



OVERQUALIFICATION, SKILL MISMATCHES AND WAGES IN PRIVATE SECTOR EMPLOYMENT IN EUROPE

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Abstract. This paper uses a sample of private sector male workers from the European Community Household Panel to examine the wage effects of educational mismatches across segments of the earnings distribution in 12 countries. We consider two types of mismatch, overqualification and skills mismatches. By differentiating between quantiles, we discriminate between groups of workers with different unobservable earnings conditions. We find that the detrimental effects of skill mismatches on wages are larger than those of overqualification in most segments of the earnings distribution. Moreover, we find that the pay penalty of educational mismatch tends to be higher among workers with higher unconditional wages. This finding suggests that the mismatch phenomenon entails wage losses over and above those attributable to unobservable earnings determinants, including ability and skills possessed by workers.

Keywords: educational mismatch, overqualification, skill mismatch, quantile regression.

JEL Classification: C29, I21, J31.

Introduction

Investing in human capital is a key tool for economic progress and, as such, a major policy issue for most governments. However, a significant proportion of the labour force in developed countries has more education than is actually required for their jobs, i.e. is overqualified¹.

¹ Using data from 25 countries, Groot, Van den Brink (2000) report that, on average, 1 out of 4 workers has excess education. This proportion ranges from about 10% to 40% in the set of estimates reported in two surveys by Hartog (2000) and McGuinness (2006).

This phenomenon raises serious efficiency concerns. Presumably, overqualified workers do not make full use of their skills, some of which are acquired through costly education, thus resulting in a waste of resources for the economy, the firm and the individual. From a temporal perspective, furthermore, the overqualification phenomenon warns that the real economic benefits of the rapid educational expansion characterizing developed economies in recent decades might be lower than previously thought.

In this paper we shed new light on the interplay between overqualification and, more generally, educational mismatches and earnings. This is done by providing Quantile Regression (QR) estimates of the effect that educational mismatches exert in different segments of the conditional earnings distribution. The data is taken from the European Community Household Panel (ECHP) and comprises 12 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Spain, Portugal and the UK. Although this survey 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 purpose².

This paper is pertinent for several reasons. The first one is comparability. Even though the link between educational mismatch and wages has been addressed for a variety of countries and years, to date there is little comparable evidence for Europe. Major differences between the studies arise not only from crucial differences in the model specifications, but also from the use of different measurement methods, diverging datasets and differently defined samples of individuals. In an earlier work, Bárcena *et al.* (2012) address this issue by using a common wage equation, the same definition of mismatch and comparable data from several European countries. Even though their analysis is confined to university graduates and overlooks overqualification issues, the present paper is close in spirit to Bárcena *et al.* (2012).

Secondly, most of the debate in the policy arena has gravitated around the question of to what extent the incidence of educational mismatches entails a productivity loss. On the one hand, overqualified workers may, in some way, be less able and lack some of the abilities and skills required to do a job commensurate with their education. In this case, the mismatch pay penalty would be a mere statistical trick reflecting an omitted variables problem rather than a real economic problem. On the other hand, the overqualification phenomenon may reflect a real missadjustment between the worker's potential and the job's productivity ceiling, as theoretically predicted by Blázquez, Jansen's (2008) matching model. This paper provides new insights into this debate by drawing on data from a variety of European countries. In the quantile regression framework, the estimates at different quantiles represent the effects of a given covariate for individuals that have the same observable characteristics but, due to unobserved earnings capacity, are located at different points of the earnings distribution. By 'unobserved earnings capacity' we refer to all those unmeasured characteristics that actually affect the worker's position in the wage distribution, including not only individual-level abilities and skills, but also contextual-level characteristics such as ethnicity, workplace conditions and geographical location. Thus, we document how workers who are overqual-

² 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.

ified within the various segments of the earnings distribution are impacted relative to their well-matched counterparts. The major advantage of this approach is that it prevents us from comparing matched individuals featuring a favourable earnings capacity with mismatched individuals subject to an unfavourable earnings condition, thus eliminating the potential bias arising from unobserved heterogeneity. Using this method and data from Northern Ireland, McGuinness, Bennet (2007) report diverging effects from mismatch in the lower and upper tails of the earnings distribution. A similar finding is reported in Bárcena *et al.* (2012) for the case of skills mismatches among European university graduates.

Thirdly, recently in the literature there has been a shift in emphasis from overqualification 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 utilized in employment and workers with excess qualifications may still lack skills that are necessary on the job. 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, McIntosh 2007; Battu, Zakariya 2011). While the overqualification phenomenon 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, 2010). This paper provides an European perspective on the subject by using comparable cross-country data and by explicitly differentiating between overqualification and skill mismatches. This refinement is relevant in the present context insofar as we find that a significant proportion of overqualified workers lack skills that are necessary in the job.

The paper is structured as follows. In Section 1 we review the literature and highlight the most relevant theoretical approaches that have been put forward to explain the overqualification phenomenon. In Section 2 we present the dataset and variables, including the definitions of overqualification and skill mismatch used in the paper. In Section 3 we present the quantile regression model. The results are presented in Section 4. Section 5 discusses the main findings and their theoretical implications. The final section contains the concluding remarks. The paper includes an appendix that describes the estimating sample and the variables used in the regressions.

1. Economic framework

Overqualification refers to the extent to which an individual possesses a level of education that is not required for his or her job. Even though the incidence of overqualification is found to differ across countries, datasets and measurement methods, it is well established that a significant proportion of the labour force has excess education.

In an international perspective, there is consistent evidence that overqualified workers earn less than their well-matched counterparts. To cite some examples, the estimated differential can be as large as 11% in Groot (1996), 12% in Dolton, Vignoles (2000), 27% in Chevalier (2003) and about 35% in Dolton and Silles (2008) for the UK; 11% in Cohn, Khan (1995) and 13% in Verdugo, R., Verdugo, N. T. (1989) for the US; 8% in Kiker *et al.* (1997) for Portugal, about 22% for men and about 8% for women in Nordin *et al.* (2010) for Sweden

(a little bit lower in Korpi, Tahlin 2009); about 24–27% for females and about 18–24% for males for Estonia in Lamo, Messina (2010); about 17.6% for men and 26.7% for women in the tertiary level, 14.1% for men and 12.7% for women in the upper secondary level for Spain in Budría, Moro-Egido (2008); and about 7% for males and 9% for females for Australia in Mavromaras *et al.* (2012). Other studies differentiate between the years required to match the educational requirement of the job and the years that exceed the educational level needed at the job. The general finding is that excess education gives a 50% lower return than the return to required education. This evidence is well-summarized in some excellent surveys by McGuinness (2006), Leuven, Oosterbeek (2011), and Quintini (2011a, b).

Overall, the empirical evidence represents a challenge to Becker's (1964) Human Capital Theory (HCT). The prediction of HCT that individuals are paid by their marginal product, which in turn will be determined by their level of human capital, is questioned by the evidence that the same level of human capital earn different wages, depending on whether or not they are overeducated. One alternative path is to admit that the earnings equation framework lacks adequate controls for a variety of characteristics that may affect both earnings and the probability of taking up mismatched work (therefore an omitted variables problem). Thus, for example, less formal measures of human capital (tenure, on-the-job training, etc.) may act as substitutes for formal schooling (substitution hypothesis). Similarly, the overeducated may lack some of the abilities and skills required to do a job commensurate with their level of education (ability-skills hypothesis). In this case, the overeducation pay penalty would be a reflection of the lower human capital implied by these shortages, and overeducation itself, a mere statistical trick.

The evidence that supports these arguments is nonetheless limited. Consistent with the substitution hypothesis, Duncan, Hoffman (1981), Sicherman (1991), and Sloane *et al.* (1999) find that overeducated workers tend to have lower levels of tenure and training. However, Groot (1996) argues that there exists a cohort effect rather than a substitution effect: younger, more educated workers find it difficult to enter high-qualified jobs since older, less educated workers, have already taken these jobs. In the same vein, Alba-Ramírez (1993) finds nothing to support the argument that on-the-job training is treated by employers as substitutes of formal education. Moreover, Dolton, Silles (2008) find that the extent and wage effects of overqualification are significant among workers with similar levels of tenure and experience.

In support of the ability-skills hypothesis, Groot (1996) finds that the pay penalty of overqualification increases with tenure. The interpretation is that as employers find out the real capabilities of their workers, they tend to discriminate against the overeducated due to their lower ability. Sloane *et al.* (1999) report that, probably due to lesser skills, overeducated workers have lower chances of being promoted. However, McGuinness (2003a) and Chevalier (2003) extend the earnings equation to control for skill differences, and find that the pay penalty of overqualification is still large and significant. Bauer (2002) uses panel data to control for unobserved heterogeneity. His results show that about 30% of the estimated penalty cannot be accounted for by unobserved individual effects. McGuinness (2003b) and Green *et al.* (1999) stress the importance of differentiating between skill mismatches and educational mismatches. McGuinness (2003b) finds that a large proportion of the wage penalty associated with being overeducated is independent of the level of skill utilization within firms. Similarly,

Green *et al.* (1999) find that the correlation between actual and required skills is far from being perfect even among non-overeducated workers. Moreover, the effects of overeducation are found to be roughly as large as the effects of overskilling³.

On the basis of this evidence, there is scope to conclude that the central predictions of HCT are unlikely to be fully explained by gaps in the earnings equation, even though including job characteristics and some form of skill and ability heterogeneity control can have an important effect on the estimated relationship between overqualification and wages. This scenario has led researchers to interpret the overqualification phenomenon within the context of alternative labour market theories. From the supply-side perspective, the Career Mobility Theory (CMT) (Galor, Sicherman 1990) suggests that workers with high levels of formal education accept positions for which they are apparently overeducated whilst they gain experience and occupation-specific human capital through training. The acquired skills are then used to move towards higher occupational levels where they make full use of their qualifications. The Job Competition Theory (JCT) (Thurow 1975) assumes that unemployed individuals are located in a particular job queue. Once they get the job, they are paid a wage that is already given for that particular job cell. This view emphasizes the importance of a person's relative position in the job queue. Specifically, over-investment in education would be the individual's optimal response to protect or improve his or her position in the queue. In the same spirit, the Signaling Theory (ST) (Spence 1973) highlights the role of education (and excess education) as a screening device used by employers.

Another group of theories concentrate on the inefficient matching between supply and demand forces. Assignment Theory (AT) (Sattinger 1993) stresses that marginal product, and thereby wages, are determined by the human capital supplied by the worker and, at the same time, by the requirements and productivity ceilings of the job. As a result of the assignment process, some workers are misallocated to jobs for which they do not have comparative advantage and consequently end up earning lower wages. The Matching Theory (MT) (Jovanovic 1979) stresses this view by focusing on search costs and imperfect information as reasons for imperfect matches.

2. Data and measurement of overqualification and skill mismatch

We use data from 12 countries included in the European Community Household Panel (ECHP, henceforth). The ECHP is a representative survey that contains personal and labour market characteristics⁴. For the present study, we use pooled data from 1994 to 2001. The dataset and the variables are described in the appendix.

We use the same estimation procedure and population group for all countries. Our estimating sample consists of private sector men aged between 21 and 60 years old, who

³ The results in Bauer (2002), Chevalier (2003) and Frenette (2004) suggest that the apparent effects of over-education are spurious and represent other unobserved ability differences, over and above skill mismatch. In the same line Chevalier, Lindley (2009) argue that unobservable skills are important in determining over education and the genuinely over-educated possess significantly less of them.

⁴ For a detailed description of the ECHP, including a technical discussion on the extent of attrition and item non-response, see Peracchi (2002).

normally work between 15 and 80 hours a week and are not employed in the agricultural sector. Self-employed individuals, as well as those whose main activity status is paid apprenticeship or training and unpaid family workers have been excluded from the sample. The case of women is disregarded on account of the added complication of potential selectivity bias. After dropping observations with missing values, these exclusion restrictions leave us with a total of 61,147 observations.

The choice of dropping public sector employees in the paper is based on several considerations: (i) relative to the private sector, the public sector has a wider union presence and a more effective use of union power that leads to a flatter wage structure (Poterba, Rueben 1994; Dustmann, Van Soest 1998; Disney, Gosling 1998; Mueller 1998); (ii) “high-floor” and “glass-ceiling” effects are present in the public sector. As a consequence the public sector compresses wages (Budría 2010) and makes it difficult to attract high-quality workforce due to lower earnings at the top part of the wage distribution (Borjas 2002); and (iii) earnings determinants differ between the two sectors (Psacharopoulos, Patrinos 2004). Due to the low number of observations in the public sector and the use of quantile regression (which requires large samples to obtain reliable estimates) we did not attempt to obtain separate results for the public sector.

Two ways of measuring educational mismatch coexist in the literature: the ‘subjective’ and the ‘objective’ approach. The subjective approach is based on the worker’s self-assessment regarding the quality of the match between his or her education and the educational requirements of the job (e.g. Chevalier 2003). A variation of this method asks workers what the minimum educational requirements are for the job, and then compares this report with the actual education level of the worker (e.g. Duncan, Hoffman 1981; Cohn, Khan 1995; Dolton, Vignoles 2000; Dolton, Silles 2008). The objective approach, in contrast, consists in finding out the educational requirements externally. A worker is regarded to be overeducated (undereducated) if he has more (less) education than is required for the job. This requirement can be determined by the formal evaluation of independent job analysts or, alternatively, using a ‘statistical’ approach in which the education requirement is given by the mean/mode education level within occupations (e.g. Verdugo, R., Verdugo, N. T. 1989; Kiker *et al.* 1997; Bauer 2002)⁵.

Due to the availability of data, in this paper we follow the subjective approach. The ECHP includes two self-assessed questions that have already been used by Alba-Ramírez, Blázquez (2002), Wasmer *et al.* (2007) and Budría, Moro-Egido (2008) to measure educational mismatch. The first question is:

- (Q1) *Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?*

⁵ All these methods have their advantages and limitations. We do not elaborate upon them for reasons of space and mostly because they have been already discussed and compared in detail. McGoldrick, Robst (1996), Battu *et al.* (2000), Groot, Van den Brink (2000) and Rubb (2004) explore the extent to which the various methods yield different estimates of the incidence and wage effects of overeducation. Despite concerns related to poor correlation between the various measures, the authors report that the alternative approaches generate broadly consistent evidence in terms of the estimated effect of overqualification on earnings.

This information is used to identify workers who are ‘overqualified’ (Q1: ‘yes’)⁶. The second question is:

- (Q2) *Have you had formal training or education that has given you skills needed for your present type of work?*

This information allows us to identify workers who are ‘skill mismatched’, i.e. workers who did not acquire the necessary skills through training and education (Q2: ‘no’).

Before moving on, two remarks are in order. First, most measures of mismatch used in the literature are exclusively based on the level of education attained by the individual. However, workers who state that they are not overqualified may have an inappropriate job match when the content, not the level, of their education is evaluated. Exploring the effects of having inappropriate qualifications seems compelling as there is no presumption that these are less important than the effects of having excess qualifications. This is why we complement the information reported in Q1 with that reported in Q2. Second, individuals with excess education are typically regarded as ‘overeducated’ in the literature. However, the term ‘overeducation’ may be seriously misleading. Workers who have excess education and, additionally, are mismatched in terms of skills can be hardly labelled as ‘overeducated’ as their formal education did not provide them with the necessary training or education. This is why among individuals with excess education (Q1: ‘yes’) we will differentiate between those who lack necessary skills (Q2: ‘no’) and those who do not (Q2: ‘yes’)⁷.

In Table 1 we report summary statistics of the incidence of overqualification and skill mismatch. The low correlation found between these two variables (0.145) indicates that they refer to quite different phenomena. The first column reports the European averages⁸. The incidence of overqualification ranges from 44.2% in Portugal to 74.3% in Finland, with an average of 57.6%. In terms of the less well-documented skill mismatch variable, the figures range from 25.4% in Germany to 76.6% in Portugal with an average of 48.6%. The proportion of adequately-educated workers (those who are neither overqualified nor skill mismatched) is as low as 18.6% on average. Furthermore, we must note that some workers are overqualified as well as skill mismatched. This proportion amounts to 24.8% in the total sample and ranges from 9.4% in Italy to 25.5% in Austria⁹.

⁶ Throughout the paper we abuse language somewhat and classify as “overqualified” workers who have excess of either qualifications or skills.

⁷ We take the liberty of referring to workers who are skill mismatched as workers who ‘lack necessary skills’. We are aware, however, that 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. As most other measures of mismatch, a limitation of our definition is that it focuses on formal education and training and disregards other sources of skills acquisition.

⁸ Throughout the paper we will refer to ‘Europe’ as an additional country. These results are obtained by pooling all the countries together and re-scaling the sampling weights so that each country’s relative size in the sample is equal to its relative size in the census data. Specifically, the sampling weight of country’s i observation j in the pooled sample is $\omega_{ji} = (\gamma_i/\alpha_i) \cdot \rho_{ji}$, where: γ_i is the ratio between country’s i population and the population of all countries included in the ECHP according to the census data; α_i is country’s i sample size relative to the ECHP sample size; and ρ_{ji} is the original sample weight of country’s i observation j .

⁹ These percentages are obtained by adding the proportion of overqualified, skill mismatched and adequately-educated workers and subtracting one.

Table 1. The incidence of overqualification and skill mismatches by country

	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
Overqualified	0.576	0.631	0.723	0.673	0.743	0.595	0.681	0.561	0.537	0.548	0.442	0.577	0.733
Skill mismatched	0.486	0.347	0.347	0.333	0.318	0.514	0.254	0.659	0.418	0.731	0.766	0.534	0.369
Adequately educated	0.186	0.255	0.170	0.233	0.185	0.168	0.237	0.113	0.243	0.094	0.107	0.160	0.149

All in all, these figures indicate that a remarkably large fraction of the European working population undertakes jobs that are not perfectly commensurate with their qualifications and skills. The large proportion of overqualified workers in our data should not come as a surprise, as a review of the literature shows that subjective measures tend to render large estimates (McGuinness 2006). Indeed, our figures are very close to the estimates reported in Wasmer *et al.* (2007), who use the same dataset and taxonomy of mismatch to provide a European perspective on the topic. Using a slightly different sample, they find that in Europe as a whole the incidence of overqualification and skill mismatch is 54.1% and 45.8%, respectively.

In Table 2 we examine the connection between mismatch status and educational attainment more closely. We consider the three educational levels that are available in the ECHP (less than upper secondary, upper secondary and tertiary education). These are based on the ISCED-97 classification (OECD 2004). One might expect that the highly educated are more likely to be overqualified and less likely to lack necessary skills, and this is what is, in fact, observed. The incidence of overqualification is increasing in the educational level, from 44.2% in the lowest education category to 70.9% in the top category. In contrast, the incidence of skill mismatch is higher among the less educated, ranging from 19.5% in the tertiary-level group to 72.8% in the less educated group. Finally, the proportion of adequately educated workers is increasing in education, ranging from 12.6% in the less than upper secondary education group to 23.9% among workers with a tertiary education. In other words, the self-reported variables seem to behave reasonably.

Table 2. The incidence of mismatch by educational levels. Pooled sample

	Total sample	Less than upper secondary	Upper secondary	Tertiary
Overqualified	0.576	0.442	0.647	0.709
Skill mismatched	0.486	0.728	0.385	0.195
Adequately educated	0.186	0.126	0.220	0.239

Finally, in Table 3 we use the pooled sample to report summary statistics for the different types of workers. Some interesting differences emerge across groups. The overqualified and the adequately educated are roughly similar in terms of demographic and job characteristics. As regards the group of skill-mismatched workers, the overqualified are more likely to have tertiary education (34.8%), a supervisory role in their job (23.0%), employer-financed training (53.2%), less experience (19.86 years), work in larger firms (43.3% work in

Table 3. Descriptive statistics by mismatch status. Pooled sample

Variables	Adequately educated	Over qualified	Skill mismatched
Proportion of the total sample	0.186	0.576	0.486
Tertiary education	0.260	0.348	0.080
Upper secondary education	0.465	0.473	0.310
Less than upper secondary education	0.275	0.179	0.609
Supervisor	0.215	0.230	0.080
Training	0.467	0.532	0.203
Ln hours	3.741	3.742	3.726
Experience	22.15	19.86	21.46
Experience squared	617.0	507.7	581.5
Tenure < 5	0.338	0.385	0.418
5 ≤ Tenure < 10	0.166	0.196	0.197
Tenure ≥ 10	0.496	0.419	0.385
Married	0.704	0.688	0.704
Immigrant	0.070	0.074	0.121
Permanent	0.739	0.708	0.675
Employees < 20	0.311	0.295	0.411
20 ≤ Employees < 100	0.277	0.261	0.269
100 ≤ Employees < 500	0.190	0.199	0.171
Employees ≥ 500	0.212	0.234	0.131
Badhealth	0.018	0.013	0.030
Unemployment experience	0.274	0.286	0.366
Legislators, senior officials and managers	0.110	0.118	0.038
Professionals	0.126	0.145	0.025
Technicians and associate professionals	0.162	0.180	0.072
Clerks	0.078	0.094	0.097
Service workers and shop and market sales work	0.042	0.058	0.087
Skilled agricultural and fishery workers	0.002	0.002	0.004
Craft and related trades workers	0.331	0.274	0.312
Plant and machine operators and assemblers	0.119	0.101	0.230
Elementary occupations	0.029	0.029	0.135

a firm with 100 employees or more), and are less likely to report bad health (1.3%). The overqualified tend to work in white-collar occupations, including ‘Professionals’ (14.5%) and ‘Technicians and associate professionals’ (18.0%), while the skill mismatched are more likely to be blue-collar workers (31.2% ‘Craft and related trades workers’, 23.0% ‘Plant and machine operators and assemblers’ and 13.5% ‘Elementary occupations’).

3. The model

Our econometric strategy is based on Koenker, Basset's (1978) quantile regression (QR). The main feature of this approach is that it allows us to examine the effects of a given covariate (overqualification and skill mismatch) among workers with different unobservable earnings capacity. The q th quantile regression estimator β_q is the solution to the optimization problem of minimizing with respect to β_q :

$$\sum_{i: y_i \geq x_i' \beta_q} q |y_i - x_i' \beta_q| + \sum_{i: y_i < x_i' \beta_q} (1-q) |y_i - x_i' \beta_q|, \quad (1)$$

where the use of β_q is intended to make clear that different choices of q produce different vectors of coefficients. In our case, y_i is the logarithm of the gross hourly wage and x_i' is the vector of covariates. The optimization problem is solved using linear programming methods, where standard errors for the vector of coefficients are obtained using bootstrap methods. The procedure is accurately described in Cameron, Trivedi (2009).

The results are based on pooled data. Although we ideally prefer a panel estimation that controls for the presence of individual unobserved effects, there is a reason for this choice. Currently available QR panel techniques are based exclusively on fixed effects (Koenker 2004). This approach disregards all the between-person information and, as a consequence, it precludes the researcher from obtaining reliable estimates on characteristics that have zero or low within-person variation. We must recall that the crux of our analysis is overqualification, skills mismatches and, indirectly, attained schooling. The within-group variation of these variables is rather low in our data¹⁰. We are aware that ignoring individual factors and the panel structure of our data makes it difficult to infer the causal relation between the covariate of interest and the outcome. However, given the low within-person variation of the education variables, we are inclined to avoid a fixed-effects estimation that produces unstable results. Our preference for pooled results can be seen thus as a working compromise to, on the one hand, outline meaningful correlations in the data and, on the other hand, to use both within and between person information.

4. Empirical results

We report the results by country and, to obtain a more general view, for Europe as a whole. All the estimates control for personal characteristics (completed education, labour market experience and squared, unemployment experience, marital status, immigrant condition, and health status), job characteristics (supervisory role, training provided by

¹⁰ Taking the total sample: of those who were overqualified in at least one year as many as 74.7% were always overqualified. Similarly, of those ever skill mismatched, 75.1% were always skill mismatched. In the same vein, the annual exit rate from overqualification (the proportion of individuals who are overqualified in year t but not in year $t + 1$) is as low as 13.2%, while the corresponding figure is 15.3% for skill mismatch. In other words, educational mismatches are mostly a permanent phenomenon. The persistence of attained schooling is even higher, with less than 11% of the sample reporting an educational upgrade over the years in the sample. These patterns are common across countries.

the employer, hours of work, job tenure, establishment size, industry and occupation) and year dummies. The regression that includes all countries contains a set of additional controls to account for country-specific effects¹¹. Still the object of our attention will be restricted to two variables: a dummy variable indicating whether the individual is overqualified and a dummy for skill mismatch¹².

4.1. Average estimates

In Table 4 we report the results of a simple OLS estimation. Before discussing the effects of overqualification and skill mismatches, we briefly comment that the rest of variables included in the analysis show the expected results.

Considering the pooled sample, we find that in Europe having tertiary education¹³, an additional year of professional experience and more than ten years of tenure raises wages by 17.3%, 1.5% and 17.1%, respectively. Workers with a supervisory role earn a wage premium of 15.3%. Training participation and working in a large firm increase wages by 5% and 10%, respectively¹⁴. Wages are around 8.8% higher among married workers and 8.6% lower among those reporting bad health. A 10% increase in the working hours reduces (hourly) wages by about 5%. Finally, immigrants as well as workers with unemployment experience earn significantly less.

Next, we turn to the main focus of our analysis: the mismatch variables. As expected, amongst all employees, the overqualified earn, on average, less than individuals working in jobs for which they have an appropriate level of education, although, the effect in the pooled sample is very small: –1.2%. Two groups of countries can be observed. In the first group (Austria, Denmark, Germany, Spain and the UK), the pay penalty of overqualification exceeds 1% and is statistically significant, ranging from 1.3% in Denmark to 5.2% in the UK. In the second group (Belgium, Finland, France, Greece, Ireland, Italy and Portugal), the corresponding figure is below 1% and fails to be statistically significant¹⁵.

¹¹ Training, firm size and unemployment experience were dropped from this regression as these variables are not available for France, Germany, Greece or the UK.

¹² The use of a categorical variable to capture the mismatch effect is inspired in previous work by Verdugo, R., Verdugo, N. T. (1989), Dolton, Vignoles (2000) and Chevalier (2003). An alternative specification is the ORU model in which years of schooling are decomposed into required, surplus and deficit years of schooling in relation to those necessary to do the job. This approach, however, is not open to us as the ECHP does not contain sufficiently detailed information on occupational categories and years of schooling.

¹³ Although the schooling coefficient is not central in the analysis, the possible endogeneity problem of schooling produces that the estimates will be biased when individuals are not randomly assigned to completed schooling levels (Leuven, Oosterbeek 2011). Addressing these endogeneity problems is far from trivial. This is illustrated by Korpi, Tahlin (2009), one of the few studies using instrumental variable methods to estimate returns to over/underschooling. As an alternative method is to apply fixed effects techniques (Bauer 2002; Dolton, Vignoles 2000; Dolton, Silles 2008; Korpi, Tahlin 2009). See McGuinness (2006) for a review of these studies.

¹⁴ The estimates for these variables are not available for the pooled sample, so the results reported come from the inspection by country.

¹⁵ For estimates also based on ECHP data and similar definitions of mismatch, see Wasmer *et al.* (2007) and Dolton, Marcenaro-Gutierrez (2009). For a detailed examination of the overqualification effect among different education groups using Spanish data, see Budría, Moro-Egido (2008).

Table 4. The impact of overqualification and skill mismatch on wages. Average effects

Variables	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
Tertiary	0.173*** 0.007	0.210*** 0.03	0.164*** 0.016	0.081*** 0.014	0.114*** 0.021	0.245*** 0.016	0.011 0.017	0.208*** 0.017	0.152*** 0.027	0.213*** 0.016	0.401*** 0.03	0.140*** 0.01	0.222*** 0.025
Upper secondary	0.060*** 0.005	0.047*** 0.015	0.042*** 0.01	0.014 0.01	0.017 0.016	0.064*** 0.01	-0.047*** 0.013	0.090*** 0.01	0.067*** 0.016	0.061*** 0.007	0.132*** 0.013	0.052*** 0.008	0.024 0.018
Overqualification	-0.012*** 0.004	-0.021** 0.01	-0.005 0.009	-0.013* 0.008	0.000 0.012	0.014 0.009	-0.031*** 0.011	0.015* 0.009	0.011 0.014	-0.009 0.006	0.008 0.007	-0.015** 0.006	-0.052*** 0.016
Skill mismatch	-0.054*** 0.004	-0.025* 0.013	-0.006 0.009	-0.041*** 0.009	-0.051*** 0.012	-0.020** 0.009	-0.023* 0.013	-0.099*** 0.011	-0.063*** 0.016	-0.026*** 0.007	-0.063*** 0.01	-0.008 0.006	-0.063*** 0.018
Supervisor	0.153*** 0.007	0.141*** 0.016	0.098*** 0.013	0.086*** 0.011	0.035** 0.016	0.149*** 0.014	0.090*** 0.016	0.288*** 0.023	0.144*** 0.021	0.144*** 0.011	0.260*** 0.022	0.197*** 0.013	0.097*** 0.027
Training		0.052*** 0.011	0.049*** 0.01	0.002 0.009	0.061*** 0.012		0.081*** 0.011	0.147*** 0.02	0.083*** 0.017	0.073*** 0.009	0.100*** 0.015	0.093*** 0.009	0.129*** 0.016
Ln hours	-0.517*** 0.016	-0.346*** 0.043	-0.618*** 0.032	-0.403*** 0.041	-0.281*** 0.045	-0.483*** 0.037	-0.578*** 0.037	-0.407*** 0.03	-0.489*** 0.043	-0.495*** 0.025	-0.528*** 0.037	-0.598*** 0.021	-0.337*** 0.048
Experience	0.015*** 0.001	0.007*** 0.002	0.016*** 0.002	0.016*** 0.002	0.016*** 0.002	0.010*** 0.002	0.009*** 0.002	0.012*** 0.002	0.023*** 0.003	0.019*** 0.001	0.016*** 0.001	0.014*** 0.001	0.014*** 0.004
Experience^2 (x1000)	-0.288*** 0.003	-0.073*** 0.052	-0.290*** 0.039	-0.307*** 0.031	-0.295*** 0.052	-0.168*** 0.04	-0.194*** 0.043	-0.144*** 0.038	-0.416*** 0.066	-0.362*** 0.026	-0.304*** 0.03	-0.206*** 0.024	-0.264*** 0.073
5 ≤ Tenure < 10	0.105*** 0.005	0.059*** 0.012	0.011 0.01	0.031*** 0.009	0.031** 0.013	0.093*** 0.011	0.147*** 0.015	0.053*** 0.011	0.175*** 0.014	0.031*** 0.006	0.01 0.008	0.067*** 0.007	0.099*** 0.019
Tenure ≥ 10	0.171*** 0.005	0.059*** 0.012	0.053*** 0.011	0.021** 0.009	0.079*** 0.015	0.154*** 0.012	0.180*** 0.014	0.123*** 0.011	0.205*** 0.017	0.049*** 0.007	0.021** 0.009	0.125*** 0.009	0.132*** 0.019

Continued Table 4

Variables	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
Married	0.088*** 0.004	0.059*** 0.011	0.063*** 0.009	0.036*** 0.008	0.031*** 0.01	0.083*** 0.009	0.105*** 0.012	0.152*** 0.011	0.194*** 0.017	0.075*** 0.006	0.073*** 0.008	0.062*** 0.007	0.050*** 0.017
Immigrant	-0.020*** 0.010	-0.074*** 0.015	0.036** 0.017	-0.043* 0.024	-0.047* 0.024	-0.017 0.015	-0.027 0.014	-0.053*** 0.017	-0.01 0.032	-0.043** 0.018	0.009 0.021	-0.022 0.021	-0.034 0.037
20 ≤ Employees < 100		0.071*** 0.012	0.063*** 0.011	0.052*** 0.01	0.070*** 0.013				0.105*** 0.017	0.081*** 0.007	0.086*** 0.008	0.091*** 0.007	
100 ≤ Employees < 500		0.134*** 0.014	0.081*** 0.013	0.098*** 0.011	0.090*** 0.014				0.188*** 0.02	0.096*** 0.008	0.117*** 0.012	0.182*** 0.01	
Employees ≥ 500		0.138*** 0.019	0.116*** 0.013	0.114*** 0.011	0.131*** 0.021				0.191*** 0.027	0.108*** 0.011	0.172*** 0.016	0.231*** 0.012	
Badhealth	-0.086*** 0.013	-0.050 0.041	-0.061* 0.035	0.007 0.028	-0.034 0.048	-0.084*** 0.029	-0.061* 0.034	-0.119 0.05	-0.277** 0.124	-0.112*** 0.018	-0.134*** 0.017	-0.080*** 0.021	-0.162** 0.064
Unemployment		-0.017 0.011	-0.045*** 0.009	-0.046 0.008	-0.030*** 0.011	-0.092*** 0.009			-0.120*** 0.014	-0.051*** 0.006	-0.034*** 0.008	-0.058*** 0.006	
R-squared	0.969	0.326	0.505	0.415	0.384	0.465	0.346	0.475	0.403	0.493	0.513	0.528	0.415
No. of obs.	61,147	4,127	2,844	4,123	2,650	6,047	4,562	5,654	3,764	7,625	7,324	10,189	2,238

Notes: i) *denotes significant at the 10% level, **denotes significant at the 5% level, and ***denotes significant at the 1% level; ii) standard errors are in smaller type; iii) the estimates are heteroskedastic-robust; iv) all results control for industry, occupation and year-specific effects; v) the results for 'Europe' control for country-specific effects.

Interestingly, we find that skill mismatches are more harmful in terms of wages than overqualification. Specifically, the pay penalty of skill mismatch (5.4%) is 4.5 times higher than for overqualification (1.2%) in the pooled sample. By countries, the skill mismatch effect fails to be statistically significant only in Belgium and Spain, while in the remaining countries it ranges from -2.0% in France to -9.9% in Greece¹⁶.

Before turning to the quantile analysis, it is worth mentioning that an important feature of our approach is comparability. The overqualification effects reported in the literature differ largely, ranging from insignificant effects up to -30% (Hartog 2000; McGuinness 2006). Such variation implicitly puts forward the question of to what extent differences across studies reflect true differences rather than differences in the model specification, the use of different definitions of educational mismatch, diverging datasets and differently defined sample of individuals. Our results, which are fully comparable across countries, suggest that the extent of variation is lower than previously thought. Specifically, the mismatch pay penalty is found to be comprised in the $0-5\%$ interval.

4.2. Quantile estimates

In this section, we will concentrate on the quantile estimates emerging from our reference specification, i.e. the specification with the full set of controls and dummy variables for overqualification and skill mismatch.

Overqualification

Table 5 reveals some differences across quantiles. In Europe as a whole, the impact of overqualification on wages ranges from a non-significant -0.8% in the 0.10th quantile (Q10) to a significant -1.2% in the 0.90th quantile (Q90). Admittedly, this differential is rather low to deserve much attention. However, inspection by country uncovers larger differences in some cases. As is apparent, in the European labour market the effects of overqualification cannot be regarded as constant across the earnings distribution. Thus, for example, in the UK an average effect of -5.2% masks a non-significant -1.6% in the first quantile and -6.9% in the 0.75 quantile. Similarly, in Germany the estimates range from negligible effects in the lower segments of the distribution to a significant -3.8% in the top quantile. The case of Spain is a notable exception, as in this case none of the selected quantiles exhibits a statistical significant coefficient. This finding seems to be at odds with the statistical significance of the (arguably small) -1.5% reported in the previous section. However, it should not be so if we consider that QR estimates tend to be less precisely measured, particularly at the two tails of the distribution due to a lower number of observations with extreme values or earnings.

¹⁶ Dropping the skill mismatch variable from the estimating equation does not substantially alter the overqualification effects reported in the paper. This is partially due to the low correlation (-0.15 in the total sample) between the two mismatch measures.

Table 5. The overqualification effect at different segments of the wage distribution

	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
OLS	-0.012***	-0.021**	-0.005	-0.013*	0.000	0.014	-0.031***	0.015*	0.011	-0.009	0.008	-0.015**	-0.052***
	0.004	0.010	0.009	0.008	0.012	0.009	0.011	0.009	0.014	0.006	0.007	0.006	0.016
Q10	-0.008	-0.001	-0.007	0.000	0.024	0.008	-0.019	-0.008	0.022	0.003	0.010	-0.010	-0.016
	0.005	0.014	0.020	0.013	0.027	0.012	0.023	0.017	0.031	0.010	0.009	0.010	0.025
Q20	-0.002	-0.001	-0.025**	-0.012	-0.012	0.008	-0.009	-0.011	0.002	-0.002	0.018**	-0.009	-0.037*
	0.004	0.011	0.012	0.010	0.021	0.009	0.017	0.011	0.019	0.008	0.009	0.008	0.019
Q25	-0.006	0.001	-0.022**	-0.011	-0.020	0.005	-0.006	0.001	0.013	-0.007	0.015*	-0.009	-0.046***
	0.004	0.011	0.011	0.010	0.018	0.008	0.017	0.009	0.016	0.007	0.008	0.007	0.016
Q30	-0.008**	0.000	-0.021*	-0.012	-0.018	0.004	-0.019	0.008	0.013	-0.008	0.018**	-0.005	-0.034**
	0.004	0.011	0.011	0.010	0.013	0.009	0.017	0.009	0.014	0.006	0.009	0.007	0.014
Q40	-0.008**	-0.012	-0.025***	-0.020**	-0.008	0.006	-0.024*	0.015*	0.003	-0.006	0.020**	-0.007	-0.042**
	0.003	0.012	0.010	0.009	0.012	0.008	0.014	0.009	0.012	0.006	0.008	0.008	0.016
Q50	-0.010***	-0.018	-0.022**	-0.020**	-0.015	0.004	-0.029**	0.022**	0.011	-0.005	0.010	-0.005	-0.037**
	0.003	0.012	0.009	0.009	0.013	0.008	0.012	0.009	0.012	0.005	0.008	0.007	0.017
Q60	-0.011***	-0.027**	-0.019**	-0.022**	-0.005	0.006	-0.020*	0.025**	0.009	-0.010*	0.009	-0.002	-0.043**
	0.003	0.012	0.009	0.009	0.012	0.010	0.011	0.010	0.012	0.005	0.009	0.007	0.018
Q70	-0.011***	-0.041***	-0.010	-0.025***	-0.009	0.018*	-0.023**	0.033***	0.009	-0.007	0.003	-0.008	-0.066***
	0.004	0.011	0.010	0.009	0.016	0.011	0.011	0.011	0.013	0.005	0.009	0.008	0.019
Q75	-0.011***	-0.044***	-0.002	-0.026***	-0.013	0.016	-0.020*	0.031***	0.018	-0.005	0.002	-0.011	-0.069***
	0.003	0.013	0.010	0.010	0.015	0.011	0.012	0.012	0.013	0.006	0.010	0.008	0.021
Q80	-0.007**	-0.051***	0.012	-0.030***	-0.017	0.019	-0.013	0.025*	0.026**	-0.007	0.002	-0.013	-0.064***
	0.004	0.014	0.012	0.011	0.015	0.012	0.014	0.013	0.013	0.008	0.011	0.008	0.022
Q90	-0.012**	-0.038**	0.035**	-0.017	-0.009	0.025	-0.038**	0.013	0.026	-0.021**	0.025	-0.015	-0.044*
	0.005	0.017	0.016	0.015	0.018	0.016	0.015	0.017	0.017	0.010	0.016	0.011	0.027
No. of obs.	61,147	4,127	2,844	4,123	2,650	6,047	4,562	5,654	3,764	7,625	7,324	10,189	2,238

Notes: i) *denotes significant at the 10% level, **denotes significant at the 5% level, and ***denotes significant at the 1% level; ii) standard errors are in smaller type; iii) OLS estimates are heteroskedastic-robust; iv) standard errors of quantile estimates have been calculated using a bootstrap method with 500 replications; v) all results control for industry, occupation and year-specific effects; vi) the results for 'Europe' control for country-specific effects.

In Table 6 we test whether variations across quantiles are significant at conventional confidence levels. The results for the pooled sample are clear cut. According to the pair-wise tests, the differential between any two of the selected quantiles is statistically significant.

Table 6. Tests for the equality of coefficients at different quantiles (p-values). Overqualification

EUROPE	Q25	Q50	Q75	Q90	Joint equality						
Q10	0.00	0.00	0.00	0.00	0.00						
Q25		0.00	0.00	0.00							
Q50			0.00	0.00							
Q75				0.00							
AUSTRIA	Q25	Q50	Q75	Q90	Joint equality	BELGIUM	Q25	Q50	Q75	Q90	Joint equality
Q10	0.82	0.25	0.01	0.08	0.03	Q10	0.35	0.43	0.81	0.11	0.01
Q25		0.09	0.00	0.04		Q25		0.96	0.09	0.00	
Q50			0.02	0.26		Q50			0.04	0.00	
Q75				0.71		Q75				0.01	
DENMARK						FINLAND					
Q10	0.36	0.13	0.07	0.33	0.33	Q10	0.06	0.12	0.17	0.28	0.28
Q25		0.27	0.17	0.72		Q25		0.67	0.69	0.62	
Q50			0.53	0.80		Q50			0.91	0.77	
Q75				0.45		Q75				0.83	
FRANCE						GERMANY					
Q10	0.74	0.76	0.62	0.39	0.60	Q10	0.53	0.65	0.96	0.46	0.38
Q25		0.97	0.30	0.19		Q25		0.10	0.42	0.13	
Q50			0.22	0.14		Q50			0.49	0.58	
Q75				0.47		Q75				0.20	
GREECE						IRELAND					
Q10	0.55	0.06	0.04	0.36	0.03	Q10	0.71	0.71	0.90	0.90	0.92
Q25		0.01	0.01	0.50		Q25		0.88	0.78	0.53	
Q50			0.38	0.55		Q50			0.58	0.41	
Q75				0.23		Q75				0.59	
ITALY						PORTUGAL					
Q10	0.21	0.30	0.37	0.04	0.27	Q10	0.50	0.95	0.55	0.36	0.34
Q25		0.74	0.84	0.17		Q25		0.54	0.24	0.54	
Q50			0.96	0.09		Q50			0.35	0.35	
Q75				0.08		Q75				0.09	
SPAIN						UK					
Q10	0.92	0.62	0.93	0.71	0.87	Q10	0.21	0.47	0.08	0.45	0.31
Q25		0.53	0.84	0.63		Q25		0.59	0.24	0.96	
Q50			0.42	0.34		Q50			0.08	0.81	
Q75				0.63		Q75				0.40	

Notes: i) The element in the Q_j column and the Q_i row is the p-value of a pair-wise test between the estimates at the j and the i quantiles, $H_0 : \beta_j = \beta_i$, $H_1 : \beta_j \neq \beta_i$; ii) the joint equality test reports the p-value of the F-test $H_0 : \beta_{0.10} = \beta_{0.20} = \dots = \beta_{0.90}$, $H_1 : \beta_m \neq \beta_n$; for some $m \neq n$; iii) p-value <0.10: significant at the 10% confidence level, p-value <0.05: significant at the 5% confidence level, p-value <0.01: significant at the 1% confidence level.

Similarly, the F-test reported in the last column indicates that differences across all quantiles are jointly significant¹⁷. By country, and using the 10% confidence level as a threshold for significant and non-significant, we find that in Austria, Belgium and Greece the F-statistics and the pair-wise tests reject the null hypothesis of joint equality of coefficients. In the remaining countries we find that although differences are not significant at the joint level, some differences emerge across quantiles. This is the case of Denmark (Q10-Q75), Finland (Q10-Q25), Germany (Q25-Q50), Italy (Q50-Q90, Q75-Q90) and the UK (Q10-Q75, Q50-Q75).

Among countries where differences across quantiles are significant, we detect two different profiles. On the one hand, the overqualification pay penalty in Austria, Denmark, Italy and the UK tends to be increasing when moving up the wage distribution. In these countries, the estimates go from insignificant in the lower quantiles to significant in the upper quantiles, and the largest effect (–5.1% in Austria, –3.0% in Denmark, –2.1% in Italy and –6.9% in the UK) is seen within the upper segment of the distribution (Table 5). This increasing profile is less apparent in Europe and Germany. In these cases, however, the estimates at Q90 and Q75 are, again, larger than at Q10 and Q25, respectively. On the other hand, we have Belgium and Greece, where the pay penalty of overqualification tends to be lower at the upper than at the lower quantiles of the earnings distribution. Finally, in Finland, France, Ireland and Spain, the impact of overqualification on wages fails to be significant in almost every quantile. Not surprisingly, we cannot reject the equality of coefficients across the distribution in these countries.

Skill mismatch

A glance at Table 7 indicates that the extent of variation across quantiles is larger for the skill mismatch effect than for the overqualification effect. Consistent with this finding, the p-values reported in Table 8 show that in many cases we reject the equality of coefficients. Thus, for example, in Austria, Belgium, France, Germany and Portugal as well as in the pooled sample the F-test indicates that differences across all quantiles are statistically significant, thus confirming the pair-wise tests. Still, in the remaining countries (Denmark, Finland, Greece, Ireland, Italy, Spain and the UK) we do not detect relevant differences across quantiles. In these countries, therefore, the effect of skill mismatch on wages can be reasonably described in an average sense.

Despite the fact that variations across quantiles are generally erratic, some general profiles can be drawn. Among the countries where differences across segments of the distribution are significant (Europe, Austria, Belgium, France, Germany and Portugal) we detect different profiles. First, in Austria and Belgium, the estimated pay penalty tends to be decreasing as we move up the earnings distribution. Second, in Europe, Germany and Portugal, the pay penalty tends to be higher at the upper than at the lower quantiles. Thus, for example, when moving from the bottom to the upper quantile, the pay penalty of skill mismatches rises from 2.3% to 4.1% in Europe, from a non-significant effect to a significant 3.5% in Germany and from 6.5% to 10.5% in Portugal. Finally, in France the estimated profile is u-shaped.

¹⁷ This outcome may seem surprising as some of the differences across quantiles are rather low. However, it should not be so if we take into account the large number of observations involved in the tests of the pooled sample (61,147). This leads to very low standard errors of the estimated coefficients and rejection of the null hypothesis (equality of coefficients).

Table 7. The skill mismatch effect at different segments of the wage distribution

	EUROPE	AUSTRIA	BELGIUM	DENMARK	FINLAND	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN	UK
OLS	-0.054*** 0.004	-0.025* 0.013	-0.006 0.009	-0.041*** 0.009	-0.051*** 0.012	-0.020** 0.009	-0.023* 0.013	-0.099*** 0.011	-0.063*** 0.016	-0.026*** 0.007	-0.063*** 0.01	-0.008 0.006	-0.063*** 0.018
Q10	-0.023*** 0.006	-0.040** 0.018	-0.008 0.016	-0.051*** 0.015	-0.040** 0.020	-0.016 0.015	0.032 0.024	-0.081*** 0.016	-0.092*** 0.035	-0.032*** 0.011	-0.065*** 0.012	-0.017 0.011	-0.058** 0.03
Q20	-0.033*** 0.004	-0.053*** 0.014	-0.025** 0.011	-0.045*** 0.010	-0.057*** 0.018	-0.020* 0.011	-0.009 0.016	-0.077*** 0.015	-0.052*** 0.02	-0.020** 0.01	-0.037*** 0.012	-0.006 0.008	-0.048*** 0.018
Q25	-0.040*** 0.004	-0.058*** 0.013	-0.026*** 0.010	-0.046*** 0.010	-0.054*** 0.018	-0.026*** 0.009	-0.024* 0.015	-0.090*** 0.014	-0.055*** 0.018	-0.020** 0.009	-0.039*** 0.011	-0.007 0.007	-0.062*** 0.021
Q30	-0.042*** 0.004	-0.054*** 0.013	-0.028*** 0.010	-0.035*** 0.010	-0.054*** 0.017	-0.037*** 0.009	-0.039*** 0.014	-0.101*** 0.014	-0.046*** 0.016	-0.027*** 0.008	-0.043*** 0.01	-0.008 0.007	-0.077*** 0.021
Q40	-0.042*** 0.004	-0.044*** 0.014	-0.011 0.010	-0.032*** 0.01	-0.050*** 0.016	-0.039*** 0.008	-0.037*** 0.014	-0.098*** 0.012	-0.057*** 0.014	-0.022*** 0.008	-0.044*** 0.012	0 0.007	-0.063*** 0.022
Q50	-0.042*** 0.004	-0.041*** 0.014	0.000 0.010	-0.036*** 0.009	-0.051*** 0.013	-0.041*** 0.008	-0.03** 0.015	-0.098*** 0.013	-0.055*** 0.016	-0.022*** 0.007	-0.048*** 0.012	0.002 0.008	-0.064*** 0.02
Q60	-0.043*** 0.003	-0.036** 0.015	-0.006 0.010	-0.040*** 0.009	-0.063*** 0.012	-0.046*** 0.009	-0.029** 0.014	-0.114*** 0.014	-0.043** 0.018	-0.020*** 0.007	-0.060*** 0.012	0.002 0.008	-0.061*** 0.024
Q70	-0.044*** 0.004	-0.018 0.016	-0.002 0.011	-0.040*** 0.01	-0.054*** 0.016	-0.040*** 0.009	-0.035*** 0.013	-0.113*** 0.012	-0.037** 0.016	-0.019*** 0.008	-0.060*** 0.015	0 0.008	-0.046** 0.021
Q75	-0.047*** 0.004	-0.008 0.020	-0.005 0.012	-0.034*** 0.011	-0.049*** 0.015	-0.035*** 0.009	-0.033*** 0.013	-0.113*** 0.013	-0.054*** 0.016	-0.023*** 0.009	-0.070*** 0.017	-0.001 0.008	-0.072*** 0.022
Q80	-0.047*** 0.004	-0.006 0.021	-0.009 0.012	-0.035*** 0.012	-0.036** 0.015	-0.034*** 0.011	-0.035*** 0.014	-0.110*** 0.016	-0.053*** 0.015	-0.028*** 0.01	-0.101*** 0.022	-0.007 0.009	-0.071*** 0.024
Q90	-0.041*** 0.006	0.001 0.024	0.011 0.020	-0.038*** 0.015	-0.025 0.022	-0.013 0.013	-0.035* 0.02	-0.091*** 0.026	-0.064*** 0.021	-0.031*** 0.012	-0.105*** 0.021	0 0.01	-0.045 0.037
No. of obs.	61,147	4,127	2,844	4,123	2,650	6,047	4,562	5,654	3,764	7,625	7,324	10,189	2,238

Notes: i) *denotes significant at the 10% level, **denotes significant at the 5% level, and ***denotes significant at the 1% level; ii) standard errors are in smaller type; iii) OLS estimates are heteroskedastic-robust; iv) standard errors of quantile estimates have been calculated using a bootstrap method with 500 replications; v) all results control for industry, occupation and year-specific effects; vi) the results for 'Europe' control for country-specific effects.

Table 8. Tests for the equality of coefficients at different quantiles (p-values). Skill mismatch

EUROPE	Q25	Q50	Q75	Q90	Joint equality						
Q10	0.00	0.00	0.00	0.00	0.00						
Q25		0.00	0.00	0.00							
Q50			0.00	0.00							
Q75				0.00							
AUSTRIA	Q25	Q50	Q75	Q90	Joint equality	BELGIUM	Q25	Q50	Q75	Q90	Joint equality
Q10	0.28	0.95	0.22	0.14	0.07	Q10	0.20	0.65	0.88	0.44	0.06
Q25		0.21	0.01	0.02		Q25		0.00	0.09	0.07	
Q50			0.05	0.06		Q50			0.66	0.58	
Q75				0.63		Q75				0.37	
DENMARK						FINLAND					
Q10	0.70	0.62	0.31	0.54	0.79	Q10	0.45	0.62	0.71	0.59	0.65
Q25		0.29	0.33	0.64		Q25		0.82	0.80	0.22	
Q50			0.85	0.84		Q50			0.92	0.22	
Q75				0.69		Q75				0.22	
FRANCE						GERMANY					
Q10	0.38	0.09	0.27	0.89	0.09	Q10	0.01	0.01	0.01	0.02	0.08
Q25		0.12	0.47	0.43		Q25		0.69	0.60	0.64	
Q50			0.51	0.04		Q50			0.81	0.82	
Q75				0.05		Q75				0.92	
GREECE						IRELAND					
Q10	0.53	0.31	0.10	0.74	0.24	Q10	0.23	0.26	0.32	0.46	0.78
Q25		0.53	0.13	0.97		Q25		0.99	0.97	0.68	
Q50			0.22	0.79		Q50			0.97	0.63	
Q75				0.27		Q75				0.56	
ITALY						PORTUGAL					
Q10	0.20	0.36	0.50	0.95	0.68	Q10	0.03	0.02	0.77	0.07	0.01
Q25		0.81	0.81	0.44		Q25		0.31	0.08	0.00	
Q50			0.93	0.46		Q50			0.12	0.01	
Q75				0.49		Q75				0.05	
SPAIN						UK					
Q10	0.30	0.11	0.17	0.21	0.58	Q10	0.87	0.83	0.68	0.78	0.95
Q25		0.22	0.50	0.54		Q25		0.93	0.71	0.64	
Q50			0.73	0.87		Q50			0.72	0.62	
Q75				0.92		Q75				0.45	

Notes: The element in the Q_j column and the Q_i row is the p-value of a pair-wise test between the estimates at the j and the i quantiles; ii) the joint equality test reports the p-value of the F-test for some $m \neq n$; iii) p-value <0.10: significant at the 10% confidence level, p-value <0.05: significant at the 5% confidence level, p-value <0.01: significant at the 1% confidence level.

5. Discussion

Our results indicate that, in general, the wage effects of educational mismatches cannot be well described in an average sense. The estimates exhibit variation across individuals that have the same observable characteristics but are located at different quantiles of the earnings distribution. There are several factors that can potentially account for this observation.

Arguably, differences in the degree of mismatch, field of education, and the interaction between mismatched work and specific job characteristics may affect individual's earnings in an important manner. In the same vein, contextual, workplace and region characteristics may play a role here. Consistent with this view, Green *et al.* (1999) and McGuinness (2003a) find that the mismatch between actual skills and skills required for the job is lower among graduates from technical and scientific fields and higher among graduates from the humanities and arts. In the present study, however, we do not explore these dimensions due to data limitations.

There is, however, one important avenue that we can explore. Unobserved earnings capacity is arguably determined by contextual characteristics, including ethnicity, workplace conditions and geographical location, among other factors, as well as by individual-level capacities, including marketable skills, academic credentials and motivations that allow a worker to earn a higher wage given a vector of observable characteristics¹⁸. Having the labour market segmented by deciles, with an individual's earnings capacity given by his or her position in the conditional distribution, the estimates at different quantiles provide snapshots of how mismatched individuals within the different capacity groups are impacted. Interestingly, we find that overqualification and skill mismatches are events that reduce wages amongst all groups. If overqualification and skill mismatches were simply a consequence of low earnings capacity and the lack of marketable skills, then their influence should be restricted to the lower segments of the earnings distribution. In contrast, we find that individuals with high unobservable earnings capacity are exposed to significant wage losses if they end up in jobs for which they are overqualified or, alternatively, in jobs for which they lack the necessary skills. Indeed, in several countries, the pay penalty of educational mismatches is *larger* precisely among workers in the upper range of the unconditional earnings distribution. As shown in the previous section, this is the case of Europe, Austria, Denmark, Germany, Italy and the UK (overqualification) and Europe, Germany and Portugal (skill mismatch).

An interesting issue is whether the patterns reported in the present paper differ between education groups. In computations not reported here we found that workers with a university degree are exposed to larger wage decreases if they enter in jobs for which they are overqualified or skills mismatched (−4.8% and −11.7%, respectively, for Europe as a whole). These figures more than double the average estimates reported in Table 4. As a related finding, the pattern and extent of variation across quantiles also differs sensitively across education groups. Specifically, differences across quantiles were generally very small among individuals with less than upper secondary education, and relatively large among individuals with a tertiary education. This matches a priori expectations, for in the labour market the extent of wage variation among workers with less education is more limited. In Europe as a whole, the incidence of skills mismatch among university graduates entails a wage penalty that ranges from −9.7% to −14.7% across the earnings distribution. Similar levels of variation were found in most countries in the sample (Belgium, Denmark, Finland, France, Ireland and the UK). In auxiliary calculations, we tested whether such differences across the distribution were significant at conventional confidence levels and found 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. We must note however that this

¹⁸ We thank an anonymous referee for his or her insights on the role of contextual characteristics.

exercise must be regarded as exploratory, for discriminating between education groups comes at the cost of reduced cell size. Thus, for example, the number of skills mismatched workers drops from 29,717 in the total sample to 2,623 when we consider only the group of workers with an university education. This observation leads us to interpret the results for specific education groups with some caution.

Using data from Northern Ireland, McGuinness, Bennet (2007) find that the pay penalty of overqualification tends to be decreasing, not increasing, as pay rises. Our results for Europe confirm this finding in only a few cases. This may be due to the fact that McGuinness, Bennet base their results on a sample of recent graduates, among which the overqualified status is more likely to have a transient nature. It may be the case that among this group the overeducated are either high-ability individuals who accept mismatched work to access high-level occupations (and high wages) or low-ability individuals who, immediately after graduation, enter low-level jobs while they search for other more suitable jobs. This would be consistent with having decreasing effects of overqualification over the wage distribution. Another difference is that McGuinness, Bennet (2007) base their results on the overqualification/non-overqualification distinction, while we additionally control for skill mismatches.

Theoretical implications

All in all, we found evidence to suggest that the mismatch phenomenon entails wage losses over and above those attributable to the unobserved earnings capacity of workers. The overqualified and, more broadly, the educational mismatched, are a distinct subset of any earnings capacity group, earning less than similarly educated peers. Taken together, these observations give support to the view that educational mismatches represent a complex phenomenon in which workers with very different backgrounds, contexts and skills see their productivity potential constrained by the job class.

From a theoretical perspective, the results give support to the Assignment Theory interpretation of the labour market (Sattinger 1993), according to which marginal product and hence earnings depend on both the individual and the job characteristics. Educational attainment and the job requirements, reflected in the mismatch status, are equally relevant for wage determination. This applies to every segment of the wage distribution. The results can hardly be reconciled with the Human Capital perspective that earnings are solely determined by the individual's education. We found that mismatched work diminishes the premium to education, particularly at the upper segment of the earnings distribution. Similarly, the results are at odds with the Job Competition paradigm (Thurow 1975), according to which wage rates are wholly related to the job class. This does not seem to be the case of high-paid jobs, where the worker's mismatch status is relevant for wage determination.

Conclusions

In this paper we used international, comparable data from 12 countries and a common earnings equation to examine the wage effects of educational mismatches across segments of the earnings distribution. We differentiated between two types of mismatch, excess education

and skills shortages. This distinction is supported by the fact that a significant fraction of apparently overeducated workers lack skills that are necessary in their jobs. We found that, in general, the earnings gap between matched and mismatched workers cannot be regarded as constant across the earnings distribution.

This result provides some insights into the causes and consequences of the mismatch phenomenon. First, it shows that seemingly equal individuals can be exposed to different pay penalties depending on their relative position in the earnings distribution. Researchers and policy makers should take this heterogeneity into account when attempting to ascertain the impact of educational mismatches on different population groups and on the total earnings distribution. To that end, focusing on averages may be seriously misleading.

Second, most of the debate in the policy arena has gravitated around the question of to what extent the incidence of mismatch entails a productivity loss. It is very difficult to determine whether the lower earnings observed for mismatched workers are caused by their mismatch, or whether individuals with lower earnings capacity end up in mismatched work. Several papers have explored this issue using panel data (Bauer 2002), proxies of skills (Chevalier 2003; McGuinness 2003b) and treatment effect models (Dolton, Silles 2008). In this paper we have provided an alternative view using QR. We have found evidence to suggest that characterizing the mismatch phenomenon as merely reflecting lower earnings capacity is an oversimplification. Workers with favourable earnings conditions can be heavily penalized in mismatched jobs. We claim, therefore, that educational mismatches are to a large extent the result of real inefficiencies in which the worker's productivity potential is constrained by the job productivity ceiling.

Third, there is substantial heterogeneity between education groups regarding the overqualification and skills mismatch prevalence rates. Relative to the low-educated, the high-educated are about 1.6 times more likely to be overqualified and 4 times less likely to be skills mismatched. This observation indicates that the two forms of mismatch refer to quite different phenomena and tend to affect workers with different education backgrounds. Researchers and policy makers should take this heterogeneity into account when attempting to prevent and reduce the labour market consequences of educational mismatches. According to the results, training policies oriented towards the acquisition of job-related skills may be particularly helpful among workers from the vocational sector or in low-skills jobs.

Fourth, there is evidence to suggest that the extent of variation in the wage effects of overqualification and skill mismatches across quantiles of the earnings distribution differs across countries. We can speculate that differences in labour market and educational institutions, the distribution of skills and educational qualifications, and the integration between schooling systems and labour markets translate into differences in the pay structure and, more specifically, into asymmetries across the distribution. Thus, for example, if the pay penalty of mismatch is related to the worker's unobserved ability, then we should observe more dispersion in countries where unobserved skills and abilities are more evenly spread within educated workers. Similarly, differences in the quality and type of educational qualifications across countries are likely to shape the extent of mismatch in the labour market and its impact on workers with different abilities. Clearly, further information on education and skills requirement in the job is needed in order to investigate these issues.

A limitation of the paper is that, given its international scope, it does not explore selection issues. Therefore, the mismatch estimates can be criticized 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. This would allow us to remove from the mismatch effect factors that simultaneously determine wages and the probability of mismatch. However, in our dataset we could not find instruments highly correlated with the probability of mismatch that were uncorrelated with earnings.

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APPENDIX

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. Individuals report personal and labour market characteristics, including educational attainment, hours worked and gross monthly wages. We have dropped workers with a monthly wage rate that is less than 10% or over 10 times the national average wage. Less than 0.2% of the working population is affected by this correction for outliers. The results reported in the paper are based on the pooled waves from 1994 to 2001. We could not include Sweden and the Netherlands in the analysis as the information on overqualification was missing for these countries. Luxembourg was not considered due to the small number of observations available. In what follows we describe the variables used in the paper, including their original name in the ECHP (in parenthesis).

Gross hourly wage. Defined as monthly gross salary in the main job divided by four times the weekly hours worked in the main job (PI211G, PE005A).

Tertiary and Upper secondary education. Two dummy variables that are activated if the maximum level of education completed by the individual is, respectively, tertiary and upper secondary education. The ECHP includes only three educational categories: less than upper secondary, upper secondary, and tertiary education. These educational categories are constructed following the ISCED-97 classification (PT022).

Overqualification. Dummy that is activated if the individual declares that he has more skills or qualifications to do a more demanding job than the one he has at the time of the interview (PE016).

Skill mismatch. Dummy that is activated if the individual declares that his or her formal training and education did not give him the skills required for his or her present type of work (PE021).

Supervisor. Dummy that is activated if the individual has a supervisory role in his or her job; zero if he has an intermediate level or a non-supervisory role (PE010).

Training. Dummy that is activated if the individual received training from his or her employee (PT028).

Log hours. Logarithm of the number of hours worked per week in the main job. (PE005A).

Experience. Defined as age minus the age when the first job was obtained (PE003, PE039).

Tenure. Defined as the difference between the year of the survey and the year of the start of the current job. We have constructed three categories: 0 to 4 years, 5 to 14 years, and 15 years or more (PE011).

Married. Dummy variable that takes the value of 1 if the individual is married or cohabiting; zero if divorced, widowed, separated or never married (PD005).

Immigrant. Dummy that is activated if the individual was born in a foreign country (PM001).

Industry. Dummy that takes the value of 1 if the individual works in the industrial sector, zero if he works in the service sector. The agricultural sector was dropped on account of the particular characteristics of this sector (PE007C).

Firm size. Individuals are asked to report the number of employees that actually work in their firm. We have constructed four categories: 1 to 19 employees, 20 to 99 employees, 100 to 499 employees, and 500 employees or more (PE008).

Badhealth. Individuals are asked to report their health status according to five categories ranging from ‘very good’ to ‘very bad’. Badhealth is a dummy that is activated when the answer is 1 (‘very bad’) or 2 (‘Bad’) (PH001).

Unemployment experience. Dummy that takes the value of 1 if the individual experienced an unemployment period before his or her current job, and zero otherwise (PE014).

Occupation. A 9-point categorical variable transformed into 9 occupation dummies (PE006C).

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