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EXPLAINING INTERNATIONAL DIFFERENCES IN MALE SKILL WAGE DIFFERENTIALS BY DIFFERENCES IN DEMAND AND SUPPLY OF SKILL*

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This paper explores the hypothesis that wage differentials between skill groups across countries are consistent with a demand and supply framework. Using micro data from 15 countries we find that about one third of the variation in relative wages between skill groups across countries is explained by differences in net supply of skill groups. The demand and supply framework does an even better job at explaining relative wages of low skilled workers.

Wage inequality between skill groups differs substantially across countries. In continental European countries skill wage differentials are typically much smaller than in the US, the UK and Canada. This is especially true at the bottom of the skill distribution. Two explanations have been put forward for these differences. The first explanation attributes these differences to differences in underlying demand and supply factors. According to this view relative wages of low skilled workers in the US are lower than elsewhere as a result of the abundant net supply of low skilled workers in the US (Nickell and Bell, 1996; Nickell and Layard, 1999). A second explanation attributes international differences in wage inequality across skill groups to differences in labour market institutions. According to this view high minimum wages, employment protection and the different role of unions are responsible for the relatively favourable labour market position of low skilled workers in continental European countries (Blau and Kahn, 1996, 2001; Devroye and Freeman, 2001).

The paper by Blau and Kahn (1996) is an important contribution to this discussion because that paper does not only present evidence in favour of the importance of institutions but also provides evidence against the demand and supply explanation. Blau and Kahn apply the demand and supply framework developed by Katz and Murphy (1992) to relate differences in relative net supply of skill groups to relative wage differentials between countries. The demand and supply model predicts that a larger relative net supply of a skill group would affect their relative wage level negatively. Blau and Kahn's empirical findings, however, show the exact opposite; while the net supply of low skilled workers in the US is lower than in other countries, their relative wages are also lower. Blau and Kahn therefore conclude that market forces 'do not appear to be consistent with the observed pattern of relative wages by skill in other countries compared to the United States' (p. 831).

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The current paper improves and extends the work by Blau and Kahn. A potential source of bias in their analysis is that workers' skill levels are derived from numbers of years of schooling and work experience. While years of schooling and years of work experience are evidently important determinants of skill levels, they are probably not very suitable for purposes of international comparisons of skill levels. The reason is that it assumes that years of schooling and years of work experience have the same meaning in terms of skill enhancement in different countries. This is unlikely to be the case. Equating a year of schooling in the US to a year of schooling in, say, Sweden, ignores the differences in the education systems between these two countries; see for example Steedman (1996); Healy and Nordin (1995). The problems with comparing years of schooling across countries are nicely illustrated by the following quote from a special issue of *The Economist*: 'Up to now, education professionals have tended to resist comparisons even of apparently similar schools within neighbourhoods. Such are the subtleties of their craft, they say, that exercises of that sort are meaningless. In Britain, where the government has begun to publish league tables of schools' results, teachers and local-authority bureaucrats remain intensely sceptical of such information. To go further, and compare a school in Manchester with one in Tampa, say, or Seoul, would strike them as simply ridiculous.' (*The Economist*, March 29th, 1997).

Evidence on this matter also comes from the Third International Mathematics and Science Study (TIMSS) and its predecessors, which reveal substantial differences among countries in the average achievement of students in eighth grade in the subjects mathematics and science (OECD, 1996*a*; Nickell and Bell, 1996). For instance, for achievement in mathematics in eighth grade, the median pupil in Korea or Japan has a score which is higher than the 75th percentile scores in The Netherlands, Germany and Canada. The 25th percentile score in the Korean or Japanese mathematics achievement distribution is higher than the median score in countries like England, Norway, Denmark and the US (OECD, 1996*a*, p. 204). In each country the average age of the pupils included is around 14 years, and in all countries involved, children have had about the same exposure to schooling. These results strongly suggest that years of schooling have different effects on skill levels in different countries.[1]

Likewise, because post-school training systems are not the same in different countries, the contribution of years of working experience to the level of skill is likely to be different as well. In relation to this, Lynch (1994) writes that 'while important differences in the structure of education exist across countries, there are even wider differences in how the various systems of post-school training affect workers'. She continues by presenting numbers showing that training incidence is very different (lower in the US than elsewhere) and also that the age profiles of training participation are different (training concentrated among young workers in Germany and high training incidence among older workers in Sweden and Japan).

This paper investigates whether international differences in between skill group wage differentials can be reconciled with a demand and supply framework

[1] The point that it is problematic to use schooling as a common currency of skill is also made by Nickell and Layard (1999).

once skill is measured on a comparable basis. We use a unique dataset which includes micro data from nearly 10,000 adult male employees in 15 countries. Besides containing information about age, earnings, level of education and labour market status, the dataset also contains information from direct measures of cognitive ability which have been developed with the explicit aim to be comparable across countries. These direct skill measures are arguably more suitable for international comparisons than a composite measure of years of schooling and experience.

Our empirical findings are strikingly different from those reported by Blau and Kahn. Using a direct measure of skill, international wage differences between skill groups are by and large consistent with differences in net supply of skill groups. This is especially true to explain the relative position of the lowest skill group.

In two recent papers Blau and Kahn (2001) and Devroye and Freeman (2001) address the same issue and use the same dataset as we do in this paper. Both studies basically decompose earnings differentials into three components: an observed skill, a price and a residual component. In their interpretation of this decomposition they attribute the part that observed skills explain to demand and supply factors. This ignores the key mechanism of a demand and supply model namely that prices depend on net supply conditions.

This paper proceeds as follows. Section 1 outlines the dataset used in this paper. It describes the different skill measures available in the dataset in somewhat more detail and presents statistics of wage inequality in the 15 countries. Section 2 describes the demand and supply framework developed by Katz and Murphy (1992) that we use to analyse differences in skill wage differentials across countries. This Section also discusses the methods and results of Blau and Kahn (2001) and Devroye and Freeman (2001). Section 3 presents the empirical results. It links differences in skill wage differentials with differences in demand and supply of different skill levels. It also contains a subsection discussing the robustness of our findings. Section 4 summarises and concludes.

1. Data

This data section starts with a description of the International Adult Literacy Survey (henceforth IALS) and pays special attention to the measurement of literacy in this survey. It then describes the relation between the IALS skill measure and the traditional skill measures education and experience. Finally it presents information about different measures of wage inequality in the IALS data and compares these to other sources.

1.1. *The IALS*

The IALS is an initiative to collect comparable data about the literacy skills of the adult populations in 20 countries: Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, The Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Sweden, Switzerland, the UK and the

US. Researchers and statistical offices in these countries developed an instrument that is believed to be capable of comparing individual performances on literacy tests between countries with different languages and cultures.

The participating countries have drawn samples from their populations from which a representative sample could be constructed for the population aged 16 to 65. For 7 countries (Canada, Germany, The Netherlands, Poland, Sweden, Switzerland and the US) the interviews were held in the first half of 1994. For the other countries information was gathered in the first half of 1998. The countries used different methods to weight their samples but these were all post-stratified to known population counts. The IALS was accompanied by an extensive quality review the results of which are reported in Murray *et al.* (1998). According to the quality review report 'a comparison of the distribution of the age and sex characteristics of the actual and weighted samples indicates that the samples were comparable to the overall populations of the IALS countries'.

In addition to the literacy tests, all participants responded to a questionnaire that gathered information about attitudes and behaviour relevant for the performance on the literacy tests. The questionnaire also included questions about labour market status, earnings, education and demographic characteristics. For five countries (Belgium, Ireland, New Zealand, Portugal and the UK) wage information has been measured in quintiles. This information is not very useful for an analysis of wage inequality. For this reason we exclude these five countries from our analysis and proceed with the remaining 15 countries. In each of these 15 countries between 2,062 and 5,660 individuals participated in the survey.

Wages are calculated from the annual or monthly income from employment.[2] In Germany, the Netherlands and Switzerland wage income was reported in 20 intervals. In the other countries wage income was reported continuously. There is sufficient information to calculate hourly wages for all countries but Sweden.[3] The wage data are closely examined in Subsection 1.4 to verify that they are indeed reliable. This gives a picture of the wage structures that is similar to the results found in Blau and Kahn (1996) and in other sources.

The subsample we use consists of males aged 18 to 65, who report to be employed at the moment of interview with non-missing wage observations. Armed forces are excluded. All results reported in this paper are obtained using sample weights.

1.2. *Skill Measures in IALS*

The measure of years of schooling that is used in the analysis is based on the following survey question.

[2] See Table A1 for an overview of sample years and earnings concepts.

[3] For Sweden information on hours worked is lacking, we only know whether a worker worked full-time or part-time. We rescaled part-time workers' wages by 40/18.

> 'During your lifetime, how many years of formal education have you completed, beginning with grade one and not counting repeated years at the same level?'

The IALS data set also includes three scales to measure individuals' literacy levels. These scales relate to prose, document and quantitative related skills. The scales are described as follows in OECD and Statistics Canada (1995):

- *Prose literacy* – the knowledge and skills needed to understand and use information from texts including editorials, news stories, poems and fiction,
- *Document literacy* – the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables and graphics; and
- *Quantitative literacy or numeracy* – the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, figuring out a tip, completing an order form or determining the interest on a loan from an advertisement.

Each of these scales ranges from 0 to 500. Only very few respondents have the maximum score of 500.[4] While the three scales clearly intend to measure different elements of a person's cognitive skills, it turns out that the three skills are very highly correlated. The partial correlations coefficients (calculated at the country level) are always in the vicinity of 0.90. This makes it useless to distinguish three separate skill measures in the analyses that follow. We therefore create an aggregate IALS measure based on the average of the three underlying scales.[5] This makes it easier to compare our results to Blau and Kahn (2001) and Devroye and Freeman (2001), who use the same procedure.

1.3. *The Relation Between Skill, Education and Experience*

Because of the importance of the various skill measures in the analysis this subsection will explore the relation between them. Figure 1 shows for each country separately the mean value of years of schooling and the IALS skill measure being the average of the three separate scales (S_{IALS}).[6]

It is immediately clear from the graph that the average level of schooling and skill as measured by S_{IALS} are positively correlated across countries. Average years of schooling per country vary from a low 9.7 in Chile to a high 14.0 in the US. Figure 1 also illustrates the possible source of bias that might arise from using a skill measure based on years of schooling in direct cross-national comparisons. When the IALS scores are used as a skill measure Sweden has the highest average score, followed by the other Scandinavian countries and the Netherlands and

[4] For an impression of how actual literacy levels translate into scores on the IALS literacy scales, we give descriptions of the requirements of some threshold levels in the appendix.

[5] The results of our analysis were virtually unchanged when the three scores were combined into one using the regression coefficients of these scores in a pooled wage regression as weights.

[6] Table A2 in the Appendix provides mean values and standard deviations of the various skill measures.

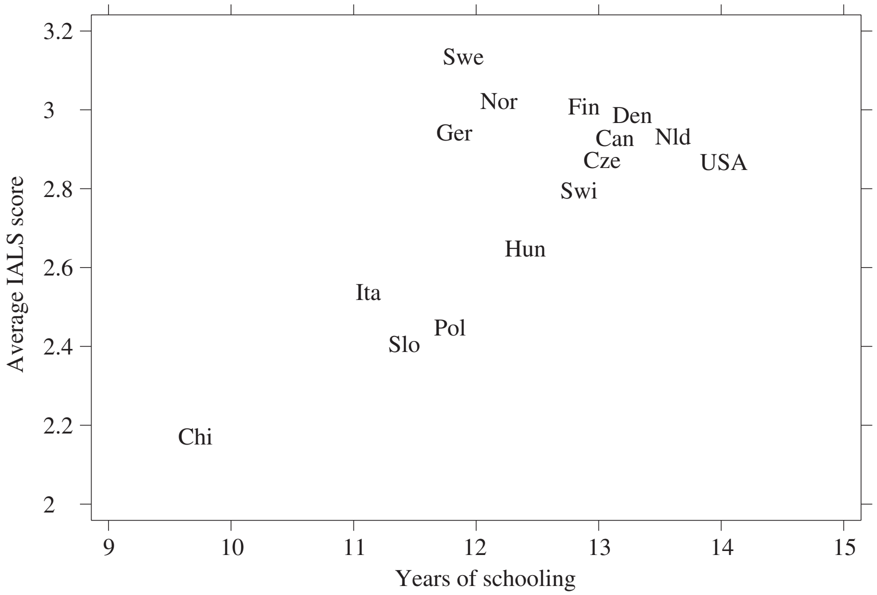

Fig. 1. *Cross Sectional Relation Between Years of Schooling and Skill*

Germany. Chile has again the lowest position. The most important change is that the US ranks highest with years of schooling but ranks ninth when the IALS scores are used as measures of skill.

The dispersion of the IALS scores (measured by the standard deviation, see Table A2 in the Appendix) is smaller in the Scandinavian countries, the Netherlands and Germany than in most of the other countries including the US. In all countries, the average levels of potential work experience are around 20 years, with a low 17.4 years in Canada and a high 23.3 years in Italy.

To get more insight into the relation between S_{IALS} on the one hand and years of schooling and experience on the other, Table 1 shows for each of the 15 countries, results from regressions of S_{IALS} on years of schooling, years of schooling squared and years of experience.[7] We do not interpret the regression results in terms of the causal effect of schooling and experience on skill levels. We are only interested in differences in the relations between these variables across countries.

In all 15 countries the relation between skill level and years of schooling is positive. But the slope of the skill-schooling profile differs greatly across countries. The slope is steepest for the Czech Republic, the US, Slovenia and Canada. These are also the countries in which the constant term is not significantly different from zero. The constant term is largest in Denmark, Sweden, the Netherlands and Germany; these are also countries with a fairly flat skill-schooling profile. The relation between skill and experience is significantly negative in 7 of the 15

[7] We also estimated skill regressions that included experience squared. Adding this variable did not add to the explanatory power and the coefficients on the experience terms turned insignificant for most countries.

Table 1

Coefficients (standard errors) from Regressions of S_{IALS} on Education and Experience

	Education	Education^2	Experience/10	Constant	Observations	R^2
Canada	0.318 (0.032)**	−0.008 (0.001)**	0.004 (0.023)	0.192 (0.250)	855	0.43
Chile	0.104 (0.020)**	−0.000 (0.001)	0.017 (0.018)	1.118 (0.122)**	715	0.48
Czech Republic	0.326 (0.055)**	−0.009 (0.002)**	−0.051 (0.018)**	0.364 (0.404)	519	0.20
Denmark	0.120 (0.025)**	−0.003 (0.001)**	−0.041 (0.011)**	1.945 (0.189)**	986	0.24
Finland	0.161 (0.029)**	−0.004 (0.001)**	−0.023 (0.015)	1.633 (0.223)**	651	0.29
Germany	0.089 (0.046)	−0.002 (0.002)	−0.022 (0.024)	2.163 (0.314)**	396	0.12
Hungary	0.146 (0.036)**	−0.003 (0.001)*	−0.096 (0.023)**	1.494 (0.250)**	382	0.24
Italy	0.243 (0.037)**	−0.006 (0.001)**	−0.039 (0.029)	0.819 (0.271)**	529	0.42
Netherlands	0.063 (0.026)*	−0.001 (0.001)	−0.054 (0.016)**	2.334 (0.213)**	759	0.24
Norway	0.178 (0.030)**	−0.005 (0.001)**	−0.030 (0.013)*	1.618 (0.213)**	966	0.21
Poland	0.119 (0.057)*	−0.001 (0.002)	−0.036 (0.027)	1.233 (0.379)**	543	0.22
Slovenia	0.216 (0.056)**	−0.004 (0.002)*	−0.079 (0.024)**	0.662 (0.383)	470	0.39
Sweden	0.076 (0.026)**	−0.001 (0.001)	−0.018 (0.016)	2.445 (0.195)**	743	0.13
Switzerland	0.227 (0.034)**	−0.006 (0.001)**	−0.037 (0.018)*	0.987 (0.263)**	607	0.32
United States	0.299 (0.030)**	−0.006 (0.001)**	0.020 (0.018)	−0.054 (0.232)	686	0.41

Notes: *Significant at the 5% level, **Significant at the 1% level.

countries. The size of this effect varies between countries which illustrates that years of work experience are likely to contribute differently to skills acquisition in different countries. The constant terms in the regressions express the average skill level of (inexperienced) workers with the lowest level of schooling. The observed differences in these constant terms are suggestive for differences in the quality of primary education between countries.

1.4. *Wage Inequality*

While the focus in this paper is on wage differentials between skill groups, we first present information about some common measures of overall wage inequality. This allows us to make a comparison with other data sources and to assess the validity of the IALS data in this respect. It should be noticed, however, that skill is an important determinant of wages so that countries that have high skill wage differentials also have high overall wage inequality.[8]

The first column in Table 2 presents the standard deviations of log hourly wages in our data. This measure of wage inequality differs substantially across the 15 countries included in the analysis; from 0.801 in Hungary to 0.416 in Denmark. Inequality is also high in Chile and Poland after which the US and Canada follow. Wage inequality is low in the Scandinavian countries; the West-European countries take an intermediate position.

Columns (2) and (6) present the distances of the 50th and 10th percentiles and the 90th and 50th percentiles in log wages. This reveals an important characteristic

[8] The rank correlation between the standard deviation of log wages and the wage differential between the highest one third of the skill distribution and lowest one third equals 0.64.

Table 2

Measures of Wage Inequality

		50–10				90–50			
	σ_{lnw} (1)	IALS (2)	OECD* (3)	GJ† (4)	BK‡ (5)	IALS (6)	OECD (7)	GJ (8)	BK (9)
Canada	0.612	0.961	0.784	0.805		0.560	0.548	0.532	
Chile	0.776	0.706				0.942			
Czech Republic	0.421	0.519	0.577			0.480	0.432		
Denmark	0.416	0.406	0.322			0.457	0.541		
Finland	0.519	0.580	0.378	0.359		0.493	0.548	0.495	
Germany	0.500	0.567	0.315		0.456	0.573	0.495		0.539
Hungary	0.801	0.718			0.462	0.965			0.661
Italy	0.501	0.613	0.470		0.478	0.647	0.501		0.486
Netherlands	0.483	0.595	0.432	0.351		0.521	0.519	0.549	
Norway	0.542	0.604	0.278		0.224	0.421	0.405		0.525
Poland	0.723	0.783				0.854			
Slovenia	0.537	0.511				0.644			
Sweden	0.473	0.511	0.307	0.337	0.382	0.501	0.482	0.497	0.452
Switzerland	0.630	0.521	0.412		0.464	0.643	0.501		0.777
US	0.628	0.888	0.723	1.003	1.040	0.698	0.693	0.622	0.552

For more details see these sources. *OECD (1996*b*). Most figures are based on gross annual or monthly earnings. For the Czech Republic, Denmark, the Netherlands and Norway data refer to both men and women. †Gottschalk and Joyce (1998). Data from Luxembourg Income Studies. Real gross annual wages or salaries for male heads of households. ‡Blau and Kahn (1996). Log hours-corrected gross or net (not reported) annual or monthly earnings.

of wage inequality in the US. While the standard deviation of log wages and the log wage differential between the 90th and 50th percentiles have intermediate values, this is not the case for the log wage differential between the 50th and 10th percentiles. This shows that wage inequality in the US is concentrated at the bottom.

The 50–10 and 90–50 log wage differentials can be compared with statistics reported in the OECD's Employment Outlook 1996 (OECD, 1996*c*), Gottschalk and Joyce (1998) and Blau and Kahn (1996). These statistics are reported in columns (3) to (5) and (7) to (9).

The wage differentials from the three sources are typically similar to ours and our numbers are in most cases not more out of range than the numbers from each of these studies individually. We conclude that the wage inequality information for different countries that emerges from the IALS data set fit well in between the figures from other sources. The stylised fact that wage inequality in the US is especially marked at the bottom as compared to other countries is also found in our data.

A first approach to investigating differences in the relation between wages and skills across countries, is to estimate similar (log) wage equations. This also provides a tentative check of the validity of the data. Table 3 reports the results for two specifications, the usual Mincerian specification with years of schooling, experience and experience squared as regressors and the same specification extended with the IALS skill measure.

The returns to schooling in the first specification differ substantially across countries, from 0.034 in Sweden to 0.103 in Chile. For the US the return to

Table 3

Wage Regressions

	Education	Experience/10	Experience^2/100	S_{IALS}/100	Constant	N	R^2
Canada	0.064 (0.008)**	0.566 (0.078)**	−0.084 (0.018)**		1.197 (0.123)**	855	0.28
	0.052 (0.008)**	0.565 (0.077)**	−0.082 (0.018)**	0.138 (0.044)**	0.955 (0.140)**	855	0.30
Chile	0.103 (0.012)**	0.104 (0.089)	0.005 (0.017)		5.217 (0.172)**	715	0.19
	0.074 (0.014)**	0.115 (0.088)	0.002 (0.017)	0.285 (0.074)**	4.883 (0.198)**	715	0.22
Czech Republic	0.052 (0.008)**	0.196 (0.077)*	−0.039 (0.017)*		3.108 (0.132)**	519	0.14
	0.046 (0.009)**	0.205 (0.077)**	−0.040 (0.017)*	0.097 (0.046)*	2.888 (0.148)**	519	0.15
Denmark	0.046 (0.004)**	0.405 (0.044)**	−0.066 (0.009)**		3.786 (0.073)**	986	0.25
	0.042 (0.004)**	0.404 (0.044)**	−0.065 (0.010)**	0.091 (0.031)**	3.567 (0.098)**	986	0.25
Finland	0.050 (0.006)**	0.301 (0.064)**	−0.035 (0.015)*		3.147 (0.097)**	651	0.14
	0.045 (0.006)**	0.301 (0.064)**	−0.034 (0.015)*	0.095 (0.054)	2.924 (0.161)**	651	0.14
Germany	0.047 (0.012)**	0.412 (0.086)**	−0.055 (0.017)**		1.673 (0.185)**	396	0.24
	0.040 (0.012)**	0.430 (0.086)**	−0.059 (0.017)**	0.152 (0.053)**	1.289 (0.242)**	396	0.26
Hungary	0.090 (0.014)**	0.263 (0.155)	−0.023 (0.039)		4.091 (0.222)**	382	0.16
	0.075 (0.016)**	0.256 (0.150)	−0.014 (0.038)	0.253 (0.096)**	3.587 (0.282)**	382	0.18
Italy	0.072 (0.005)**	0.579 (0.077)**	−0.085 (0.017)**		1.189 (0.106)**	529	0.41
	0.065 (0.005)**	0.561 (0.077)**	−0.080 (0.017)**	0.090 (0.041)*	1.045 (0.129)**	529	0.42
Netherlands	0.044 (0.005)**	0.444 (0.086)**	−0.065 (0.019)**		2.087 (0.128)**	759	0.22
	0.035 (0.006)**	0.433 (0.085)**	−0.059 (0.019)**	0.233 (0.054)**	1.523 (0.142)**	759	0.26
Norway	0.044 (0.006)**	0.493 (0.077)**	−0.081 (0.016)**		3.599 (0.117)**	966	0.14
	0.039 (0.007)**	0.488 (0.077)**	−0.079 (0.016)**	0.098 (0.046)*	3.368 (0.157)**	966	0.15
Poland	0.099 (0.010)**	0.379 (0.107)**	−0.062 (0.024)**		1.391 (0.171)**	543	0.16
	0.098 (0.011)**	0.380 (0.107)**	−0.062 (0.024)**	0.012 (0.046)	1.374 (0.191)**	543	0.16
Slovenia	0.080 (0.008)**	0.258 (0.109)*	−0.031 (0.024)		4.954 (0.144)**	470	0.21
	0.067 (0.009)**	0.252 (0.108)*	−0.028 (0.023)	0.116 (0.041)**	4.817 (0.159)**	470	0.22
Sweden	0.034 (0.005)**	0.364 (0.064)**	−0.055 (0.012)**		3.697 (0.102)**	743	0.14
	0.028 (0.005)**	0.369 (0.063)**	−0.055 (0.012)**	0.129 (0.034)**	3.356 (0.131)**	743	0.16
Switzerland	0.049 (0.008)**	0.668 (0.120)**	−0.106 (0.024)**		1.906 (0.179)**	607	0.24
	0.032 (0.008)**	0.675 (0.118)**	−0.105 (0.024)**	0.236 (0.048)**	1.436 (0.210)**	607	0.27
United States	0.092 (0.008)**	0.511 (0.074)**	−0.079 (0.018)**		0.732 (0.139)**	686	0.31
	0.063 (0.010)**	0.517 (0.073)**	−0.081 (0.018)**	0.238 (0.047)**	0.454 (0.144)**	686	0.35

Notes: Standard errors in parentheses. *significant at the 5% level, **significant at the 1% level.

schooling according to the IALS data set equals 0.092, which is an estimate well within the range commonly found for this country. For 8 out of 15 countries the return to schooling falls in the narrow range of 0.044 to 0.064. This is consistent with results reported elsewhere.

The second row for each country extends the first equation by including the IALS score. These specifications reveal that when the IALS score is included as regressor the return to schooling estimates decline in all countries. This is caused by the positive correlations between years of schooling and the cognitive score. The decline in the return to schooling differs between countries. On the one extreme stands Poland where the return to schooling is hardly affected by inclusion of the IALS score in the wage equation. At the other extreme are Switzerland and the US where the return to schooling drops to about two thirds of its initial value when the cognitive score is included. The labour market returns to cognitive skills also differ across countries. Here we observe a dichotomy: in Chile, Hungary, the Netherlands, Switzerland and the US the return to skill is substantial, in the other countries the return to skill after controlling for years of schooling is much lower. The experience profiles differ across countries. The profiles are steepest in Switzerland, Italy, Canada and the US and are (relatively) flat in Chile, Hungary, Czech Republic and Slovenia.

2. Method

Katz and Murphy (1992) developed a framework of demand and supply of skill to analyse changes in wage inequality in the US over time. Here we introduce this framework in terms of our application to differences in wage inequality between skills groups across countries. Like other models of wage structure that focus on the role of demand and supply for different labour inputs, implementation and interpretation of the Katz and Murphy framework requires that workers are classified in observable skill categories (Katz and Autor, 1999, p. 1489). This implies that differences in residual wage inequality across countries are not addressed. This is not because we think such differences are unimportant but because it is difficult to reach unambigous conclusions based on analyses of residual wage inequality (Katz and Autor, 1999, p. 1480).

Based on a skill index *S*, the workforces of different countries are divided into three skill groups: low, intermediate and high. The cutoff levels between the groups are determined by the skill distribution in a baseline country (b). A person is assigned to the low skill group if his level of skill is in the lowest one third of the skill distribution in the baseline country. Persons with skill levels in the middle and top one third of the skill distribution in the baseline country are assigned to the intermediate and high skill groups, respectively.

The relative demand index for skill group $k \in \{low, middle, high\}$ in country j is defined as

$$d_{k,j} = \ln\left(1 + \sum_o c_{ok} \frac{\Delta E_o}{E_{k,b}}\right) \tag{1}$$

where c_{ok} is the share of skill group k in occupation-industry cell o in the baseline country, ΔE_o is the difference in shares of total labour input employed in cell o

between country j and the baseline country, and $E_{k,b}$ is the share of total labour input accounted for by skill group k in the baseline country (which equals $\frac{1}{3}$). This demand index is a measure for the degree to which the occupation-industry structure in country j favours skill group k relative to the baseline country.

The supply index for skill group k in country j is:

$$s_{k,j} = \ln(E_{k,j}/E_{k,b}) \tag{2}$$

where $E_{k,j}$ and $E_{k,b}$ are the shares of total labour input consisting of skill group k in country j and the baseline country, respectively. The supply index expresses the relative share of each skill group in a country's work force relative to the baseline country. Combining the two indexes gives the net supply index for skill group k in country j as:

$$\bar{s}_{k,j} = s_{k,j} - d_{k,j}. \tag{3}$$

Also define the wage of skill group k relative to skill group l in country j as $w_{k/l,j}$.

The difference in relative net supply of each pair of skill groups in country j : $\bar{s}_{k,j} - \bar{s}_{l,j}$, can now be confronted with the wage differential between these skill groups in country j relative to the wage differential between these groups in the baseline country: $w_{k/l,j} - w_{k/l,b}$. According to the demand and supply model these two differences should covary negatively. If, for instance, the net supply of low skilled relative to high skilled workers is smaller in Germany than in the US (as baseline country) then the demand and supply model predicts that the wage spread between low and high skilled workers is smaller in Germany than in the US.

When plotting $w_{k/l,j} - w_{k/l,b}$ against $\bar{s}_{k,j} - \bar{s}_{l,j}$ all combinations are predicted to lie in the second and fourth quadrants. With 15 countries, one of which is the baseline country, and three skill groups, we can make 42 of such pairwise comparisons; for all 14 remaining countries relative to the baseline country we can compare low versus high skilled, intermediate versus low skilled and intermediate versus high skilled. According to the demand and supply model these 42 combinations ought to lie north-west or south-east of each other. Larger (smaller) relative net supply of a skill group should be accompanied by lower (higher) relative wages of that group. This implies that a regression line through the 42 combinations is predicted to have a negative slope. We will test this hypothesis by estimating regression equations of the following form

$$(w_{k/l,j} - w_{k/l,b}) = \alpha + \beta(\bar{s}_{k,j} - \bar{s}_{l,j}) + \varepsilon_j$$

where it is expected that $\beta < 0$ and where it holds that the higher the absolute value of β is, the more responsive relative wages of skill groups are to changes in the relative net supply of skill groups.

The choice of a baseline country determines the cutoff levels between the three skill groups and determines the benchmark occupation-industry structure. Results may differ substantially for different choices of baseline country. This is unfortunate because the choice of baseline country is arbitrary. We address this by repeating the analysis 15 times; one time with each country as the baseline country. This results in $42 \times 15 = 630$ combinations. These are all plotted in one graph and we estimate the linear equation which gives the best fit. Since these combinations are not independent we model this dependence in the covariance matrix by taking the clustered nature of the data by country into account. In addition standard errors are heteroscedasticity robust (White-Huber type standard errors).

Applying a competitive framework does not mean that we advocate the narrow view that demand and supply forces are the sole determinants of wage differentials. Institutions may matter as well and may lead to deviations from the competitive outcome. Our approach accords with the view expressed by Katz and Autor (1999, p. 1506) that '[t]he basic idea is to see how far one can go with a pure competitive framework'. This framework only leads to a prediction about the signs of the covariance of relative wages and relative net supply and of the slope of a regression line through the observed combinations. When these signs are correct we may infer that market forces are not undone by institutions. The framework does not permit us to decompose wage differentials into a 'demand and supply'-component and an 'institutions'-component. It also does not allow us to investigate whether demand and/or supply have been shifted by institutions. This would take us beyond the research question of this paper. In addition there is the more fundamental problem of identifying exogenous changes in institutions, a point also made by Katz and Autor (1999, p. 1507) when they write that '[t]he attribution of wage structure movements to institutional changes may be problematic to the extent evolution of institutions reflects responses to market forces rather than exogenous events.'

In two recent papers Blau and Kahn (2001) and Devroye and Freeman (2001) suggest a decomposition into a 'demand and supply'-component and an 'institutions'-component. Both papers, however, ignore the key mechanism of a demand and supply model namely that wage differentials between skill groups depend on net supply conditions. Interestingly, both papers employ the same dataset as we use here, although in both instances only a subset of the countries included in the current paper are used. We briefly summarise the approaches and results of the two papers.

Blau and Kahn (2001) apply the decomposition method developed by Juhn *et al.* (1993) to attribute international differences in wage inequality to three effects: a measured characteristics effect due to differences in the distribution of measured characteristics of workers; a wage coefficient effect due to differences in the rewards to measured characteristics; and a wage equation residual effect which is unexplained and which may capture effects of unobserved characteristics, unobserved prices and measurement error. The relative importance of these three components in explaining wage inequality between the US and other countries differs between men and women and between the top and bottom half of the wage distribution (the 50–10 percentile difference and the 90–50 percentile difference). The measured characteristics effect is largest for men at the bottom; on average accounting for 47% of the total 50-10 log wage differential between the US and other countries. Leaving 24 and 29% for the other two effects. In contrast, the wage coefficient effect is largest for women at the top; on average accounting for 66% of the total 90–50 log wage differential between the US and other countries. The other two effects account for −12% and 46%. Devroye and Freeman (2001) perform a fairly similar decomposition of the standard deviation of log earnings. They find that the differences between the coefficients in the earnings equations between the US and European Union countries (Germany, Netherlands, Sweden) explain five times more of the greater dispersion in the US than does the higher dispersion of skills in the US.

In both papers it is suggested that differences in the distribution of characteristics (skills) capture the impact of differences in demand and supply factors while differences in wage coefficients are related to differences in wage setting institutions. Differences in wage coefficients may, however, also reflect differences in supply and demand factors. When the net supply of skilled workers is small the skill premium is likely to be larger. Devroye and Freeman (2001) are aware of this point when they write that 'the variance decomposition arguably understates the effects of changes in the dispersion of skills' (p. 13). But they do not present an estimate of the magnitude of this bias. Thus while their approach in first instance generates an estimate of the relative importances of differences in skill dispersion and differences in wage coefficients, it turns out that their approach only provides us with an estimate of the lower bound of the importance of differences in skill distributions (differences in supply).[9]

3. Demand and Supply Analysis

This Section contains three subsections. The first subsection replicates the analysis in Blau and Kahn (1996) using the IALS data. That is, we follow Blau and Kahn and construct a skill measure based on a world wide wage equation including years of schooling and years of experience as skill determinants based on the information in the IALS data. Using this skill measure (S_{BK}) we apply Katz and Murphy's demand and supply model. This tests whether we achieve the same conclusion as Blau and Kahn did using a different dataset. The second subsection repeats the analysis but now using IALS's direct skill measure (S_{IALS}). The final subsection reports results regarding the robustness of our findings.

3.1. *Results based on S_{BK}*

This subsection presents the results of the demand and supply analysis as outlined in Section 2 using S_{BK} as skill measure. This analysis confronts the differences in skill wage differentials across countries with information about net supply of the various skill groups. This confrontation is visualised in the four panels of Figure 2 which plots $(\bar{s}_{k,j} - \bar{s}_{l,j})$ against $(w_{k/l,j} - w_{k/l,b})$. The demand and supply model predicts all observations will lie in the second and fourth quadrants. The panels also include the regression lines through these combinations which are predicted to have a negative slope. The top half of Table 4 reports the results from the regressions.

[9] Devroye and Freeman (2001, p. 13) suggest that at most 37% of the US-EU difference in the dispersion of earnings can be attributed to demand and supply. This is however merely the R-squared of their wage regression. There is no reason to believe that a richer specification would give the same 'upper bound', nor that demand and supply do not affect residual wage inequality.

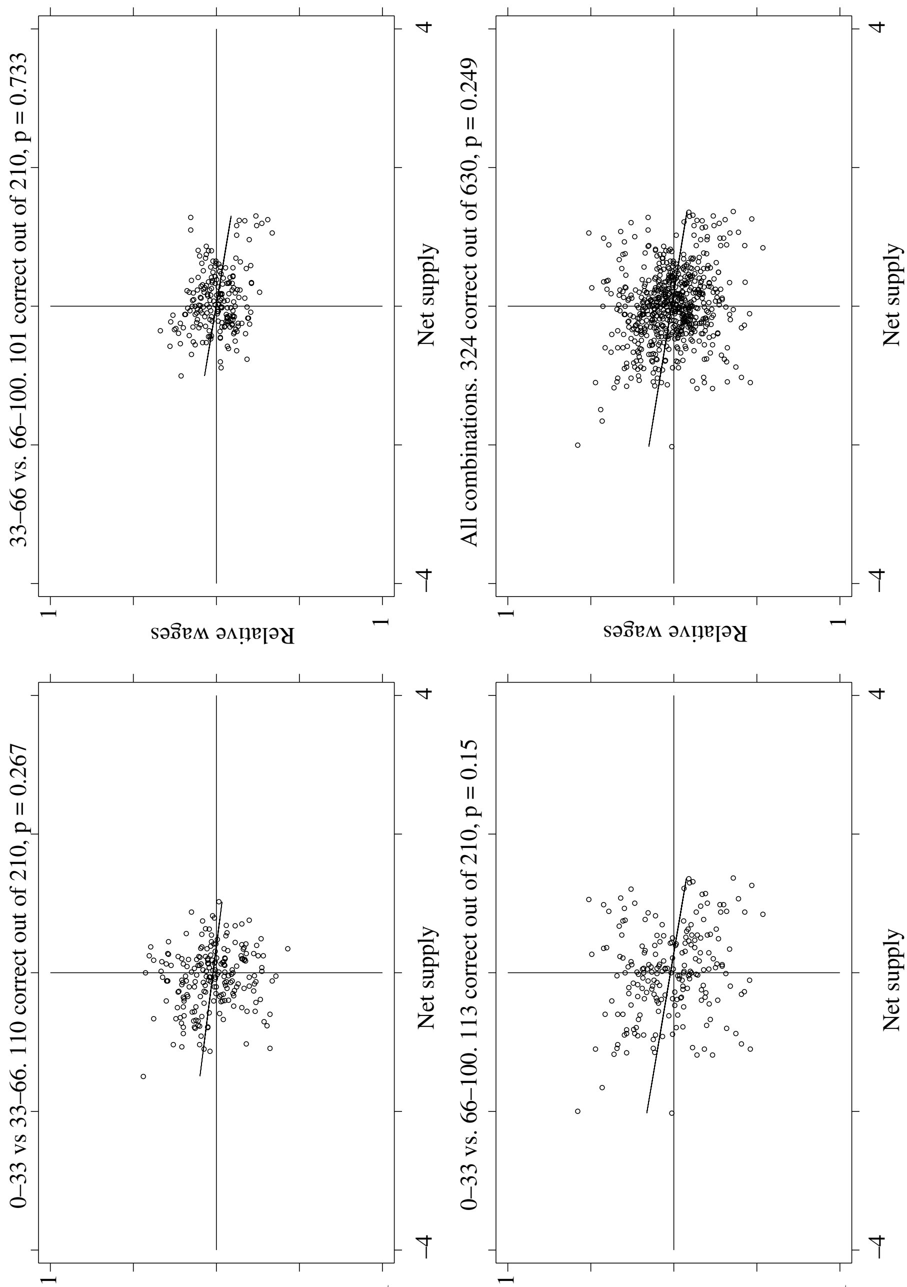

Fig. 2. *Relative Wages and Net Supply,* S_{BK}

The first panel in Figure 2 graphs the relative wages against the relative net supply for the comparison of the lower third versus the middle third of the skill distribution and shows 110 correct predictions. The probability that there are at least 110 correct predictions out of 210 when done randomly is 0.267.[10] We therefore do not reject the hypothesis that relative wages are unrelated to relative net supply. The regression reported in Table 4 shows the same result; although the estimated elasticity is negative it is not statistically significant and very little of the variation in relative wages is explained. The second panel graphs relative wages and net supply for the comparison of the middle versus the upper part of the skill distribution. Here too we cannot reject the hypothesis that relative wages are unrelated to relative net supply with 101 correct cases. The estimated elasticity is again negative but insignificant. The third panel shows the comparison between the lower and upper third of the skill distribution and again no relation is found between relative wages and relative net supply. Finally, the last panel pools all comparisons and shows that only 324 out of 630 cases the predicted pattern is observed. The estimated elasticity is negative but remains insignificant.

Hence, with a different dataset and the same skill measure, the same conclusion as in Blau and Kahn (1996) arises: the demand and supply framework does a poor job in explaining international differences in skill wage inequality. This establishes that any differences we may find below, are due to the different skill measures and are not caused by peculiarities of the dataset.

3.2. *Results based on S_{IALS}*

Figure 3 shows the results of the confrontation of skill wage differentials and the net supply indexes of skill groups when S_{IALS} replaces S_{BK}. The first panel again graphs the relative wages against the relative net supply for the comparison of the

Table 4

Demand and Supply Regressions

	$(\bar{s}_{kj} - \bar{s}_{lj})$	R-squared
Results based on S_{BK}		
0–33 vs. 33–66	−0.053 (0.040)	0.02
33–66 vs. 66–100	−0.069 (0.054)	0.07
0–33 vs. 66–100	−0.070 (0.067)	0.04
Total	−0.068 (0.052)	0.04
Results based on S_{IALS}		
0–33 vs. 33–66	−0.165 (0.036)**	0.58
33–66 vs. 66–100	−0.016 (0.026)	0.01
0–33 vs. 66–100	−0.100 (0.007)**	0.44
Total	−0.100 (0.009)**	0.33

Notes: Robust standard errors are reported that take into account clustering at the country level. **significant at the 1% level.

[10] If a quadrant is chosen randomly the probability of a single good prediction is 0.5. The probability that there are k correct predictions out of n comparisons follows a binomial distribution.

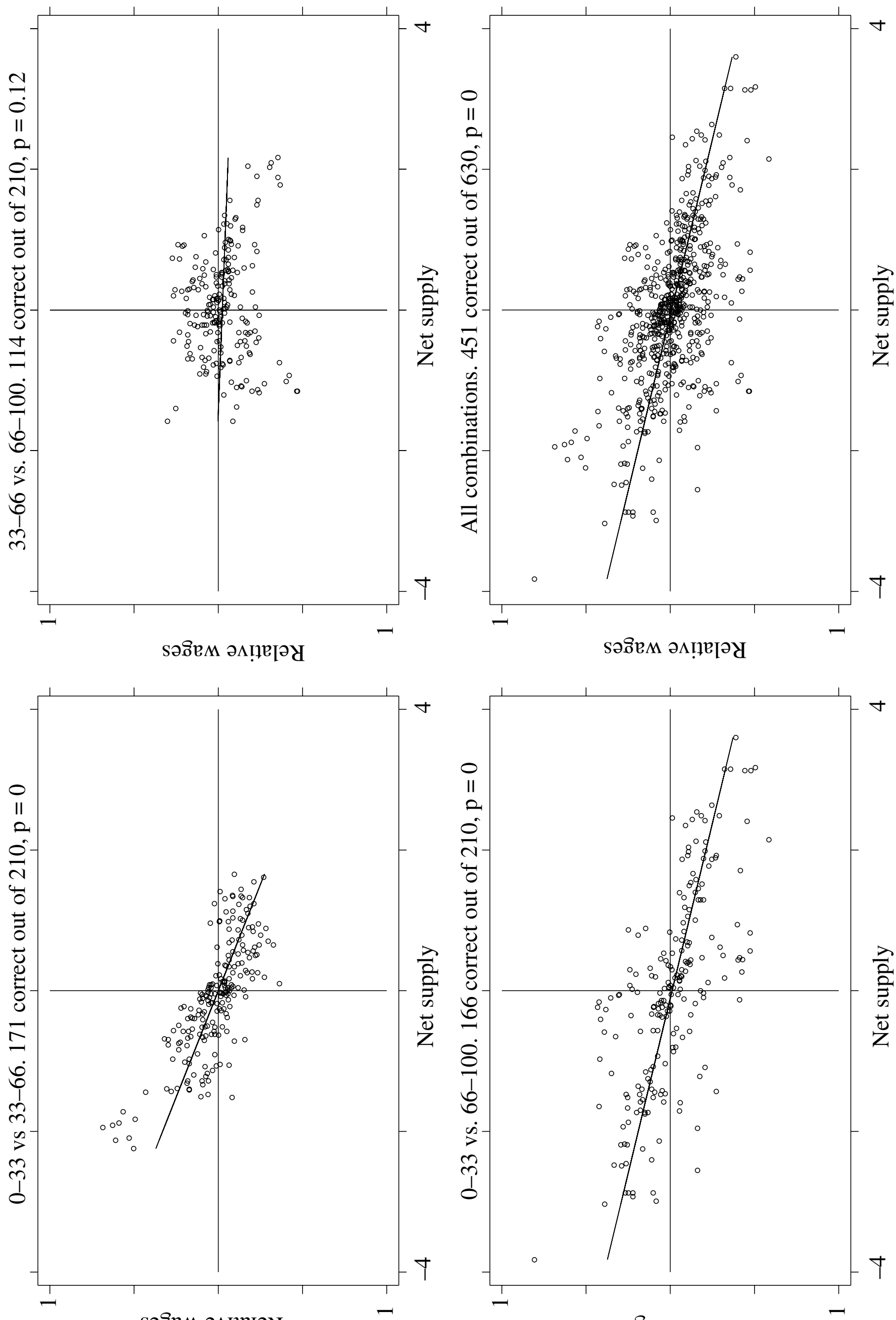

Fig. 3. *Relative Wages and Net Supply,* S_{IALS}

lower third versus the middle third of the skill distribution but this time shows 171 correct predictions out of 210, this is highly significant ($p < 0.001$). The regression results reported in Table 4 confirm this and show that the estimated elasticity is highly significant and equals −0.165. Nearly 60% of the variation in skill wage differentials is explained by relative net supply. Comparing the lower third with the upper third of the skill distribution in the bottom left panel of Figure 3 also shows a significant relation between relative wages and net supply. The estimated elasticity of −0.100 and highly significant. Here 44% of the variation in relative wages is explained by relative net supply.

The picture in the top right panel, which graphs the relative wages of the middle and top of the skill distribution vs the relative net supply, is different. Only 114 out of 210 comparisons are correct and no significant relation is found. This picture changes when country dummies are added to the regression. The estimated elasticity now becomes −0.05 and is significant (not reported in Table 4). The reason behind this result is that the North American countries and especially the US are outliers. The other estimates do not change.

Overall 451 of the 630 pairwise comparisons turn out to have the correct sign; the probability of having at least as many correct combinations when the odds of a negative sign and a positive sign are equal, is less than 0.001. Regressing relative wages on relative net supply gives and elasticity of −0.100 where one third of the variation in relative wages is explained by relative net supply. This shows that the conclusion whether relative wages are consistently explained by a demand and supply model crucially depends on the skill measure employed. Using S_{IALS} instead of S_{BK} shows that one third of relative wages between skill groups between countries is explained by a demand and supply framework.[11] The demand and supply explanation does an even better job at explaining relative wages at the bottom of the skill distribution. This is important since it was especially the stylised fact of low relative wages of low skilled in the US that motivated Blau and Kahn's paper.

3.3. *Robustness*

Devroye and Freeman (2001) argue that the IALS skill measure may not provide a good measure of the skills among immigrants in the US since the tests are conducted in English. This may bias our findings to the extent that fluency in a country's official language is less important for labour market performance than for performance on the IALS tests.

As a check on the appropriateness of using S_{IALS} vs S_{BK} we regressed wages on S_{IALS} separately for migrants and non-migrants in the US (Columns (1) and (3) in Table 5). Doing so we could not reject the hypothesis that the coefficient on S_{IALS} is equal for both groups. This contrasts with a regression of wages on education

[11] To be more precise, the demand and supply framework explains one third of across country differences in wage differentials when one distinguishes only three skill groups. Of course, with only three skill groups a large fraction of overall wage inequality is within groups; between groups differences explain about one third of overall inequality.

Table 5

Wage Regressions US for Migrants and Non-migrants

	Non-migrants		Migrants	
	(1)	(2)	(3)	(4)
S_{IALS}	0.451 (0.058)**		0.341 (0.064)**	
Education		0.099 (0.012)**		0.073 (0.010)**
Experience		0.567 (0.085)**		0.143 (0.159)
Experience^2		−0.092 (0.021)**		−0.005 (0.035)
Constant	1.313 (0.173)**	0.616 (0.179)**	1.631 (0.143)**	1.207 (0.238)**
N	528	528	158	158
R-squared	0.15	0.32	0.20	0.28

Note: **Significant at the 1% level.

and experience and experience squared where the equality of the coefficients for these two groups is strongly rejected (Columns (2) and (4) in Table 5). Since the coefficients are lower for migrants these results suggest that the opposite of what Devroye and Freeman (2001) claim might be the case and that using S_{BK} will in fact overestimate migrants' skill level.

As a final robustness check we repeated the analyses excluding migrants in all countries. The results are very similar to those reported in the previous subsection. Overall the estimated elasticity (standard error) is −0.093 (0.01) and the R-squared is 0.31. The estimated low/high elasticity now becomes −0.157 (0.035), R-squared equals 0.59, the middle/high elasticity is −0.010 (0.028) with an R-squared of 0.003 and, finally, the estimated low/high elasticity equals −0.092 (0.007) and the R-squared equals 0.41.

4. Conclusion

This paper argues that using a skill measure which is a composite of years of schooling and experience is inappropriate for purposes of international comparisons. As an alternative the analyses use information from direct skill measures which have been developed with the explicit aim of being comparable across countries. The results show that the use of this alternative skill measure reverses the conclusions. While Blau and Kahn (1996) conclude that differences in skill wage differentials across countries are inconsistent with a demand and supply model of skill, we find the opposite. This is the key result of this paper, and suggests that the results of Blau and Kahn are an artifact of the skill measure they use and of the implicit assumption contained therein that educational institutions and institutions of training systems do not matter.

This finding does not depend on any peculiarity of the data. Country-specific levels of wage inequality are quite similar to levels of wage inequality reported in other studies. Estimation results from wage regressions are also in line with results commonly reported in the literature. Moreover, when using Blau and Kahn's skill measure results are obtained that are similar to theirs.

With the direct skill measure, the demand and supply model is particularly successful in explaining international differences in wage differentials between low skilled workers and intermediate skilled workers, and between low skilled workers and high skilled workers. The approach is less successful in explaining the differences between intermediate and high skill groups. One speculative explanation for this is that the type of cognitive skills measured by the IALS tests are necessary to escape the lower part of the wage distribution but are not sufficient to guarantuee a position in the higher part of the wage distribution. To get into the higher part presumably requires other types of skills as well.

It is not suggested that our findings are evidence that demand and supply factors are the only forces relevant for explaining international differences in male wage inequality, thereby denying the relevance of institutions. But opposed to Blau and Kahn who argue that labour market institutions tell the whole story, the analysis shows that demand and supply factors play definitely a role. The relative contributions of institutions and market forces are, however, still unknown.

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Appendix

A.1. *Description of IALS scales*[12]

To obtain a prose score below 225, a respondent should be unable to perform tasks that 'tend to require the reader to locate one or more pieces of information in the text, but several distractors may be present, or low-level inferences may be required. Tasks above this level (above 225 but below 276) also begin to ask readers to integrate two or more pieces of information, or to compare and contrast information'. In contrast to this, to obtain a score

Table A1
Sample Period and Earnings Concept by Country

Country	Year	Earnings concept	Sample size
Canada	1993	Annual gross	855
Chile	1997	Annual gross	715
Czech Republic	1997	Annual gross	519
Denmark	1997	Annual gross	986
Finland	1997	Annual gross	651
Germany	1993	Monthly net	396
Hungary	1997	Monthly gross	382
Italy	1997	Annual gross	529
Netherlands	1993	Annual net	759
Norway	1996	Annual gross	966
Poland	1993	Annual net	543
Slovenia	1997	Annual gross	470
Sweden	1993	Annual gross	743
Switzerland	1993	Annual net	607
US	1993	Annual gross	686

[12] The information is taken from OECD and Statistics Canada (1995); this publication provides also examples of questions and exercises at the different levels.

Table A2

Sample Means (standard deviations) of the Various Skill Measures

	Education	Experience/10	S_{BK}	$S_{IALS}/100$
Canada	13.08 (3.51)	1.70 (1.13)	2.65 (0.32)	2.92 (0.60)
Chile	9.65 (4.02)	2.15 (1.30)	2.46 (0.29)	2.15 (0.58)
Czech Republic	12.99 (2.76)	2.16 (1.12)	2.74 (0.29)	2.89 (0.47)
Denmark	13.21 (3.34)	2.11 (1.18)	2.74 (0.29)	2.96 (0.40)
Finland	12.83 (3.55)	1.98 (1.12)	2.69 (0.28)	2.99 (0.43)
Germany	11.77 (3.47)	2.09 (1.18)	2.62 (0.31)	2.92 (0.47)
Hungary	12.34 (3.11)	1.78 (1.07)	2.62 (0.31)	2.63 (0.48)
Italy	11.08 (4.07)	2.31 (1.18)	2.61 (0.31)	2.52 (0.62)
Netherlands	13.41 (4.17)	1.80 (1.13)	2.70 (0.31)	2.94 (0.43)
Norway	12.12 (2.79)	2.19 (1.18)	2.67 (0.26)	3.00 (0.41)
Poland	11.74 (2.95)	2.00 (1.02)	2.63 (0.25)	2.43 (0.64)
Slovenia	11.47 (3.04)	1.98 (1.01)	2.61 (0.26)	2.40 (0.61)
Sweden	11.84 (3.75)	2.26 (1.22)	2.65 (0.30)	3.12 (0.51)
Switzerland	12.90 (3.37)	1.93 (1.26)	2.67 (0.29)	2.83 (0.54)
United States	13.94 (3.24)	1.88 (1.08)	2.76 (0.31)	2.85 (0.65)

Notes: S_{BK} is a weighted average of education, experience/10 and experience squared/100. Weights are the coefficients on these variables in a pooled wage regression. Coefficients (standard errors) are respectively equal to 0.075 (0.002), 0.461 (0.016) and −0.068 (0.004).

above 375 on the prose scale, tasks 'require the reader to search for information in dense text that contains a number of plausible distractors. Some require readers to make high-level inferences or use specialised knowledge'.

The comparable requirements on the quantitative scale read as follows. For a score above 225 (and below 276) 'tasks typically require readers to perform a single arithmetic operation (frequently addition or subtraction) using numbers that are easily located in the text or document. The operation to be performed may be easily inferred from the wording of the question or the format of the material (for example, a bank deposit or an order form)'. To obtain a quantitative score above 375 'tasks require the reader to perform multiple operations sequentially, and they must disembed the features of the problem from the material provided or rely on background knowledge to determine the quantities or operations needed'.

The range 0 to 225 on the document scale requires individuals to 'locate a piece of information based on a literal match. Distracting information, if present, is typically located away from the correct answer. Some tasks may direct the reader to enter personal information onto a form'. At the high end of the scale (above 376) the tasks 'require the reader to search through complex displays of information that contain multiple distractors, to make high-level inferences, or use specialised knowledge'.

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