KU LEUVEN

CENTER FOR ECONOMIC STUDIES

DISCUSSION PAPER SERIES
DPS15.18

AUGUST 2015

Why is wage inequality so high in the United States? Pitching cognitive skills against institutions (once again)

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Why is wage inequality so high in the United States? Pitching cognitive skills against institutions (once again)

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Abstract

We revisit the relationship between cognitive skills and wage inequality using data from the Survey of Adult Skills (PIAAC). We argue that previous research suffered from a number of methodological shortcomings, and we offer a single and unified analytical framework for assessing the contribution of skills (including demand and supply conditions) and labour market institutions to wage inequality. Contrary to most previous research, we find that skills are at least as important as labour market institutions in explaining higher wage inequality in the United States.

1. Introduction

Earnings inequality in the United States has been rising fast and is now the highest in the OECD area. Workers at the 90th percentile (P90) earn 5.1 times as much as those at the 10th percentile (P10). This ratio is up from 3.7 in 1975, and compares to just 2.3 in Sweden and 3.4 across the OECD on average.[1]

This high and rising inequality has generated a growing interest among policy makers and researchers alike in its causes and possible remedies. This has been further spurred by an increasing understanding of, and consensus about, the significant costs brought by high inequality. These include, among others: reduced social mobility (Krueger, 2012), lower social cohesion and trust (Stiglitz, 2012), and a range of health and social problems (Pickett and Wilkinson, 2011), including higher crime (Brush, 2007; Choe, 2008).

In addition, and despite earlier arguments that inequality was a necessary evil in the pursuit of economic growth (Kaldor, 1957, Kuznets, 1955, Mirrlees, 1971; Lazear and Rosen, 1981) – economists and international organisations are now increasingly in agreement that inequality may be detrimental to growth (Clarke, 1992; Ncube, Anyanwu and Hausken, 2013; Ostry, Berg and Tsangarides, 2014; Cingano, 2014). Their reasoning ranges from the relatively cautious argument that inequality hurts growth because it leads to redistributive pressures (Persson and Tabellini, 1994; Alesina and Rodrik, 2014) to claims that inequality is damaging to growth because it: generates social conflict (Benhabib and Rustichini, 1996; Perotti, 1996); prevents the talented poor from undertaking profitable investments in physical and human capital (Galor and Zeira, 1993; Banerjee and Newman, 1993); or even catalyses financial crises (Rajan, 2010).

The causes of rising inequality are also increasingly understood, particularly in the United States where a rich literature has flourished on the subject. One strand of this literature focuses on labour market institutions, policies and practices as the primary explanations for inequality. The fall in the real value of

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the minimum wage is a widely cited cause (DiNardo, Fortin and Lemieux, 1996; DiNardo and Lemieux, 1997; Lee, 1999; Autor, Manning and Smith 2014), as is the decline in union power (Blau and Kahn, 1996; Fortin and Lemieux, 1997; Card, 2001; Card, Lemieux and Riddell, 2004; DiNardo, Fortin and Lemieux, 1996; Firpo, Fortin and Lemieux, 2011; Western and Rosenfeld, 2011). Lemieux, McLeod and Parent (2007) have also identified performance pay as an important source of wage inequality.

Another, and almost unrelated, strand of the literature has focused on the role of skills in explaining rising wage inequality in the United States. A commonly advanced argument is that technological change is skill-biased, thereby leading to an increase in demand for skilled workers. Given that the supply of educated workers has not kept pace with this rise in demand, the returns to skill (and therefore inequality) have risen (Juhn, Murphy and Pierce, 1993; Juhn, 1999; Goldin and Katz, 2008; Autor, 2014). At the same time, the number of job opportunities for middle-skilled workers has shrunk as routine tasks have become increasingly automated (Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006) or offshored to countries with lower wages and other costs (Blinder, 2009). This polarisation of employment growth in the United States has resulted in wage polarisation, exacerbating the trend in wage inequality (Firpo, Fortin and Lemieux, 2011; Autor and Dorn, 2013; Boehm, 2014).

However, while it is now widely accepted that changes in the supply of, and demand for, skills have contributed to rising wage inequality in the United States, another strand of research remains inconclusive about the role of skills in explaining differences in the level of wage inequality between the United States and other countries. Blau and Kahn (1996) used a demand and supply model in the spirit of Katz and Murphy (1992) to analyse 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. Their results suggested that market forces appeared to have very little explanatory power, from which they concluded that institutions must be the main driver of international differences in wage inequality.

Leuven, Oosterbeek and van Ophem (2004), however, showed that Blau and Kahn's (1996) results were driven by the use of years of schooling and work experience as proxies for skill. Using the more direct measures of cognitive skills contained in the International Adult Literacy Survey (IALS), they found that about a third of the variation in relative wages between skill groups across countries could be explained by differences in the net supply of skill. They also concluded that the demand and supply framework did an even better job at explaining relative wages of low-skilled workers: nearly 60% of the variation in the skill wage differential between the lower and middle thirds of the skill distribution could be explained by relative net supply, and 44% of the variation between the lower and upper thirds of the skill distribution.

In their response to Leuven, Oosterbeek and Van Ophem (2004), Blau and Kahn (2005) also used the IALS data, but applied the Juhn, Murphy and Pierce (1993) decomposition method instead to analyse the shares of international differences in wage inequality that could be attributed to skill endowments, prices and a residual, respectively. Using this approach, Blau and Kahn (2005) insisted that their previous conclusions remained essentially unchanged, i.e. that higher labour market prices played a quantitatively more important role in explaining higher wage inequality in the United States than differences in the distribution of cognitive skills.[2] More recent research (Jovicic, 2015; Paccagnella, 2015; Pena, 2015) using data from the Survey of Adult Skills (PIAAC) and decomposition methods identical (or similar) to Blau and Kahn (2005), reaches essentially the same conclusions.

However, Leuven, Oosterbeek and van Ophem (2004) were right to point out that such decomposition exercises are essentially static in nature and ignore the fact that the price of skill itself is determined by the relative supply of, and demand for, skill. In other words: differences in skills prices cannot simply be interpreted as reflecting differences in institutional set-ups. They will, to some extent, also reflect the relative scarcity of skills.

In this paper, we throw a fresh look at the extent to which higher wage inequality in the United States can be blamed on skills, and we make a number of important contributions to the literature. First, we bring a much improved dataset to the debate, including greater country coverage and better information on wages.[3] Second, we draw on recent methodological advances and use simulation techniques in the spirit of DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010) to build counterfactual wage distributions to analyse the contribution of skills (and how they are rewarded) to international differences in wage inequality.[4] Third, we extend these simulations to take account for demand and supply conditions (similar to the method used by DiNardo, Fortin and Lemieux, 1996). Fourth, we propose a new method for analysing the role of skill inequality in explaining wage inequality. And, finally, our approach also allows us to simulate the effect of different labour market institutions on wage inequality, thereby bridging the two separate literatures discussed above (i.e. the "institutional" and the "market force" strands of the inequality literature).[5] In fact, the greatest contribution of our paper is that it offers a single and unified analytical framework for assessing the importance of skills (including demand and supply conditions) and labour market institutions to international differences in wage inequality.[6]

Our results suggest that higher skills inequality in the United States accounts for 15% of the difference in wage inequality with other countries (as measured by the Gini index), while differences in the demand for and supply of skills can explain just over a quarter. In comparison, higher minimum wages in other countries account for only 7% of the difference in wage inequality with the United States, and higher union coverage for two fifths.

The remainder of this paper proceeds as follows. In section 2, we describe the data we use and provide some descriptive statistics. Section 3 analyses the extent to which higher wage inequality in the United States can be attributed to skills and skills prices, while Sections 4, 5 and 6 discuss the contributions of skill inequality, demand and supply factors, and institutions, respectively. Section 7 offers some concluding remarks.

2. Data and descriptive statistics

Leuven, Oosterbeek and van Ophem (2004) demonstrated the importance of using direct measures (rather than proxies) of skill to analyse the relationship between skill and wage inequality.[7] The OECD's adult literacy surveys, which assessed the skills of adults in a comparable manner across a number of countries, are therefore an ideal source of information to carry out such analyses. The first of these surveys, the International Adult Literacy Survey (IALS), was carried out in the 1990s in a total of 23 countries/regions around the world. This was the data used by Devroye and Freeman (2001), Leuven, Oosterbeek and van Ophem (2004) and Blau and Kahn (2005) – although they were only able to use a subset of these countries (see below). Between 2003 and 2008, the OECD ran the Adult Literacy and Lifeskills (ALL) Survey in a total of 10 countries. As far as we are aware, this survey was never used to analyse the relationship between skills and wage inequality. The latest of the OECD surveys (and the one we use in this paper) is the Survey of Adult Skills (PIAAC), the first round of which covered 24 countries/regions over the period 2008-2013.[8]

PIAAC directly assessed the proficiency of around 166 000 adults (aged 16-65) from 24 countries in literacy, numeracy and problem solving in technology-rich environments. In addition, the survey gathered data on individuals' labour market status, contract type, wages, bonuses, education, work 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, we use data for the 22 OECD countries/regions covered by PIAAC (i.e. leaving out Cyprus and the Russian Federation). Our dataset presents a number of advantages over the IALS samples used by the aforementioned studies, particularly in terms of country coverage and the quality of wage information. Devroye and Freeman (2001) focus on just four countries (the United States, Sweden, Germany and the Netherlands) because "good measures of earnings for individuals" were available only for those countries. In addition, the data they use for Germany and the Netherlands were only available in 20 unevenly-represented categories – a problem which the authors tried to circumvent by generating a random component to the earnings of workers in those countries. Leuven, Oosterbeek and van Ophem (2004) manage to include 15 of the IALS countries, but for three of them wages were reported in intervals. Finally, Blau and Kahn (2005) focus on the nine advanced IALS countries only (excluding Germany), but earnings for two of their countries were top-coded. In contrast to these studies, our dataset includes 22 OECD countries, each with continuous wage and skills measures.

Table 1 shows mean wages and skills for the 22 OECD countries included in our sample, as well as of their level of dispersion. Our measure of gross hourly wages includes bonuses and is expressed in purchasing power parity corrected USD. As our measure of skills, we use individuals' continuous score in numeracy, measured on a 500-point scale.[9] Both wage and skill dispersion are measured using the ratios of: the 90th to the 10th percentiles (P90/P10), the 90th to the 50th percentiles (P90/P50), the 50th to the 10th percentiles, as well as by the Gini index.

Table 1: Summary statistics: Levels and dispersion of skills and wages

		Skill					Hourly wage				
	N	Mean	P90/P10	P90/P50	P50/P10	Gini	Mean	P90/P10	P90/P50	P50/P10	Gini
Australia	4371	276	1.60	1.21	1.32	0.104	18.9	3.14	1.90	1.65	0.250
Austria	2943	279	1.54	1.19	1.29	0.095	19.1	3.05	1.83	1.67	0.250
Canada	16116	271	1.66	1.22	1.35	0.109	20.4	3.94	1.94	2.03	0.280
Czech Republic	2630	279	1.49	1.18	1.26	0.087	9.0	2.88	1.68	1.71	0.240
Denmark	4448	286	1.52	1.19	1.28	0.092	23.8	2.58	1.55	1.66	0.210
England/N. Ireland (UK)	4801	271	1.63	1.23	1.33	0.107	18.4	3.53	2.07	1.71	0.300
Estonia	3972	277	1.51	1.19	1.26	0.089	9.6	4.71	2.24	2.10	0.320
Finland	3251	292	1.51	1.19	1.26	0.091	19.3	2.54	1.70	1.50	0.200
Flanders (B)	2736	287	1.54	1.19	1.30	0.094	22.2	2.61	1.67	1.56	0.210
France	3696	261	1.73	1.23	1.40	0.117	15.6	2.56	1.77	1.45	0.220
Germany	3382	278	1.60	1.20	1.33	0.101	18.8	4.22	1.88	2.25	0.290
Ireland	2784	265	1.61	1.22	1.32	0.105	21.6	3.57	2.08	1.71	0.290
Italy	1815	255	1.66	1.22	1.36	0.110	16.1	3.42	1.99	1.72	0.270
Japan	3262	292	1.46	1.17	1.25	0.083	16.1	4.08	2.32	1.76	0.330
Korea	3097	268	1.52	1.18	1.29	0.092	17.8	5.83	2.68	2.18	0.390
Netherlands	3162	287	1.51	1.18	1.28	0.091	21.5	3.24	1.79	1.81	0.250
Norway	3553	286	1.55	1.19	1.30	0.097	24.3	2.44	1.60	1.52	0.200
Poland	3908	267	1.59	1.22	1.31	0.101	9.3	3.89	2.15	1.81	0.310
Slovak Republic	2505	285	1.44	1.17	1.24	0.082	8.9	4.01	2.15	1.87	0.320
Spain	2456	258	1.61	1.20	1.34	*0.103*	15.0	3.60	2.05	1.75	0.280
Sweden	2888	287	1.55	1.19	1.30	0.096	18.7	2.18	1.59	1.37	0.170
United States	2793	261	1.75	1.24	1.41	0.120	21.5	4.81	2.40	2.01	0.340

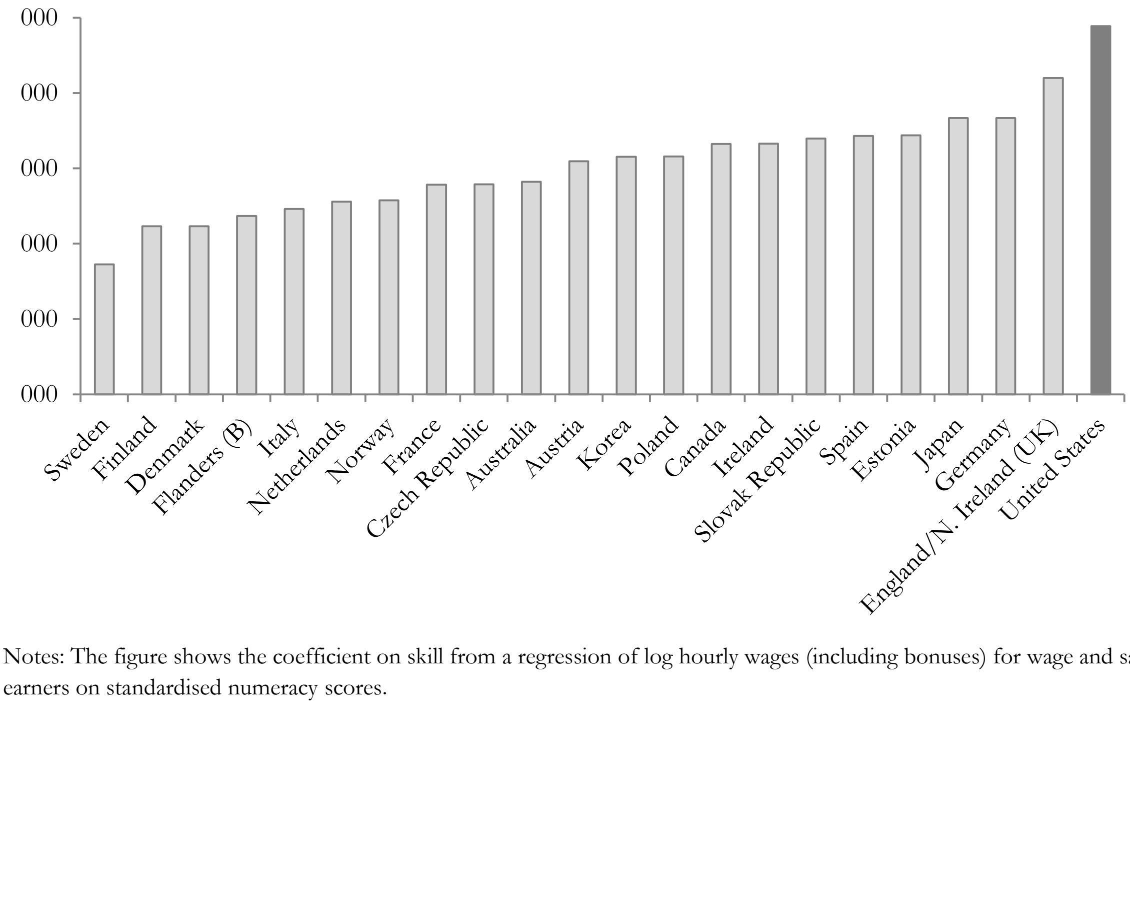
Notes: Data refer to wage and salary earners only. Wages are trimmed, by country, at the top and bottom percentiles.

The United States has one of the lowest skill levels of the countries included in the sample – only Spain and Italy perform worse. The average numeracy score in the United States is more than 30 points (10%) lower than in Finland and Japan, the highest performing countries in the PIAAC sample. In addition, the United States has the highest level of skills inequality, both at the top and at the bottom of the skills distribution. The P90/P10 ratio in the United States is over 50% higher than that observed in the Slovak Republic, the country in the sample with the most equal skills distribution.[10] Finally, Table 1 shows that high skills inequality in the United States goes paired with high wage inequality, which is second to Korea only. Inequality in the United States is particularly high at the top of the wage distribution (P90/P50), while bottom-half wage inequality is higher still in Canada, Estonia, Korea and Germany.

The table also suggests that there may only be a weak cross-country relationship between skills and wage inequality. While there are countries, like the United States, where both skill and wage inequality are high (e.g. Canada, Germany and Italy), and others where both skill and wage inequality are low (e.g. the Scandinavian countries), there are also countries that combine high skill inequality with low wage inequality (e.g. France) and some that combine low skill inequality with high wage inequality (e.g. Japan and Korea). A slightly stronger (albeit still weak) negative relationship exists between the average level of skill and wage inequality: countries with more skilled workforces tend to have lower wage inequality.

Finally, countries differ not only in terms of the skills of their workforce, but also in how these skills are rewarded in the labour market. Figure 1 shows that the return to skill is highest in the United States. In fact, the return to skill in the United States is nearly three times greater than in Sweden, the country with the lowest returns. Critically for the analysis that follows, the return to skill in the United States is also highly non-linear – i.e. rising in skill level (see Figure A.1 in the Annex). Other countries that exhibit strongly increasing returns to skill include Slovakia, Canada and the United Kingdom, whereas the returns to skill are fairly constant along the skills distribution in countries like Belgium, Sweden and Finland.

Figure 1: Returns to skill



Notes: The figure shows the coefficient on skill from a regression of log hourly wages (including bonuses) for wage and salary earners on standardised numeracy scores.

3. The contribution of skills and skills prices to wage inequality: The standard decomposition approach and its limitations

The standard approach for analysing the contribution of skills to differences in wage inequality across countries is to decompose these differences into an endowment (skill) effect and a price effect. The particular methodology for doing these decompositions varies: Devroye and Freeman (2001) and Jovicic (2015) use a simple variance decomposition; Blau and Kahn (2005) and Pena (2015) apply the Juhn, Murphy and Pierce (1993) decomposition, while Paccagnella (2015) resorts to unconditional quantile regressions (Firpo, Fortin and Lemieux, 2009).

In this paper, we use an altogether different methodology, and simulate alternative wage distributions using reweighting techniques in the spirit of DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010). According to Fortin, Lemieux and Firpo (2011), this reweighting approach should be the preferred method for aggregate decompositions, and we favour this approach for two reasons.[11] The first is its simplicity and transparency which, in our opinion, make it less vulnerable to potential error. The second, and perhaps more important, reason is its flexibility. Indeed, as will become clear later on in this paper, this methodology not only allows us to analyse the impact of the (full) skills distribution on wage inequality, but can also be extended to incorporate demand and supply conditions as well as the impact of a number of labour market institutions. The main attraction of this approach therefore lies in the possibility that it offers to build a unified methodological framework to analyse and compare the impacts of skills, market forces and institutions on wage inequality.

In this section, the reweighting technique is used to analyse the importance of skill endowments and skill prices on wage inequality, in line with the standard approach followed in the literature. For the endowment effect, we are interested in knowing what would happen to wage inequality in the United States if it had the same skills distribution as a comparator country, x. To model this, we attach more/less weight to individuals in the United States whose skills are more/less common in the comparator country. This is achieved by replacing the original sample weights $\omega_{i,US}$ for individual i in the United States with counterfactual weights $\omega'_{i,US} = \omega_{i,US}\Psi_{S,x}$, where $\Psi_{S,x}$ represents the reweighting factor. In practice, we obtain the reweighting factor by first dividing the samples for both countries into S bins of 5 skills points each,[12] and then computing the ratio of the shares θ of total employment in each country in each of these skills bins – i.e. $\Psi_{S,x} = \frac{\theta_{S,x}}{\theta_{S,US}}$. Holding skills prices constant, this reweighting results in an alternative wage distribution for the United States. Standard wage dispersion and inequality measures can then be computed and compared to those estimated on the original wage distribution, and the difference between these wage inequality measures can be attributed to the effect of skills.

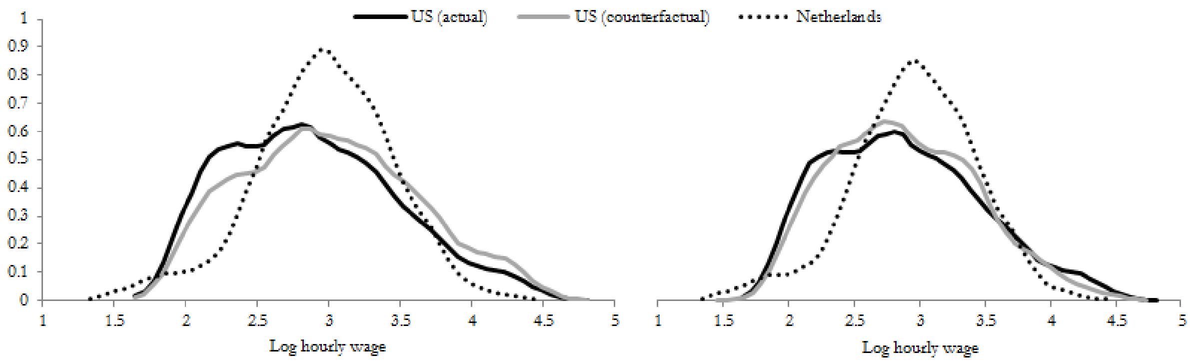
To estimate the price effect, we want to know what would happen to wage inequality in the United States if the skills of its workforce were rewarded in the same way as in a comparator country x, holding the distribution of skills constant. To model this, we base our approach on Lemieux (2002, 2010) and we start, once again, by dividing the samples for the two countries into S bins of 5 skills points each. We then estimate the conditional mean of log wages of skill group S in the United States ($y_{S,US}$) and in the comparator country ($y_{S,x}$), and the difference between these two average wages is added to each individual's original wage to estimate his/her new counterfactual wage $y'_{i,US}$:

$$y'_{i,US} = y_{i,US} + \left(y_{S,x} - y_{S,US}\right)$$

Figure **2** provides an idea of what these two wage simulations look like in practice and shows the reweighted wage distributions for the United States obtained by applying: (i) the Dutch skills distribution and (ii) Dutch skills prices. The choice of the Netherlands as comparator country is somewhat arbitrary, but reflects the fact that this is a country that combines high skill levels with low inequality in both skills and wages. In panel A, which applies the Dutch skills distribution to the United States, the United States wage distribution shifts somewhat to the right, but its height lowers and its dispersion increases (i.e. it becomes more unequal – a counterintuitive result to which we shall return below). In panel B, which applies the Dutch return to skill, the United States distribution becomes narrower (i.e. less unequal).

Figure 2: The United States wage distribution before and after applying the Netherlands' skill distribution and prices

A. US before and after Netherlands skills distribution **B.** US before and after Netherlands skills prices



Notes: Epanechnikov kernel density plots (evaluated at 50 points).

Table *2* repeats this exercise for all the other countries in the PIAAC data and shows what proportion of the difference in wage inequality between the United States and each country can be attributed to differences in skills endowments and skills prices, respectively. Consistent with the previous literature, differences in the return to skill can explain a much larger proportion of the higher wage inequality in the United States than can differences in skill endowments. Approximately one third of the higher P90/P10 wage ratio is due to higher skills prices in the United States.

By contrast, in most cases, the P90/P10 wage ratio (and the Gini) would increase (rather than decrease) if the United States adopted the skills distribution of the comparator country – a result driven primarily by increases in the P50/P10 wage ratio. This counterintuitive result (also obtained by Paccagnella, 2015 and Pena, 2015) is the result of: (i) relatively low skills levels in the United States and (ii) significantly higher marginal returns to skill in the top half of the distribution (see Figure A.1 in the Annex). Increasing the skills of the workforce in the United States would therefore mechanically lead to an increase in wage inequality at the bottom of the wage distribution, as the wages of those at the P50 would increase faster than those at the P10.[13] This result is clearly unrealistic and highlights a first limitation of using decomposition methods for analysing the contribution of skills to international differences in wage inequality. In reality, of course, one would expect an increase in overall skill levels to lead to a fall in the price of skill. Yet the standard decomposition methods, by taking a comparative static approach to what is essentially a dynamic phenomenon, are therefore unable to account for differences in net supply and demand conditions. This was part of Leuven, Oosterbeek and van Ophem's (2004) critique of Blau and Kahn (2005).

Table 2: Proportion (%) of the difference in wage inequality with the United States explained by skills endowments and skills prices

	Skills endowments				Skill prices			
	P90/P10	P90/P50	P50/P10	Gini	P90/P10	P90/P50	P50/P10	Gini
Australia	-9.5	4.9	-24.8	-0.9	35.0	37.8	26.3	26.1
Austria	-5.6	12.4	-30.8	1.3	25.9	27.3	18.8	20.8
Canada	-19.7	0.7	397.1	-1.3	55.3	33.5	-420.3	33.6
Czech Republic	-1.5	12.9	-31.3	4.1	18.1	22.6	3.7	15.2
Denmark	-11.4	3.9	-39.2	-0.6	30.0	26.7	28.7	20.8
England/N. Ireland (UK)	-10.5	3.5	-22.0	-0.1	18.1	21.3	13.1	19.7
Estonia	-33.8	55.1	97.6	21.7	309.1	68.6	-53.4	64.5
Finland	-18.6	-0.5	-34.0	-0.9	27.5	32.2	15.4	19.1
Flanders (B)	-13.1	2.7	-30.7	-1.2	27.6	29.3	18.5	19.6
France	2.9	4.2	1.0	1.2	25.7	29.1	17.0	20.1
Germany	-27.9	7.9	44.2	-1.4	63.7	25.1	-21.5	28.4
Ireland	8.3	16.1	0.4	8.7	30.1	46.2	12.6	28.4
Italy	14.8	17.5	9.2	12.4	36.3	42.1	24.8	29.1
Japan	-50.7	31.7	-70.0	3.2	43.7	149.8	17.1	77.8
Korea	-13.2	-39.4	22.5	-18.0	-31.0	-43.1	-18.9	-24.2
Netherlands	-17.9	6.2	-74.8	-0.6	34.5	31.4	36.4	26.5
Norway	-12.9	1.1	-28.1	-2.0	25.9	25.7	19.2	18.8
Poland	7.7	27.2	-13.8	14.1	41.8	53.7	26.6	44.1
Slovak Republic	-11.9	40.4	-91.9	16.5	27.5	38.0	9.7	45.2
Spain	19.9	26.9	9.5	16.2	24.9	30.3	16.0	17.3
Sweden	-12.4	2.1	-23.9	-1.3	28.0	30.2	18.0	18.9

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by skills and skills prices, respectively. For example, 35.0% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by different returns to skill in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's skills distribution or skills prices were adopted.

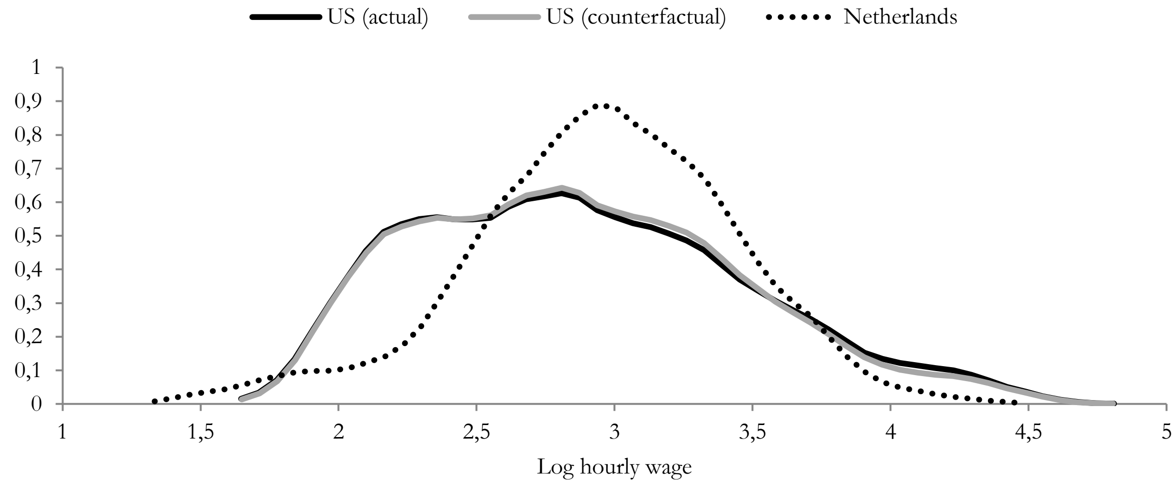
In the remainder of this paper, we seek to address these limitations of the standard approach. First, we argue that, in the presence of strong skill price effects, a decomposition exercise that looks at skill inequality rather than at the full skill distribution results in more sensible estimates of the contribution of skills to wage inequality. Second, we explicitly consider demand and supply conditions in assessing the importance of skills for wage inequality. Importantly, we are the first to do so within a single and coherent methodological framework, using the same reweighting techniques to analyse the effects of skills inequality, market forces, as well as institutional arrangements.

4. Skill inequality and wage inequality

In this section, we use the reweighting techniques to analyse the impact of skills inequality on wage inequality. The approach is similar to the one used above to simulate the impact of skill endowments – except that the skill variable is now demeaned to remove level effects (and therefore undesired/counterintuitive price effects).

Figure ***3*** illustrates the effect on the United States wage distribution of applying the de-meaned Dutch skills distribution (i.e. Dutch skills inequality). The effect is relatively small, but a slight compression of the wage distribution can be observed.

Figure 3: The United States wage distribution before and after applying Dutch skills inequality



Notes: Epanechnikov kernel density plots (evaluated at 50 points).

Table 3 repeats this exercise for all the other countries in the sample and shows to what extent differences in wage inequality in the United States can be attributed to its higher level of skills inequality. The results are more in line with what one would expect. For example, if skills inequality in the United States were similar to that observed in the Slovak Republic (the country with the most equal skills distribution, as measured by the Gini), then the difference in wage inequality between the United States and the Slovak Republic would fall by 64% (as measured by the Gini index). Conversely, if skills inequality in the United States were similar to that observed in France (the country with the second highest level of skills inequality), then the difference in wage inequality between the United States and France would fall by 1.2% only. On average, higher skills inequality in the United States accounts for 15% of its higher wage inequality (as measured by the Gini index). Skills inequality also explains a significantly larger part of higher wage inequality in the United States at the top (24%) than at the bottom of the wage distribution (4%). As argued later, this is likely to be because wages at the bottom of the distribution are determined less by skills and more by labour market institutions.

Table 3: Proportion (%) of the difference in wage inequality with the United States explained by skills inequality

	P90/P10	P90/P50	P50/P10	Gini
Australia	8.3	11.4	2.9	5.5
Austria	12.2	15.0	5.6	9.5
Canada	9.1	8.4	-7.3	5.1
Czech Republic	15.5	18.4	5.3	13.0
Denmark	9.7	10.9	4.2	6.3
England/N. Ireland (UK)	7.7	15.3	-0.3	8.7
Estonia	265.9	75.6	-21.5	54.4
Finland	9.6	12.7	3.3	6.1
Flanders (B)	8.9	11.2	3.0	5.8
France	2.5	4.1	0.4	1.2
Germany	22.3	12.8	0.1	11.3
Ireland	12.9	22.5	2.7	11.6
Italy	9.2	14.7	1.1	7.3
Japan	40.0	163.7	8.8	75.0
Korea	-28.4	-44.1	-10.6	-24.7

Netherlands	15.7	16.1	11.3	10.7
Norway	7.3	9.1	2.6	4.6
Poland	20.5	30.4	8.4	20.7
Slovak Republic	40.4	54.8	15.8	64.3
Spain	19.3	27.2	7.9	13.6
Sweden	6.7	9.5	1.5	4.1

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by skills inequality. For example, 8.3% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by lower skills inequality in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's skills inequality were adopted. This only happens in cases where the comparator country's skill inequality is higher than in the United States.

5. Factoring in the demand for and supply of skills

Leuven, Oosterbeek and van Ophem (2004) argued that one of the weaknesses of the analysis by Blau and Kahn (2005) (a weakness that also applies to the most recent papers by Paccagnella, 2015 and Pena, 2015), is that they fail to account for differences across countries in the relative demand for, and supply of, skills. Indeed, the higher price effects found by these authors will, to some extent, reflect differences in such market conditions. Leuven, Oosterbeek and van Ophem (2004) address this issue by adapting a methodology developed by Katz and Murphy (1992) to relate differences in wages between skill groups to changes in the demand for, and supply of, those skills. Their results show that about one third of the variation in relative wages between skill groups across countries can be explained by differences in the net supply of skill groups. However, because they: (i) use a different methodology; and (ii) look at relative wages between skills groups (rather than measures of wage inequality), it is difficult to compare their results to what has been obtained elsewhere in the literature. For these reasons, we propose a way of incorporating relative demand and supply conditions in the reweighting framework used so far, based on a similar exercise performed by DiNardo, Fortin and Lemieux (1996) for analysing changes in wage inequality in the United States over time - but never, to our knowledge, applied in any other context since.

The basic intuition behind our approach is to see what would happen to wages for skill group *S* in the United States, should the supply and demand conditions for that skill group reflect those prevalent in the comparator country *x*. To implement this in practice, we divide the sample into *S* skill groups of 10 points each.[14] For each skill group in the United States, we then derive supply and demand indices relative to those prevalent for the same skill group in country *x*. The supply index $\Delta S_{S,x}^{US}$ is defined simply as the share $\varepsilon_{S,US}$ of skill group *S* in the total labour force in the United States, relative to the share $\varepsilon_{S,x}$ occupied by that skill group in the comparator country, *x*:

$$\Delta S_{S,x}^{US} = \ln\left(\frac{\varepsilon_{S,US}}{\varepsilon_{S,x}}\right) \quad (1)$$

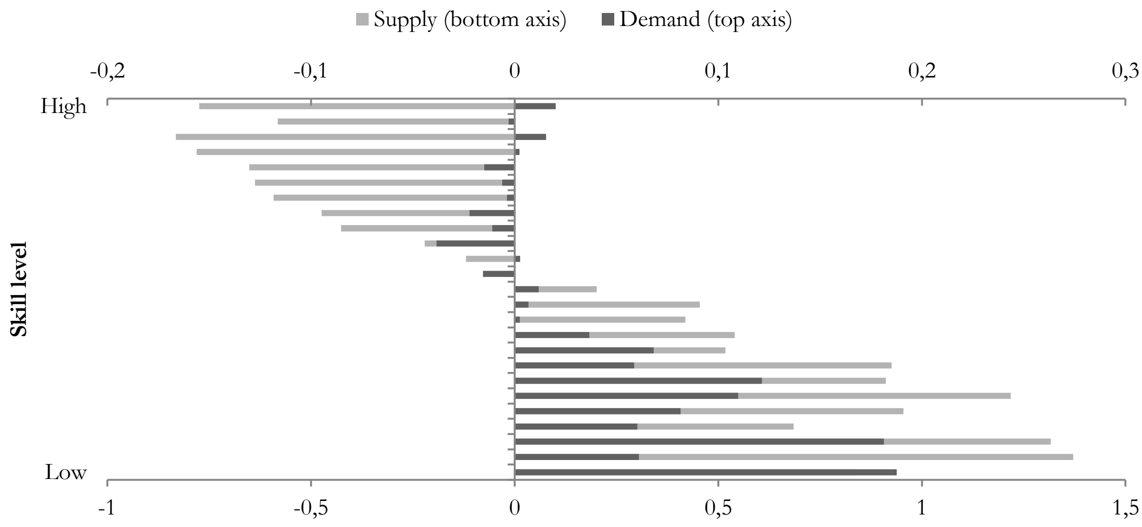
In building the demand index, $\Delta D_{S,x}^{US}$, we follow the approach proposed by Blau and Kahn (1996) and Leuven, Oosterbeek and van Ophem (2004) and measure the degree to which the occupation-industry structure[15] *O* in the United States favours skill group *S* in comparison to country *x*. Specifically:

$$\Delta D_{S,x}^{US} = \ln\left[1 + \sum_{o} \frac{\theta_{S,o,x}}{\varepsilon_{S,x}} \left(\theta_{o,US} - \theta_{o,x}\right)\right] \quad (2)$$

Where $\theta_{o,US}$ and $\theta_{o,x}$ are the total shares of employment in occupation-industry cell *O* in the United States and country *x*, respectively; $\theta_{S,o,x}$ is skill group *S*'s share of employment in occupation-industry cell *O* in the comparator country; and $\varepsilon_{S,x}$ is the share of skill group *S* in the total workforce of the comparator country. In essence, this index captures: (i) the relative importance of occupation *O* in the United States; and (ii) the "average" demand for skill group *S* in occupation *O* in the comparator country. Combining these two factors therefore results in a measure of the relative demand for skill group S in the United States.

Figure 4 illustrates what these supply and demand indices look like when the United States is compared to the Netherlands. As the figure shows, the United States has a relatively high supply of low-skilled workers in comparison to the Netherlands, while the opposite is true for high-skilled workers. The demand index shows that the demand for high-skilled workers in the United States is about the same as in the Netherlands, while the demand for low-skilled workers is comparatively higher.

Figure 4: The supply of and demand for skills in the United States versus the Netherlands



Notes: The figure shows, for each level of skill, the difference between in the supply and demand indices between the United States and the Netherlands. For example, for the most skilled group of workers (top bars), the supply line is negative (indicating that the United States has a lower supply of skilled workers than the Netherlands), while the demand line is marginally positive (indicating that the United States has a higher demand for the most skilled workers).

Table ***4*** shows what the demand for, and supply of, skills in the United States look like compared to the other countries in the sample. As the negative values in the first column indicate, the demand for low-skilled workers is lower in the United States than in most other countries – with the exception of the Scandinavian countries, Australia, Canada and Belgium, where the demand for low-skilled workers is even lower. By contrast, the supply of low-skilled workers in the United States is the highest amongst the countries included in the sample, with the exception of Spain. This picture is inverted when looking at high-skilled workers, for which there is relatively high demand in the United States, but low supply. Only in Canada, the Netherlands and Norway is the demand for high-skilled workers greater. The supply of high-skilled workers, however, is higher in 15 out of the 21 other countries. Overall, the differences in the supply of skills between the United States and the other countries are much larger than the differences in demand.

Table 4: The demand for and supply of skills relative to the United States

	Low-level skills*		High-level skills*	
	Demand	Supply	Demand	Supply
Australia	0.002	0.580	0.055	-0.386
Austria	-0.032	0.932	0.068	-0.404
Canada	0.058	0.405	-0.034	-0.326
Czech Republic	-0.086	1.273	0.209	-0.266
Denmark	0.023	1.040	0.016	-0.569
England/N. Ireland (UK)	-0.039	0.303	0.079	-0.194
Estonia	-0.080	1.012	0.107	-0.237
Finland	0.012	1.247	0.031	-0.701
Flanders (B)	0.008	0.918	0.025	-0.624
France	-0.044	0.044	0.087	0.068
Germany	-0.044	0.641	0.112	-0.426
Ireland	-0.036	0.370	0.088	0.162
Italy	-0.149	0.057	0.339	0.644
Japan	-0.003	1.680	0.090	-0.675
Korea	-0.133	0.647	0.211	0.368
Netherlands	0.097	0.928	-0.005	-0.597
Norway	0.058	0.860	-0.001	-0.623
Poland	-0.084	0.341	0.167	0.041
Slovak Republic	-0.085	0.845	0.074	-0.315
Spain	-0.093	-0.035	0.258	0.796
Sweden	-0.027	0.894	0.023	-0.656

* Low (high)-level skills are defined as the bottom (top) ten skills intervals (out of a total of 25).

In the next step, we use these indices to estimate what part of the (log) wage differential $\Delta\hat{y}_{Sx}^{US}$ between the United States and the comparator country can be attributed to differences in the supply of and demand for skill:

$$\Delta\hat{y}_{Sx}^{US} = \beta_S \Delta S_{Sx}^{US} + \beta_D \Delta D_{Sx}^{US} \quad (3)$$

Where the parameters β_S and β_D are estimated by regressing Δy_{Sx}^{US} (the log of the ratio of wages of skill group S in the United States over those in country x) on a constant, α, the indices of demand and supply for skill group S in the United States relative to those in country x, as well as country fixed effects, ρ_x:

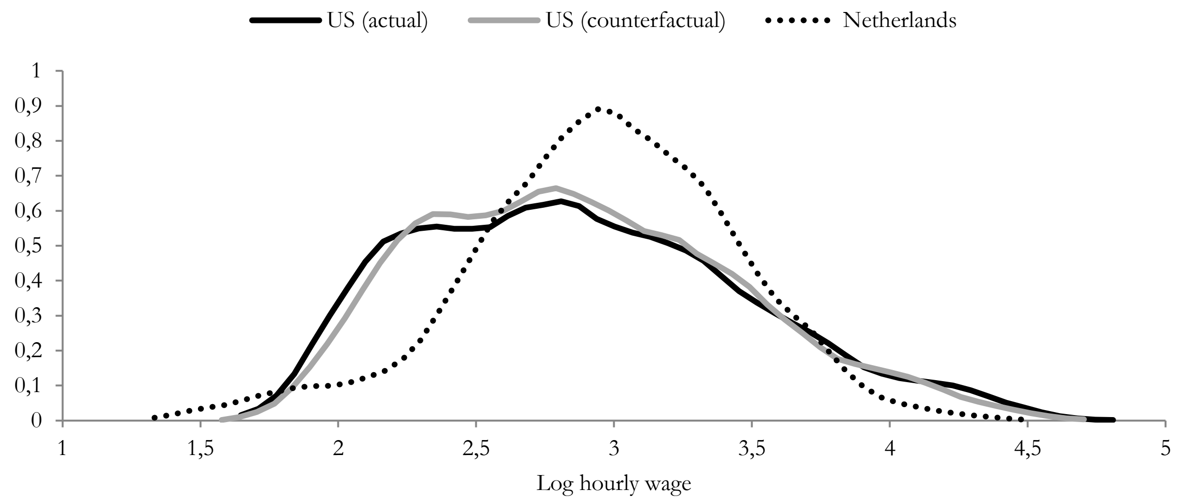
$$\Delta y_{Sx}^{US} = \alpha + \beta_S \Delta S_{Sx}^{US} + \beta_D \Delta D_{Sx}^{US} + \rho_x + \varepsilon_{Sx}^{US} \quad (4)$$

In practice, this regression is run on 21 country x 25 skill group (i.e. 525) observations. As expected, β_S is negative (i.e. an increase in the relative supply of skilled workers in the United States would lead to a fall in their wages relative to the comparator country) and β_D positive (i.e. an increase in the relative demand for skilled workers in the United States would increase the wages of skilled workers in the United States relative to those in the comparator country).

In the next and final step, the predicted wage differential ($\Delta\hat{y}_{Sx}^{US}$) obtained from equation (3) is subtracted from the original wage of each individual in skill group S in the United States, to give us the counterfactual wage of that individual if demand and supply conditions of the comparator country prevailed in the United States.

Figure ***5*** shows that applying the supply and demand conditions of the Netherlands to the United States (i.e. increasing the net supply of skill in the United States) would result in a reduction in wage inequality in the United States.

Figure 5: The United States wage distribution before and after adjusting for Dutch supply and demand for skill



Notes: Epanechnikov kernel density plots (evaluated at 50 points).

Table 5 repeats this exercise for every comparator country included in the sample, and summarises the extent to which higher wage inequality in the United States can be attributed to different demand and supply conditions. Looking at the Gini coefficient, on average 27.8% of the difference in wage inequality between the United States and other countries can be explained by differences in the demand for, and supply of, skills (20.6% excluding Japan, which is an outlier). Interestingly (and in line with results obtained using a different methodology by Broecke, Quintini and Vandeweyer, 2015), the importance of market forces appears to be greater at the top of the distribution (where it explains 38.1% of the difference in wage inequality with other countries) than at the bottom of the wage distribution (where it explains just 0.4% of the difference). In Broecke, Quintini and Vandeweyer (2015), we speculated that this might be because the wages of workers in the bottom of the distribution are determined less by market forces and more by labour market institutions, like the minimum wage and other wage-setting arrangements – while the opposite is likely to be true for workers at the top of the wage distribution.

Table 5: Proportion (%) of the difference in wage inequality with the United States explained by demand and supply conditions

	P90/P10	P90/P50	P50/P10	Gini
Australia	23.0	23.2	18.8	13.9
Austria	30.6	28.0	29.0	19.7
Canada	21.1	9.6	-218.0	9.5
Czech Republic	33.7	31.1	31.9	25.7
Denmark	22.9	19.2	24.2	13.1
England/N. Ireland (UK)	26.2	28.1	21.6	23.3
Estonia	463.7	88.7	-102.4	87.1
Finland	24.6	27.1	15.8	15.2
Flanders (B)	24.4	25.2	17.1	14.7
France	6.1	3.6	7.0	4.6
Germany	82.1	29.0	-34.7	36.7
Ireland	12.0	10.7	11.9	8.1
Italy	13.5	12.9	12.1	9.6
Japan	99.9	318.4	47.9	172.8
Korea	-34.1	-23.8	-54.0	-26.7

Netherlands	31.0	26.3	37.5	19.1
Norway	20.6	19.2	16.8	12.1
Poland	37.0	39.6	31.8	29.8
Slovak Republic	68.1	68.3	65.3	84.7
Spain	4.2	-7.1	16.2	0.0
Sweden	20.1	22.3	11.9	11.9

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by differences in supply and demand conditions. For example, 23% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by differences in the demand for, and the supply of, skilled workers in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's demand and supply conditions were adopted.

In Table 6, we decompose the difference in wage inequality explained by market forces (and reported in Table 5) into the portions attributable to demand and supply, respectively. We do this following the same procedure as above, except that equation (4) is used to estimate two counterfactual wages: one using $\beta_S \Delta S_{Sx}^{US}$ (holding demand constant); and the other using $\beta_D \Delta D_{Sx}^{US}$ (holding supply constant). The decomposition is not exact but shows that in most cases (and consistent with Table 4) it is differences in the supply of skills between the United States and the other countries that account for the differences in wage inequality. There are some interesting exceptions, however. In the cases of Ireland, Italy, Poland and Spain, for example, differences with the United States in the demand for skill play a more important role in explaining higher wage inequality. Canada, the Netherlands and Norway are also interesting examples, given that wage inequality in the United States would be even greater if it had the same demand for skills as in those countries.

Table 6: Decomposition of the proportion (%) of the difference in wage inequality with the United States explained by demand and supply conditions

	P90/P10		P90/P50		P50/P10		Gini	
	Demand	Supply	Demand	Supply	Demand	Supply	Demand	Supply
Australia	5.7	21.9	5.6	19.9	4.8	20.6	2.6	11.6
Austria	6.4	24.0	7.5	20.3	3.4	24.8	4.6	15.8
Canada	-8.9	33.7	-0.9	16.3	153.8	-333.7	-5.1	14.1
Czech Republic	20.6	18.7	19.8	12.7	17.2	26.2	14.0	13.7
Denmark	0.7	22.3	2.2	18.1	-2.7	24.6	0.2	12.9
England/N. Ireland (UK)	10.3	15.7	11.9	16.7	7.6	12.9	11.0	12.9
Estonia	196.3	361.2	45.1	54.3	-31.0	-99.6	34.4	55.7
Finland	2.7	24.7	4.1	25.9	0.4	17.4	1.4	14.7
Flanders (B)	2.0	22.6	1.1	21.9	2.6	17.9	1.2	13.7
France	7.4	-1.5	10.5	-6.4	2.6	3.4	4.7	-0.2
Germany	31.7	64.1	11.6	21.3	-12.2	-29.1	13.6	25.2
Ireland	12.2	-2.0	15.2	-10.1	8.1	5.4	10.0	-2.4
Italy	34.5	-20.1	40.1	-29.2	23.3	-5.4	22.8	-17.4
Japan	21.6	89.8	80.8	264.2	6.6	48.1	33.6	149.4
Korea	-35.8	-2.1	-42.5	9.5	-32.4	-18.2	-26.7	2.0
Netherlands	-4.7	33.6	-1.0	29.2	-12.6	39.0	-2.8	21.3
Norway	-1.6	21.2	1.8	20.7	-5.8	16.0	-0.7	12.8
Poland	34.4	9.7	37.0	-0.9	29.3	19.6	27.1	2.3
Slovak Republic	31.4	48.6	24.0	38.3	40.0	61.2	28.1	61.8
Spain	30.4	-23.7	37.4	-33.1	19.3	-9.4	20.2	-24.1
Sweden	1.3	19.8	2.8	21.3	-0.8	12.4	1.2	11.0

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by differences in supply and demand conditions, respectively. For example, 5.7% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by differences in the demand for skills. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's demand and supply conditions were adopted.

6. The role of institutions

When we decomposed higher wage inequality in the United States into a skill endowment and a skill price effect, we argued that the latter reflected a mixture of two factors: (i) different demand and supply conditions (which were analysed in the previous section); and (ii) differences in labour market institutions that affect the way skills are rewarded. In what follows, we apply the same wage simulation techniques used so far to analyse the role of minimum wages and union coverage in explaining higher wage inequality in the United States. The choice of institutions to be analysed was determined primarily by the fact that both of these have been found to have had a significant impact on wage inequality in the United States (see brief literature review in the introduction).

Table 7 shows how the minimum-to-average wage ratio[16] and the union coverage rate in the United States compare to those in the other countries included in our sample. While not all countries have a statutory minimum wage, at 27.2%, the United States has the lowest minimum-to-average wage ratio amongst the countries that do. Minimum wages are particularly high in Belgium, Ireland, Australia, the Netherlands and France, where they exceed 40% of the average wage. At 12.4%, the United States also has the second-lowest union coverage rate, compared to 56.6% on average across the countries included in the sample but close to 100% in some countries (Austria, Belgium, Sweden and France).

Table 7: Minimum wages and union coverage rates

	Minimum-to-average wage (%)	Union coverage rate (%)
Australia	44.0	45.0
Austria	..	99.0
Canada	39.6	28.8
Czech Republic	30.6	40.9
Denmark	..	85.0
England/N. Ireland (UK)	38.8	31.2
Estonia	31.6	25.0
Finland	..	89.5
Flanders (B)	43.4	96.0
France	49.8	92.0
Germany	..	61.1
Ireland	43.7	42.2
Italy	..	85.0
Japan	33.3	16.0
Korea	34.5	10.0
Netherlands	41.6	84.3
Norway	..	74.0
Poland	38.5	28.9
Slovak Republic	35.8	35.0
Spain	34.4	73.2
Sweden	..	91.0
United States	27.2	13.1

Source: OECD (2015), "Earnings: Minimum wages relative to median wages", OECD Employment and Labour Market Statistics (database). DOI: http://dx.doi.org/10.1787/data-00313-en. Minimum wages refer to 2012. Minimum wages refer to the adult national minimum wage or, in the absence of a national minimum wage, to the weighted average of regional minimum wages. In the case of the United States, average wages are obtained by the OECD from the U.S. Bureau of Labor Statistics, Employment and Earnings, and refer to the average hourly earnings of production and non-supervisory workers. ICTWSS (Visser ,2013) for union coverage (latest year available). Current Population Survey (2011) for US union coverage rate.

In what follows, we estimate the extent to which higher wage inequality in the United States might be related to its lower minimum wage and union coverage rate. To do this, we simulate alternative wage distributions as before. In the case of minimum wages, the approach is relatively straightforward: we impose the minimum wage of the comparator country onto the United States wage distribution so that any worker earning less that the new minimum wage simply moves up to this new level. In doing so, we abstract away from: (i) non-coverage and non-compliance (both in the United States and in the comparator country[17]); (ii) possible spill-over effects on wages above the minimum; and (iii) dis-employment effects from increasing the minimum wage.[18]

PIAAC does not hold information on union coverage. To get round this problem, we proceed in three steps. First, we use external data sources to estimate the probability of each individual in the United States PIAAC data being covered by a union. Second, we assign union coverage status to those individuals with the highest predicted probabilities of being covered by a union, subject to a number of constraints. Third, we use this union coverage variable to reweight the United States data to simulate the degree of union coverage in the other PIAAC countries. This last step then allows us to estimate the contribution of union coverage to higher wage inequality in the United States.

To be more precise, in step one, we use data from the 2011 Current Population Survey (CPS) to estimate the likelihood of union coverage. We do this using a linear probability model with gender, age, industry, occupation and working time regime (part-time/full-time) as explanatory variables. The coefficients obtained from this regression are subsequently used to predict the probability of union coverage for each individual in the United States PIAAC data.

In step two, we rank all observations in the United States PIAAC data in descending order of (predicted) probability of union coverage,[19] and assign union coverage status, starting from the observation with the highest union coverage probability. We continue to do so one observation at a time, until the quota for characteristic c is reached, after which no more observations with that characteristic are assigned union coverage, and so on until all characteristic quotas have been filled.[20]

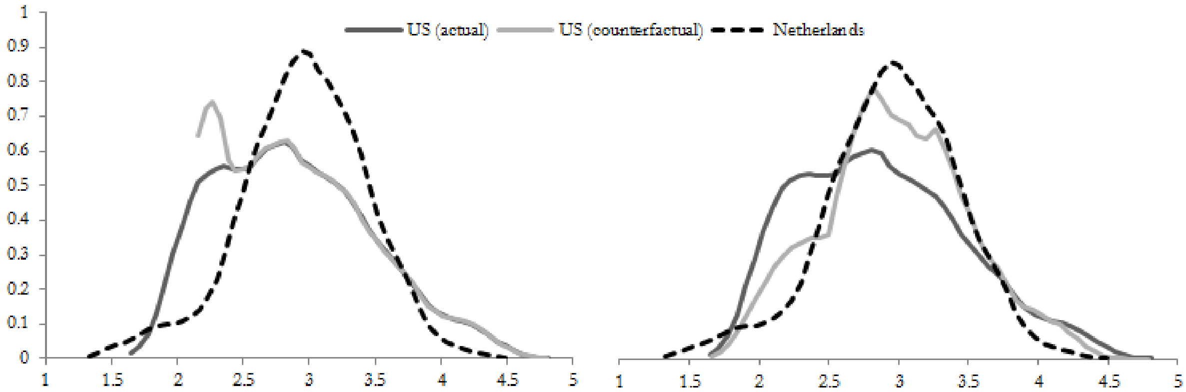
In step three, we use the union coverage variable thus derived to reweight the United States data until we obtain union coverage rates similar to those in each of the other PIAAC countries. This is achieved simply by multiplying the survey weights of each observation that has union coverage by the ratio of the union coverage rate in the comparator country to union coverage rate in the United States, $\frac{UC_x}{UC_{US}}$ and the survey weights of all other observations by $\frac{1-UC_x}{1-UC_{US}}$.

For illustrative purposes,

Figure ***6*** shows what would happen to the wage distribution in the United States if the latter: (i) adopted the Dutch minimum-to-average wage ratio; and (ii) had similar union coverage rates as in the Netherlands. By construction, the minimum wage only affects the bottom of the wage distribution, while union coverage rates significantly alter the entire wage distribution, leading to an important fall in wage inequality in the United States.

Figure 6: The United States wage distribution before and after applying the Dutch minimum wage and union coverage rate

A. US before and after Dutch minimum wage **B.** US before and after Dutch union coverage



Notes: Epanechnikov kernel density plots (evaluated at 50 points).

The full results from the institutional simulations are presented in Table 8. The lower minimum wage in the United States accounts for 66.3% of the difference with France in bottom-half wage inequality. In many cases, however, the minimum wage in the United States cannot explain any of the difference in wage inequality with the other countries and, on average, it accounts for less than 7% of the cross-country differences in the Gini coefficient. By contrast, lower union coverage in the United States accounts for a significant share of the differences in wage inequality with other countries, particularly in the top half of the wage distribution. The overall contribution of differences in union coverage to differences in wage inequality (as measured by the Gini coefficient) is 39.5%.

Table 8: Proportion (%) of the difference in wage inequality with the United States explained by the minimum wage and union coverage

	Minimum wage				Union coverage (CPS)			
	P90/P10	P90/P50	P50/P10	Gini	P90/P10	P90/P50	P50/P10	Gini
Australia	22.6	0.0	44.7	11.4	22.7	45.4	-10.2	23.8
Austria	..	..	..	..	54.9	75.0	15.8	67.5
Canada	7.0	0.0	-136.1	7.3	13.5	25.0	254.5	17.4
Czech Republic	0.0	0.0	0.0	0.1	15.9	28.4	-15.5	18.7
Denmark	..	..	..	..	36.5	46.7	3.2	37.3
England/N. Ireland (UK)	1.1	0.0	2.0	7.7	16.7	39.6	-7.2	26.4
Estonia	0.0	0.0	0.0	1.1	101.1	52.9	27.5	37.9
Finland	..	..	..	..	38.5	57.7	6.2	39.5
Flanders (B)	14.4	0.0	29.6	7.0	43.9	59.1	11.9	44.7
France	39.7	0.3	66.3	17.9	42.9	68.0	9.7	47.1
Germany	..	..	..	..	80.7	60.4	30.4	64.7
Ireland	28.0	0.0	49.3	18.0	24.7	66.8	-17.5	36.1
Italy	..	..	..	..	58.5	95.7	3.8	70.3
Japan	0.0	0.0	0.0	3.3	8.4	23.9	4.4	11.9
Korea	0.0	0.0	0.0	-1.8	4.5	3.6	6.3	4.0
Netherlands	9.1	0.0	29.7	7.7	51.7	65.2	5.4	57.2
Norway	..	..	..	..	28.8	43.2	-0.7	30.6
Poland	0.4	0.0	0.7	9.2	12.8	45.7	-24.0	29.8
Slovak Republic	0.0	0.0	0.0	6.2	34.7	66.4	-17.2	65.7
Spain	0.0	0.0	0.0	1.3	54.4	100.5	-6.2	66.6
Sweden	..	..	..	..	36.7	52.0	9.6	33.2

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by minimum wages and union coverage rates, respectively. For example, 22.7% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by a different union coverage rate in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's minimum wage or union coverage rate were adopted

7. Conclusion

In this paper, we have revisited the role that skills play in explaining higher wage inequality in the United States. Contrary to most previous research, we find that skills do matter to wage inequality – both their supply (in relation to demand) as well as the way they are distributed. Any policy package aimed at reducing wage inequality in the United States would therefore only be comprehensive if it contained measures aimed at addressing both the low level of skills in the United States, as well as the high degree of inequality in the way that these skills are distributed. In addition, the paper has shown that labour market institutions also matter. Higher wage inequality in the United States can be blamed in part on the relatively low level of the minimum wage, although the contribution of the latter is relatively modest. In comparison, the low rate of union coverage in the United States appears to play a far more important in explaining higher wage inequality compared to other OECD countries.

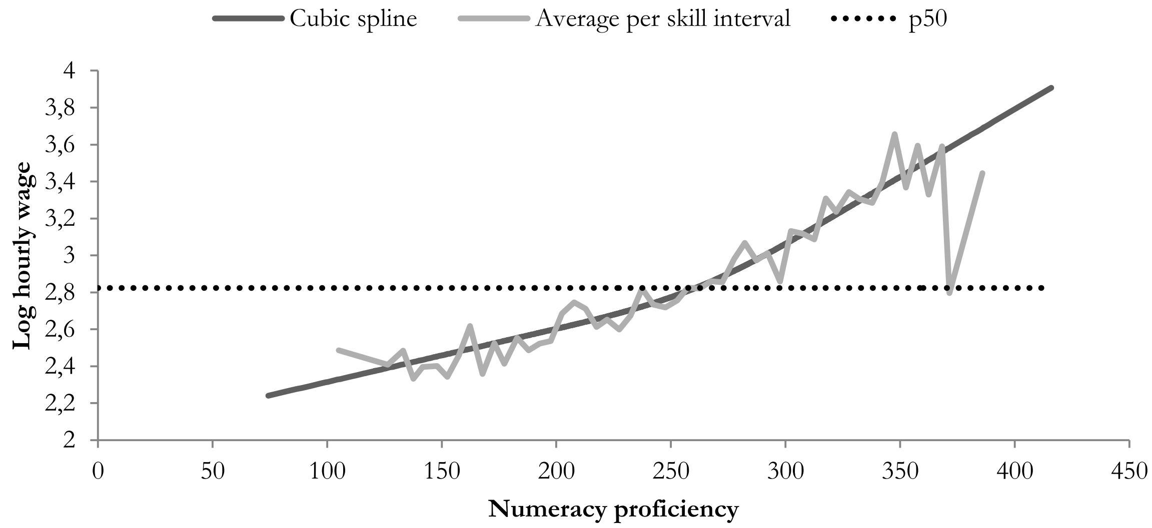
As closing remarks, two important points deserve to be raised. The first of these is that, while the present paper has separately estimated the importance of labour market institutions and skills on wage inequality, the two are, of course, highly dependent on one another. On the one hand, institutions can determine the demand for skills: for example, if minimum wages (including bargained wages) and non-wage costs are high, employers are likely to offshore part of their activity where this is possible or, alternatively, invest in labour-saving technologies. Similarly, if high income taxes reduce the wage premium to be gained from investing in skills, then individuals may be deterred from making human capital investments (or move abroad in pursuit of higher returns). Vice versa, if the demand for skills is high, then this will stimulate investment in skills (or attract workers from abroad). The second point to be made is that institutions are, of course, highly endogenous: societies that are more homogenous are likely to choose institutions that reflect this – which may, in turn, have an impact on the relative supply of skills groups. This interdependence and endogeneity imply that it may not be possible to change just one institution and obtain the desired effect on wage inequality. Alternatively, it could mean that policy interventions have multiplier effects beyond the results hoped for. These are important points to bear in mind for policy makers concerned with reducing inequality.

Acknowledgements

We are grateful to Thomas Lemieux, Maarten Goos and Joep Konings for comments on earlier versions of this paper, as well as to participants at the 30th Annual Congress of the European Economic Association held in Mannheim, Germany, 24-27 August 2015. This work should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and remaining errors are exclusively those of the authors.

Annex

Figure A.1: Returns to skills in the United States



Notes: The "average per skill interval" shows the average wage in each skill interval S (of 5 skill points each), as described above. The "cubic spline" shows the fitted values of a cubic spline fit (with three knots).

References

Alesina, A. and D. Rodrik (1994), "Distributive politics and economic growth", *The Quarterly Journal of Economics*, Vol. 109/2, pp. 465-490.

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

Autor, D. and D. Dorn (2013), "The growth of low-skilled service jobs and the polarization of the US labor market", *American Economic Review*, Vol. 103/5, pp. 1553-1597.

Autor, D., L.F. Katz and M.S. Kearney (2006), "The polarization of the U.S. labor market", *The American Economic Review*, Vol. 96/2, pp. 189-194.

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

Autor, D., A. Manning and L. Smith (2015), "The contribution of the minimum wage to U.S. wage inequality over three decades: A reassessment", unpublished manuscript, MIT Economics Department, http://economics.mit.edu/files/3279.

Banerjee, A. and A. Newman (1993), "Occupational choice and the process of development", *Journal of Political Economy*, Vol. 101/2, pp. 274-298.

Benhabib, J. and A. Rustichini (1996), "Social conflict and growth", *Journal of Economic Growth*, Vol. 1/1, pp. 125-142.

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.

Blinder, A.S. (1973), "Wage discrimination: Reduced form and structural estimates", *Journal of Human Resources*, Vol. 8/4, pp. 436-455.

Boehm, M. (2014), "The wage effects of job polarization: Evidence from the Allocation of Talents", unpublished working paper, http://www.econ.uzh.ch/eiit/Events/sinergiaconference2014/abstractsandpapers2014/Boehm_Michael_The_Wage_Effects_of_Job_Polarizations.pdf.

Broecke, S., G. Quintini and M. Vandeweyer (2015), "Wage inequality and cognitive skills: Re-opening the debate", paper presented at the NBER/CRIW conference on "Education, skills, and technical change: Implications for future U.S. GDP growth", Washington, DC, 16-17 October 2015.

Brush, J. (2007), "Does income inequality lead to more crime? A comparison of cross-sectional and time-series analyses of United States counties", *Economics Letters*, Vol. 96/2, pp. 264-268.

Card, D. (2001), "The effect of unions on wage inequality in the U.S. labor market", *Industrial and Labor Relations Review*, Vol. 54/2, pp. 296-315.

Card, D., T. Lemieux and W.C. Riddell (2004), "Unions and wage inequality", *Journal of Labor Research*, Vol. 25/4, pp. 519-559.

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

Choe, J. (2008), "Income inequality and crime in the United States", *Economics Letters*, Vol. 101/1, pp. 31-33.

Clarke, G.R.G. (1992), "More evidence on income distribution and growth", *World Bank Policy Research Working Papers*, No. 1064.

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

DiNardo, J. and T. Lemieux (1997), "Diverging male wage inequality in the United States and Canada, 1981-1988: Do institutions explain the difference?" *Industrial and Labor Relations Review*, Vol. 50/4, pp. 629-651.

DiNardo, J., N.M. Fortin and T. Lemieux (1996), "Labor market institutions and the distribution of wages:, 1973-1992: A semiparametric approach", *Econometrica*, Vol. 65/5, pp. 1001-1044.

Firpo, S., N.M. Fortin and T. Lemieux (2009), "Unconditional quantile regressions", *Econometrica*, Vol. 77/3, pp. 953-973.

Firpo, S., N.M. Fortin and T. Lemieux (2011), "Occupational tasks, and changes in the wage structure", *IZA Discussion Papers*, No. 5542.

Fortin, N. M. and T. Lemieux (1997), "Institutional changes and rising wage inequality: Is there a linkage?" *Journal of Economic Perspectives*, Vol. 11/2, pp. 75-96.

Fortin, N., T. Lemieux and S. Firpo (2011), "Decomposition methods in economics", in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics, Volume 4A*, Elsevier North Holland, pp. 1-102.

Galor, O. and J. Zeira (1993), "Income distribution and macroeconomics", *Review of Economic Studies*, Vol. 60/1, pp. 35-52.

Goldin, C.D. and L.F. Katz (2008), *The Race between Education and Technology*, Harvard 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*, Vol. 52/3, pp. 424-443.

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.

Kaldor, N. (1957), "A model of economic growth", *The Economic Journal*, Vol. 67/ 268, pp. 591-624.

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.

Kuznets, S. (1955), "Economic growth and income inequality", *The American Economic Review*, Vol. 45/1, pp 1-28.

Lazear, E.P. and S. Rosen (1981), "Rank-order tournaments as optimum labor contracts," *Journal of Political Economy*, Vol. 89/5, pp. 841–64.

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. 115/3, 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.

Lemieux, T., W.B. MacLeod and D, Parent (2007), "Performance pay and wage inequality," *NBER Working Paper Series*, No. 13128.

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.

Mayer, G. (2004), *Union Membership Trends in the United States*. Washington, DC: Congressional Research Service.

Mirrlees, J. (1971), "An exploration in the theory of optimum income taxation", *Review of Economic Studies*, Vol. 38/114, pp. 175-208.

Ncube, M., J. Anyanwu and K. Hausken (2013), "Inequality, economic growth, and poverty in the Middle East and North Africa (MENA)", *African Development Bank Group Working Paper Series*, No. 195.

OECD (2013), "Earnings: Minimum wages relative to median wages", *OECD Employment and Labour Market Statistics* (database). DOI: http://dx.doi.org/10.1787/data-00313-en.

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".

Perotti, R. (1996), "Growth, income distribution, and democracy", *Journal of Economic Growth*, Vol. 1/2, pp. 149-187.

Persson, T. and Tabellini, G. (1994), "Is inequality harmful for growth?" *The American Economic Review*, Vol. 84/3, pp. 600-621.

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

Rajan, R. (2010), *Fault Lines: How Hidden Fractures Still Threaten the World Economy*, Princeton, Princeton University Press.

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

Visser, J. (2013), "ICTWSS: Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts in 34 countries between 1960 and 2012", Amsterdam, Amsterdam Institute of Advanced Labour Studies

Western, B. and J. Rosenfeld (2011), "Unions, norms, and the rise in U.S. wage inequality", *American Sociological Review*, Vol. 76/4, pp. 513-537.

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[1] These figures are taken from the OECD Earnings Database. Data for the United States are from the Current Population Survey and reflect gross usual weekly earnings of full-time workers aged 16 and over.

[2] At around the same time, Devroye and Freeman (2001) also use the IALS, but a different type of decomposition method, to reach essentially the same conclusions as Blau and Kahn (2005).

[3] Paccagnella (2015) and Pena (2015) use the same data as us, however Pena (2015) does not have access to continuous wage data for five of the countries, including the United States. Paccagnella (2015) does not face this limitation.

[4] While Pena (2015) simply uses the Juhn, Murphy and Pierce (1993) decomposition, Paccagnella (2015) turns to unconditional quantile regressions in the spirit of Firpo, Fortin and Lemieux (2009). As argued later in this paper, we believe that our choice of methodology is better suited for analysing the relationship between skills and wage inequality and, in particular, to extend the analysis to incorporate market forces as well as institutions. Another, more specific, limitation of the approach taken by Paccagnella (2015) is that his application of the unconditional quantile regression method only allows for an analysis of the effect of overall, average skill levels (and not the entire skills distribution) on wage inequality.

[5] Both Paccagnella (2015) and Pena (2015) fail to account for the demand for skills (shown to be important by Leuven, Oosterbeek and van Ophem, 2004), and neither paper models the impact of institutions. Instead, and in line with much of the previous research in this field, both authors simply assume that the price effect can be attributed to differences in labour market institutions, without testing that assumption.

[6] In a companion paper (Broecke, Quintini and Vandeweyer, 2015) we use the PIAAC data and replicate more closely the previous debate on skills and wage inequality, including the Katz and Murphy (1992) demand and supply model. The findings of that paper confirm Leuven, Oosterbeek and van Ophem's (2004) finding that demand and supply is likely to an important determinant of wage inequality. However, because demand and supply are analysed using a different methodology to that used for analysing the importance of skills levels, it is difficult to make an assessment of the relative importance of these two factors. In addition, while other papers have argued that labour market institutions play an important role in explaining international differences in wage inequality, their results are also difficult to compare to the role played by skills. Coming up with a method for comparing the relative importance of all these factors was the primary motivation for the present paper and is what, in our eyes, sets it apart from the other literature on the topic.

[7] The correlation between years of education and numeracy is approximately 0.5 across the 22 countries included in this paper.

[8] A second round of the survey is being carried out from 2012 to 2016 in Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey.

[9] Throughout the paper, numeracy is used as the skill variable of choice, however virtually identical results are obtained when using literacy instead.

[10] Differences in the distribution of skills across countries may be driven by differences in socio-demographic characteristics. Even when controlling for gender, number of children, age, age squared, and whether individuals are foreign-born or not, the United States still has the highest level of skills inequality of the 22 countries analysed in this paper.

[11] Unconditional quantile regressions have become a popular decomposition method. However, as argued by Fortin, Lemieux and Firpo (2011), the approximations applied by this method can be problematic in the presence of minimum wages (i.e. unsmooth wage distributions). This is another reason why we prefer to use the reweighting method in the present paper.

[12] Bigger intervals are created at the top and bottom of the skill distribution to guarantee a sufficient number of observations.

[13] Note that this would not happen in the top half of the wage distribution, since the wages of those at the P50 and the P90 would increase at about the same rate.
[14] The size of the skill intervals is set at 10, rather than at 5 as in the previous analyses, to guarantee a sufficient number of observations per skill-industry group.
[15] We use the same occupation-industry classification as Blau & Kahn (1996) and Leuven et al. (2004), i.e. three occupation groups (managers and professionals; clerical and sales workers; craft workers, operatives, laborers and service workers) and six industry groups (agriculture; mining, manufacturing and construction; transportation, communication and public utilities; trade; finance, insurance, real estate and services; government).
[16] The minimum-to-average wage ratio was chosen instead of the minimum-to-median purely for modelling reasons. Indeed, the United States has the lowest minimum-to-average wage ratio of the countries included in the sample, but the same is not true of the minimum-to-median. Given that it would be much more difficult (and less interesting) to simulate what would happen if the minimum wage decreased in the United States, the minimum-to-average wage ratio is a more obvious choice than the minimum-to-median.
[17] The degree of non-coverage and non-compliance is low, with on average 2.8% of wage-earners across the sample reporting a wage below the minimum wage (ranging from 0% in the United States to 9.2% in Korea). Our results will nevertheless reflect both: (i) the effect of increasing the minimum wage; and (ii) the effect of moving to full compliance/coverage. To see what difference non-compliance and non-coverage make to our results, we re-ran the models after first assuming full compliance/coverage in each country (i.e. the wage of every individual reporting a wage below the national minimum wage was replaced with the national minimum wage). The effect of increasing the minimum wage was then calculated in comparison to this "full compliance and coverage" baseline scenario. While there is no impact on inequality measuring interdecile wage ratios, the average contribution of the minimum wage to explaining differences in the Gini coefficient drops from 6.9% to 6.5%.
[18] As a robustness check, we tested how sensitive our results are to the assumption of no dis-employment effects. To do this, we first calculate the distance *d* (in percentage terms) between individual *i*'s wage and the new imposed minimum wage. The probability *p* of becoming unemployed for that individual is then computed as $p = e*d$, where *e* is the elasticity of employment with respect to the minimum wage. The total employment loss *u* is then estimated as $u = \sum p * \frac{\omega i}{\sum \omega i}$, where ω_i is the weight attached to observation *i* and $\frac{\omega i}{\sum \omega i}$ therefore represents the share of observation *i* in the sample. With an employment elasticity of e=0.2, we find that employment losses are small (0.2% on average) and are therefore unlikely to affect our wage inequality results significantly. Indeed, assuming that employment losses are concentrated amongst those workers with the lowest wages, the contribution of the minimum wage to explaining higher wage inequality in the United States (as measured by the Gini index) falls from 6.9% to 6.8%.
[19] Observations with the same union coverage probability are ranked in descending order of age. Observations with the same union coverage probability and age are further ranked in descending order of firm size.
[20] Using this procedure, we obtain an average union coverage rate of 12.4% in the United States, close to the actual union coverage rate of 13.1%. We also find that workers covered by unions are primarily concentrated at the top of the wage distribution. Further analysis suggests that this is driven by the wage premium attached to being covered by a union. When we simulate non-union wages for workers covered by unions, we find that union workers shift towards the upper-middle end of the new (simulated) wage distribution. This finding is consistent with earlier findings from Card (2001) and Card, Lemieux and Riddell (2004), who showed that union membership among males was concentrated in the (upper)-middle of the wage distribution, and female union membership rates in the (upper-)middle and top. Mayer (2004) also found that union membership is highest among workers with advanced college degrees.