EMPLOYER LEARNING AND STATISTICAL DISCRIMINATION IN OECD COUNTRIES

Stijn Broecke, OECD, Paris

Using the Survey of Adult Skills (PIAAC), this paper documents how the returns to education and skills proficiency change with experience for a sample of 22 OECD countries. The paper also analyses the changing contribution of these factors to the overall variance in wages as individuals gain more experience. Evidence broadly consistent with the theory of employer learning and statistical discrimination is found in: Austria, Germany and the Netherlands; Denmark, Finland, Norway and Sweden; and Australia, Canada and the United States. Preliminary analysis unearths little evidence that certain education or labour market institutions might be systematically related to the presence or not of employer learning. Indeed, the results presented in this paper indicate that employer learning with statistical discrimination is found in groups of countries which, on the face of it, are very different from one another (e.g. Germany, Austria and the Netherlands v. Australia, Canada and the United States). This suggests that employer learning may arise in different countries for different reasons, and that it is more the complex interactions between different institutions and policies that might matter.

Introduction

Farber and Gibbons (1996) argue that when workers enter the labour market wages initially only reflect easily observable characteristics of productivity, such as educational attainment. As workers accumulate experience in the labour market, however, employers learn about (and reward) additional elements of productivity that were initially unobserved (e.g. numeracy and other information-processing skills). Using data from the US National Longitudinal Survey of Youth (NLSY), they present evidence that is consistent with their model's predictions.

Altonji and Pierret (2001), building on this theory, suggest that employers set starting wages by statistically discriminating among young workers on the basis of these easily observed characteristics. As employers learn about the true quality of workers, however, wages are increasingly correlated with harder-to-observe correlates of productivity (e.g. skills), while the return to easily observable characteristics (such as education) falls. Also using NLSY data (for men only) they find that employers in the United States statistically discriminate on the basis of education.

The predictions of these theories have since been tested and confirmed in a number of OECD countries. A review of the literature results in evidence of employer learning[1] in: Australia (Cheung, 2010), Canada (Pan, 2005), for university graduates in Chile (Bordón, 2013), Germany (Bauer and Haisken-DeNew, 2001), for New Zealand born women of European descent (but not men) (Gill, 2012), Switzerland (Falter, 2007), and the United Kingdom (Galindo-Rueda, 2002); while Lange (2007) cites evidence for three developing countries as well (Ghana, India and Pakistan).

The theory has also been tested on a number of different sub-groups, mostly defined on the basis of educational attainment or occupation. Arcidiacono, Bayer and Hizmo (2010) find favourable evidence in the case of high school graduates, but not for college graduates who they find tend to be paid in accordance

with their ability from the beginning of their careers. Light and McGee (2013), however, show that this result hinges on how the start date of graduates' careers is defined. Using career start dates tied to permanent rather than first-observed school exit, they find that employer learning is equally evident for high school and college graduates. Looking at different occupational categories, Bauer and Haisken-DeNew (2001) find that employer learning only takes place for blue-collar workers at the lower end of the wage distribution - although Galindo-Rueda (2002) finds stronger evidence in the case of white-collar workers.

Other authors have tested the theory on a range of different skills. Pasche (2009), for instance, finds that employer learning and statistical discrimination take place with non-cognitive as well as cognitive ones (a finding confirmed by Petre, 2013). Similarly, Light and McGee (2012) separate skills into various types and conclude that, although employer learning exists for each skill type, the extent of it depends both on the type of skill as well as its importance.

Two important extensions to the theory were brought by Schönberg (2007) and Lange (2007), respectively. Schönberg (2007) asks whether employer learning is symmetric (all employers have the same information about workers' productivity) or asymmetric (the current employer has private and more/better information about workers' productivity) – and finds that learning is mostly the former (i.e. public – Farber and Gibbons, 1996).

Lange (2007) investigates the speed of employer learning and finds that employers learn quickly.[2] He estimates that it takes on average three years for any initial expectation error on the part of employers about workers' productivity to decline by approximately 50%. Pasche (2009) estimates that the speed of employer learning is even faster when non-cognitive abilities are included on top of cognitive ones as proxies for productive ability. As pointed out by Pasche (2009), rapid employer learning matters, as it "is a key component of a meritocratic labor market". Finally, Mansour (2012) finds that the speed of employer learning varies across occupations: in some, employers learn about their workers' productivity over time, as suggested by the employer learning literature, while in other occupations employers appear to acquire enough information about worker productivity at the time of hire so that little learning takes place subsequently.

The contribution of this paper to the literature is two-fold. First, it tests the theory of employer learning and statistical discrimination across a wide range of countries, and it does so by applying a consistent methodology to comparable data across these countries. This matters because, as suggested in a working paper by Hanushek and Zhang (2006) employer learning may be a characteristic very specific to some countries.[3] If this is the case, then labour markets in different countries may function very differently, and the signals that employees send to employers as well as the characteristics which get rewarded in the labour market may vary substantially, with implications for education and labour market policy, as well as in terms of how efficiently labour markets might operate. This paper finds the most consistent evidence in favour of the theory of employer learning and statistical discrimination in: Austria, Germany and the Netherlands; Finland and Sweden; and Canada and the United States. Weaker, but broadly consistent evidence is also found in Australia, Denmark and Norway. For the remaining set of countries, the evidence is less supportive, and sometimes even conflicting.[4]

Second, the paper shows that employer learning manifests itself not only through an increase in the coefficient on proxies for ability/productivity, but also through the increased importance of these variables in explaining the variance in wages across individuals as they gain more experience. To show this, a methodology developed by Fields (2003) to decompose changes in income inequality is adapted to decompose the explained variance in wages across individuals into the components attributable to education and to ability, respectively.

The remainder of this paper proceeds as follows. The next section discusses the methodologies used in the paper to assess employer learning and statistical discrimination, while the third section presents the data used and offers some descriptive statistics. The results section begins with a visual exploration of the extent of employer learning across the 22 countries examined, followed by more formal tests of employer learning and statistical discrimination. The final section discusses the findings in light of the countries' education and labour market institutions.

Methodology

Three approaches will be taken in this paper to analyse the changing importance of education and skills with experience in explaining individuals' wages. The first approach consists in a visual exploration of how these returns evolve with experience, based on flexible earnings regressions which estimate these returns at each year of experience. This is followed by an application of the Altonji and Pierret (2001) methodology, which has now become standard in the literature, to formally test for employer learning and statistical discrimination. The final analysis tests whether employer learning manifests itself not only through an increase in the coefficients on less-observable correlates of productivity (i.e. skills), but also through changes in the proportion of the variance in wages these variables explain.

Visualising the returns to education and skill with experience

To fix ideas, the paper will start with a visual exploration of how the returns to education and skills change with experience. The returns to years of education and skill are estimated flexibly at each level of experience by regressing log wages (Y) on years of schooling (S) and skill proficiency (Z), interacted with a complete set of experience dummy variables (D_X) taking the value of one if experience is X and zero otherwise:

$$Y = \beta_0 + \sum_X \beta_{S,X}(S \cdot D_X) + \sum_X \beta_{Z,X}(Z \cdot D_X) + \varepsilon \quad (1)$$

This regression is run separately for each country, and the estimated coefficients on S and Z are subsequently plotted against experience (X) to provide a picture of how the returns to schooling and skills evolve as individuals gain more experience in the labour market.

Formal tests for employer learning and statistical discrimination

To formally test for employer learning and statistical discrimination, the methodology proposed by Altonji and Pierret (2001) is used, which consists in a basic OLS regression of log wages (Y) on years of schooling (S) and skill proficiency (Z), each of which are interacted with experience (X):

$$Y = \beta_0 + \beta_S S + \beta_{S,X}(S \cdot X) + \beta_Z Z + \beta_{Z,X}(Z \cdot X) + f(X) + \varepsilon \quad (2)$$

It is these interactions of schooling and skills with experience which allow testing for employer learning and statistical discrimination. In the case of employer learning, the interaction between education and experience should be non-increasing ($\beta_{S,X} \leq 0$) while the interaction between skills and experience non-decreasing ($\beta_{Z,X} \geq 0$).[5] If S and Z are positively correlated (so that S is informative about Z), then statistical discrimination in the presence of employer learning would imply both that the interaction between education and experience is decreasing ($\beta_{S,X} < 0$) and that the interaction between skills and experience is increasing (($\beta_{Z,X} > 0$).[6]

Decomposing the variance in wages

Employer learning and statistical discrimination manifest themselves through changes in the coefficients on education and ability, but it could also have an effect on the proportion of variance explained by these variables. Indeed, both a variable's coefficient and its contribution to the overall variance are measures of its importance, and a large coefficient does not necessarily translate into a large R-squared. Both pieces of information are useful in deciding on the relative importance of explanatory factors. In the case of employer learning with statistical discrimination, one would expect the proportion of variance in wages explained by education to fall with experience, while the proportion of variance in wages explained by ability should rise.

To analyse the contribution of education and skills to the variance in wages across individuals, a methodology developed by Fields (2003) is adapted, which was originally designed to analyse the level of income inequality in a country and its change over time. Fields' approach consists in decomposing the explained portion of the regression (R-squared) into weights for each of the factors. The decomposition is "exact" in the sense that the variance of Y is decomposed exactly into the sum of components attributable to each regressor and the residual.

Starting with a simple regression of the form:

$$Y = \beta_0 + \beta_S S + \beta_Z Z + \varepsilon \tag{3}$$

And denoting the resulting parameter estimates as:

$$(\hat{\beta}_0\ \hat{\beta}_S\ \hat{\beta}_Z) \tag{4}$$

The portion of the total variance s(X) explained by each variable can be expressed as:

$$s(X_S) = \frac{cov[X_S\hat{\beta}_S, Y]}{var(Y)} \tag{5}$$

And

$$s(X_Z) = \frac{cov[X_Z\hat{\beta}_Z, Y]}{var(Y)} \tag{6}$$

And the contribution of each variable to the explained variance p(X) can be obtained simply by dividing each s(X) by the total explained variance (R-squared):

$$p(X_S) = \frac{s(X_S)}{R^2} \tag{7}$$

And:

$$p(X_Z) = \frac{s(X_Z)}{R^2} \tag{8}$$

Where by construction the p(X)'s sum to 100%.[7]

Data

The data used for the analysis is the Survey of Adult Skills – a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC) – which, in 2012, assessed the proficiency of around 166 000 adults (aged 16-65) from 24 countries[8] in literacy, numeracy and problem-solving in technology-rich environments, and also collected data on their skills use in the workplace. The achieved samples range from a minimum of around 4 500 (Sweden) to a maximum of nearly 27 300 (Canada). In this paper, the focus is only on the 22 OECD countries in the sample (i.e. excluding the Russian Federation and Cyprus).

Numeracy proficiency will be used as the standard measure of skills in the analysis that follows but, because of the high correlation between the various skills measures in PIAAC, the overall conclusions reached are robust to the use of alternative skills measures.[9] PIAAC measures each of the skill domains on a 500-point scale. For analytical purposes, scores in the subsequent analyses are standardised (across the OECD) to have a mean of two and a standard deviation of one.

Before the skill assessment, all participants also responded to a background questionnaire that gathered information about their labour-market status, wages, education, experience, and demographic characteristics.

Table 1 below provides some descriptive statistics for each of the 22 countries included in the analysis, including information on: sample sizes, average skills proficiency, years of education and (actual) experience,[10] as well as hourly wages.[11] Note that the sample is restricted to employed individuals with 40 years of experience or less[12] and, in each country, wages are trimmed to exclude the top and bottom percentiles.[13]

Skill proficiency is highest in Japan, the Nordic countries, Flanders and the Netherlands, while it is lowest in Italy and Spain. The average years of education range between a low 11.5 in Italy to a high 15.4 in Ireland, while experience ranges between 14.3 years (Korea) and 19.2 years (Flanders), on average. Finally, hourly wages are highest in Norway and Denmark (around 24 PPP $US) and lowest in the Czech and Slovak Republics (around 9 PPP $US).

Table 1. Descriptive statistics

Country	N	Skill	Years of education	Experience	Wages (PPP $US)
Australia	5,121	2.16	14.8	17.3	19.1
		(0.97)	(2.37)	(11.3)	(14.6)
Austria	3,592	2.25	12.2	18.2	19.1
		(0.89)	(2.58)	(11.1)	(10.5)
Canada	18,320	2.10	13.6	18.5	20.6
		(0.99)	(2.54)	(11.4)	(16.6)
Czech Republic	3,431	2.26	13.5	18.2	9.2
		(0.79)	(2.54)	(10.8)	(6.1)
Denmark	4,660	2.38	12.9	19.1	23.7
		(0.92)	(2.65)	(11.6)	(10.1)
England/N. Ireland (UK)	5,453	2.05	13.2	18.3	18.1
		(0.99)	(2.29)	(11.2)	(16.6)
Estonia	4,935	2.22	12.6	17.7	11.5
		(0.82)	(2.57)	(11.3)	(53.4)
Finland	3,657	2.48	13.0	18.2	19.8
		(0.90)	(2.87)	(11.6)	(17.5)
Flanders (B)	3,244	2.42	13.1	19.2	22.5
		(0.90)	(2.60)	(10.9)	(11.3)
France	4,271	1.90	12.0	18.2	15.8
		(1.03)	(3.40)	(11.3)	(8.2)
Germany	3,851	2.23	13.8	18.2	18.8
		(0.95)	(2.58)	(11.7)	(12'.0)
Ireland	3,442	1.95	15.4	16.7	21.6
		(0.94)	(2.89)	(10.7)	(12.9)
Italy	2,750	1.76	11.5	17.4	16.3
		(0.93)	(3.84)	(10.7)	(10.2)
Japan	3,562	2.50	13.3	17.9	16.6
		(0.81)	(2.34)	(10.9)	(17.2)
Korea	4,292	1.94	13.1	14.3	18.9
		(0.83)	(3.08)	(10.4)	(21.4)
Netherlands	3,683	2.41	13.6	17.6	21.5
		(0.88)	(2.57)	(11.0)	(11.5)
Norway	3,718	2.37	14.4	17.6	24.4
		(0.97)	(2.43)	(11.3)	(12.8)
Poland	4,924	1,99	13.4	16.0	9.7
		(0.90)	(2.93)	(11.2)	(8.5)
Slovak Republic	3,184	2.36	13.8	18.0	8.9
		(0.77)	(2.61)	(11.1)	(6.6)
Spain	3,193	1.79	12.2	16.9	15.3
		(0.90)	(3.49)	(10.4)	(10.5)
Sweden	3,120	2.42	12.6	18.6	18.8
		(0.96)	(2.34)	(11.7)	(7.2)
United States	3,200	1.84	13.7	18.0	21.0
		(1.07)	(2.99)	(11.5)	(27.5)

a. Standard deviations in parentheses.

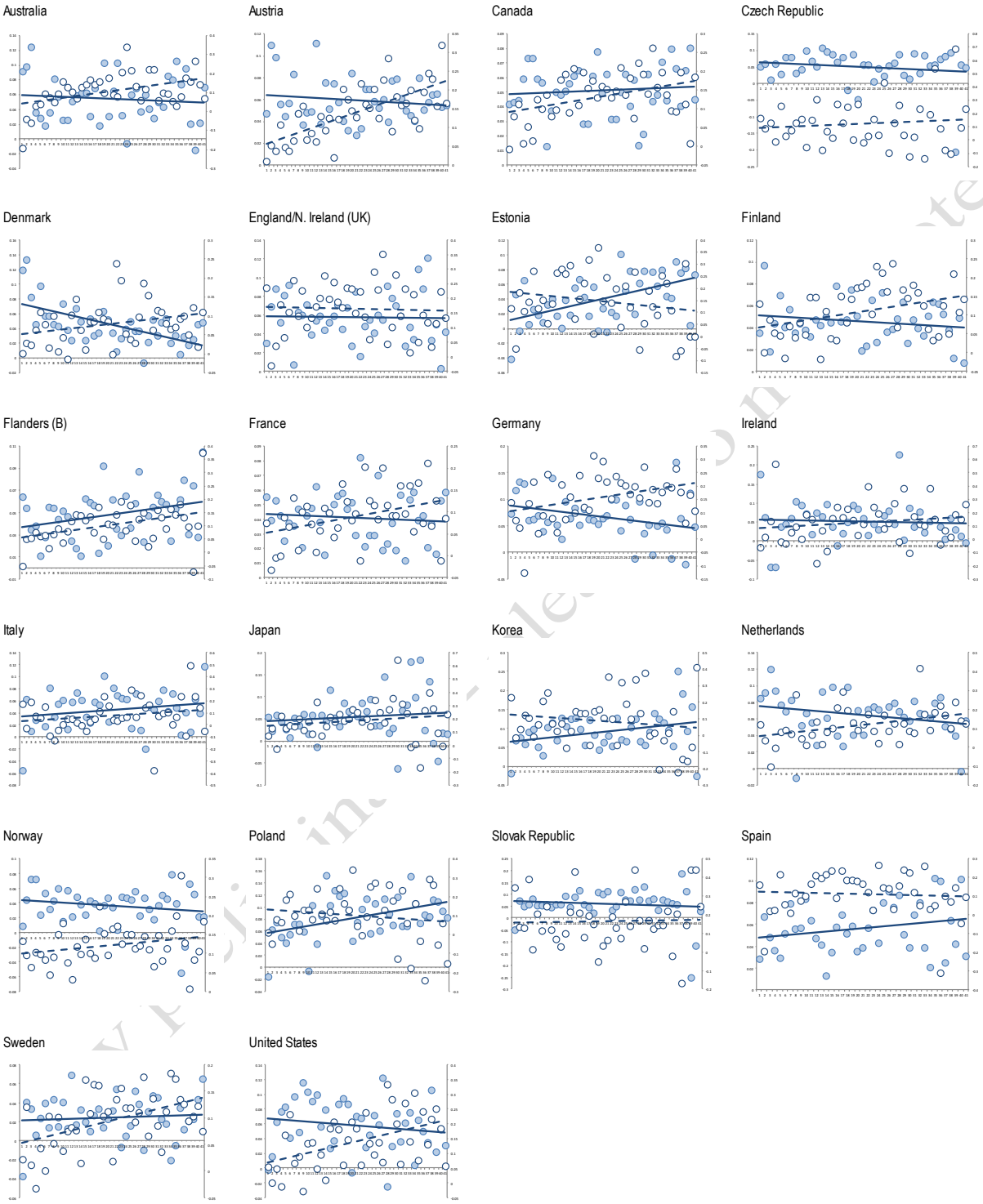
Results

Visually exploring the returns to education and skills

Figure 1 plots, for each of the countries in the sample, the return to both education and skills at each level of experience obtained using equation (1). The blue dots and full lines represent the returns to education, while the white dots and dashed lines are for the returns to skill. The straight lines are simple linear regressions of the returns to education and skills, respectively, on experience.

The return to education appears relatively constant in many countries, although more distinct falls with experience can be observed in Denmark, Finland, Germany, the Netherlands and the United States. In some countries, however, the return to education appears to increase with experience. These are: Estonia, Flanders, Korea, Poland and Spain. An increase in the return to skill with experience is far more common across the countries studied.

Figure 1. The returns to education and skill proficiency with experience, by country



Formally testing for employer learning and statistical discrimination in OECD countries

Table 2 explores the returns to education and skill proficiency and how they change with experience using the Altonji and Pierret (2001) methodology. Across all countries considered, the (unweighted) average return to one additional year of schooling is 5.8%, while a standard deviation increase in numeracy scores is associated with an increase in wages of 8.2% on average.[14]

Table 2. The returns to education and skill proficiency with experience

	Years of education		Years of education x Experience		Skill		Skill x Experience		N	R-sq
	b	s.e.	b	s.e.	b	s.e.	b	s.e.		
Australia	0.070	(0.00547)***	-0.001	(0.000259)**	0.037	(0.0124)**	0.004	(0.000641)***	4171	0.29
Austria	0.082	(0.00559)***	-0.001	(0.000282)***	0.041	(0.0166)*	0.004	(0.000827)***	2936	0.40
Canada	0.057	(0.00278)***	0.000	(0.000132)	0.086	(0.00721)***	0.002	(0.000347)***	15522	0.34
Czech Republic	0.065	(0.00804)***	-0.001	(0.000390)	0.102	(0.0262)***	0.001	(0.00124)	2570	0.16
Denmark	0.079	(0.00398)***	-0.002	(0.000187)***	0.049	(0.0117)***	0.001	(0.000561)*	4050	0.42
England/N. Ireland (UK)	0.061	(0.00568)***	0.000	(0.000283)	0.161	(0.0134)***	0.000	(0.000653)	4304	0.33
Estonia	0.023	(0.00770)**	0.001	(0.000365)**	0.171	(0.0239)***	-0.001	(0.00117)	3823	0.13
Finland	0.054	(0.00431)***	0.000	(0.000194)*	0.060	(0.0136)***	0.003	(0.000665)***	3183	0.32
Flanders (B)	0.040	(0.00585)***	0.000	(0.000247)	0.065	(0.0163)***	0.002	(0.000749)**	2708	0.36
France	0.043	(0.00464)***	0.000	(0.000208)	0.040	(0.0147)**	0.003	(0.000691)***	3632	0.30
Germany	0.105	(0.00677)***	-0.002	(0.000341)***	0.084	(0.0192)***	0.003	(0.000915)***	3293	0.37
Ireland	0.056	(0.00878)***	0.000	(0.000433)	0.061	(0.0253)*	0.003	(0.00136)*	2731	0.19
Italy	0.037	(0.00582)***	0.000	(0.000300)	0.015	(0.0229)	0.003	(0.00117)*	1831	0.24
Japan	0.036	(0.00859)***	0.001	(0.000429)*	0.137	(0.0255)***	0.003	(0.00121)*	3121	0.26
Korea	0.072	(0.00797)***	0.001	(0.000442)	0.064	(0.0275)*	0.002	(0.00167)	3139	0.21
Netherlands	0.083	(0.00578)***	-0.001	(0.000294)**	0.056	(0.0188)**	0.003	(0.000943)**	3071	0.39
Norway	0.054	(0.00489)***	-0.001	(0.000245)**	0.094	(0.0123)***	0.001	(0.000654)	3458	0.33
Poland	0.065	(0.00527)***	0.001	(0.000275)***	0.109	(0.0172)***	-0.001	(0.000930)	3879	0.26
Slovak Republic	0.056	(0.00842)***	0.001	(0.000403)	0.144	(0.0280)***	0.000	(0.00139)	2466	0.18
Spain	0.051	(0.00597)***	0.000	(0.000295)	0.107	(0.0217)***	0.001	(0.00110)	2451	0.31
Sweden	0.029	(0.00471)***	0.000	(0.000230)	0.053	(0.0115)***	0.002	(0.000564)***	2767	0.25
United States	0.068	(0.00771)***	0.000	(0.000367)	0.074	(0.0207)***	0.003	(0.00102)**	2280	0.36

* p<0.05 ** p<0.01 *** p<0.001

Each row presents selected results from a regression of log hourly wages (including bonuses) for wage and salary earners (in PPP corrected $US) on years of education, standardised (at country level) numeracy proficiency scores, experience, interactions of experience with education and numeracy, as well as experience squared. Earnings data are trimmed at the top 1% and bottom 1%, and experience is restricted to 40 years or less. All analysis is weighted.

In only a handful of countries is there strong evidence in favour of the employer learning and statistical discrimination theory (i.e. a statistically significant drop in the return to education with experience, combined with a statistically significant increase in the return to numeracy skill with experience).[15] These countries are: Australia, Austria, Denmark, Germany and the Netherlands.

The return to education falls with experience in only six of the 22 countries analysed, while in four of them the return to education increases (Estonia, Finland, Japan and Poland). By contrast, the return to skill proficiency increases with experience in 14 of the countries considered. Finally, it is worth pointing out the relatively high R-squared obtained in these regressions (around 0.29 on average, but as high as 0.4 in some cases) - despite the relatively simple and parsimonious specification. This suggests that experience, education and skills (even if measured very rudimentarily) can explain a relatively large portion of the variance in wages.

Experience can be poorly measured, however, and could lead do downward bias in the estimates. Table 3 therefore reproduces the analysis from Table 2, but instruments experience with potential experience.[16] The return to education now falls with experience in 12 of the countries, and strong evidence of employer learning and statistical discrimination is found in seven of them: Austria, Canada, Finland, Germany, the Netherlands, Sweden and the United States. Weaker evidence (i.e. where both coefficients have the right sign, but only one is statistically significant) can also be found in: Australia, Denmark, Ireland and Norway. Finally, an increasing return to education with experience is now found in only one country (the Slovak Republic).

Table 3. The returns to education and skill proficiency with experience (instrumented)

	Years of education		Years of education x Experience		Skill		Skill x Experience		N	R-sq
	b	s.e.	b	s.e.	b	s.e.	b	s.e.		
Australia	0.108	(0.00679)***	-0.002	(0.000374)***	0.077	(0.0158)***	0.001	(0.000880)	4154	0.27
Austria	0.118	(0.00743)***	-0.003	(0.000392)***	0.065	(0.0243)**	0.003	(0.00120)*	2934	0.36
Canada	0.104	(0.00337)***	-0.003	(0.000184)***	0.080	(0.00945)***	0.003	(0.000503)***	15464	0.31
Czech Republic	0.056	(0.0109)***	0.000	(0.000564)	0.109	(0.0353)**	0.000	(0.00170)	2562	0.15
Denmark	0.115	(0.00478)***	-0.003	(0.000287)***	0.056	(0.0149)***	0.001	(0.000850)	4039	0.39
England/N. Ireland (UK)	0.058	(0.00727)***	0.000	(0.000429)	0.141	(0.0168)***	0.002	(0.000898)	4287	0.30
Estonia	0.046	(0.00983)***	0.000	(0.000521)	0.207	(0.0302)***	-0.003	(0.00160)	3822	0.14
Finland	0.072	(0.00504)***	-0.001	(0.000283)***	0.038	(0.0174)*	0.004	(0.000987)***	3181	0.29
Flanders (B)	0.049	(0.00827)***	0.000	(0.000367)	0.052	(0.0232)*	0.003	(0.00107)*	2691	0.32
France	0.059	(0.00670)***	-0.001	(0.000305)	0.051	(0.0207)*	0.002	(0.000964)	3563	0.26
Germany	0.166	(0.00957)***	-0.004	(0.000484)***	0.064	(0.0282)*	0.004	(0.00137)**	3258	0.34
Ireland	0.095	(0.0121)***	-0.001	(0.000612)*	0.103	(0.0315)**	0.001	(0.00171)	2724	0.15
Italy	0.049	(0.00962)***	0.000	(0.000459)	0.004	(0.0355)	0.004	(0.00163)*	1819	0.22
Japan	0.044	(0.0123)***	0.000	(0.000592)	0.197	(0.0370)***	-0.001	(0.00167)	3118	0.20
Korea	0.148	(0.0126)***	-0.003	(0.000612)***	0.130	(0.0420)**	-0.001	(0.00199)	3121	0.16
Netherlands	0.157	(0.00848)***	-0.004	(0.000451)***	-0.001	(0.0252)	0.005	(0.00128)***	3057	0.35
Norway	0.092	(0.00611)***	-0.002	(0.000351)***	0.092	(0.0168)***	0.002	(0.000973)	3449	0.31
Poland	0.084	(0.00727)***	0.000	(0.000410)	0.128	(0.0227)***	-0.002	(0.00125)	3875	0.24
Slovak Republic	0.045	(0.0115)***	0.001	(0.000573)*	0.198	(0.0395)***	-0.003	(0.00193)	2464	0.18
Spain	0.078	(0.00891)***	-0.001	(0.000429)	0.131	(0.0322)***	0.000	(0.00151)	2411	0.27
Sweden	0.049	(0.00575)***	-0.001	(0.000342)*	0.026	(0.0146)	0.004	(0.000817)***	2747	0.25
United States	0.105	(0.00979)***	-0.002	(0.000556)**	0.097	(0.0273)***	0.003	(0.00145)*	2271	0.34

* p<0.05 ** p<0.01 *** p<0.001

Each row presents selected results from a regression of log hourly wages (including bonuses) for wage and salary earners (in PPP corrected $US) on years of education, standardised (at country level) numeracy proficiency scores, experience (instrumented using potential experience), interactions of (instrumented) experience with education and numeracy, as well as (instrumented) experience squared. Earnings data are trimmed at the top 1% and bottom 1%, and experience is restricted to 40 years or less. All analysis is weighted.

In a true model of employer learning with statistical discrimination, the return to skill would initially be zero. Table 3 shows that this is only the case in two of the countries in which employer learning was observed (the Netherlands and Sweden). However, once the importance of the initial return to skill is assessed, an interesting finding emerges. Estimating, by country, the number of years required to achieve one standard deviation increase in skills, and using this estimate to express the initial return to skill as a percentage of the initial return to education, it is found that, in countries where employer learning and statistical discrimination was observed, the return to skill is much lower (at only 10% of the return to education) than in countries where employer learning was not observed (where the initial return to skill is nearly a third of the initial return to education). This lends at least some credence to the claim that what is observed can be interpreted as true employer learning.

Putting the return to skill in terms of the return to education also reveals something about the relative importance of employer learning. Estimated across all countries pooled, one standard deviation in numeracy skill is equivalent to around 6.6 years of education – so the return to skill is actually relatively low in comparison to the return to education. Secondly, taking the coefficients reported in Table 3 for the countries where strong evidence in favour of employer learning and statistical discrimination was found, and assuming linear trends, it would take nearly 25 years of experience for the return to education to fall to half its initial value, while the return to skill would double in about 16 years.[17]

An analysis of the proportion of variance in explained by education and skills

This section explores whether the proportion of variance explained by education and skills proficiency changes as individuals acquire more labour market experience. As discussed in the methodology section, a method developed by Fields (2003) is applied to decompose the variance in earnings explained by the aforementioned factors. In practice, the sample for each country is divided into two different experience groups: 'low' experience (0-15 years) and 'high' experience (16-40 years), and the variance decomposition is applied to each of these groups separately. In the case of employer learning and statistical

discrimination, one would expect the importance of education in explaining earnings to fall with experience, while the importance of skill should increase. Table 4 presents the results from the analysis.

Table 4. The proportion of (total) variance in wages explained by education and skill proficiency

	Education		Skill	
	0-15	16-40	0-15	16-40
Australia	14.3%	11.1%	5.1%	11.8%
Austria	28.1%	11.5%	4.0%	12.1%
Canada	18.7%	8.0%	5.3%	14.6%
Czech Republic	10.3%	8.0%	5.0%	5.2%
Denmark	30.4%	7.5%	3.4%	7.8%
England/N. Ireland (UK)	9.8%	9.3%	12.3%	15.3%
Estonia	3.5%	3.7%	6.6%	5.6%
Finland	19.1%	12.1%	4.0%	13.6%
Flanders (B)	11.6%	13.6%	6.2%	10.2%
France	10.8%	12.7%	5.0%	10.0%
Germany	30.0%	10.4%	4.3%	11.9%
Ireland	8.1%	7.1%	3.8%	6.2%
Italy	13.0%	11.8%	4.3%	4.6%
Japan	8.5%	5.8%	10.7%	8.1%
Korea	14.3%	10.4%	1.7%	3.5%
Netherlands	23.5%	10.1%	1.6%	10.2%
Norway	19.4%	6.5%	9.0%	10.6%
Poland	13.8%	24.9%	5.1%	3.5%
Slovak Republic	7.0%	14.7%	6.4%	5.3%
Spain	17.7%	17.2%	6.6%	8.9%
Sweden	10.8%	6.4%	4.2%	14.4%
United States	19.5%	15.5%	7.5%	17.2%

How to read this table: each cell shows the proportion of variance explained by a certain factor in a certain country and for a certain experience group. For example, in Australia, education explains 14.3% of the variance in wages for individuals with 0-15 years of experience, while for individuals with 16-40 years of experience, it explains 11.1%. The results are obtained from a simple regression, run by country, of log hourly wages (including bonuses) for wage and salary earnings (in PPP corrected $US) on years of education, standardised (at country level) and numeracy proficiency. Earnings data are trimmed at the top 1% and bottom 1%, and experience is restricted to 40 years or less. All analysis is weighted.

In 18 out of the 22 countries, the variance in wages explained by skills increases with experience, while in the remaining four (Estonia, Japan, Poland and the Slovak Republic) it falls. Similarly, the variance in wages explained by education falls with experience in 17 of the countries, while it increases only in Estonia, Flanders, France, Poland and the Slovak Republic. In general, these results are therefore consistent with employer learning in: Austria, Germany and the Netherlands; Denmark, Norway, Finland and Sweden; and Australia, Canada and the United States; England/Northern Ireland and Ireland; as well as in Spain, Italy, the Czech Republic, and Korea. In these countries, the variance in wages explained by education falls from 17.9% to 10.2% between the groups with 0-15 and 16-40 years of experience, respectively, while the variance explained by skills proficiency increases from 5.1% to 10.5%. Employer learning therefore appears to play a relatively important role in some countries in determining differences in wages.

Discussion

In this final section, a range of labour market and education institutions/policies are analysed to try and establish a possible link with employer learning and statistical discrimination. Implicit in some of the literature is that employer learning is the hallmark of efficient labour markets, where 'efficient' is taken to mean 'flexible' – i.e. with limited employment protection, and no or little collective bargaining and/or wage regulation (Bauer and Haisken-DeNew, 2001; Hanushek and Zhang, 2006). In such labour markets, it is argued, employers have the freedom to 'learn' about the true productivity of workers and adjust their wages accordingly - contrary to more 'rigid' labour markets, where employers supposedly have less leeway in adjusting wages since these are set either by collective agreements or high minimum wages. Sometimes, and given the relationship between employer learning and signalling theories of education, such arguments have been supplemented with assumptions around how education systems function. In particular, it has been hypothesised that in systems that are more vocational and/or where there is less variability in the quality of education, true productivity is more easily observed by employers at the point of hiring, and so there would be less need for employer learning (Bauer and Haisken-DeNew, 2001).

Even a very basic look at the data, however, suggests that the true story has to be more complicated than what has been maintained in the literature to date. Table 5 explores differences across countries in terms of educational systems (quality variability and prevalence of vocational education), the cost of hiring (minimum wage as a proportion of median wages and the tax wedge), and employment protection legislation (EPL) on regular, as well as temporary contracts. Table 6 presents unionisation rates as well as some key characteristics of wage setting institutions (the extent of bargaining coverage, the predominant level at which bargaining takes place, and the extent of coordination in wage setting).

Table 5. Education, cost of hiring and employment protection legislation

	Education		Cost of hiring		EPL	
	Quality variability[a]	VET[b]	Minimum Wage[c]	Tax Wedge[d]	Regular Contracts[e]	Temporary Contracts[f]
Austria	240	57	-	49	2.4	2.2
Germany	252	56	-	50	3.0	1.8
Netherlands	242	32	0.47	39	2.9	1.2
Denmark	214	42	-	39	2.3	1.8
Norway	231	32	-	38	2.3	3.4
Finland	219	38	-	43	2.2	1.9
Sweden	236	31	-	43	2.5	1.2
Australia	249	19	0.53	27	1.9	1.0
Canada	231	12	0.45	30	1.5	0.2
United States	233	-	0.38	31	1.2	0.3
Estonia	209	32	0.36	40	2.1	3.0
Slovak Republic	261	68	0.47	40	2.3	2.4
Czech Republic	244	74	0.36	42	2.7	2.1
Poland	234	58	0.47	36	2.4	2.3
Spain	228	8	0.44	41	2.3	3.2
Flanders (B)	268	26	0.51	56	2.9	2.4
France	256	30	0.62	50	2.8	3.8
Italy	241	32	-	48	2.8	2.7
England/N. Ireland (UK)	245	-	0.47	32	1.6	0.5
Ireland	219	13	0.48	26	2.1	1.2
Japan	242	-	0.38	31	2.1	1.3
Korea	254	-	0.42	21	2.2	2.5

a. Quality variability is defined as the score difference between the 90th and 10th percentile on the PISA 2012 mathematics test sat by 15-year-olds. Source: PISA 2012, Figure I.2.24

b. VET is defined as the proportion of 25-64 year-olds whose highest qualification is upper secondary vocational upper secondary. Source: EAG 2013, Table A1.5a

c. Minimum wage is defined as the ratio of the minimum wage to the median wage of full-time workers. Source: OECD stat. Data is for 2012.

d. Tax wedge is defined as the difference between between total labour costs to the employer and the corresponding net take-home pay for single workers without children, at average earnings levels, expressed as a proportion of total labour costs. Source: OECD Taxing Wedges 2013, Table 0.1.

e. Strictness of employment protection against individual and collective dismissal on regular contracts (2013) - on a scale from 0 (least restrictions) to 6 (most restrictions).

f. Regulation on temporary forms of employment - on a scale from 0 (least restrictions) to 6 (most restrictions).

Table 6. Unionisation and wage setting characteristics

	Union Membership[a]	Bargaining Coverage[b]	Level[c]	Coordination[d]
Austria	28	99	3	4
Germany	18	61	3	4
Netherlands	18	84	3	3
Denmark	69	85	3	4
Norway	55	74	3	4
Finland	69	90	5	5
Sweden	68	91	3	4
Australia	18	45	2	2
Canada	27	29	1	1
United States	11	13	1	1
Estonia	8	25	1	1
Slovak Republic	17	35	2	2
Czech Republic	27	41	1	2
Poland	15	29	1	1
Spain	16	73	4	4
Flanders (B)	50	96	5	5
France	8	92	2	2
Italy	36	85	3	3
England/N. Ireland (UK)	26	31	1	1
Ireland	33	42	1	3
Japan	18	16	1	4
Korea	10	10	1	3

a. Union Membership measures the percentage of employees who are member of a union. Data is for 2011, except Denmark, Estonia, Poland, Spain and France (2010) and Czech Republic (2000). Source: OECD Stat.

b. Bargaining coverage = employees covered by collective (wage) bargaining agreements as a proportion of all wage and salary earners in employment with the right to bargaining, expressed as percentage, adjusted for the possibility that some sectors or occupations are excluded from the right to bargain.

c. The predominant level(s) at which wage bargaining takes place: 5 = Bargaining predominantly takes place at central or cross-industry level and there are centrally determined binding norms or ceilings to be respected by agreements negotiated at lower levels; 4 = Intermediate or alternating between central and industry bargaining; 3 = Bargaining predominantly takes place at the sector or industry level; 2 = Intermediate or alternating between sector and company bargaining; 1 = Bargaining predominantly takes place at the local or company level

d. Coordination of wage-setting: 6 = state-imposed bargaining; 5 = state-sponsored bargaining; 4 = Inter-associational by peak; associations; 3 = Intra-associational ("informal centralisation"); 2 = Pattern bargaining; 1 = Uncoordinated bargaining.

As a reminder, this paper found the most convincing evidence in favour of employer learning in the following groups of countries: Austria, Germany and the Netherlands; Denmark, Finland, Norway and Sweden; and Australia, Canada and the United States. At the same time, little support for the theory was found in: Estonia, Poland, the Czech and Slovak Republics; Flanders, France, Italy and Spain; England/Northern Ireland and Ireland; and Japan and Korea. While it is true that the most liberal of these sets of countries (Australia, Canada and the United States) exhibited employer learning and the most regulated one (Flanders, France, Italy and Spain) did not, Tables 5 and 6 show that there are no obvious education and/or labour market characteristics linking together countries where employer learning was detected. Similarly, there is significant heterogeneity in labour market institutions and policies in countries were no employer learning was observed. Some countries where regulation and protection are low (e.g. England/Northern Ireland and Ireland, but also Estonia, Poland, the Czech and Slovak Republics) showed no strong evidence of employer learning. Yet other countries, characterised by high bargaining coverage

rates, sector (rather than company) level bargaining, and highly coordinated wage setting mechanisms (Austria, Germany and the Netherlands, but also the Scandinavian countries) did.

At the same time, it is striking that the countries in which employer learning was detected (or not) can be divided into sub-groups of 'similar' countries sharing a common set of characteristics. Non-European Anglo-Saxon, Germanic and Scandinavian countries display employer learning, while Central/Eastern European, Western and Southern European, European Anglo-Saxon and Asian countries do not. This suggests that employer learning may arise in different countries for different reasons and that, while no single education or labour market institution can explain the presence of employer learning, the answer may lie in the complex interaction between these institutions. Although a detailed examination of the interactions between education and labour market policies and institutions is beyond the scope of this paper, the remainder of this section will highlight at least some of the key institutional differences between the sub-groups of countries identified.

Beginning with the Scandinavian countries, an interesting difference with Flanders, France and Spain (but not Italy), is the lack of a statutory minimum wage. The same is true for both Austria and Germany, where minimum wages are set by industry/sector and through collective bargaining rather than through national legislation. Therefore one possible explanation for employer learning in these countries might be the lack of a national wage floor which would allow wages to reflect productivity more closely than in countries where an identical minimum wage is set across all sectors and regions. This could be particularly true for low-skilled, young workers with little experience, for whom the minimum wage tends to have more bite. Another interesting feature of Scandinavian countries is also a lower cost of hiring relative to Western and Southern European nations, and more flexible EPL. While Austria, Germany and the Netherlands have relatively high levels of protection on regular contracts as well as a high tax wedge, the use of temporary contracts is relatively easy.

Turning to countries with more decentralised wage bargaining (Eastern/Central European countries, and England/Northern Ireland and Ireland), it is difficult to explain why employer learning is not observed. While vocational education is more common in the Central and Eastern European countries than it is in Australia, Canada and the United States, so it is in Austria, Germany and the Netherlands. One key difference between these two groups of countries is, of course, the general health of the economy and labour market, with unemployment rates significantly higher in Central and Eastern European countries, which might constrain wage developments. In addition, regulation on temporary contracts is relatively strict in the Central/Eastern European countries. The lack of employer learning in England/Northern Ireland and Ireland is perhaps even harder to explain, and is unlikely to be attributable to their marginally stricter EPL (compared to Australia, Canada and the United States), higher union membership and bargaining coverage. One possible explanation in the case of these countries is that wage setting mechanisms have changed significantly in recent decades (Visser, 2013) and so cohort effects could be drowning the effect of experience.[18] Indeed, the United Kingdom has witnessed significant decentralisation of wage bargaining (but so have France and Australia) and the coordination of wage bargaining weakened significantly in Ireland (but also in Italy and Australia).

Finally, no employer learning was observed in either Japan or Korea. While these countries rely also on enterprise-based bargaining, the level of coordination is significantly higher (e.g. through trend-setting in Japan). In addition, wages in these countries tend to be based on seniority rather than productivity (Hwang 2006).

To sum up, it is difficult to conclude anything definite about the relationship between education and labour market policies and institutions on the one hand, and the presence of employer learning on the other. This is not entirely surprising, given that similar associations between wage bargaining systems and the linking of pay to productivity more generally are difficult to establish (Eurofound, 2014) and, equally, that

a robust relationship between differences in bargaining organisation and differences in macro-economic performance is difficult to identify (OECD, 2004).

As a concluding comment, it is also not entirely clear that employer learning should necessarily be a sign of efficient labour markets, as is often assumed in the literature. Countries in which no employer learning is observed could, in fact, be doing much better at signalling the true productivity of young workers to potential firms, making employer learning redundant. Similarly, a situation could be imagined where wage bargaining institutions cause, rather than hinder, employer learning if wages for new recruits are initially set by agreements (and therefore do not necessarily reflect productivity), but companies do have some leeway to reward the most productive workers over time. In this context it is important to remember that collectively agreed pay is only one part of actual compensation paid to workers, partly because the latter also includes overtime payments, bonuses, stock options and other forms of variable pay, and partly because not all workers will be covered by collective agreements. One fruitful avenue for future work in this field might therefore be the search for alternative models of employer "learning" – or at least theories to explain why returns to skill increase with experience, while those to education fall.

References

Altonji, J.G. and C.R. Pierret (2001), "Employer learning and statistical discrimination", *The Quarterly Journal of Economics*, Vol. 116/1, pp. 313-350.

Altonji, J.G and C.R. Pierret (1996), "Employer learning and the signalling value of education", NBER Working Papers, No. 5438, NBER, Cambridge, MA.

Arcidiacono, P., P. Bayer and A. Hizmo (2010), "Beyond signalling and human capital: Education and the revelation of ability", *American Economic Journal: Applied Economics*, Vol. 2/4, pp. 76-104.

Bauer, T.K. and J.P. Haisken-DeNew (2001), "Employer learning and the returns to schooling", *Labour Economics*, Vol. 8/2, pp. 161-180.

Bordón, P. (2013), "Employer learning in Chile", Mimeo, June.

Cheung, S.L. (2008), "A test of employer learning in the labour market for young Australians", *Applied Economics Letters*, Vol. 17/1, pp. 93-98.

Eurofound (2014), *Pay in Europe in the 21st Century*, Publications Office of the European Union, Luxembourg.

Falter, J.-M. (2007), "Does the apprenticeship system affect employer learning? Evidence from Switzerland", Mimeo, University of Geneva, Geneva.

Farber, H.S. and R. Gibbons (1996), "Learning and wage dynamics", *Quarterly Journal of Economics*, Vol. 111/4, pp. 1007-1047.

Fields, G. (2004), "Regression-based decompositions: A new tool for managerial decision-making", http://www.ilr.cornell.edu/directory/downloads/fields/Author_decomposingRegressions_mar04.pdf.

Fields, G. (2003), "Accounting for income inequality and its change: A new method, with application to the distribution of earnings in the United States", Research in Labor Economics, Vol. 22, Cornell University Press, pp. 1-38.

Fiorio, C.V. and S.P. Jenkins (2007), "INEQRBD: Stata module to calculate regression-based inequality decomposition", http://ideas.repec.org/c/boc/bocode/s456960.html.

Galindo-Rueda, F. (2003), "Employer learning and schooling-related statistical discrimination in Britain", *IZA Discussion Papers*, No. 778, IZA, Bonn.

Gill, P. (2012), "Employer learning and statistical discrimination in the New Zealand labour market", Doctoral Thesis, University of Otago, Dunedin.

Hanushek, E. and L. Zhang (2009), "Quality-consistent estimates of international schooling and skill gradients", *Journal of Human Capital*, Vol. 3/2, pp. 107-143.

Hanushek, E. and L. Zhang (2006), "Quality-consistent estimates of international returns to skills", *NBER Working Paper Series*, No. 12664.

Hwang, S.K (2006), "Wage structure and skill development in Korea and Japan", Japan Institute for Labour Policy and Training, Tokyo.

Lange, F. (2007), "The speed of employer learning", *Journal of Labor Economics*, Vol. 25/1, pp. 1-35.

Light, A. and A. McGee (2013), "Does employer learning vary by schooling attainment? The answer depends on how career start dates are defined", Mimeo, University of Chicago, Chicago.

Light, A. and A. McGee (2012), "Employer learning and the "importance" of skills", *IZA Discussion Papers*, No. 6623, IZA, Bonn.

Mansour, H. (2012), "Does employer learning vary by occupation?", *Journal of Labor Economics*, Vol. 30/2, pp. 415-444.

OECD (2004), "Wage setting institutions and outcomes" in *OECD Employment Outlook 2004*, OECD Publishing, Paris.

Pan, S.-Y. (2005), *Employer Learning and Statistical Discrimination in the Canadian Labour Market*, Doctoral Thesis, University of Saskatchewan, Saskatoon.

Pasche, C. (2009), "A multiple ability approach to employer learning", Mimeo, University of Geneva, Geneva.

Petre, M. (2013), "Employer learning about noncognitive skills", Mimeo, University of Texas, Austin.

Schönberg, U. (2007), "Testing for asymmetric employer learning", Journal of Labor Economics, Vol. 25/4, pp. 651-691.

Visser, J. (2013), *Data Base on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960-2011 (ICTWSS)*, Amsterdam Institute for Advanced Labour Studies, Amsterdam.

[1] The test for statistical discrimination is not entirely the same as that of employer learning, although the two appear sometimes to be confounded in the literature. For this reason, the short literature review presented here is indiscriminate about whether or not the papers actually test statistical discrimination or not.

[2] Although Altonji and Pierret (1996) already provided an earlier estimate of the rate at which employers learn about worker productivity.

[3] Hanushek and Zhang (2006) use data from the International Adult Literacy Survey (IALS - a precursor to PIAAC). Their sample includes 13 countries: Chile, the Czech Republic, Denmark, Finland, Germany, Hungary, Italy, the Netherlands, Norway, Poland, Sweden, Switzerland and the United States.

[4] With the exception of the United Kingdom, these findings are therefore consistent with what has been found in the literature to date. It is interesting to note that, again with the exception of the United Kingdom, no research on employer learning exists for the countries in which this paper finds no evidence in favour of the theory. Could this be a case of publication bias?

[5] Farber and Gibbons (1996) show that employer learning does not imply that the coefficient on S in a wage regression will change with experience. Because they use the part of Z which is not correlated with S, their model predicts an increasingly large association between wages and this variable as experience increases.

[6] As pointed out by Altonji and Pierret (2001), this is fully consistent with Farber and Gibbon's (1996) analysis of the orthogonal component Z. In particular, introducing the interaction between Z and X into the wage model affects the interaction between X and S only if Z and S are correlated. In robustness checks, the analysis has been re-run using the component of skill that is orthogonal to education, but this does not change the overall conclusions reached in this paper. Results are available upon request.

[7] For a more complete description of the decomposition the reader can refer to Fields (2004). In practice, the method can be applied in Stata with the user-written programme ineqrbd (Fiorio and Jenkins, 2007).

[8] 21 OECD countries: Australia, Austria, Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States; one region: Flanders (Belgium); as well as two of the OECD's partner countries: Cyprus and the Russian Federation.

[9] Other measures have also been tested, such as the average of numeracy and literacy scores, with no significant impact on the overall findings of the paper.

[10] The measure of experience refers to actual work experience and was collected as the number of years where at least six months were spent in paid work.

[11] The measure of wages used includes bonuses and is for wage and salary earners only (i.e. we exclude the self-employed) It is expressed in PPP corrected $US.

[12] This is done primarily to avoid empty experience x wage cells for the oldest individuals.

[13] The sample includes both private and public sector workers. The main analysis has been re-run on the sub-sample of private sector workers only, but this makes no significant difference to the overall results obtained in the paper.

[14] One standard deviation in numeracy skills is equivalent to around 6.6 years of education (as derived from a simple, pooled regression of numeracy scores on years of education, trimming 1% top and bottom earners, and including the employed with 40 years of experience or less only). Education therefore has a considerably larger effect on wages than skills.

[15] Although even in these countries, the initial return to experience is not zero – an issue that will be addressed later in this paper.

[16] This is following Altonji and Pierret (2001). Actual experience is regressed on potential experience, and a predicted value of experience is obtained. This is done by country. In a robustness check, the prediction was further broken down by gender. This produces strong evidence in favour of employer learning in Australia and Norway, while the evidence in the case of Sweden turns to only broadly consistent.

[17] One might argue that tenure could play a more important role than experience (gained in several different organisations) – i.e. that employer learning is "private" rather than "public". To test for this assumption, tenure as well as interactions of tenure with education and skills can be added to the Altonji and Pierret (2001) model (equation 2). If the information about worker productivity acquired by employers is public, then the schooling and skill interaction terms with tenure should not be significantly different from zero, as tenure does not convey any additional information on worker productivity. If the information acquired about productivity is private, however, then the schooling and ability interactions with tenure should respectively be negative and positive. Running such regressions on the OECD countries included in the Survey of Adult Skills results in some significant tenure and schooling/skill interactions – however the size of these coefficients is so small that it is safe to conclude that employer learning is public (in line with most findings in the literature). Results of these additional regressions are available upon request.

[18] Indeed, one general weakness of the data used in this paper is its cross-sectional nature. The identification strategy relies on the key assumption that cohort effects are non-existent and, in particular, that they do not confound experience effects.