality in the United States; and (ii) the country coverage in PIAAC which is different from the one of IALS.

On the whole, however, the most important conclusion that emerges from the above analysis is that, despite our different (and, we believe, improved) methodology, our findings are largely consistent with those of Blau and Kahn (2005) – i.e. differences in skills endowments across countries cannot account for much of the differences in wage inequality.

The second set of findings presented in Table 2 are also consistent with both Blau and Kahn (2005) and Paccagnella (2015) – i.e. skills prices can account for a significantly larger share of higher wage inequality in the United States than can skills endowments. The contribution of skills prices ranges from 18% in the Czech Republic to nearly 64% in Germany, and can explain nearly one third on average of the higher wage inequality in the United States (excluding both Estonia and Korea, two clear outliers). Skills prices also tend to play a slightly more important role in explaining wage inequality at the top than at the bottom of the wage distribution: this is the case in 18 of the 21 country comparisons shows in Table 2.

[9] Blau and Kahn (2005) also find some negative effects, but these are at the top of the wage distribution (p90/P50), and for males.

[10] These results are not shown, but are available from the authors upon request

Table 2. The role of skills endowments and skills prices in explaining higher wage inequality in the United States

	(i) Skills endowments			(ii) Skills prices			(iii) Skills endowments and prices		
	P90/P10	P90/P50	P50/P10	P90/P10	P90/P50	P50/P10	P90/P10	P90/P50	P50/P10
Australia	-9.5	4.9	-24.8	35.0	37.8	26.3	23.7	36.1	4.3
Austria	-5.6	12.4	-30.8	25.9	27.3	18.8	15.9	29.2	-7.3
Canada	-19.7	0.7	397.1	55.3	33.5	-420.3	40.4	32.6	-132.6
Czech Republic	-1.5	12.9	-31.3	18.1	22.6	3.7	16.5	27.0	-10.6
Denmark	-11.4	3.9	-39.2	30.0	26.7	28.7	15.1	23.4	-8.1
England/N. Ireland (UK)	-10.5	3.5	-22.0	18.1	21.3	13.1	11.4	27.2	-5.0
Estonia	-33.8	55.1	97.6	309.1	68.6	-53.4	260.6	96.6	12.7
Finland	-18.6	-0.5	-34.0	27.5	32.2	15.4	13.0	29.4	-10.6
Flanders (B)	-13.1	2.7	-30.7	27.6	29.3	18.5	15.4	27.6	-6.5
France	2.9	4.2	1.0	25.7	29.1	17.0	26.4	30.7	16.8
Germany	-27.9	7.9	44.2	63.7	25.1	-21.5	30.8	23.1	10.7
Ireland	8.3	16.1	0.4	30.1	46.2	12.6	32.8	55.0	9.3
Italy	14.8	17.5	9.2	36.3	42.1	24.8	49.1	56.7	34.8
Japan	-50.7	31.7	-70.0	43.7	149.8	17.1	-11.7	113.2	-43.6
Korea	-13.2	-39.4	22.5	-31.0	-43.1	-18.9	-42.4	-69.9	-9.9
Netherlands	-17.9	6.2	-74.8	34.5	31.4	36.4	15.4	29.9	-26.7
Norway	-12.9	1.1	-28.1	25.9	25.7	19.2	11.5	20.8	-5.6
Poland	7.7	27.2	-13.8	41.8	53.7	26.6	41.9	64.8	14.7
Slovak Republic	-11.9	40.4	-91.9	27.5	38.0	9.7	13.5	58.9	-58.7
Spain	19.9	26.9	9.5	24.9	30.3	16.0	40.2	52.1	22.8
Sweden	-12.4	2.1	-23.9	28.0	30.2	18.0	15.7	27.3	-2.1

Notes: The table shows the proportion of higher wage inequality in the United States that can be attributed to differences in: (i) the skills distribution; (ii) skills prices; and (iii) the skills distribution and skills prices together. For example, 4.9% of the difference in the P90/P50 ratio between the United States and Australia can be explained by differences in the skills distribution between the two countries. Negative values indicate that the difference in wage inequality between the United States and the comparator country would increase if the United States had the characteristics of the comparator country.

While Blau and Kahn (2005) at least acknowledged the possibility that higher skills prices could reflect market forces as well as differences in institutions, the more recent research using PIAAC simply ignores this argument. Paccagnella (2015) concludes that the greater contribution of skills prices to wage inequality "suggests that economic institutions […] are the main determinants of wage inequality", but without actually proving this point. Similarly, Pena (2015) somewhat hastily concludes that institutional factors are more important than market forces, but she only "controls" for the latter by including additional demographic factors in her model. Finally, Jovecic (2015) presents a few simple correlations between labour market institutions and measures of wage inequality (all of which are significant and have the "right" sign), and concludes from this that "institutions have more power" in explaining international differences in wage inequality than skills do.

We will return to the importance of market forces in explaining higher inequality in the next section of this paper. Before we do so, the final three columns in Table 2 show the combined effect of skills and skills prices in explaining higher wage inequality in the United States. Only in the cases of Korea and Japan do these explain a negative part of the difference in wage inequality with the United States. In the other countries, the joint contribution of skills and skills prices ranges from 11.4% in the case of England/Northern Ireland to 49% in the case of Italy (excluding Estonia, which is a clear outlier). These results are not surprising given that they combine the modest, negative effects of skills endowments with the larger, positive effects of skills prices.

4. The role of demand and supply

One weakness of the wage simulation method used above (but which applies equally to the methods used by Devroye and Freeman, 2001; Blau and Kahn, 2005; Jovecic, 2015; Paccagnella, 2015; and Pena, 2015) is that it analyzes the role of skills from a static perspective. However, as pointed out by LOV (2004), this is not realistic and the price of skill should be seen as reflecting at least in part the outcome of the dynamic interaction between demand and supply: if the supply of skills increases relative to demand, then one would expect both the price of skills and inequality to fall.

The idea that the returns to skill (and therefore inequality) depend on demand and supply factors was first introduced by Tinbergen (1975), who famously described inequality as a "race between education and technology". Technological change was argued to be skills-biased – i.e. it increases the demand for more skilled workers and therefore their wage premium in the labor market. To keep inequality in check, the supply of skills needs to increase to meet that demand. It is now widely accepted that the increase in inequality in the United States over the past few decades can be partly blamed on the fact that the supply of educated workers has not kept pace with the rise in demand for them (Juhn, Murphy and Pierce, 1993; Juhn, 1999; Goldin and Katz, 2008; Autor, 2014). While more recent theories of routine-biased technological change have refined this argument somewhat, they still maintain a central role for skills in explaining rising wage inequality in the United States (Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2006, 2008; Autor and Dorn, 2013; Autor, 2015).

The findings from the previous section, and the results obtained by Blau and Kahn (2005) and Paccagnella (2015), among others, therefore appear at odds with the story that rising wage inequality in the United States was to a large extent related to changes in the demand for, and the supply of, skills. One possible explanation for this inconsistency is that the decomposition methods used in the literature fail to account for the dynamic interaction between the demand and supply of skills. To gain a better understanding of how the supply of skills interacts with the demand for skills and what effect this may have on wage inequality (through its effect on the price of skills), this section applies a different methodology developed by Katz and Murphy (1992) and used by a number of researchers since to investigate the relationship between the net supply of cognitive skills and wage differentials between skill groups (Blau and Kahn, 1996; LOV, 2004). The only difference is that, instead of looking at wage differentials between skill groups, the analysis that follows focuses on standard, interdecile measures of wage inequality.

To implement the Katz and Murphy (1992) methodology, we follow an approach similar to both Blau and Kahn (1996) and LOV (2004). In a first step, the workforce of the average PIAAC country is divided into three skills groups of equal size corresponding to the low-, medium- and high-skilled, respectively. The thresholds defined by these groups (in numeracy points) are then applied to each of the 22 countries included in the sample to classify workers as either low-, medium- or high-skilled. Because the distribution of skills varies from country to country, applying these PIAAC average thresholds will result in different-sized groups of low-, medium- and high-skilled workers in each one of these countries. For example, Table 3 shows that in Japan, 47.4% of the working age population is high-skilled according to this definition, but that in both Italy and Spain more than 50% is low-skilled. Equally, the workforce in the United States is relatively low-skilled, with 45.8% low-skilled workers and only 24.6% high-skilled workers.

Table 3. Proportion of high-, medium- and low-skilled individuals in the labor force, by country (in %)

Country	Low	Medium	High
Australia	34.3	32.2	33.4
Austria	28.0	35.2	36.9
Canada	36.5	31.4	32.0
Czech Republic	26.7	38.1	35.2
Denmark	26.8	32.7	40.5
England/N. Ireland (UK)	39.7	31.1	29.2
Estonia	28.8	37.9	33.3
Finland	24.7	31.7	43.6
Flanders (B)	25.7	32.1	42.2
France	43.8	31.0	25.2
Germany	31.9	31.5	36.6
Ireland	42.5	34.1	23.4
Italy	50.9	31.4	17.7
Japan	18.7	33.9	47.4
Korea	35.5	38.7	25.8
Netherlands	24.6	32.1	43.2
Norway	26.3	32.1	41.7
Poland	40.0	34.5	25.4
Slovak Republic	26.1	36.3	37.6
Spain	50.1	33.1	16.8
Sweden	25.6	32.3	42.1
United States	45.8	29.6	24.6

The next step is to construct indices which measure how the demand and supply for each skill group in the United States compare to those in the other PIAAC countries. We start by building asupply index $Supply_{s,x}$ which intends to measure the relative supply of skills group s in the United States compared to country x:

$$Supply_{s,x} = \ln\left(\frac{\varepsilon_{s,US}}{\varepsilon_{s,x}}\right)$$

Where $\varepsilon_{s,x}$ and $\varepsilon_{s,US}$ are the shares of the labor force accounted for by skill group s in country x and the United States, respectively (as reported in Table 3). Intuitively, the supply index compares the relative importance of each skill group in the United States labour force with country x's shares used as the norm.

We then build a demand index $Demand_{s,x}$ which measures the degree to which the occupation-industry structure[11] in the United States favors skill group s in comparison to country x:

$$Demand_{s,x} = \ln\left(1 + \sum_{o} \frac{\theta_{s,o,x}}{\varepsilon_{s,x}} (\theta_{o,US} - \theta_{o,x})\right)$$

Where $\theta_{s,o,x}$ is skill group s's share of employment in occupation-industry cell o in country x; $\theta_{o,x}$ and $\theta_{o,US}$ are the total shares of employment in cell o in country x and the United States, respectively; and

[11] Industry-occupation cells are defined in the same way as in Blau and Kahn (1996) and LOV (2004).

$\varepsilon_{s,x}$ is the share of skill group s in the total workforce of country x. The demand index therefore represents the average difference in the employment shares of each occupation/industry between the United States and the comparator country – weighted by the skill intensity of each industry/occupation relative to the overall skill intensity in the comparator country.[12] If employment in the United States were strongly concentrated in industry/occupation cells that employ a large share of skilled workers compared to country x, the demand index would be high (and vice versa).[13] Table 4 shows the difference between the demand index for the United States and every other country, and for each of the three skills groups. It shows clearly that the demand for high-skilled workers in the United States is higher than in most other countries, while the demand for low-skilled workers is lower. To some extent, this is driven by the industry-occupation structure of employment in the United States. Indeed, when we look at employment shares by industry-occupation structure in the United States compared to those of the other countries included in PIAAC (Annex B), we notice that demand in the United States is relatively high in some high-skill industry/occupation combinations (e.g. managers and professionals in government and in finance, insurance, real estate and services). By contrast, the employment share of craftworkers, operatives, labor and service workers is relatively low in the United States.

Table 4. Difference in the demand for high-, medium- and low-skilled workers between the United States and other PIAAC countries

	Low	Middle	High
PIAAC	-0.026	-0.012	0.037
Australia	-0.013	-0.013	0.026
Austria	-0.031	-0.003	0.024
Canada	0.044	-0.012	-0.042
Czech Republic	-0.133	-0.019	0.109
Denmark	0.002	-0.003	0.001
England	-0.048	-0.008	0.071
Estonia	-0.052	0.000	0.042
Finland	-0.027	-0.017	0.026
Flanders	0.022	-0.008	-0.007
France	-0.072	0.010	0.103
Germany	-0.048	-0.030	0.063
Ireland	-0.049	-0.004	0.094
Italy	-0.092	0.023	0.205
Japan	-0.086	-0.015	0.039
Korea	-0.138	0.009	0.155
Netherlands	0.058	-0.003	-0.031
Norway	0.019	-0.013	-0.001
Poland	-0.102	-0.010	0.156
Slovakia	-0.055	0.014	0.025
Spain	-0.094	0.024	0.213
Sweden	-0.007	-0.009	0.011

In the final step, because market forces reflect the interaction between supply and demand, a "net supply" index is calculated by subtracting the demand index from the supply index:

$$\overline{Supply_{s,x}} = Supply_{s,x} - Demand_{s,x}$$

[12] Country x is chosen to calculate these weights. This is an arbitrary choice, with no effect on the results.

[13] This demand index implicitly assumes that the demand for labour is a derived demand reflecting the composition of output by industry and occupation. It therefore treats output as an intermediate product.

The hypothesis we then want to test is whether differences across countries in the relative net supply of skills ($\overline{Supply}_{s,x} - \overline{Supply}_{s',x}$,) can explain cross-country differences in wage inequality (as measured by inderdecile wage ratios). Intuitively, the larger the supply of skill group *s* relative to demand in the United States compared to country *x*, the worse off we expect skill group *s* to be in the United States compared to country *x*. For example, if the net supply of high- relative to low-skilled workers is lower in the United States than it is in Sweden, then we would expect to see higher wage inequality in the United States than in Sweden. Indeed, juxtaposing the information from Tables 3 and 4, we see that the United States combines a low supply of high-skilled workers with a high demand for such workers, while in Sweden the high demand for high-skilled workers is matched by a high supply – which would help explain why inequality is higher in the United States. While there are other countries with a low supply of high-skilled workers (e.g. Italy and Spain), these countries also have a low demand for high-skilled workers and, therefore, lower wage inequality than the United States.

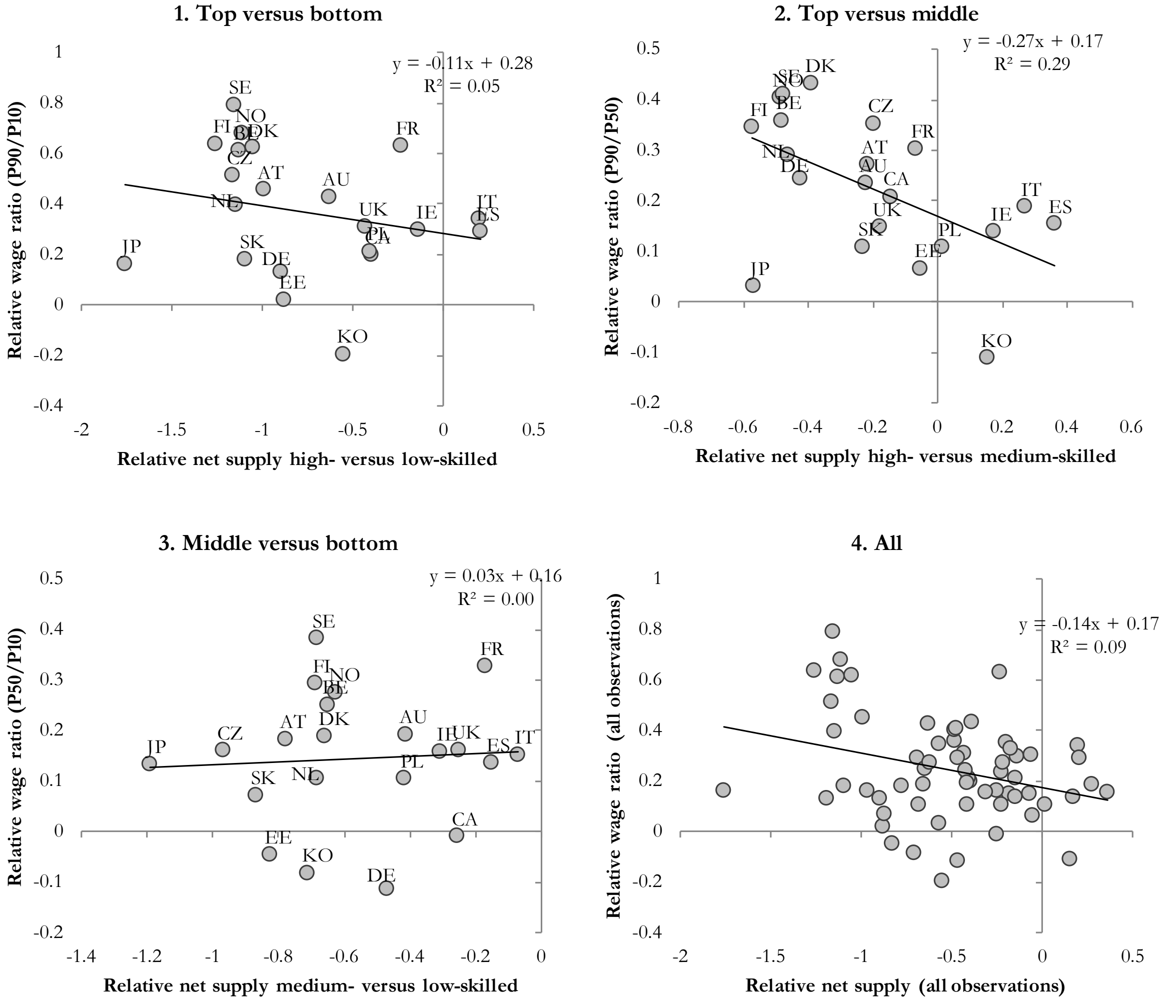
The relationship between the relative net supply of skills and wage inequality is shown in graphical form in Figure 4. The first graph plots the relationship between the relative net supply of high- versus low-skilled workers, on the one hand, and the P90/P10 wage ratio, on the other. Each observation shows the extent to which the United States differs with respect to that particular country. Taking Sweden as an example again, the graph confirms that the United States has a much lower relative net supply of high- versus low-skilled workers, as well as a significantly higher P90/P10 wage ratio. While the relationship is negative overall, it is not particularly strong: only 5% of higher wage inequality in the United States can be explained by the higher net supply of skilled workers in other countries.

The second graph in Figure 4 shows that the relationship is much stronger at the top of the wage distribution: the higher relative net supply of high- versus medium-skilled workers in other countries accounts for 29% of the higher P90/P50 ratio in the United States. The effect size is also quite large: a 1% increase in the relative net supply of high-skilled workers in the United States would reduce the top-half wage inequality by 0.27%. By contrast, the third graph shows that the net supply of skills explains nothing of the higher wage inequality at the bottom of the wage distribution (P50/P10). Finally, the fourth graph combines all the observations of the previous three graphs and shows that, overall, differences in the relative net supply of skills can explain 9% of differences in wage inequality between the United States and other countries.[14,15]

[14] LOV (2004) found that differences in the relative net supply of skills could account for 58% of the cross-country variance in skills premia between medium- and low-skilled workers; and 44% in the case of high- versus low-skilled workers. There are some important differences between our analysis and that of LOV (2014). The first of these is that we focus on wage inequality while they look at relative skills premia. The second difference lies in the fact that we define our skills groups using "absolute" thresholds based on the PIAAC average, while they define them relative to one specific country. Because their approach means that the results are sensitive to the choice of reference country, they repeat the analysis as many times as there are countries in their sample. This boosts their sample size which, in turn, increases their R-squared. When we repeat our analysis to replicate exactly the methodology used by LOV (2004), we find that the relative net supply of skills can explain 19% of the cross-country variance between medium-and low-skilled workers; and 22% in the case of high- versus low-skilled workers. These estimates are considerably lower than those found by LOV (2014). It is difficult to say whether the difference represents a real change over time in the relationship between net skills supplies and relative wages of skills groups, or whether it can be explained by the difference in samples. Countries included in their sample but not in ours are: Chile, Hungary, Slovenia and Switzerland. Conversely, countries included in our sample, but not in theirs, are: Australia, Austria, England/Northern Ireland, Estonia, Flanders, France, Ireland, Japan, Korea, the Slovak Republic and Spain.

[15] Blau and Kahn (1996) also carry out a demand and supply analysis to quantify the extent to which higher wage inequality in the United States could be explained by differences in the relative supply of, and demand for, educated workers – but they conclude that market forces appear to have little explanatory power. However, Blau and Kahn (1996) derive workers' skill levels simply from the number of years of schooling and work experience, and LOV (2004) show that the Blau and Kahn (1996) results change substantially once more direct measures of skill are used.

Figure 4. Net supply of skills and wage inequality



5. Controlling for institutional characteristics

The previous analysis demonstrated that the demand and supply of skills appear to be correlated with wage inequality. However, one may argue that this correlation is, in fact, driven by differences in labor market institutions which happen to be correlated with differences in skills demand and supply. To test for the robustness of the findings obtained in the previous section, we therefore run a series of regressions identical to those reported in Figure 4, but add controls for labor market institutions, policies and practices as well. The results from this analysis are reported in Table 5. The first column of each panel simply reproduces the regressions from Figure 4, which shows that a significant portion of the difference in top-half wage inequality between the United States and other countries can be explained by differences in the net supply of high- versus medium-level skills, but that skills do not appear to explain the higher inequality in the United States in the bottom half of the wage distribution.

Table 5. Net supply of skills, wage inequality and labor market institutions

Panel (i) Dependent variable: P90/P10 (in logs, relative to US)

	(i)	(ii)	(iii)	(iv)	(v)	(vii)	(vii)
Net supply of skills (high v. low)	-0.111	-0.143*	-0.104	-0.121**	-0.110**	-0.131*	-0.138***
	(0.093)	(0.075)	(0.084)	(0.044)	(0.050)	(0.071)	(0.036)
Statutory minimum wage (MW dummy)[a]		-0.384**					0.003
		(0.146)					(0.149)
Level of minimum wage[b] x MW dummy		-0.987**					-0.198
		(0.456)					(0.405)
Employment protection legislation[c]			-0.377*				0.038
			(0.206)				(0.195)
Bargaining coverage				-0.306***			-0.242***
				(0.035)			(0.069)
Size of public sector[d]					-0.415***		-0.209
					(0.074)		(0.128)
Generosity of unemployment benefits[e]						-0.482***	0.041
						(0.135)	(0.114)
Constant	0.284***	0.395***	0.026	-0.134**	0.264***	0.097	-0.057
	(0.075)	(0.096)	(0.150)	(0.057)	(0.051)	(0.084)	(0.149)
N	*21*	*21*	*21*	*21*	*21*	*21*	*21*
R^2	*0.053*	*0.427*	*0.133*	*0.712*	*0.571*	*0.289*	*0.818*
Adjusted R^2	*0.003*	*0.325*	*0.037*	*0.68*	*0.523*	*0.209*	*0.721*

Panel (ii) Dependent variable: P90/P50 (in logs, relative to US)

	(i)	(ii)	(iii)	(iv)	(v)	(vii)	(vii)
Net supply of skills (high v. medium)	-0.270**	-0.198*	-0.263**	-0.179***	-0.187***	-0.250**	-0.163***
	(0.11)	(0.095)	(0.101)	(0.042)	(0.063)	(0.100)	(0.031)
Statutory minimum wage (MW dummy)[a]		-0.178*					0.039
		(0.088)					(0.075)
Level of minimum wage[b] x MW dummy		-0.325					0.136
		(0.285)					(0.226)
Employment protection legislation[c]			-0.237**				-0.029
			(0.110)				(0.109)
Bargaining coverage				-0.161***			-0.123***
				(0.019)			(0.029)
Size of public sector[d]					-0.207***		-0.105**
					(0.045)		(0.048)
Generosity of unemployment benefits[e]						-0.283***	-0.054
						(0.080)	(0.047)
Constant	0.170***	0.263***	0.006	-0.027	0.176***	0.073*	-0.028
	(0.032)	(0.039)	(0.087)	(0.027)	(0.024)	(0.036)	(0.088)
N	*21*	*21*	*21*	*21*	*21*	*21*	*21*
R^2	*0.288*	*0.507*	*0.385*	*0.812*	*0.657*	*0.539*	*0.889*
Adjusted R^2	*0.25*	*0.42*	*0.317*	*0.792*	*0.619*	*0.488*	*0.829*

Panel (iii) Dependent variable: P50/P10 (in logs, relative to US)							
	(i)	(ii)	(iii)	(iv)	(v)	(vii)	(vii)
Net supply of skills (medium v. low)	0.027	-0.105	0.03	-0.053	-0.038	-0.003	-0.14
	(0.070)	(0.084)	(0.066)	(0.066)	(0.086)	(0.079)	(0.080)
Statutory minimum wage (MW dummy)[a]		-0.185**					-0.033
		(0.081)					(0.096)
Level of minimum wage[b] x MW dummy		-0.605**					-0.337
		(0.227)					(0.213)
Employment protection legislation[c]			-0.135				0.067
			(0.157)				(0.185)
Bargaining coverage				-0.131***			-0.119*
				(0.029)			(0.062)
Size of public sector[d]					-0.182***		-0.101
					(0.058)		(0.087)
Generosity of unemployment benefits[e]						-0.153	0.091
						(0.099)	(0.097)
Constant	0.160***	0.135	0.067	-0.061	0.114**	0.089	-0.038
	(0.048)	(0.079)	(0.097)	(0.057)	(0.050)	(0.061)	(0.120)
N	*21*	*21*	*21*	*21*	*21*	*21*	*21*
R^2	*0.004*	*0.29*	*0.042*	*0.411*	*0.347*	*0.087*	*0.58*
Adjusted R^2	*-0.049*	*0.165*	*-0.065*	*0.346*	*0.274*	*-0.015*	*0.354*

Robust SE in parentheses. * 10%, ** 5%, *** 1%.
Notes: All variables are relative to the US (and in logs)
a. Dummy variable indicating countries that have a minimum wage. Countries that do not have a minimum wage are: Finland, Sweden Norway, Denmark, Germany, Austria and Italy.
b. Minimum wage relative to median wage of full-time workers.
c. Strictness of employment protection legislation - individual and collective dismissal (regular contracts).
d. Employment in general government as a percentage of the labor force.
e. Net replacement ratio (NRR), which is defined as the average of the net unemployment benefit (including SA and cash housing assistance) replacement rates for two earnings levels, three family situations and 60 months of unemployment.
Source: OECD Statistics for EPL and minimum wage (2012); ICTWSS version 4 for bargaining coverage (latest available); PIAAC for share permanent and part-time (2012); OECD Government at a Glance, 2013 (2011, 2010 for Germany, Ireland, Norway, Sweden, and the United Kingdom); OECD Tax-Benefit Model for unemployment benefits (2012).

In subsequent columns, we include a series of controls for labor market institutions, policies and practices[16]: the level at which statutory minimum wages are set (with a dummy to control for countries that do not have a statutory minimum wage); the strictness of employment protection legislation; the bargaining coverage rate; the size of the public sector; and the generosity of unemployment benefits. In the final column, all controls are added simultaneously.

All the aforementioned institutions could be argued to reduce wage inequality, either directly or indirectly. The impact of statutory minimum wages is perhaps the most obvious one, as they directly boost the wages of workers at the bottom of the distribution.[17] Even in countries with no statutory minimum wage, a large part of the workforce is covered by wage floors specified in sector- and/or occupation-level collective agreements which, in combination with high collective bargaining coverage, are a functional equivalent of a binding minimum wage (Garnero, Kampelmann and Rycx, forthcoming). Wage inequality could therefore be expected to be lower in countries with higher bargaining coverage.[18] Strict employment protection legislation might have a more indirect effect by reducing employment overall, and

[16] These institutional controls are added one at the time to avoid issues of collinearity.
[17] See DiNardo, Fortin and Lemieux (1996), Lee (1999) and Autor, Manning and Smith (2014) for evidence of the link between minimum wages and inequality in the United States.
[18] See Blau and Kahn (1996), DiNardo, Fortin and Lemieux (1996) and Firpo, Fortin and Lemieux (2011) for the impact of falling union coverage on wage inequality in the United States.

of low-skilled, low-wage workers in particular. Because wages paid to low-skilled workers in the public sector may be higher than those that would be dictated by the market, the size of the public sector may also be inversely related with wage inequality. Finally, generous unemployment benefits may raise the reservation wages of the unemployed to the extent that low-skilled workers decide not to work for low wages, indirectly compressing the wage distribution. Further details about the construction of the variables can be found in the notes to Table 5.

The results show that the relative net supply of high- versus medium-level skills (panel (ii)) always remains significant in explaining higher wage inequality in the United States, regardless of which institutional control is included in the regression. By contrast, the relative net supply of medium- versus low-skilled workers is never statistically significant (Panel (iii)). In panel (i), which reports the results for the P90/P10 wage ratio, the coefficient of the skills variable is insignificant in the regression without institutional controls, but it turns statistically significant in most of the regressions with institutional controls. This suggests that differences in the net supply of skills can explain differences in the 90-10 gap within countries with similar institutional setups.

Overall, this robustness check corroborates the previous conclusion that the supply of skills seems to matter for wage inequality, particularly at the top of the wage distribution. All the institutional controls also have the expected, negative impact on inequality. However, it is worth repeating that, based on the analysis presented here, these relationships cannot necessarily be interpreted as causal. As mentioned above, there is a high degree of collinearity between the institutional variables. Indeed, institutions within a country do not evolve in isolation, and one would therefore expect a high degree of interdependence between them. Also, the analysis treats policies as exogenous factors affecting inequality, but there may be reason to be concerned by endogeneity: institutions may be introduced or adjusted in response to changes in inequality. Given that data are only available for one point in time we cannot include country fixed effects and country level institutions at the same time in the regression model. The results from these regressions should therefore not be interpreted as causal links, but rather as interesting statistical correlations.

6. Wage compression and employment effects

So far, we have shown that wage inequality is significantly higher in the United States than it is in most other OECD countries. We have also argued that differences in skills are likely to play some role in explaining this higher wage inequality. However, skills could only explain part of the gap and, as seen in Section 5, labor market policies and institutions also have a compressing effect on the wage distribution. One key mechanism through which they achieve this is by artificially raising the wages of those at the bottom of the distribution, possibly above the level that would arise under free market conditions. By looking at wages alone, we may therefore be ignoring another, important aspect of inequality, which is inequality in employment outcomes. Indeed, in countries with stronger labor market institutions, wage inequality might be lower, but so might the employment rates of the least skilled. If unemployment and other out-of-work benefits are lower than what individuals would earn in the labor market, more compressed wage distributions could result in more unequal earnings distributions if a large portion of low-skilled workers are forced out of a job.

In this section, we explore to what extent higher wage inequality in the United States might be compensated for by a higher employment rates among the low-skilled. To shine light on this issue, we once again split the workforce of each country into high-, medium- and low-skilled groups using the same skill group definitions derived in Section 4. Table 6 shows the employment and unemployment rates of each of these skills groups, by country. Employment rates are generally higher in the United States than they are in other countries. However, the differences in employment rates between the various skill groups in the United States are comparable to those observed on average across the PIAAC countries. In the United States, the low-skilled (medium-skilled) are 26% (9%) less likely to be employed than the high-skilled, while the equivalent PIAAC averages are 26% and 10%, respectively. The least-skilled in the United States are therefore not more likely to be in employment relative to the more skilled – which contradicts the wage compression hypothesis. Overall, there is a slight negative relationship between wage inequality (as measured by the P90/P10) and the percentage difference in employment rates between high- and low-skilled groups (although this is significant only at the 10% level). Countries like Japan and Korea have relatively high wage inequality but small differences in the employment rate of different skills groups; while Scandinavian countries tend to have low wage inequality, but relatively large differences in the unemployment rates of different skills groups.

Turning to unemployment rates, there is even less support for the wage compression hypothesis in the United States: the low-skilled (medium-skilled) are 3.6 (2.1) times more likely to be unemployed than the high-skilled. The equivalent PIAAC average ratios are 2.5 and 1.6, respectively. Again, there is very little evidence of a relationship between wage inequality and the relative unemployment rates of skills groups across countries. Some countries with much lower wage inequality than the United States have similar unemployment ratios between skills groups (e.g. Sweden), while others have much higher unemployment gaps (e.g. Flanders). Overall, these results do not suggest that higher wage inequality in the United States results in better relative employment outcomes for the low-skilled - which is consistent with earlier findings from Nickell and Bell (1996), Freeman and Schettkat (2001) and Howell and Huebler (2005), as well as with more recent analysis by Jovecic (2015).

Table 6. Employment and unemployment rates, by skill group and country (%)

	Employment rate			Unemployment rate		
	Low-skilled	Medium-skilled	High-skilled	Low-skilled	Medium-skilled	High-skilled
Australia	61.8	76.8	81.9	8.0	4.8	5.0
Austria	64.0	72.7	81.2	5.9	4.8	3.3
Canada	66.3	78.4	84.3	8.4	4.8	3.5
Czech Republic	56.1	65.0	73.4	10.8	7.2	3.7
Denmark	57.0	73.9	83.8	9.7	7.8	3.7
England/N. Ireland (UK)	59.9	74.4	81.7	13.6	6.8	3.6
Estonia	60.9	71.8	81.6	12.4	8.5	3.8
Finland	54.1	70.8	78.5	10.1	5.9	4.4
Flanders (B)	56.4	70.0	78.2	4.0	2.8	2.4
France	57.0	65.6	73.9	11.8	9.2	5.6
Germany	63.2	77.6	84.1	9.6	4.8	2.6
Ireland	51.6	64.5	74.2	17.6	12.0	7.9
Italy	48.7	59.2	73.6	17.5	12.9	7.2
Japan	65.7	70.1	76.4	1.9	3.6	2.4
Korea	66.7	68.1	67.2	4.4	3.7	4.2
Netherlands	60.7	75.9	84.8	8.7	5.2	3.1
Norway	65.0	77.7	88.1	7.1	4.3	2.3
Poland	53.1	63.3	72.0	13.2	9.3	6.8
Slovak Republic	42.1	62.8	71.6	23.0	9.0	6.4
Spain	48.4	64.9	76.5	25.7	15.4	10.1
Sweden	57.9	73.9	83.0	12.4	7.0	3.4
United States	63.5	78.4	85.7	14.5	8.3	4.0
PIAAC average	58.2	70.7	78.9	11.4	7.2	4.5

Notes: PIAAC average is the unweighted average of the country employment and unemployment rates.

An alternative way of assessing the employment effects of wage compression is to look at whether the skills of the unemployed differ from the skills of the employed. If wage compression were pushing the least skilled into unemployment, one would expect the unemployed to be significantly less skilled than the employed. Table 7 reports the average numeracy scores for the unemployed and employed, by country. While the average skill level of the unemployed is (nearly) always lower than that of the employed, the employed-to-unemployed average skills ratio ranges from 1 in Korea to 1.14 in England/Northern Ireland. In the United States, this ratio (1.10) tends to be quite high as well (i.e. the unemployed are relatively less skilled compared to the employed than they are in other countries). Once again this is inconsistent with the idea that higher wage inequality might be the price paid for higher employment rates among the low-skilled.

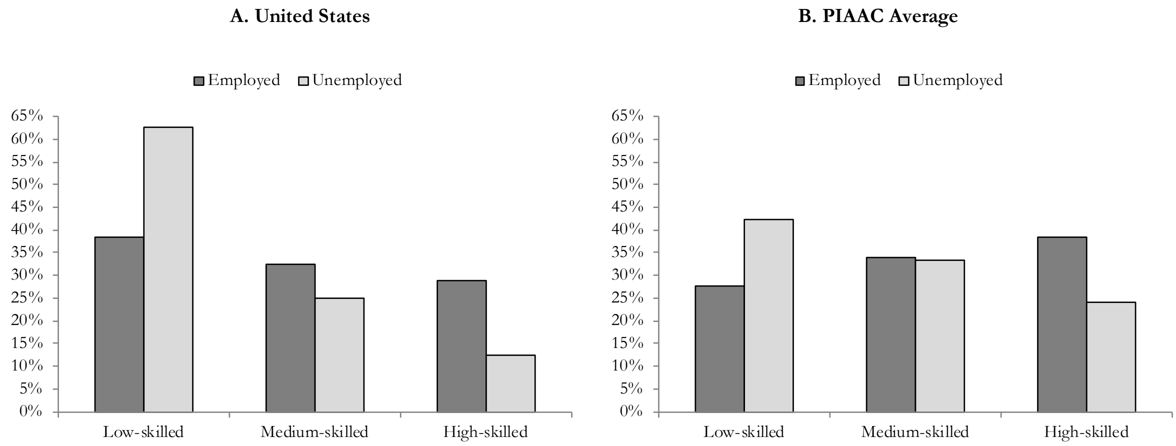
While Table 7 looked at the average skills of the employed and unemployed in each country, Figure 5 sheds some light on how these skills are distributed. It shows the proportion of the employed and unemployed who are low-, medium- and high-skilled, respectively. Compared to the PIAAC average, the unemployed in the United States are disproportionately low-skilled, but this will partly reflect the fact that skills are generally lower in the United States. More importantly, the proportion of unemployed among the low-skilled is 1.63 times the proportion of employed among the low-skilled, while this ratio is 1.54 across PIAAC on average.

Table 7. Average skills by employment status and country (points)

	Employed	Unemployed	P-value
Australia	275	262	0.002
Austria	280	265	0.001
Canada	272	249	0.000
Czech Republic	281	259	0.000
Denmark	286	265	0.000
England/N. Ireland (UI	270	237	0.000
Estonia	278	258	0.000
Finland	290	271	0.000
Flanders (B)	287	278	0.036
France	261	245	0.000
Germany	278	248	0.000
Ireland	264	247	0.000
Italy	255	236	0.000
Japan	291	286	0.286
Korea	264	264	0.925
Netherlands	287	265	0.000
Norway	285	257	0.000
Poland	267	251	0.000
Slovak Republic	285	258	0.000
Spain	256	235	0.000
Sweden	287	255	0.000
United States	260	236	0.000

Notes: PIAAC average is the unweighted average of the country skill levels. The P-values reported are from a test of the equality of mean skill levels between the employed and unemployed.

Figure 5. Distribution of skill-levels among employed and unemployed: US vs. PIAAC average



Notes: PIAAC average is the unweighted average of the country shares.

7. Conclusion

The collection and publication of new data from internationally comparable assessments of cognitive skills has sparked renewed interest in the relationship between skills and wage inequality (e.g. Jovecic, 2015; Paccagnella, 2015; Pena, 2015). While the earlier literature on this topic had been divisive and did not come to any definite conclusions about the role of skills, the more recent literature has tended to ignore an entire side of the earlier argument and claims that skills matter very little to explaining international differences in wage inequality. This assertion seem counterintuitive, however, given: (i) that skills play an important role at the individual level in terms of determining wages (Hanushek et al. 2015); and (ii) that skills/routine-biased technological change have played a crucial role in labor market polarization and rising inequality (Juhn, 1999; Goldin and Katz, 2008; Autor and Dorn, 2013; Auto, Katz and Kearney, 2006). The primary purpose of this paper was therefore to fully revive the earlier literature on cognitive skills and wage inequality and to show that, despite the availability of new data, this earlier polemic remains unsettled. Indeed, as the results in this paper have shown, there does appear to be a role for skills in explaining international differences in wage inequality, which operates primarily through the relative balance between supply and demand. What has been missing to date, however, is the methodology to make comparable assessments of the importance of skills and labor market institutions in determining wage inequality. This would require a unified framework for analysis, and should be a priority for future research.

References

Autor, D.H. (2015), "Why are there still so many jobs? The history and future of workplace automation", *Journal of Economic Perspectives*, Vol. 29/3, pp. 3-30.

Autor, D.H. (2014), "Skills, education, and the rise of earnings inequality among the other 99 percent", *Science*, Vol. 344/6186, pp. 843-851.

Autor, D.H., and D. Dorn (2013), "The growth of low-skill service jobs and the polarization of the US labor market", *American Economic Review*, Vol. 103/5, pp. 1553-97.

Autor, D.H., L.F. Katz and M.S. Kearney (2006), "The polarization of the U.S. labor market", *American Economic Review*, Vol. 96/2, pp. 189-94.

Autor, D.H., L.F. Katz and M.S. Kearney (2008), "Trends in U.S. wage inequality: Revising the revisionists", *Review of Economics and Statistics*, Vol. 90/2, pp. 300–23.

Autor, D.H., F. Levy, and R.J. Murnane (2003), "The skill content of recent technological change: An empirical exploration", *Quarterly Journal of Economics*, Vol. 118/4, pp. 1279-1333.

Autor, D.H., A. Manning and C.L. Smith (2014), "The contribution of the minimum wage to U.S. wage inequality over three decades: A reassessment".

Blau, F.D. and L.M. Kahn (2005), "Do cognitive test scores explain higher U.S. wage inequality?" *The Review of Economics and Statistics*, Vol. 87/1, pp. 184-193.

Blau, F.D. and L.M. Kahn (1996), "International differences in male wage inequality: Institution versus market forces", *The Journal of Political Economy*, Vol. 104/4, pp. 791-837.

Cingano, F. (2014), "Trends in income inequality and its impact on economic growth", *OECD Social, Employment and Migration Working Papers*, No. 163.

Devroye, D. and R. Freeman (2001), "Does inequality in skills explain inequality of earnings across advanced countries?" *NBER Working Paper Series*, No. 8140, National Bureau of Economic Research, Cambridge MA.

DiNardo, J., N.M. Fortin and T. Lemieux (1996), "Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach", *Econometrica*, Vol. 64/5, pp. 1001-1044.

Fortin, N.M., T. Lemieux and S. Firpo (2010), "Decomposition methods in economics", *NBER Working Paper Series*, No. 16045.

Freeman, R. and R. Schettkat (2001), "Skill compression, wage differentials, and employment: Germany vs the US", *Oxford Economic Papers*, Vol. 3, pp. 582-603.

Garnero, A., S. Kampelmann and F. Rycx (forthcoming), "Sharp teeth or empty mouths? Revisiting the minimum wages bite with sectoral data", British Journal of Industrial Relations.

Goldin, C.D. and L.F. Katz (2008), *The Race between Education and Technology*, Harvard University Press.

Hanushek, E.A., G. Schwerdt, S. Wiederhold and L. Woessmann (2015), "Returns to skills around the world: Evidence from PIAAC," *European Economic Review*, Vol. 73/C, pp. 103-130

Howell, D. R., Huebler, F. (2005), 'Wage compression and the unemployment crisis: labour market institutions, skills, and inequality-unemployment tradeoffs', in Howell, D. R. (ed.), *Fighting Unemployment: The Limits of Free Market Orthodoxy*, Oxford University Press.

Jovicic, S. (2015), "Wage inequality, skill inequality, and employment: Evidence from PIAAC", *Schumpeter Discussion Papers*, No. 2015-007.

Juhn, C. (1999), "Wage inequality and demand for skill: Evidence from five decades", *Industrial and Labor Relations Review*.

Juhn, C., K.M. Murphy and B. Pierce (1993), "Wage inequality and the rise in the returns to skill", *Journal of Political Economy*, Vol. 101/3, pp. 410-442.

Katz, L.F. and K.M. Murphy (1992), "Changes in relative wages, 1963-1987: Supply and demand factors", *The Quarterly Journal of Economics*, Vol. 107/1, pp. 35-78.

Krueger, A. (2012), "The rise and consequences of inequality", remarks delivered at the Center for American Progress, 12 January 2012, Washington, DC.

Lee, D.S. (1999), "Wage inequality in the United States during the 1980s: Rising dispersion or falling minimum wage?" The Quarterly Journal of Economics, Vol. 114/3, pp. 977-1023.

Lemieux, T. (2010), "What do we really know about changes in wage inequality?" in K.G. Abraham, J.R. Spletzer and M. Harper (eds.), *Labor in the New Economy*, University of Chicago Press.

Lemieux, T. (2002), "Decomposing changes in wage distributions: A unified approach", *Canadian Journal of Economics*, Vol. 35/4, pp. 646-688.

Leuven, E., H. Oosterbeek and H. van Ophem (2004), "Explaining international differences in male skill wage differentials by differences in demand and supply of skills", *The Economic Journal*, Vol. 114/495, pp. 466-486.

Nickell, S. and B. Bell (1996), "Changes in the distribution of wages and unemployment in OECD countries", *The American Economic Review*, Vol. 86/2, pp. 302-308.

OECD (2014), *OECD Employment Outlook 2014*, OECD Publishing, Paris.

OECD (2013), *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*, OECD Publishing, Paris.

Ostry, J.D., A. Berg and C.G. Tsangarides (2014), "Redistribution, Inequality, and Growth", IMF Staff Discussion Notes, No. 14/02.

Paccagnella, M. (2015), "Skills and wage inequality: Evidence from PIAAC", *OECD Education Working Papers*, No. 114.

Pena, A.A. (2015), “Revisiting the effects of skills on economic inequality: Within- and cross-country comparisons using PIAAC”, working paper for presentation at “Taking the Next Step with PIAAC: A Research-to-Action Conference”.

Pickett, K. and R. Wilkinson (2011), *The Spirit Level: Why Greater Equality Makes Societies Stronger*, Bloomsbury Press.

Salvedra, W. and D. Checchi (2014), “Labour-market institutions and the dispersion of wage earnings”, *IZA Discussion Paper Series*, No. 8820.

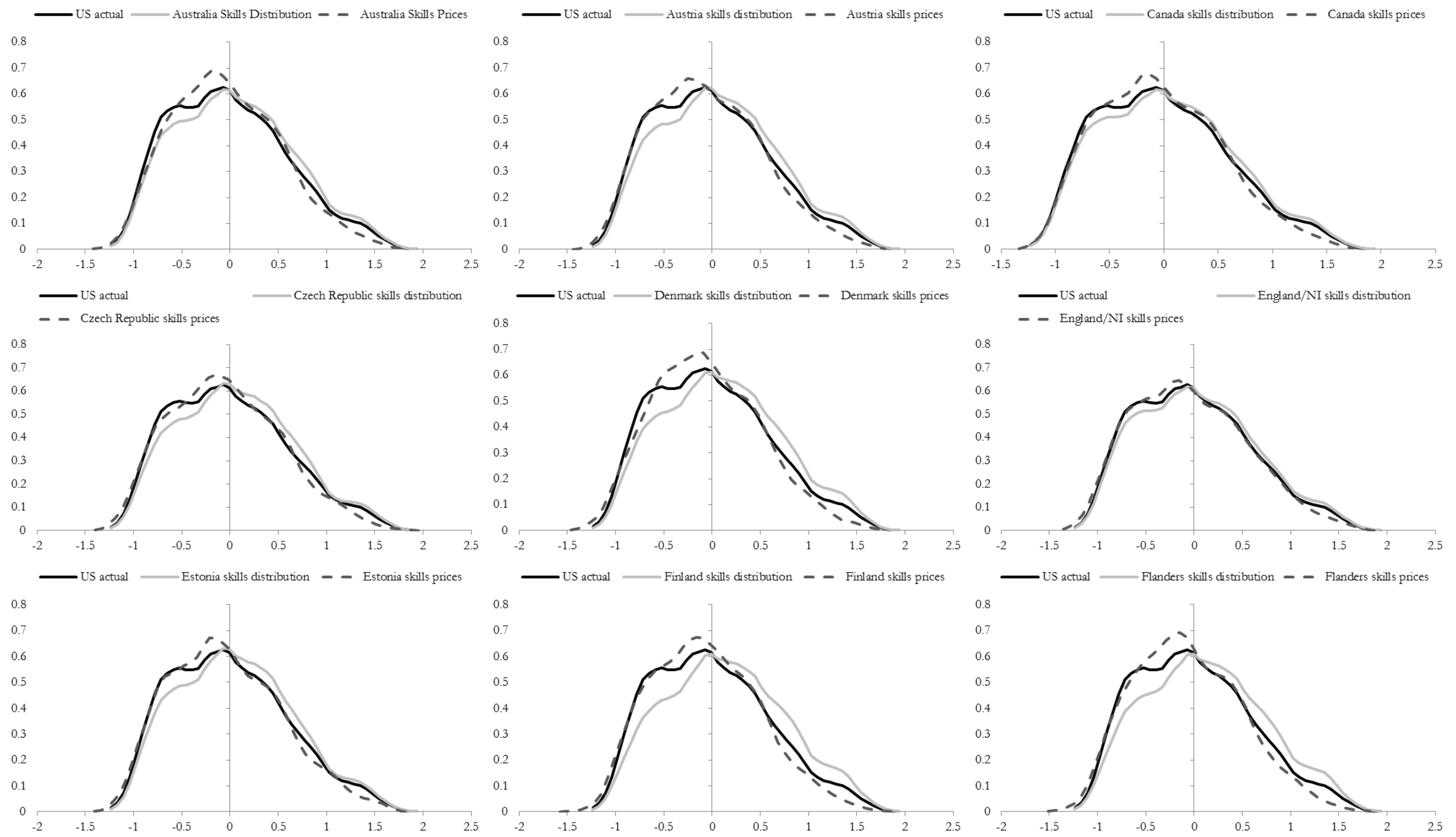
Stiglitz, J. (2012), *The Price of Inequality: How Today's Divided Society Endangers Our Future*, W. W. Norton & Company.

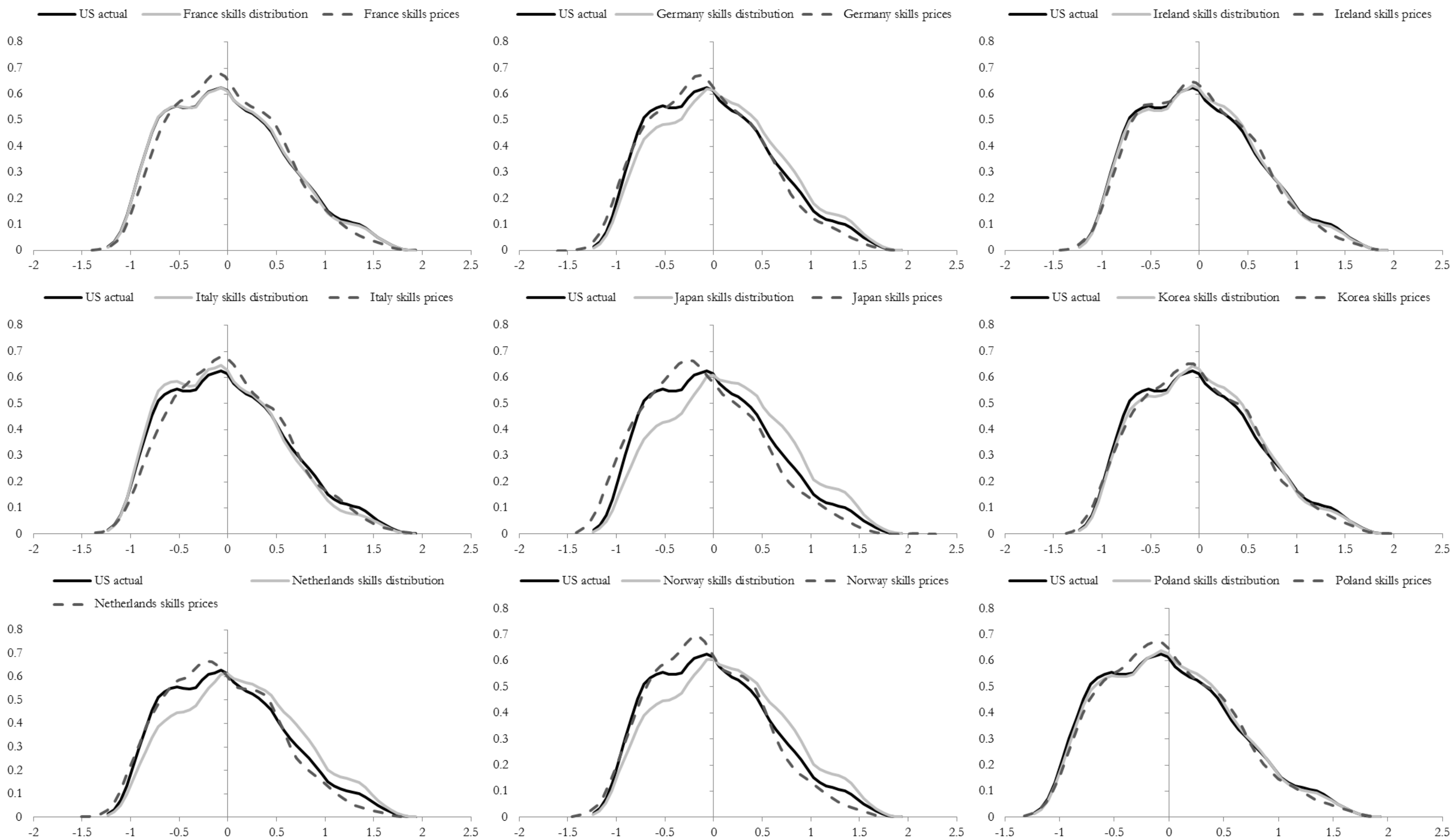
Suen, W. (1997), “Decomposing wage residuals: Unmeasured skill or statistical artefact?”, *Journal of Labor Economics*, Vol. 15/3, pp. 555-566.

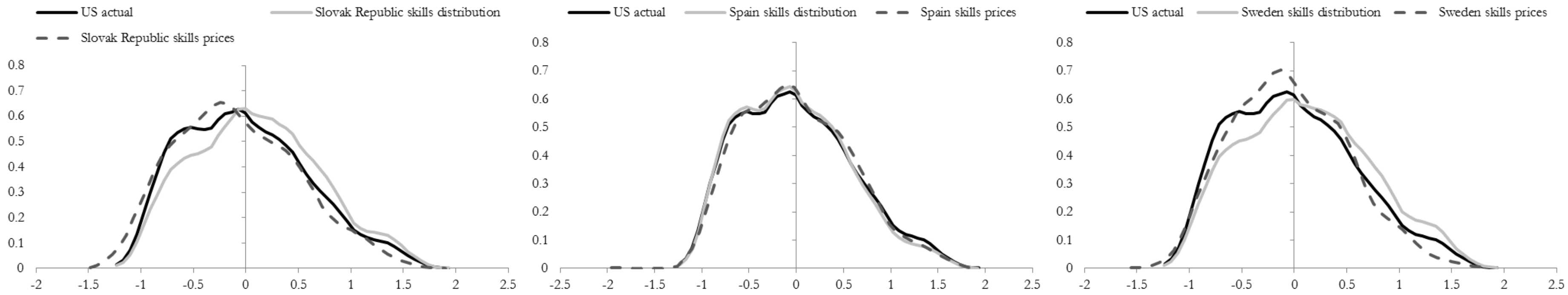
Tinbergen (1975), *Income Distribution: Analysis and Policies*, Elsevier.

Yun, M. (2009), “Wage differentials, discrimination and inequality: A cautionary note on the Juhn, Murphy and Pierce decomposition method”, *Scottish Journal of Political Economy*, Vol. 56/1, pp. 114-122.

Annex A: Wage simulations of skill endowment and price effects




US actual
France skills distribution
France skills prices
US actual
Germany skills distribution
Germany skills prices
US actual
Ireland skills distribution
Ireland skills prices
US actual
Italy skills distribution
Italy skills prices
US actual
Japan skills distribution
Japan skills prices
US actual
Korea skills distribution
Korea skills prices
US actual
Netherlands skills distribution
Netherlands skills prices
US actual
Norway skills distribution
Norway skills prices
US actual
Poland skills distribution
Poland skills prices


US actual
Slovak Republic skills distribution
Slovak Republic skills prices
US actual
Spain skills distribution
Spain skills prices
US actual
Sweden skills distribution
Sweden skills prices
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
-2.5
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
2.5

Annex B: Industry-occupation employment shares, by country (%)

Industry	Finance, insurance, real estate and services	Government	Agriculture	Trade	Agriculture	Mining, manufacturing and construction	Transportation, communication and public utilities	Government	Finance, insurance, real estate and services
Occupation	Craftworkers, operatives, laborers and service workers	Craftworkers, operatives, laborers and service workers	Craftworkers, operatives, laborers and service workers	Craftworkers, operatives, laborers and service workers	Clerical and sales workers	Craftworkers, operatives, laborers and service workers	Craftworkers, operatives, laborers and service workers	Clerical and sales workers	Clerical and sales workers
PIAAC	3.69	2.42	2.45	2.91	0.13	14.41	3.82	8.36	7.57
Australia	3.79	1.78	2.00	4.25	0.18	13.16	3.82	7.48	7.12
Austria	3.51	2.94	3.91	3.03	0.07	13.27	3.38	5.92	8.70
Canada	2.95	1.40	1.70	3.75	0.07	10.61	3.16	5.87	7.88
Czech Republic	2.15	2.54	1.81	3.04	0.27	24.96	5.14	5.36	5.20
Denmark	3.80	2.71	1.79	3.43	0.10	12.80	3.09	9.12	5.77
England/N. Ireland (UK)	4.29	1.55	0.67	3.17	0.07	11.39	5.48	14.15	8.95
Estonia	3.37	2.27	3.37	2.43	0.09	19.80	4.52	4.83	4.83
Finland	3.13	2.79	3.10	2.87	0.09	13.58	4.60	9.38	7.63
Flanders (B)	3.65	3.60	1.31	2.32	0.03	12.01	3.65	8.06	5.32
France	4.59	7.41	2.69	3.34	0.06	11.71	3.44	9.70	6.27
Germany	4.29	2.35	1.42	2.76	0.19	16.82	3.69	7.06	7.60
Ireland	3.99	2.74	4.40	2.84	0.20	11.11	3.99	10.9	9.71
Italy	4.59	2.52	4.14	2.83	0.08	21.59	4.37	4.55	10.63
Japan	2.44	1.63	2.19	2.09	0.04	15.63	3.68	9.84	10.89
Korea	4.03	1.79	3.12	3.46	0.01	16.83	4.19	5.76	12.18
Netherlands	2.98	1.94	0.64	2.84	0.10	8.70	2.31	9.85	6.35
Norway	2.98	1.85	1.69	1.64	0.18	9.44	2.96	13.88	4.82
Poland	2.63	2.41	7.36	2.58	0.03	21.19	3.75	4.07	5.26
Slovak Republic	2.33	2.61	1.84	2.29	0.33	21.27	4.38	4.86	5.60
Spain	7.15	2.42	3.60	4.13	0.59	11.53	3.40	7.55	11.9
Sweden	3.66	1.39	1.95	1.70	0.09	12.62	3.85	14.28	5.29
United States	5.52	1.40	0.69	3.32	0.11	9.85	3.63	9.89	9.69
Average numeracy score	242.9	250.3	251.9	255.0	257.6	258.2	259.0	262.1	263.2

Industry	Trade	Transportation, communication and public utilities	Mining, manufacturing and construction	Trade	Government	Agriculture	Finance, insurance, real estate and services	Mining, manufacturing and construction	Transportation, communication and public utilities
Occupation	Clerical and sales workers	Clerical and sales workers	Clerical and sales workers	Managers and professionals	Managers and professionals	Managers and professionals	Managers and professionals	Managers and professionals	Managers and professionals
PIAAC	7.35	1.98	2.32	3.62	17.62	0.25	9.58	7.06	4.44
Australia	7.60	1.62	2.28	5.52	17.98	0.13	11.33	5.20	4.78
Austria	8.29	2.06	2.42	3.91	17.35	0.37	9.05	8.03	3.81
Canada	6.99	1.41	1.27	5.02	20.43	0.18	14.05	8.20	5.06
Czech Republic	6.02	3.11	3.21	3.53	11.79	0.18	7.81	9.03	4.85
Denmark	6.80	1.56	1.54	3.40	22.46	0.35	9.10	6.13	6.06
England/N. Ireland (UK)	7.47	1.62	1.42	2.60	15.75	0.14	11.36	5.31	4.61
Estonia	5.75	1.72	1.11	5.62	17.83	0.60	8.60	8.12	5.15
Finland	6.51	2.03	1.43	3.23	18.35	0.29	9.38	7.22	4.37
Flanders (B)	5.35	2.73	3.05	3.85	22.06	0.16	9.43	8.93	4.48
France	5.77	1.89	1.28	3.57	16.59	0.23	7.71	9.26	4.49
Germany	7.97	2.95	4.03	2.09	17.14	0.16	8.81	7.18	3.50
Ireland	8.15	1.47	1.61	2.61	16.68	0.25	10.64	4.76	3.96
Italy	7.89	1.99	2.19	2.34	12.69	0.33	8.49	5.86	2.90
Japan	10.06	2.39	3.72	2.88	12.73	0.05	5.96	8.89	4.88
Korea	11.14	1.98	6.70	2.02	11.37	0.01	8.28	5.00	2.12
Netherlands	6.68	2.14	2.72	4.56	24.60	0.17	11.35	7.33	4.73
Norway	10.61	1.51	1.27	4.58	22.12	0.06	8.95	6.47	4.99
Poland	8.12	1.65	2.17	3.31	17.43	0.45	6.57	7.18	3.85
Slovak Republic	6.90	2.00	1.60	4.25	14.54	0.73	8.62	9.99	5.85
Spain	6.76	2.41	3.59	2.73	16.13	0.39	8.59	4.21	2.95
Sweden	5.11	1.80	1.11	4.76	18.77	0.21	12.55	5.64	5.22
United States	6.04	1.55	1.37	2.47	20.13	0.23	12.71	7.06	4.33
Average numeracy score	266.0	275.6	276.7	288.4	289.1	290.1	295.4	296.2	304.0

Notes: Industry-occupation combinations are ranked in ascending average numeracy score.