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# **Can over-education account for the positive association between education and within-groups wage inequality?**

## **A note**

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### **Abstract**

International evidence shows that returns to education are increasing when moving up along the wage distribution. While researchers have focused on the inequality implications of this finding, little attention has been paid to its causes. This paper asks whether the over-education phenomenon is responsible for the observed pattern. To that purpose, recent data from the European Community Household Panel and several measures of over-education based on the worker's self-assessment are used. The results show that over-education is not a convincing explanation.

**Keywords:** Returns to education, over-education, quantile regression.

**JEL-Codes:** C29, D31, I21

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## **0. Introduction**

Recent international research has used the quantile regression technique to show that returns to education tend to be increasing when moving up along the wage distribution (Buchinsky, 1994, Machado and Mata, 2001, Pereira and Martins, 2002, 2004). This has been called ‘the inequality increasing effect of education’ (Machado and Mata, 2005, p. 457): if we give more education to workers who have the same observable characteristics but are located at different quantiles of the wage distribution, then their wages will become more dispersed.

This finding adds to the educational debate by warning policy makers that education may promote earnings differences. If conditional wage dispersion is higher among more educated individuals, then an educational expansion may raise overall wage inequality by raising the weight of the high-spread group. In this scenario, assessing the sources of the positive association between education and wage dispersion is of crucial importance, as countries where such sources are operating might wish to reverse the underlying causes.

This paper asks to what extent the over-education phenomenon accounts for the inequality increasing effect of education. The causes and consequences of over-education have recently attracted the attention of many researchers<sup>1</sup>. It has been documented that over-educated workers earn i) less than workers who have the same

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<sup>1</sup> Using international data, Groot and Van den Brink (2000) find that about one fourth of the working population is over-educated. For a survey on the topic, see Hartog (2000).

education but hold jobs for which they are adequately educated, and ii) more than workers in the same jobs who have less education (Alba, 1993, Sloane *et al.*, 1999, Dolton and Vignoles, 2000). Therefore, we expect that, relative to the adequately-educated, over-educated workers are located at lower quantiles of the earnings distribution and earn a lower return from their educational investment.

Then the question in this paper is: can over-education account for the tendency of education to be less rewarded at lower deciles of the wage distribution? This hypothesis has not been empirically tested to date, even though many researchers have suggested it<sup>2</sup>.

The next section describes the dataset and the definitions of over-education used in the paper. Section 2 calculates quantile returns to education and inspects whether over-education accounts for the differences in the returns across quantiles. Section 3 presents concluding remarks. Appendix A contains the detailed estimation results.

## **1. Data and definitions of over-education**

The data is taken from the most recent wave (2001) of the European Community Household Panel dataset (ECHP). This survey contains useful information on personal and labour market characteristics, including maximum level of education completed,

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<sup>2</sup> For instance, Machin (1996), Green *et al.* (1999), Pereira and Martins (2002) and Fersterer and Winter-Ebmer (2003). As Pereira and Martins (2004, p. 365) put it, “a situation where highly-schooled workers take jobs with a low skill requirement and consequent low pay would be consistent with this result”.

hours worked and monthly wage, for a variety of European countries. I take Portugal as case study, for in this country the inequality increasing effect of education has been found to be particularly acute (Pereira and Martins, 2002, 2004).

I restrict the sample to male wage earners aged between 18 and 60, who work normally between 15 and 80 hours a week, and are not employed in the agricultural sector. These restrictions leave us with a final sample of 2,065 individuals.

There are several approaches<sup>3</sup> to measure the extent of over-education. Following most other authors, I use the worker's self assessment regarding the match between the worker's skills and the firm's job requirements. In particular, I use two questions included in the ECHP,

- *Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?*
- *Have you had formal training or education that has given you skills needed for your present type of work?*

The previous questions provide us with different definitions of over-education (Alba and Blázquez, 2002). I define as

- 1) 'weakly over-educated' those workers that answer 'yes' to both the above questions

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<sup>3</sup> These approaches are basically three: job analysis, realized matches, and the worker's self-assessment. For further details, see Dolton and Vignoles (2000).

- 2) ‘incorrectly qualified’ those workers who answer ‘no’ to both the above questions<sup>4</sup>
- 3) ‘strongly over-educated’ those workers that answer ‘yes’ to the first question and ‘no’ to the second question, that is, those who have excess qualifications and whose formal training and education did not provide them with the skills needed in their jobs.

In the sample, the proportion of ‘weakly over-educated’, ‘incorrectly qualified’ and ‘strongly over-educated’ workers is, respectively, 16.6, 42.3 and 25.1 per cent.

## 2. Empirical models and results

I proceed by comparing the quantile returns to education of two wage equations. The first one corresponds to a standard specification,

$$\ln w_i = \alpha_\theta + \delta_{\theta 1} \exp_i + \delta_{\theta 2} \exp_i^2 + \beta_{\theta 1} \text{uppersec}_i + \beta_{\theta 2} \text{tertiary}_i + e_{\theta i} \quad (1)$$

where  $\ln w$  is the logarithm of hourly wages and  $\exp$  is experience, while  $\text{uppersec}$  and  $\text{tertiary}$  are dummies that are activated if the maximum education level attained by the individual  $i$  is, respectively, upper secondary or tertiary education. The excluded education category is ‘less than upper secondary education’<sup>5</sup>.

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<sup>4</sup> Even though this situation does not correspond to over-education strictly speaking, it reflects a qualification mismatch that is worth exploring.

<sup>5</sup> In the ECHP the education variable is coded in three levels. These were constructed following the ISCED-97 classification (OECD, 2003).

The second specification extends the standard model to include over-education dummies,

$$\ln w_i = \alpha_\theta + \delta_{\theta 1} \exp_i + \delta_{\theta 2} \exp_i^2 + \beta_{\theta 1} \text{uppersec}_i + \beta_{\theta 2} \text{tertiary}_i + \beta_{\theta 3} \text{overuppersec}_i + \beta_{\theta 4} \text{overtertiary}_i + u_{\theta i} \quad (2)$$

where *overuppersec* and *overtertiary* are, respectively, controls for over-education in the upper secondary and tertiary level<sup>6</sup>. I run this regression using the three alternative definitions of educational mismatch: weak over-education (Control 1), incorrect qualification (Control 2) and strong over-education (Control 3).

Figures 1 and 2 present the quantile returns to education arising from the different specifications<sup>7</sup>. The corresponding estimates are reported in Appendix A. The main finding is that returns to education are increasing over the wage distribution, and over-education can not account for this fact. In line with previous work, the coefficients of the standard model are increasing when moving from the lower to the upper quantiles. And, in the extended models, the quantile-return profile is as increasing over the wage distribution as in the standard model.

----- Insert Figures 1 and 2 about here -----

To provide a more detailed view, Tables 1 and 2 report return differentials between selected quantiles. Note how it is that differences across quantiles do not diminish after

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<sup>6</sup> The use of over-education dummies in a wage regression is in the spirit of Verdugo and Verdugo (1989), Dolton and Vignoles (2000) and Chevalier (2003).

<sup>7</sup> Note that these returns are measured in a comprehensive way, i.e., all indirect influences of education on wages – occupation, sector, etc. – are attributed to education itself.

introducing controls for over-education. Thus, for example, the .90-.10 spread, .324 in the standard model, is as high as .483 in model with Control 1, .333 with Control 2, and .273 with Control 3. This pattern applies to both the secondary and the tertiary level, to any definition of over-education, and to any region of the wage distribution considered<sup>8</sup>.

----- Insert Tables 1 and 2 about here -----

The last column of Tables 1 and 2 reports the p-values of the F-tests for the equality of coefficients at all quantiles. In the tertiary level, differences across quantiles remain statistically significant after introducing the over-education dummies. In the secondary level, differences turn out to be non-significant in the standard model as well as in the extended models.

Overall, the results show that the magnitude and significance of the differences in the returns across quantiles remain practically unaffected after controlling for over-education. I argue, therefore, that the inequality increasing effect of education documented by previous works can not be attributed to the over-education phenomenon.

### **3. Conclusions**

Returns to education are typically increasing when moving up along the wage distribution. While researchers have focused on the inequality implications of this finding, little attention has been paid to the analysis of its causes.

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<sup>8</sup> Notwithstanding this, the over-education dummies are jointly significant in all regressions. The p-values of the F-tests are 0.00 with Control 1, 0.00 with Control 2, and 0.04 with Control 3.



The results presented here warn policy makers that the positive association between education and within-groups earnings dispersion hinges on factors other than over-education. To the extent that these other factors are mostly unknown, further research needs to be done. A candidate explanation is ability. If ability interacts positively with education, then returns to education must be higher among workers at high-pay jobs, i.e., with more ability<sup>9</sup>. A second explanation has to do with qualifications, as differences in the returns within high-educated people may be due to differences in the type and quality of the qualifications provided by universities.

In the future, the acquisition of new data containing detailed information on the individual's educational qualifications and ability tests would enormously help in the task of understanding the sources of wage dispersion within education groups in Portugal.

## Appendix A

Table 1A  
OLS and quantile returns to education – Standard model

	OLS	$\theta = .10$	$\theta = .20$	$\theta = .30$	$\theta = .40$	$\theta = .50$	$\theta = .60$	$\theta = .70$	$\theta = .80$	$\theta = .90$
TERTIARY	<b>.949***</b> (.047)	.776*** (.122)	.848*** (.067)	.878*** (.053)	.963*** (.049)	1.003*** (.058)	1.038*** (.043)	1.070*** (.043)	1.079*** (.045)	1.100*** (.064)
UPPER SECONDARY	<b>.381***</b> (.031)	.282*** (.072)	.308*** (.047)	.334*** (.044)	.387*** (.034)	.398*** (.030)	.413*** (.029)	.412*** (.033)	.419*** (.034)	.389*** (.049)

Note: i) \*\*\* signals significant at the 1% level; ii) OLS estimation is heteroskedastic-robust; iii) quantile standard errors are obtained using 500 replications.

<sup>9</sup> Arias *et al.* (2001) test this hypothesis. The results are not conclusive, however. They find that once ability is controlled for, the tendency of education to be more rewarded at high-pay jobs, though less acute, is still existent.

Table 2A  
OLS and quantile returns to education – Model with Control 1

	OLS	$\theta = .10$	$\theta = .20$	$\theta = .30$	$\theta = .40$	$\theta = .50$	$\theta = .60$	$\theta = .70$	$\theta = .80$	$\theta = .90$
TERTIARY	<b>.931</b> <sup>***</sup> (.075)	.682 <sup>***</sup> (.191)	.846 <sup>***</sup> (.110)	.843 <sup>***</sup> (.078)	.958 <sup>***</sup> (.093)	1.079 <sup>***</sup> (.086)	1.040 <sup>***</sup> (.060)	1.096 <sup>***</sup> (.064)	1.076 <sup>***</sup> (.076)	1.165 <sup>***</sup> (.111)
UPPER SECONDARY	<b>.290</b> <sup>***</sup> (.037)	.192 <sup>***</sup> (.093)	.244 <sup>***</sup> (.039)	.248 <sup>***</sup> (.047)	.302 <sup>***</sup> (.047)	.326 <sup>***</sup> (.036)	.313 <sup>***</sup> (.044)	.326 <sup>***</sup> (.035)	.308 <sup>***</sup> (.054)	.304 <sup>***</sup> (.066)

Note: i) <sup>\*\*\*</sup> signals significant at the 1% level; ii) OLS estimation is heteroskedastic-robust; iii) quantile standard errors are obtained using 500 replications.

Table 3A  
OLS and quantile returns to education – Model with Control 2

	OLS	$\theta = .10$	$\theta = .20$	$\theta = .30$	$\theta = .40$	$\theta = .50$	$\theta = .60$	$\theta = .70$	$\theta = .80$	$\theta = .90$
TERTIARY	<b>.955</b> <sup>***</sup> (.049)	.777 <sup>***</sup> (.127)	.848 <sup>***</sup> (.075)	.895 <sup>***</sup> (.053)	.956 <sup>***</sup> (.046)	1.030 <sup>***</sup> (.058)	1.045 <sup>***</sup> (.042)	1.068 <sup>***</sup> (.042)	1.078 <sup>***</sup> (.047)	1.110 <sup>***</sup> (.067)
UPPER SECONDARY	<b>.438</b> <sup>***</sup> (.033)	.352 <sup>***</sup> (.068)	.391 <sup>***</sup> (.056)	.420 <sup>***</sup> (.044)	.452 <sup>***</sup> (.030)	.474 <sup>***</sup> (.034)	.466 <sup>***</sup> (.030)	.476 <sup>***</sup> (.033)	.445 <sup>***</sup> (.036)	.431 <sup>***</sup> (.047)

Note: i) <sup>\*\*\*</sup> signals significant at the 1% level; ii) OLS estimation is heteroskedastic-robust; iii) quantile standard errors are obtained using 500 replications.

Table 4A  
OLS and quantile returns to education – Model with Control 3

	OLS	$\theta = .10$	$\theta = .20$	$\theta = .30$	$\theta = .40$	$\theta = .50$	$\theta = .60$	$\theta = .70$	$\theta = .80$	$\theta = .90$
TERTIARY	<b>.963</b> <sup>***</sup> (.049)	.845 <sup>***</sup> (.122)	.848 <sup>***</sup> (.063)	.906 <sup>***</sup> (.062)	.987 <sup>***</sup> (.049)	1.032 <sup>***</sup> (.058)	1.042 <sup>***</sup> (.048)	1.080 <sup>***</sup> (.046)	1.098 <sup>***</sup> (.049)	1.118 <sup>***</sup> (.067)
UPPER SECONDARY	<b>.408</b> <sup>***</sup> (.034)	.325 <sup>***</sup> (.075)	.324 <sup>***</sup> (.051)	.355 <sup>***</sup> (.050)	.405 <sup>***</sup> (.038)	.411 <sup>***</sup> (.034)	.437 <sup>***</sup> (.035)	.447 <sup>***</sup> (.038)	.449 <sup>***</sup> (.039)	.454 <sup>***</sup> (.050)

Note: i) <sup>\*\*\*</sup> signals significant at the 1% level; ii) OLS estimation is heteroskedastic-robust; iii) quantile standard errors are obtained using 500 replications.

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## Tables

Table 1  
Dispersion across quantiles – Tertiary education

	.90–.10	.90–.50	.50–.10	.70–.30	.70–.50	.50–.30	F-test <sup>(a)</sup> (p-value)
STANDARD MODEL	.324	.097	.227	.192	.067	.125	.016
MODEL WITH CONTROL 1	.483	.086	.397	.253	.017	.236	.014
MODEL WITH CONTROL 2	.333	.080	.253	.173	.038	.135	.009
MODEL WITH CONTROL 3	.273	.086	.187	.174	.048	.126	.012

Note: (a) The F-test tests whether the coefficients at all quantiles (.10, .20, ..., .90) are statistically different.  
P-value < 0.05: significantly different at the 5% level; p-value < 0.01: significantly different at the 1% level.

Table 2  
Dispersion across quantiles – Secondary education

	.90–.10	.90–.50	.50–.10	.70–.30	.70–.50	.50–.30	F-test <sup>(a)</sup> (p-value)
STANDARD MODEL	.137	.021	.116	.078	.014	.064	.301
MODEL WITH CONTROL 1	.112	.022	.134	.078	.000	.078	.220
MODEL WITH CONTROL 2	.078	-.043	.122	.056	.000	.054	.248
MODEL WITH CONTROL 3	.124	.038	.086	.092	.036	.056	.171

Note: (a) The F-test tests whether the coefficients at all quantiles (.10, .20, ..., .90) are statistically different.  
P-value < 0.05: significantly different at the 5% level; p-value < 0.01: significantly different at the 1% level.

# Figures

Figure 1  
OLS and quantile returns to tertiary education

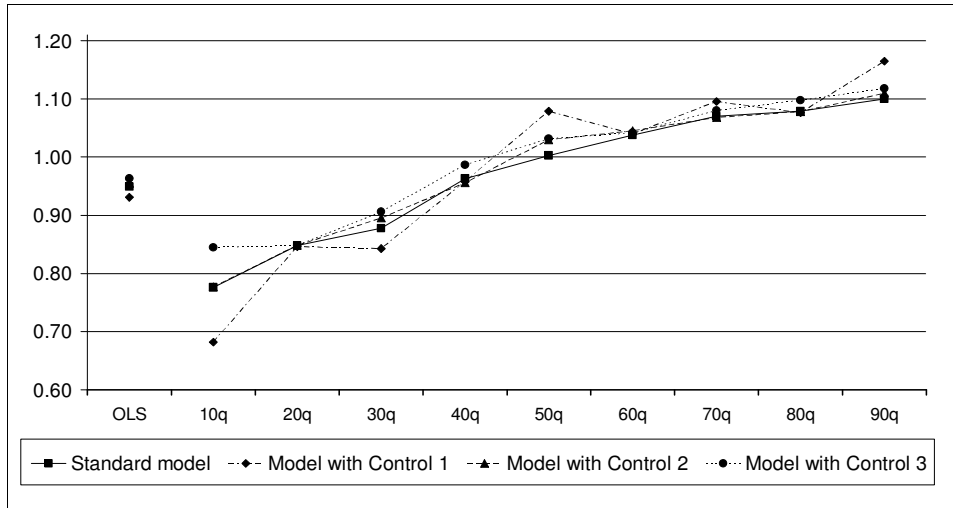


Figure 2  
OLS and quantile returns to secondary education

