Skill Mismatches and Wages among European University Graduates

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July 2011

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forthcoming in *Applied Economics Letters*

Abstract

This paper uses comparable international data to examine the extent and wage effects of skill mismatches among European university graduates. The results show that the mismatched earn on average 11.7% less than their well-matched counterparts. This effect, however, cannot be regarded as constant across the conditional earnings distribution: workers with lower unobserved earnings capacity tend to be exposed to greater wage loses when they end up in mismatched jobs.

Keywords: skill mismatch, pay-penalty, inequality
JEL-Codes: C29, I21, J31

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1. Introduction

Recently in the literature there has been a shift in emphasis from overeducation to skill mismatches. These terms refer to quite different phenomena. Measures of overeducation may not capture the extent to which a worker's skills are utilised in employment and workers with excess qualifications may still lack skills that are necessary on the job. The rising prevalence of overeducation as we move towards more educated groups contrasts with the loose relationship between qualifications and skill mismatches. From an individual point of view, the determinants of skill mismatches and overeducation are found to differ, and the correlation between these two indicators is weak (Green and McIntosh, 2007; Battu, 2011).

The goal of this paper is twofold. First, while the impact of overeducation on wages has been widely documented in the literature, the labour market effects of skill mismatches are less known. Recent evidence based on Australian and UK data suggests that these effects may be large (Mavromaras et al., 2009; Mavromaras et al., 2010; McGuinness and Sloane, 2010). This paper provides a European perspective on the subject by using comparable data from the 1994-2001 waves of the European Community Household Panel (ECHP henceforth). Although the ECHP is not the most up-to-date dataset available in the profession, the survey's eight-wave panel structure and the inclusion of educational mismatch measures makes it appealing for this research purpose[4]. The paper solely focuses on workers with a tertiary education. This is a critical group for European educational policies insofar as i) the private returns from higher education act to attract prospective students, and ii) increasing participation in higher education is one of the main pillars of the recently launched European Union Europe 2020 strategy for smart, sustainable and inclusive growth (European Commission, 2010). From a practical perspective, neglecting lower educational levels avoids mixing workers that may largely differ in terms of educational tracks, training participation and acquired skills.

The results are used to test whether a non-trivial interaction exists between skill mismatches and unobserved ability. Despite rising education levels in Europe during

[4] Unfortunately, the successor of the ECHP, the European Union Statistics on Income and Living Conditions, does not contain information on skills utilisation nor on the education requirements of jobs.

recent decades, the changing demand for specific skills in the labour market and the inability of training schemes and educational systems to provide workers with the necessary background has resulted in a proportion of individuals reporting skills deficits. According to the available evidence, this proportion is impressively large, ranging from 50% of the working population (Allen and van der Velden, 2001) to nearly two-thirds (Green and McIntosh, 2007). This raises the question of to what extent the incidence of skill mismatches entails a productivity loss. On the one hand, the mismatch pay penalty may reflect a real misadjustment between the worker's potential and the job's productivity ceiling. In this case, the real economic benefits of such an educational upgrade might be lower than previously thought. Alternatively, the mismatched may in some way be less able and lack specific abilities required to access jobs that match their skills. In this case, the mismatch pay penalty would be a mere statistical trick reflecting an omitted variables problem rather than a real economic problem. This paper provides useful insights into this debate by using quantile regression (QR). In the QR framework, the estimates at different quantiles represent the effects of a given covariate for individuals that have the same observable characteristics but, due to unobservable earnings capacity, are located at different points of the earnings distribution. Assuming that unexplained earnings capacity is given by individuals' unobserved ability, the results document how workers who are mismatched within the various ability segments of the earnings distribution are impacted relative to their well-matched counterparts. This approach, which is very similar to that used in McGuinness and Bennet (2007) and Budría and Moro-Egido (2008) for the study of overqualification, prevents the analysis from comparing higher ability matched individuals with lower ability mismatched individuals, thus eliminating the potential bias.

The dataset and variables are presented in Section 2. Section 3 briefly describes the model. The results are given in Section 4. Finally, conclusions are drawn in Section 5.

2. Data and measurement of skill mismatch

The paper uses data from 12 countries included in the 1994-2001 waves of the ECHP. The dataset and the variables are described in Appendix A. The estimating sample consists of tertiary-educated, private-sector males aged 24 to 60 years old who normally work between 15 and 80 hours a week and are not employed in the agricultural sector. Selfemployed individuals, as well as those whose main activity is paid apprenticeship or training and unpaid family workers have been excluded from the sample[5]. The final sample consists of 15,658 observations.

Workers are classified as either matched or mismatched depending on whether they have acquired or not the necessary skills through training and education. This information is taken from the following ECHP question "*Have you had formal training or education that has given you skills needed for your present type of work?*"[6]. Although not comparable, this question is similar to other questions used in complementary research[7].

Table 1 shows that the incidence of skill mismatches ranges from 10.7% in Germany to 43.3% in Italy, with an average of 20.9%. These figures are below the estimates based on the total population (second column) but still quite impressive among university graduates.

---------- Insert Table 1 about here -------

3. The model

The earnings equation is estimated using Koenker and Basset's (1978) quantile regression:

$$ln\ w_i = \alpha_\theta + \delta_\theta X_i + \beta_{\theta 1}\ mismatch_i + e_{\theta i} \qquad with\ Quant_\theta(ln\ w_i \mid X_i) = X_i \beta_\theta$$

where $ln\ w_i$ is the logarithm of the net hourly wage, X_i is a vector of controls and β_θ is the vector of parameters. $Quant_\theta(ln\ w_i \mid X_i)$ denotes the θth conditional quantile of $ln\ w$ given X. All the estimates control for personal characteristics (labour market experience and squared, unemployment experience, marital status, immigrant condition, and health status),

[5] The case of women is disregarded on account of the added complication of potential selectivity bias.

[6] There might be individuals who have not had formal education and training for unskilled jobs, but who have acquired the necessary background through other sources, including peer observation, learning by doing and general work experience. Although these channels are typically less relevant, they might be important for a small fraction of uneducated individuals working in low level jobs. By restricting the sample to tertiary educated workers we preclude this concern.

[7] Thus, for example, in Battu (2011) the central question is 'Your current job offers you sufficient scope to use your knowledge and skills'. In Mavromaras et al. (2009), overskilling in Australia is measured according to the responses on a 1-7 scale to 'I use many of my skills and abilities in my current job'. An alternative question in Mavromaras et al. (2010) is 'How well do the skills you personally have match the skills you need to do your present job?'.

job characteristics (supervisory role, establishment size, training provided by employer, job tenure, hours of work, industry and occupation), and year dummies[8].

4. Empirical Results

Table 2 shows that the wage effects of skill mismatch in the European labour market are generally large and statistically significant. According to the average (OLS) estimates reported in the first row, the mismatched earn on average 11.7% less than their well-matched counterparts. By countries, this pay-penalty ranges from 5.6% in France to 26.8% in Austria, and only fails to be statistically significant in Italy.

---------- Insert Table 2 about here -------

Interestingly, inspection of the QR estimates warns that these effects cannot be simply described in an average sense. In Europe as a whole, the incidence of mismatch entails a wage penalty that decreases from 14.7% to 9.7% when moving from the bottom to the top quintile of the earnings distribution. This can be better seen in Figure 1, where the estimates by quantiles are depicted, along with the 5% confidence interval and the OLS estimate. This observation suggests that a non-trivial interaction exists between skills mismatches and unobserved earnings capacity. Conditional on observable characteristics, low ability workers (i.e. those located at the lower quintiles) are exposed to higher earnings loses if they end up in mismatched work. Indeed, this is the case of most countries in the sample: Belgium, Denmark, Finland, France, Ireland and the UK. The opposite applies to Austria, Germany, and Spain, where the mismatch effect tends to be lower and less significant in the lower segments of the distribution. Finally, in Greece and Portugal the higher and more significant effects are concentrated in the intermediate quantiles. In auxiliary calculations, we tested whether such variations across the distribution are significant at conventional confidence levels. This resulted in a large set of pair-wise tests between estimates. The results, available upon request, show that in most countries (Austria, Belgium, Denmark, France, Germany, Greece, Portugal and Europe as a whole) the equality of coefficients between selected quantiles must be rejected.

[8] Training, firm size and unemployment experience were not available for France, Germany, Greece or the UK.

All in all, the results have important implications for the interpretation of the phenomenon. When the labour market is segmented by ability deciles with individual ability indexed by the individual's position in the conditional distribution, the estimates at different quantiles provide snapshots of how mismatched individuals within the different ability groups are impacted. A distinct feature of the analysis is that it does not rely on test scores or degree classification to proxy for ability. Rather, it exploits a broad definition of ability, including all those unmeasured characteristics that actually affect the worker's position in the wage distribution. If skill mismatches are a consequence of low ability and the lack of marketable skills, then their influence should be restricted to the lower segments of the earnings distribution. This seems to be the case in most countries. Still, individuals with high unobservable earnings capacity are also exposed to significant wage losses if they end up in jobs for which they lack the necessary skills. The estimated coefficients in the 70, 80 and 90 quintiles fail to be statistically significant only in Portugal and France.

5. Conclusions

The mismatch estimates can be criticised for being 'ex-post' rather than 'ex-ante' effects. Even though quantile regression allows for a non-trivial interaction between unobservable characteristics and the mismatch status, it would be informative to test whether the results change much when the mismatch variable is instrumented. Admittedly, the international scope of the paper comes at the cost of abstracting from endogeneity issues that can be properly addressed only by means of more extensive datasets at the national level.

Acknowledgements

Financial support from the Spanish Ministry of Education through grant SEJ2009-11117 is gratefully acknowledged.

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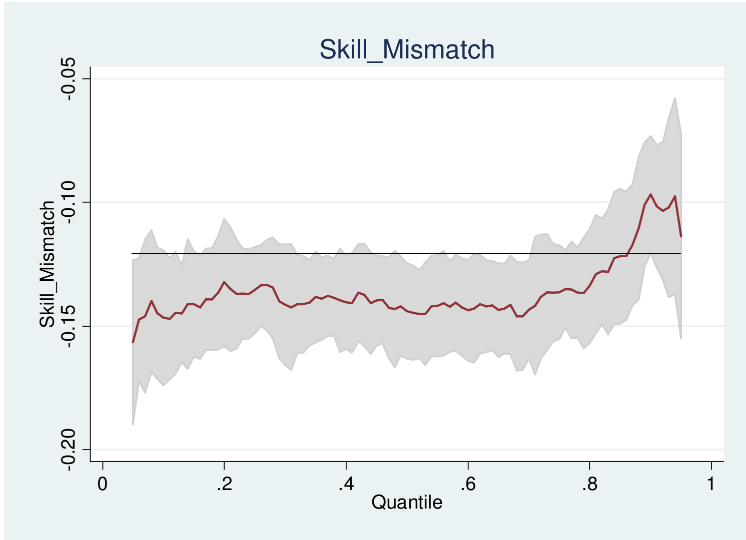
Appendix A. Description of data source and estimating samples

The European Community Household Panel (ECHP) is a sample of households and individuals who are interviewed over time. It is available from 1994 to 2001 for fifteen European countries. Workers with a monthly wage rate that is less than 10% or over 10 times the national average wage were dropped from the analysis. Sweden, the

Netherlands and Luxembourg were also excluded due to item non-response in crucial variables. The construction of the variables used in the paper is described in Budría and Moro-Egido (2009).

Appendix B. Figures and Tables

Figure 1. Quantile-return profile of the skill mismatch pay penalty – Europe



Panel a. Notes: Grey area: 5% confidence intervals; Solid line: quantile estimates; Dashed line: OLS estimate.

Table 1. The incidence of skill mismatches

	University Graduates	Total population
Europe	0.209	0.519
	(0.407)	(0.500)
Austria	0.122	0.324
	(0.328)	(0.468)
Belgium	0.128	0.338
	(0.334)	(0.473)
Denmark	0.179	0.324
	(0.384)	(0.468)
Finland	0.118	0.326
	(0.323)	(0.469)
France	0.318	0.513
	(0.466)	(0.500)
Germany	0.107	0.256
	(0.309)	(0.437)
Greece	0.385	0.669
	(0.487)	(0.471)
Ireland	0.121	0.420
	(0.326)	(0.494)
Italy	0.433	0.729
	(0.496)	(0.444)
Portugal	0.102	0.751
	(0.302)	(0.433)
Spain	0.208	0.512
	(0.406)	(0.500)
UK	0.115	0.370
	(0.319)	(0.483)

Notes: Source: ECHP 1994-2001. Standard errors are in parenthesis.

Table 2. The skill mismatch effect at different segments of the wage distribution - Tertiary education

	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
OLS	-0.117***	-0.268***	-0.075***	-0.150***	-0.166***	-0.056**	-0.096**	-0.174***	-0.205***	-0.039	-0.165**	-0.166***	-0.182***
	(0.016)	(0.053)	(0.025)	(0.021)	(0.034)	(0.026)	(0.044)	(0.029)	(0.040)	(0.026)	(0.079)	(0.020)	(0.063)
Q10	-0.147***	-0.063	-0.107***	-0.200***	-0.152***	-0.066	-0.087	-0.041	-0.326**	-0.050	-0.145*	-0.145***	-0.169***
	(0.012)	(0.083)	(0.031)	(0.033)	(0.040)	(0.044)	(0.069)	(0.049)	(0.155)	(0.045)	(0.083)	(0.037)	(0.063)
Q20	-0.132***	-0.135*	-0.142***	-0.205***	-0.153***	-0.063**	-0.082	-0.119***	-0.172*	-0.039	-0.201***	-0.117***	-0.219***
	(0.011)	(0.072)	(0.033)	(0.026)	(0.042)	(0.030)	(0.059)	(0.031)	(0.093)	(0.040)	(0.080)	(0.027)	(0.084)
Q25	-0.135***	-0.177***	-0.155***	-0.203***	-0.156***	-0.067***	-0.105**	-0.129***	-0.155**	-0.049	-0.253***	-0.127***	-0.279***
	(0.010)	(0.072)	(0.035)	(0.022)	(0.039)	(0.027)	(0.050)	(0.029)	(0.072)	(0.037)	(0.083)	(0.023)	(0.088)
Q30	-0.142***	-0.159**	-0.137***	-0.210***	-0.166***	-0.078***	-0.073	-0.157***	-0.168***	-0.028	-0.217***	-0.129***	-0.289***
	(0.010)	(0.070)	(0.034)	(0.019)	(0.037)	(0.027)	(0.063)	(0.029)	(0.052)	(0.028)	(0.074)	(0.021)	(0.094)
Q40	-0.140***	-0.223***	-0.093***	-0.208***	-0.192***	-0.085***	-0.056	-0.169***	-0.173***	-0.035	-0.222***	-0.122***	-0.169*
	(0.010)	(0.084)	(0.029)	(0.031)	(0.034)	(0.027)	(0.047)	(0.031)	(0.039)	(0.026)	(0.074)	(0.021)	(0.094)
Q50	-0.144***	-0.295***	-0.112***	-0.159***	-0.194***	-0.079***	-0.101***	-0.173***	-0.185***	-0.063**	-0.283***	-0.146***	-0.198***
	(0.011)	(0.092)	(0.032)	(0.035)	(0.039)	(0.029)	(0.039)	(0.032)	(0.040)	(0.030)	(0.071)	(0.021)	(0.078)
Q60	-0.144***	-0.333***	-0.085***	-0.117***	-0.148***	-0.070**	-0.152***	-0.210***	-0.193***	-0.068**	-0.266***	-0.157***	-0.210***
	(0.011)	(0.089)	(0.030)	(0.025)	(0.043)	(0.029)	(0.049)	(0.034)	(0.050)	(0.031)	(0.106)	(0.021)	(0.070)
Q70	-0.143***	-0.277***	-0.086**	-0.105***	-0.188***	-0.051	-0.100**	-0.172***	-0.191***	-0.061*	-0.137	-0.202***	-0.165**
	(0.011)	(0.079)	(0.035)	(0.023)	(0.045)	(0.042)	(0.050)	(0.038)	(0.056)	(0.033)	(0.134)	(0.027)	(0.080)
Q75	-0.136***	-0.299***	-0.063**	-0.112***	-0.160***	-0.041	-0.125***	-0.155***	-0.176***	-0.051	-0.149	-0.190***	-0.131
	(0.009)	(0.083)	(0.030)	(0.024)	(0.053)	(0.047)	(0.048)	(0.042)	(0.055)	(0.040)	(0.129)	(0.029)	(0.081)
Q80	-0.134***	-0.329***	-0.052	-0.104***	-0.172**	-0.016	-0.127**	-0.149***	-0.138***	-0.047	-0.134	-0.206***	-0.144*
	(0.011)	(0.094)	(0.034)	(0.029)	(0.070)	(0.047)	(0.058)	(0.044)	(0.050)	(0.046)	(0.137)	(0.033)	(0.086)
Q90	-0.097***	-0.402***	-0.069*	-0.124***	-0.085	0.044	-0.092	-0.080	-0.137	0.043	-0.156	-0.198***	-0.191
	(0.016)	(0.109)	(0.038)	(0.039)	(0.061)	(0.043)	(0.082)	(0.068)	(0.089)	(0.061)	(0.168)	(0.038)	(0.212)
OLS R-squared	0.9522	0.3547	0.2146	0.2346	0.1673	0.2248	0.1951	0.3444	0.4350	0.3278	0.2547	0.2668	0.1429

Notes: i) * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level; ii) standard errors are in brackets; iii) OLS estimates are heteroskedastic-robust; iv) standard errors of quantile estimates have been calculated using a bootstrap method of 500 replications; v) All results control for completed education, labour market experience and squared, unemployment experience, marital status, immigrant condition, health status, supervisory role in the job, training provided by the employer, hours of work, job tenure, establishment size, industry, occupation and year-specific effects; vi) The results for 'Europe' control for country-specific effects.