Vocational training and earnings in Portugal

Hartog, J.; Pereira, P.T.; Cabral Vieira, J.A.

Published in:
Economia

Vocational Training and Earnings in Portugal

Joop Hartog *
Pedro T. Pereira**
José A. C. Vieira ***

Abstract

This paper examines the relationship between wages and vocational training in Portugal. For this purpose, we estimate a semi-logarithmic wage equation using OLS and quantile regression techniques. The results indicate that in some cases vocational training has a positive impact on wages. This is valid for the mean (OLS) and for each conditional quantile of the wage distribution. The paper casts some doubt on the market value of the skills acquired within the apprenticeship system and in the vocational training schools. The results also suggest that the effect of training on wages is not statistically different across different quantiles of that distribution. Therefore, there is no loss of information when we only use the OLS estimator.

Keyworks: wage equation, vocational training, quantile regression

* University of Amsterdam
Address: Roetersstraat 11, 1018 WB Amsterdam, The Netherlands
E-mail: hartog@fee.uva.nl

** Faculdade de Economia da Universidade Nova de Lisboa
Address: Tv. Estêvão Pinto, 1099-032 Lisboa, Portugal
E-mail: ppereira@fe.unl.pt

** * Universidade dos Açores
Address: Rua Mãe de Deus, 9500 P. Delgada, Portugal
E-mail: josevieira@notes.uac.pt

Acknowledgements:
We are thankful to an anonymous referee for helpful suggestions. Financial support from program PRAXIS XXI, grant PRAXIS/2/2.1/CSH/781/95, SAPIENS 99, grant 33089/99 and FEDER is acknowledged.

1. Introduction

Labour force training has become increasingly important since it helps to upgrade the labour force skills. This role is probably reinforced in the Portuguese case where the working population has received little schooling. Indeed, vocational training has been considered as a key factor to enhance the productivity of the Portuguese workers and consequently their salaries. This idea has led to an increased amount of public funds to subsidise training. Most of these have come from the European Union.

Vocational training has been provided by public and private entities. It has also been provided within the schooling system. This type of education was abolished in the second half of the seventies and re-established over the 1980s. In particular, we must highlight the implementation of the apprenticeship system and the creation of vocational training schools.

It is mostly claimed that training is necessary in Portugal but little is known about the real effect of training received by the workers. This paper examines the relationship between training and wages and constitutes an additional contribute to overcome this shortcoming (see Saraiva 1999).

The outline of the paper is as follows. Next section describes the data set. Section 3 presents the estimation methods. The estimation results are presented in section 4. Finally, section 5 concludes and summarises.

2. Data

We use the first wave of the European Community Household Panel (ECHP). This is a representative data set conducted in 1994 which includes some variables on vocational training undertaken by the individual. The data also includes information on variables such as net monthly wages, hours of work per week, age, gender, occupation, firm size and industry affiliation.

Descriptive statistics are in Table 1 in the appendix. As we can observe, the level of schooling within the labour force is quite low. More than 70% of the workers have at most attained six years of education. Of the individuals in the sample, 39% are female, 73.9% work in the private sector, and 5% are part-timers. The average age is 37.6 years.

With respect to the training variables, the following questions have been asked just after inquiring on the highest education completed by the individual:

- *Apart from this education, have you completed any vocational training course?*

If so, indicate which ones of the following types of vocational courses have you ever undertaken:

Training 1: *Specific vocational training at a college;*
Training 2: *Specific vocational training of one year or longer duration at a vocational school or training centre;*
Training 3: *Specific vocational training of one year or longer duration in a working environment (i.e. at a firm, without complementary instruction at a school or college);*
Training 4: *Specific vocational training of one year or longer duration within a system providing both work experience and complementary instruction elsewhere (i.e. any form of 'dual' system including apprenticeship);*
Training 5: *Any training or apprenticeship of less than one year duration;*

As we can see, only 9.9% of the workers in the sample have attained vocational training. When we split the sample by gender, the figures are 9.4% form men and 10.7% for women. These seem to be very low values for the international standard (see Lynch, 1994).

In order to assess the wage-effect of training we first estimate a human capital wage equation including a dummy called *training* which assumes value 1 if the individual has attained training and 0 otherwise. In order to distinguish by types of training, we also run a regression which includes a set of dummy variables training 1 to training 5 (see the description above). No training is used as the reference category.

3. Methodology

In order to analyse the effect of training on wages we undertake a regression analysis. Suppose that wages are generated by a linear model of the type:

$$\ln w_i = x_i^{'}\beta + \varepsilon_i \qquad i=1,...,N \qquad \beta\in R^k \tag{1}$$

where ln w_i denotes the logarithm of net hourly wages, x_i is a vector of observed explanatory variables and ε_i is a stochastic error. The covariates x_i include a vector of ones and variables such as education, age, gender, occupation, firm size and industry affiliation. It also includes controls for vocational training attended by the worker, which is the main concern of this paper. This is firstly tackled through a dummy variable which takes the value 1 if the individual attended training. However, as individuals in our data undertake different types of training we also consider a regression with a dummy variable for each type. In both cases the reference group is those respondents who have had no training of any sort.

Equation (1) was estimated by OLS and by quantile regression estimators. The OLS estimator allows us to estimate the effect of the exogenous on the conditional mean of the wage distribution. However, the conditional expectation describes a partial aspect of the statistical relationship among variables. It may, therefore, be important to examine that relationship at different points of the conditional distribution function. This type of analysis may be of particular interest when analysing data sets characterised by a significant degree of heterogeneity. Indeed, recent studies which use the quantile regression technique conclude that restricting the analysis to average effects misses some important features of the wage structure (see Buchinsky, 1994, Chamberlain, 1994, Machado and Mata, 1997, Fitzenberger and Kurz, 1997, and Vieira, 1999). These authors have analysed the wage-effect of variables such as education, experience, tenure, firm size and industry affiliation among others. As far as we know, no study aimed at analysing the wage effect of training has used such a technique. In particular, this prevents any comparison of our results with others from other countries.

The quantile regression technique was introduced by Koenker and Basset (1978). They define the θth regression quantile as the solution to the problem:

$$\min_{\beta \in R^k} \left[\sum_{(i:\ln w_i \geq x_i'\beta)} \theta \left| \ln w_i - x_i'\beta \right| + \sum_{(i:\ln w_i < x_i'\beta)} (1-\theta) \left| \ln w_i - x_i'\beta \right| \right], \quad \theta \in (0,\ 1) \qquad (2)$$

By a variation of θ, different quantiles can be obtained. The least absolute deviation (LAD) estimator of β is a particular case within this framework. This is obtained by setting θ=0.5 (the median regression). The first quartile is obtained by setting θ=0.25, and so on. As we increase θ from 0 to 1, we trace the entire distribution of y, conditional on x. This problem does not have an explicit form, but it can be solved by linear programming methods. In this study it is solved by linear programming techniques suggested in Armstrong et al. (1979).

In practice, obtaining standard errors for the coefficients in quantile regression is a difficult problem and one for which the literature provides only sketchy guidance. In the present study we used a bootstrap method. We also used bootstrapping to calculate the relevant standard errors and test to what extent the differences between coefficients associated to different quantiles are statistically different. In each of these cases we used 100 repetitions (see details in the Appendix).

4. Empirical Results

4.1 OLS Regressions

As we can see in Table 2, training affects wages positively. On average, those who have undertaken training are paid 15-17% more than those without no training.[1] These figures are reduced to 7-12% when we add controls for occupations, industry, firm size and others to wage equation. This indicates that the premium associated to training participation is also determined by the allocation of the workers to particular occupations, industries or firms.[2]

The results just mentioned indicate that training increases wages, but they do not differentiate by type of training. As we can see in Table 3, both men and women who have received vocational training at a college (training 1) and those who have received any training or apprenticeship of less than one year duration (training 5) earn higher wages than the reference group. The same occurs men who have received specific vocational training of one year or longer duration in a working environment (training 3), but not for women whose coefficient is not statistically significant.

It is interesting to observe that specific vocational training of one year or longer duration at a vocational school or training centre (training 2) and specific vocational training of one year or longer duration within a system providing both work experience and complementary instruction elsewhere such as any form of 'dual' system including apprenticeship (training 4) do not generate wages above those of the reference group. This may indicate that the vocational training schools or the apprenticeship system do not produce skills which are rewarded in the labour market. A possible interpretation could be that enrolment in this type of education is sometimes interpreted as a negative signal of ability. However, this result requires some caution because of the small number of observations in the corresponding cells.

4.2 Quantile Regressions

The results in panel A of Table 4 indicate that vocational training increase wages across the whole conditional wage distribution. The coefficients estimated for selected quantiles are all statistically different from zero at the 1% level. At a first glance the

---

[1] Calculated as $\Delta = \left[\exp(\hat{\beta}) - 1\right] \times 100$, where $\hat{\beta}$ denotes the estimated coefficient associated to the binary variable *training*.

[2] The results in Table 2 are based on the OLS estimator and may consequently be undermined by a selection bias problem. This problem could be solved by using instrumental variables or a two-step method similar to that proposed by Heckman (1979). Largely because the data set has no variables that can be used as satisfactory identifiers, the present analysis ignores any correction. We are aware, however, that this is a case where self-selection may be relevant.

impact of training on wages seems to vary across that distribution. However, the results in panel B of Table 4 do not reject the equality of the coefficients associated to different quantiles at the 5% level.

Table 5 includes quantile regression estimates for a wage equation which distinguishes by type of education. Training 1 and training 5 have a positive effect on wages. This fits in with the OLS results. A first look at the figures seems to indicate that there are differences across the distribution. For instance, for the whole sample the effect of training 1 on wages is positive across the entire distribution. However, it is interesting to note that there are differences when we split the sample by gender. The coefficients are not statistically significant at the 9th decile and at the 1st decile for men and women, respectively. Similarly, there seems to exist differences in the other types of training. However, and for all types of training, the inter-quantile equality hypothesis testing included in panel B of Table 5 does not reject equality between pairs coefficients across the conditional wage distribution. From this point of view, the quantile regression does not add much to final conclusions.

5. Conclusions

This paper was an attempt to evaluate the wage-effect of training in Portugal. The results indicate that in some cases vocational training has a positive impact on wages. This is valid for the mean (OLS) and for each conditional quantile of the wage distribution. The results also cast some doubt on the market value of the skills acquired within the apprenticeship system and in the vocational training schools. Those who have received training within these entities do not receive higher wages than those with no training do. The same results appear in Saraiva (1999) who used a different data set and therefore are robust.

The results suggest that the effect of training on wages is not statistically different across different quantiles of that distribution. In such a case, there is no loss of information when we only use the OLS estimator. The findings also indicate that a simple look at the coefficients of the quantile regression may be not enough to retrieve valid conclusions. In particular, inter-quantile equality testing seems important.

The OLS coefficient of 0.095 for training is slightly higher than the one (0.0716) obtained in Saraiva (1999), but both are in the range of values obtained for other European Countries; Austria (females between 0.0161 and 0.0492, males between 0.0212 and 0.133 in Fersterer and Winter-Ebmer (1999)), Finland (females between

0.03 and 0.058, males between 0.085 and 0.109 in Asplund (1999)) and the Netherlands (sample with both genders between 0.04 and 0.16 in Groot and al. (1994)). These results are higher than the ones obtained for Norway (Barth and Roed (1999) and for Switzerland (Weber and Wolter (1999).

Similar results for the different types of training were obtained in Dolton et al. (1994), who looked at the impact of government-led training on the wages of young workers in Britain and compared it with the impact of training acquired on the job or off the job from the private sector. They concluded that government training alone has small or even negative effects on wages. However, on-the-job training provided by an employer and off-the-job training obtained from the private sector both have a significant impact on wages.

As a final remark, we must say that more attempts to evaluate the effect of training on wages in Portugal are needed. We are aware that our analysis contains some shortcomings. In particular, the selectivity bias problem arises some concerns and we intend to control for it in a near future. The creation of a longitudinal data-set based upon several waves of the ECHP seems an important step in order to pursue such a goal.

References

Asplund R. (1999) "Earnings and Human Capital: Evidence for Finland", in R. Asplund and P. Pereira (ed.), *Returns to Human Capital in Europe – a Literature Review*, Helsinki, ETLA, 43-84.

Armstrong, R.; Frome, E. and Kung, D. (1979) "Algorithm 79-01: a revised simplex algorithm for the absolute curve fitting problem", *in Communications in Statistics, Simulation, and Computation* B8(2), New York: Marcel Decker.

Barth E. and Roed, M. (1999) "The Return to Human Capital in Norway: A Review of the Literature", in R. Asplund and P. Pereira (ed.), *Returns to Human Capital in Europe – a Literature Review*, Helsinki, ETLA, 227-258.

Buchinsky, M. (1994) "Changes in the U.S. Wage Structure 1963-1987: An application of quantile regression", *Econometrica*, 62, 405-458.

Chamberlain, G. (1994) "Quantile Regression, Censoring and the Wage Structure", in C. Sims and J.J. Laffond (eds.) *Proceedings of the Sixth World Congress of the Econometrics Society, Barcelona*, Spain. New York: Cambridge University Press: 171-209.

Dolton, P., Makepeace, G. and Treble, J. (1994) "Public- and Private-Sector Training of Young People in Britain", in Lisa Lynch (ed.) *Training and the Private Sector: International Comparisons*, Chicago: University of Chicago Press, 283-297.

Fersterer, J. and Winter-Ebmer, R. (1999) "Human Capital and Earnings in Austria", in R. Asplund and P. Pereira (ed.), *Returns to Human Capital in Europe – a Literature Review*, Helsinki, ETLA, 13-28.

Fitzenberger, B. and Kurz, C. (1997) "New Insights on Earnings Trends across Skill Groups and Industries in Germany", Diskussionspapiers 38, Center for International Labour Economics, Universität Konstanz.

Groot, W., Hartog, J. and Oosterbeek, H. (1994) "Returns to Within-Company Schooling of Employees: The Case of the Netherlands", in Lisa Lynch (ed.) *Training and the Private Sector: international Comparisons*, Chicago: University of Chicago Press, 299-307.

Heckman, J. (1979) "Sample Selection as a Specification Error", *Econometrica*, 47, 153-161.

Koenker, R. and Basset, G. (1978) "Regression Quantiles", *Econometrica*, 50, 43-62.

Lynch, L. (1994) *Training and the Private Sector: international Comparisons*, Chicago: University of Chicago Press.

Machado, J. and Mata, J. (1997) "Earning Functions in Portugal 1982-1994: Evidence from Quantile Regressions", paper presented at the workshop *The Portuguese Labour Market in International Perspective*, Lisbon, July 18-19.

Saraiva, A. F. (1999), “Incidência e Impacto Salarial da Formação Profissional em Portugal”, *Economia,* XXIII, 27-43

Vieira, J. A. (1999) *The Evolution of Wage Structures in Portugal 1982-1992*, Ph.D Dissertation, Amsterdam: Tinbergen Institute Research Series 197.

Weber, B. and Wolter, S. “Wages and Human Capital: Evidence from Switzerland”, in R. Asplund and P. Pereira (ed.), *Returns to Human Capital in Europe – a Literature Review*, Helsinki, ETLA, 325-350.

Appendix

1. Quantile Regression Standard Errors and Inter-quantile Equality Testing

The standard errors of the coefficients and those for testing the equality of coefficients between different quantiles were obtained trough bootstrapping. This procedure treats a sample of N observations as if they were the population of interest. N observations are randomly drawn with replacement from the N observations in the data set. A quantile regression model is then applied to this generated data set. The procedure is repeated *k* times (in this particular case k=100). Each of these times yields an estimated vector of parameters $b^{i}_{\theta=j}$, where i denotes the repetition number and j indicates the quantile number. This builds a data se for the b-vectors.

The standard error of the coefficient associated to the quantile j is then estimated as:

$$s = \left[\frac{1}{k-1} \sum_{i=1}^{k} (b^{i}_{\theta=j} - \bar{b}_{\theta=j}) \right]^{0.5}$$

, where $\bar{b}^{i}_{\theta=j}$ is the mean value of $b^{i}_{\theta=j}$ (i=1,...,k).

Regarding the standard error for the inter-quantile equality test of the type $b_{\theta=j} - b_{\theta=r} = 0$, it was estimated as:

$$s' = \left[\frac{1}{k-1} \sum_{i=1}^{k} (b^{i}_{\theta=j} - b^{i}_{\theta=r} - \overline{b_{\theta=j} - b_{\theta=r}}) \right]^{0.5}$$

, where $\overline{b_{\theta=j} - b_{\theta=r}}$ is the mean value of $b^{i}_{\theta=j} - b^{i}_{\theta=r}$.

2. Estimation Results

Table 1

Means of selected variables

	all workers	men	women
ln (hourly wages)	6.10	6.14	6.04
lower secondary	.128	.122	.138
upper secondary	.115	.092	.152
university	.069	.051	.098
age	37.6	38.1	36.8
2 years < tenure with the employer ≤ 14 years	.497	.479	.526
tenure with the employer > 14 years	.348	.372	.310
private sector	.739	.760	.706
female	.391		
part-time worker	.049	.021	.093
professionals	.053	.038	.077
technicians and associate professionals	.088	.076	.106
clerks	.122	.088	.174
service workers and salesmen	.166	.117	.243
skilled agricult. and fishery workers	.039	.053	.019
craft and related trades workers	.226	.290	.125
plant mach. operators and assemblers	.100	.131	.053
elementary occupations	.183	.174	.196
mining and manufacturing	.233	.229	.242
construction and electricity	.125	.197	.014
wholesale, retail, rest. and hotels	.183	.166	.209
transportation and financing	.077	.095	.048
public administration	.145	.159	.122
education and health	.113	.042	.226
other social and personal services	.056	.025	.104
5 employees ≤ firm-size < 20 employees	.219	.248	.175
20 employees ≤ firm-size < 50 employees	.113	.110	.117
50 employees ≤ firm-size < 100 employees	.071	.062	.085
100 employees ≤ firm-size <500 employees	.096	.098	.093
firm-size ≥ 500 employees	.045	.047	.042
firm-size missing	.274	.255	.303
training	.099	.094	.107
training 1	.011	.007	.016
training 2	.018	.016	.023
training 3	.008	.010	.004
training 4	.007	.006	.008
training 5	.056	.056	.056
# of observations	3598	2193	1405

Note: All variables are dummies, except ln (hourly wages).

Table 2

OLS wage equations (training=1 if has received vocational training, 0 otherwise**)**

	all workers				men				women			
intercept	4.91	(.058)*	5.60	(.105)*	4.85	(.075)*	5.48	(.117)*	4.82	(.090)*	5.68	(.219)*
lower secondary	.327	(.019)*	.159	(.018)*	.334	(.027)*	.189	(.024)*	.325	(.029)*	.092	(.027)*
upper secondary	.521	(.023)*	.243	(.023)*	.459	(.034)*	.196	(.033)*	.588	(.031)*	.228	(.034)*
university	1.11	(.031)*	.576	(.046)*	1.06	(.050)*	.585	(.069)*	1.15	(.038)*	.494	(.067)*
age	.046	(.003)*	.032	(.003)*	.050	(.004)*	.034	(.004)*	.037	(.005)*	.028	(.004)*
age squared/100	-.049	(.004)*	-.033	(.004)*	-.055	(.005)*	-.036	(.004)*	-.038	(.007)*	-.031	(.006)*
2 years < tenure ≤ 14 years	.082	(.018)*	.053	(.016)*	.066	(.024)*	.036	(.023)	.111	(.025)*	.086	(.023)*
tenure > 14 years	.229	(.022)*	.154	(.020)*	.192	(.029)*	.123	(.027)*	.284	(.032)*	.206	(.029)*
female	-.197	(.013)*	-.197	(.013)*	-	-	-	-	-	-	-	-
training	.149	(.025)*	.095	(.021)*	.154	(.032)*	.114	(.028)*	.141	(.037)*	.067	(.029)*
F-statistic	409		184		219		91.1		243		109	
adj. R^2	.505		.634		.443		.576		.579		.717	
σ	.374		.322		.381		.332		.362		.296	
N	3598		3598		2193		2193		1405		1405	
controls for industry, firm size, occupations, part-time, private firm	no		yes		no		yes		no		yes	

* Significant at the 1% level.

Table 3

OLS wage equations (training split by types; no training is the reference category**)**

	all workers				men				women			
intercept	4.91	(.058)*	5.59	(.105)*	4.85	(.075)*	5.47	(.117)*	4.83	(.090)*	5.68	(.219)*
lower secondary	.330	(.020)*	.160	(.019)*	.333	(.027)*	.188	(.024)*	.329	(.029)*	.094	(.027)*
upper secondary	.517	(.023)*	.240	(.023)*	.451	(.033)*	.191	(.033)*	.590	(.031)*	.228	(.034)*
university	1.09	(.032)*	.574	(.046)*	1.04	(.053)*	.574	(.068)*	1.14	(.039)*	.495	(.066)*
age	.046	(.003)*	.032	(.003)*	.051	(.004)*	.035	(.004)*	.037	(.005)*	.028	(.004)*
age squared/100	-.050	(.004)*	-.034	(.004)*	-.055	(.005)*	-.036	(.004)*	-.038	(.007)*	-.031	(.006)*
2 years < tenure ≤ 14 years	.082	(.017)*	.053	(.016)*	.066	(.024)*	.035	(.023)*	.112	(.025)*	.087	(.023)*
tenure > 14 years	.226	(.022)*	.153	(.020)*	.191	(.029)*	.123	(.026)*	.282	(.032)*	.205	(.029)*
female	-.198	(.013)*	-.197	(.013)*	-	-	-	-	-	-	-	-
training 1	.339	(.081)*	.236	(.056)*	.412	(.154)*	.326	(.091)*	.272	(.089)*	.152	(.064)**
training 2	.057	(.059)	.069	(.050)	.098	(.082)	.122	(.075)	.002	(.082)	.005	(.063)
training 3	.204	(.084)**	.122	(.070)***	.265	(.098)*	.181	(.078)**	.077	(.134)	-.043	(.131)
training 4	.057	(.086)	.048	(.076)	-.002	(.126)	.033	(.121)	.114	(.114)	.041	(.081)
training 5	.150	(.028)*	.083	(.025)*	.143	(.036)*	.093	(.033)*	.163	(.046)*	.076	(.038)**
F-statistic	285		165		148		82.1		163		97.3	
adj. R^2	.507		.634		.446		.578		.580		.717	
σ	.374		.322		.381		.332		.361		.296	
N	3598		3598		2193		2193		1405		1405	
controls for industry, firm size, occupations, part-time, private firm	no		yes		no		yes		no		yes	

* Significant at the 1% level   ** Significant at the 5% level   *** Significant at the 10% level

Table 4

Quantile regression wage equations (training=1 if has received vocational training, 0 otherwise**)**

Panel A: Regression coefficients (a)					
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
all workers	.0743 *(.028)**	.0889 *(.020)**	.0870 *(.018)**	.1343 *(.022)**	.1146 *(.029)**
men	.1299 *(.043)**	.0979 *(.030)**	.1046 *(.025)**	.1101 *(.035)**	.1835 *(.045)**
women	.0466 *(.039)*	.0977 *(.033)**	.0871 *(.024)**	.1149 *(.030)**	.0808 *(.047)*
Panel B: Inter-quantile equality hypothesis testing (b)					
	all workers				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.481	.325	1.61	.719
.25		-	-.069	1.57	.504
.50			-	1.86**	.541
.75				-	-.486
	men				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.739	.565	-.360	.560
.25		-	.202	.257	1.05
.50			-	.136	1.05
.75				-	1.15
	women				
	.10	**.25**	**.50**	**.75**	**.90**
quantiles					
.10	-	1.09	.773	1.05	.588
.25		-	-.266	.417	-.264
.50			-	.823	-.126
.75				-	-.693

(a) The coefficients indicate the estimated values associated to the dummy variable for *training*. All equations include and intercept and covariates for education, age, part-time worker, tenure, gender, occupation, industry, firm-size and private ownership, Bootstrapped standard errors are in parentheses.

(b) t-values for the test: $(\beta_{\theta=row} - \beta_{\theta=column}) = 0$.

* Significant at the 1% level ** Significant at the 10% level.

Table 5

Quantile Regression wage equations (training split by types; no training is the reference category**)**

Panel A: Regression coefficients (a)					
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
all workers:					
training 1	.2734 *(.085)**	.1844 *(.055)**	.1888 *(.057)**	.2198 *(.061)**	.3299 *(.085)**
training 2	-.0213 *(.056)*	.0306 *(.041)*	.0992 *(.043)***	.0561 *(.045)*	.0637 *(.069)*
training 3	.0572 *(.088)*	.0392 *(.062)*	.1243 *(.064)****	.1777 (.066)*	.3149 *(.093)**
training 4	.0631 *(.104)*	.0390 *(.067)*	-.0373 *(.069)*	.0104 *(.075)*	.1801 *(.106)****
training 5	.0986 *(.039)***	.1000 *(.024)**	.0786 *(.025)**	.1388 *(.027)**	.1113 *(.041)**
men:					
training 1	.3593 *(.105)**	.2631 *(.094)**	.2593 *(.094)**	.2528 *(.125)***	.1832 *(.130)*
training 2	.0673 *(.076)*	.0276 *(.063)*	.0995 *(.064)*	.0503 *(.087)*	.2113 *(.099)***
training 3	.0979 *(.070)*	.1031 *(.079)*	.2391 *(.077)**	.1936 *(.106)****	.3420 *(.122)**
training 4	-.0924 *(.112)*	.0776 *(.104)*	-.0495 *(.089)*	.0723 *(.136)*	.0530 *(.145)*
training 5	.1538 *(.041)**	.1095 *(.035)**	.1075 *(.034)**	.1215 *(.048)***	.1571 *(.053)**
women:					
training 1	.0977 *(.085)*	.1294 *(.055)***	.2177 *(.057)**	.1656 *(.069)***	.2052 *(.101)***
training 2	.0074 *(.074)*	-.0022 *(.052)*	.0664 *(.047)*	.0431 *(.062)*	-.0331 *(.078)*
training 3	-.0051 *(.060)*	-.1822 *(.098)*	-.0921 *(.100)*	.0161 *(.117)*	.0192 *(.074)*
training 4	.0969 *(.047)***	.0379 *(.077)*	.0103 *(.074)*	-.0680 *(.090)*	.1438 *(.147)*
training 5	.0711 *(.048)*	.1455 *(.033)**	.1153 *(.031)**	.1096 *(.039)**	.0979 *(.052)****

Table 5 (cont.)

Panel B: Inter-quantile equality hypothesis testing - all workers (b)					
	training 1				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.881	-.717	-.380	.285
.25		-	.059	.388	.962
.50			-	.366	.856
.75				-	.757
	training 2				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.909	1.67***	1.12	.672
.25		-	1.02	.329	.258
.50			-	-.838	-.213
.75				-	.078
	training 3				
	.10	**.25**	**.50**	**.75**	**.90**
.10	-	-.248	.500	.907	1.69***
.25		-	.087	1.24	1.86***
.50			-	.479	1.17
.75				-	1.05
	training 4				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.200	-.918	-.270	.533
.25		-	-.949	-.174	.850
.50			-	.323	1.53
.75				-	1.02
	training 5				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.030	-.375	.745	.175
.25		-	-.719	1.01	.183
.50			-	1.66	.552
.75				-	-.562

Table 5 (cont.)

Panel C: Inter-quantile equality hypothesis testing - men (b)					
	training 1				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.870	-.577	-.503	-.772
.25		-	-.026	-.058	-.432
.50			-	-.041	-.376
.75				-	-.324
	training 2				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.472	.324	-.121	.516
.25		-	.890	.201	.767
.50			-	-.563	.530
.75				-	.928
	training 3				
	.10	**.25**	**.50**	**.75**	**.90**
.10	**-**	-.047	1.19	.573	1.13
.25		-	1.10	.627	1.33
.50			-	-.358	.593
.75				-	.943
	training 4				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	1.20	.238	.684	.398
.25		-	-.930	-.022	-.066
.50			-	.559	.310
.75				-	-.063
	training 5				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.847	-.683	-.463	.030
.25		-	-.051	.234	.520
.50			-	.267	.547
.75				-	.468

Table 5 (cont.)

Panel D: Inter-quantile equality hypothesis testing - women (b)					
	training 1				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.238	.735	.460	.051
.25		-	.801	.316	.451
.50			-	-.557	-.071
.75				-	.316
	training 2				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.100	.510	.299	-.266
.25		-	.823	.416	-.216
.50			-	-.284	-.810
.75				-	-.910
	training 3				
	.10	**.25**	**.50**	**.75**	**.90**
.10	-	-.957	-.381	.094	.098
.25		-	.516	.814	.875
.50			-	.555	.448
.75				-	.016
	training 4				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	-.573	-.529	-.835	.206
.25		-	-.216	-.605	.467
.50			-	-.497	.615
.75				-	1.08
	training 5				
quantiles	**.10**	**.25**	**.50**	**.75**	**.90**
.10	-	.975	.454	.403	.290
.25		-	-.632	-.487	-.631
.50			-	-.133	-.283
.75				-	-.228

(a) The coefficients indicate the estimated values associated to the dummy variables *training 1* to *training 5*. All equations include and intercept and covariates for education, age, part-time worker, tenure, gender, occupation, industry, firm-size and private ownership, Bootstrapped standard errors are in parentheses.

(b) t-values for the test: $(\beta_{\theta=row} - \beta_{\theta=column}) = 0$.

* Significant at the 1% level ** Significant at the 5% level *** Significant at the 10% level