Wage effects of cognitive skills and educational mismatch in ten European countries

Lucía Mateos Romero (Universidad de Extremadura)

Inés P. Murillo Huertas (Universidad de Extremadura)

Mª del Mar Salinas Jiménez (Universidad de Extremadura)

Javier Salinas Jiménez (Universidad Autónoma de Madrid)

Abstract

This paper aims to analyze the returns to education and educational mismatch in ten European countries taking account not only of years of education but also of basic skills that workers have actually acquired. Using PIAAC database, the results indicate that both years of education and skills contribute to determine wages, with higher returns to years of education as the level of skills increases. It is also found that returns to years of required education and educational mismatch vary depending on the skills acquired by workers, with a higher premium to years of over-education among workers with higher levels of skills. These results tend hence to support the hypothesis of skills heterogeneity and highlight the need of taking account of individuals' skills when analyzing the returns to education and educational mismatch.

Keywords: educational mismatch; cognitive skills; educational performance.

JEL Classification: I21; J31

1. Introduction

The study of the economic effects of education has known a great interest since the development of human capital theory, in the middle of the 1960s, with the decisive contributions by Schultz (1960, 1962), Becker (1964), or Mincer (1974). According to this theory, education can be considered as a form of investment and its returns will depend on the economic effects of education in terms of higher productivity, which in turn will result in a greater probability of employment, better working conditions and higher wages throughout the individual's working life. The empirical literature largely confirms these positive effects of investment in human capital, both from a macroeconomic perspective, emphasizing the positive influence of human capital on productivity and economic growth (Barro, 1991; Mankiw et al. 1992), and from a microeconomic perspective, pointing to positive individual returns in terms of employment conditions and higher wages (see Card, 1999; and Harmon et al., 2003).

However, there is a growing dissatisfaction with the use of variables related to formal education (such as completed levels of education or years of schooling) as a proxy for human capital since these variables might not reflect the skills actually acquired by individuals. In this sense, Borghans et al. (2001) highlight that similar investments in education may lead to the acquisition of different levels of skills by different individuals or to the acquisition of skills which can be rewarded by the market in different ways. Moreover, as a result of mismatches, the labor market might not take advantage of all the skills acquired by individuals. In addition, these authors highlight that the acquisition (and also the depreciation) of skills continues after schooling, so the educational variables do not actually reflect the available individuals skills at any given time.

In this context, the analysis of the economic effects of human capital has recently advanced with the development of standardized tests to measure the skills actually acquired by individuals. At the macro level, several works on human capital and economic growth highlights the role played by acquired skills, and not only by years of schooling, on productivity growth (Hanushek and Kimko, 2000; Barro, 2001; Hanushek and Woessmann, 2008). At the micro level, the empirical evidence also confirms the role of skills on the probability of employment and on received wages (see, for example, McIntosh and Vignoles, 2001; or Green and Riddell, 2003).

Besides, most developed countries have made substantial investments in education and schooling and higher education participation rates have increased markedly in recent decades. However, part of the knowledge acquired through education might be underused if it does not match with the labor market requirements. Thus, considering the labor market supply and demand sides together, one finds that the educational mismatch has grown in most of the developed countries (see McGuiness, 2006).

The literature that examines the economic effects of the educational mismatch has already a long tradition, dating back to the seminal work by Duncan and Hoffman (1981), where a distinction is made between the educational level attained by the individuals and that required to perform their job. The empirical evidence tends to confirm that both the human capital accumulated by individuals and the job requirements affect wages, with overeducated workers receiving higher wages than their properly matched coworkers but lower wages than the individuals who, with the same level of education, carry out a job for which they are properly educated (for a comprehensive review of this literature, see Hartog, 2000).

It is often argued, however, that part of the educational mismatch could actually reflect differences in skills acquired by individuals with similar levels of education. Some authors hence defend the need to take account of skills heterogeneity when analyzing educational mismatch. In this line, Chevalier (2003) differentiates between 'apparently' overeducated workers, who possess a higher educational level than that required for their job but who show similar levels of skills as their properly educated coworkers, and 'genuinely' overeducated workers, who do indeed suffer an underutilization of their skills at work.

Allen and Van der Velden (2001) also highlight the differences in human capital accumulated by individuals who achieve similar levels of education and analyze to what extent educational mismatch does correspond to a mismatch in skills. When studying the economic effects of labor mismatch, these authors point to educational mismatch and skills mismatch as being different phenomena, with educational mismatch significantly affecting wages while skill mismatch shows a greater impact on job satisfaction and on the probability of quitting a job. Other studies also tend to confirm these differences between educational and skill mismatches (Di Pietro and Urwin, 2006; Green and McIntosh, 2007), suggesting that there is not a univocal relationship between education and skills.

However, studies analyzing the economic effects of education taking account of skills actually acquired by the individuals are relatively scarce, probably due to the lack of statistical data. Recently, the OECD has developed the Programme for the International Assessment of Adult Competencies (PIAAC)[1], which offers valuable data that allows one to analyze the economic effects of education taking account not only of the amount of education received but also of its quality as reflected in the acquisition of

[1] Other OECD programs prior to PIAAC (2013-nowadays) were IALS (1994-1998) and ALLS (2003-2006).

cognitive skills. In this context, the objective of this study is to analyze the economic effects of education and educational mismatch in ten European countries[2] considering both the years of schooling and the core skills actually acquired by the individuals. The rest of the paper is structured as follows. Section 2 briefly presents the theoretical framework to analyze the economic effects of education at the microeconomic level. Section 3 develops the empirical analysis, presenting the database and the variables used in this study and then discussing the main empirical results. The paper closes with a section summarizing the main conclusions of the study.

2. Theoretical framework: the analysis of returns to education

We find different theories underlying the origin of differences in productivity and wages and the possible existence of educational mismatch. The human capital theory assumes that an individual's wage in the labor market depends on her marginal productivity, which is determined by the human capital accumulated through formal education, on-the-job training, and experience (Schultz, 1960; Becker, 1964). According to this approach mismatches between demand and supply in the labor market are a temporary phenomenon since, in the long-run, returns will adjust to workers productivity.

From a different perspective, the job competition model (Thurow, 1975) assumes that job characteristics determine wages since most of the workers' skills are acquired in the workplace and not through formal education. In this sense, individuals invest in education not with the aim of increasing their productivity but to compete for the best available jobs. Overeducation is explained, in this context, as a response of the

[2] Belgium, Czech Republic, Denmark, Finland, Italy, Netherlands, Norway, Poland, Slovak Republic and Spain,

individuals to defend their relative position in the labor market. In a similar vein, the signaling theory (Spence, 1973) suggests that individuals invest in education to send signals to employers about their abilities. The idea behind this theory is that employers can not directly observe workers' skills, so they form their expectations about workers' productivity according to their educational achievements.

Finally, the assignment theory (Sattinger, 1993) takes into account both the supply and the demand sides of the labor market, with wages being determined by both job and individual productive characteristics. This theory explains wage differences considering that job characteristics limit and impose a ceiling to individual productivity, so the degree in which workers can use their skills will depend, at least to some extent, on the characteristics of the job.

The empirical analysis of these theories bases on the framework proposed by Mincer (1974), with the estimation of a wage equation that relates individuals' years of schooling and experience with their earnings. The basic equation to estimate is as follows:

$$\ln(w_i) = \alpha + \beta S_i + \gamma_1 E_i + \gamma_2 E_i^2 + \delta X + u_i \qquad (1)$$

where w represents the wage received by individuals (i), S refers to years of schooling, E is the experience get in the labor market and u is an error term. Besides, X is a vector of control variables usually included in the estimations (e.g. individual, job or industry characteristics).

In order to assess whether there are differences in returns to education depending on the job's requirements, Duncan and Hoffman (1981) proposed a variant of the mincerian wage equation where years of schooling (S) are decomposed into years of required education in the workplace (Sr), years of over-education (So) and years of undereducation (*Su*). This specification, usually known as ORU (Over-, Required-, and Under-education), takes the following form:

$$\ln(w_i) = \alpha + \beta_o S_{oi} + \beta_r S_{ri} + \beta_u S_{ui} + \gamma_1 E_i + \gamma_1 E_i^2 + \delta X + u_i \qquad (2)$$

According to this specification wages are determined both by the labor demand (*Sr*) and by the deviations between the demand and supply sides (*So* and *Su*), which provides a more general framework to estimate returns to education. This specification has also the advantage of allowing different returns to years of required, over- and under-education rather than imposing a single rate of return to every year of schooling.

3. Empirical analysis

To analyze the economic effects of education we estimate different specifications of models (1) and (2), taking account not only of years of education but also of the level of skills actually acquired by the individuals. The analysis is done for a pool of ten European countries and grouping them in more homogeneous blocs (Nordic, Mediterranean, Continental and Eastern blocs)[3].

Estimates are run using the PIAAC database, developed by the OECD (OECD, 2013)[4]. This database aims to study the skills of adult population and provides detailed information on various socio-demographic variables (e.g. age, gender, marital status, nationality) and on the training and employment characteristics of individuals (e.g. education, employment status, experience, wage and overqualification). PIAAC assesses three basic skills: literacy, numeracy and problem solving in technology-rich environments, although this last skill was not evaluated in several countries. In order to

[3] Nordic bloc: Denmark, Finland and Norway; Mediterranean bloc: Italy and Spain; Continental bloc: Belgium and Netherlands; Eastern bloc: Czech Republic, Poland and Slovak Republic.

[4] All technical information and access to the PIAAC database can be found in http://www.oecd.org/skills/piaac/publicdataandanalysis/

assess these basic skills, a test is carried out for each individual in each of these areas. Then, the Item Response Theory is applied to get the scores of each individual. This procedure aims to cover the lack of response to some items included in the tests, assigning a score based on the answers provided by individuals with similar characteristics. It thus provides a posteriori distribution of individuals skills from which ten random values, called plausible values, are extracted. Each plausible value measures the performance of the individual on a 0 to 500 points scale, so that different levels of skills performance can be set.

In this study the sample was limited to employees for whom data is available for all control variables. Since the sample selection in the PIAAC database does not follow a pure random sampling, the Jackknife procedure is applied in the econometric analysis, allowing to take account of weights included in the PIAAC database for each individual in the sample and its 80 replications when standard errors are estimated, thus ensuring that the estimates are representative of the entire adult population aged 16 to 65 years.

Regardless of the existence of educational mismatch, we first focus on the mincerian classic equation (1), where the dependent variable is the hourly wage (in logarithms) and as exogenous variables we consider some variables related to the human capital of workers, their individual characteristics and their employment status. As human capital variables we include the individual's years of schooling and experience (and years of experience squared). In addition, not only years of education are considered, but also the skills actually acquired by the individuals, introducing the PIAAC scores achieved on the numeracy tests[5]. Besides, several control variables are considered, related to the characteristics of the individuals: gender and nationality (native or foreign); and to the employment status: firm size, doing supervisory tasks,

[5] Estimates were also run with literacy scores; the obtained results were quantitatively and qualitatively similar (estimations are available upon request).

public or private firm, type of contract (indefinite or not), occupational status (full or part time), activity sector (primary, secondary, construction or services) and type of work (skilled, semi-skilled white collar, semi-skilled blue collar or elementary)[6]. Country dummies were also introduced to control for country heterogeneity. The descriptive statistics of these variables are presented in Table 1.

Table 1. Descriptive statistics

	Pool		**Nordic**		**Mediterranean**		**Continental**		**Eastern**	
Variable	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**
Hourly wage	14.96	17.68	22.21	14.95	14.55	10.04	20.89	28.28	9.82	19.47
Schooling (years)	12.69	3.31	13.40	2.76	11.83	3.67	13.37	2.60	13.47	2.82
Numeracy	268.23	49.94	287.22	48.96	255.87	49.13	287.37	47.28	271.51	46.97
Experience	17.48	11.44	19.37	12.49	17.28	10.84	18.59	11.68	16.87	11.76
Males	0.53	0.50	0.49	0.50	0.55	0.50	0.52	0.50	0.53	0.50
Females	0.47	0.50	0.51	0.50	0.45	0.50	0.48	0.50	0.47	0.50
Native	0.91	0.28	0.91	0.29	0.88	0.33	0.90	0.30	0.99	0.11
Foreign	0.09	0.28	0.09	0.29	0.12	0.33	0.10	0.30	0.01	0.11
Small firm	0.61	0.49	0.58	0.49	0.66	0.47	0.51	0.50	0.58	0.49
Medium firm	0.22	0.42	0.24	0.43	0.19	0.39	0.27	0.44	0.25	0.43
Large firm	0.17	0.37	0.18	0.38	0.15	0.36	0.22	0.41	0.17	0.37
Supervisor	0.25	0.43	0.25	0.43	0.24	0.43	0.32	0.47	0.24	0.42
Public sector	0.27	0.44	0.35	0.48	0.23	0.42	0.28	0.45	0.30	0.46
Indefinite	0.75	0.43	0.84	0.37	0.75	0.43	0.78	0.41	0.70	0.46
Full time	0.77	0.42	0.74	0.44	0.79	0.41	0.58	0.49	0.87	0.34
Primary sector	0.03	0.17	0.02	0.14	0.04	0.19	0.01	0.09	0.03	0.18
Secondary sector	0.21	0.41	0.14	0.34	0.20	0.40	0.16	0.36	0.27	0.45
Construction	0.07	0.26	0.07	0.25	0.07	0.26	0.05	0.22	0.09	0.28
Services	0.69	0.47	0.77	0.42	0.69	0.47	0.78	0.41	0.61	0.49
Skilled	0.38	0.49	0.47	0.50	0.32	0.47	0.49	0.50	0.39	0.49
White collar	0.29	0.45	0.29	0.45	0.31	0.46	0.30	0.46	0.23	0.42
Blue collar	0.23	0.42	0.17	0.24	0.24	0.43	0.13	0.33	0.30	0.46
Elementary	0.10	0.31	0.07	0.26	0.13	0.34	0.08	0.28	0.08	0.28

Source: own elaboration from PIAAC data. Descriptive statistics calculated for 30581 observations for the pooled sample, 11160 observations for the Nordic bloc, 4442 observations for the Mediterranean bloc, 5935 observations for the Continental bloc and 9044 observations for the Eastern bloc, using sample weights and the Jackknife procedure.

Table 2 shows the estimates from different wage equations, based on the classic mincerian equation (column 1) and including scores of numeracy skills instead of years of schooling (column 2) and both years of schooling and skills scores being jointly considered (column 3). The estimates for this last specification including both years of

[6] A detailed description of each variable used in this study, as well as original variables in the PIAAC database, can be found in the Annex.

schooling and skills scores for the different blocs of European countries are shown in columns 4-7. The obtained results when estimating the basic mincerian equation give a return to years of schooling around 3.9%. The estimates for the control variables are statically significant and show the expected effects according to previous literature, so we shall not extend here in its analysis. When PIAAC scores in numeracy skills are introduced as a proxy for human capital, instead of years of schooling, most of the control variables retain their significance, although in some cases the magnitude of the estimated effects varies. Numeracy skills show a positive and significant effect on wages, with an increase of around 0.14% on wages for any additional point reached in this skill. When years of schooling and skills level are simultaneously considered, both the amount of education (measured by years of schooling) and the quality of education (measured by the skills acquired) are significant in explaining wages. The effect of years of schooling is robust to the introduction of numeracy skills, although the effect of this variable is slightly reduced, with a return around 3.5% for each additional year of schooling. This return to schooling is greater in the Continental, Eastern and Nordic blocs (4.9%, 4.7% and 3.7%, respectively) and lower in the Mediterranean countries (2.7%). The effects of numeracy skills also decrease when considering both the skills acquired and the years of schooling, but remain statistically significant with an estimated effect close around 0.08%. The greatest returns to skills are estimated for Eastern bloc, with a return of 0.12%, whereas for the rest of countries the returns to numeracy skills vary between 0.07% for the Mediterranean countries and 0.08% for Continental and Nordic blocs.

Table 2. Mincerian equations with education and cognitive skills

	Pool			Nordic	Mediterranean	Continental	Eastern
	1	2	3	4	5	6	7

Schooling	0.0394***		0.0351***	0.0370***	0.0277***	0.0487***	0.0468***
	(0.00198)		(0.00214)	(0.00156)	(0.00306)	(0.00306)	(0.00547)
Numeracy		0.00141***	0.000818***	0.000788***	0.000696***	0.000785***	0.00119***
		(0.000119)	(0.000128)	(0.000104)	(0.000222)	(0.000152)	(0.000242)
Experience	0.0178***	0.0165***	0.0174***	0.0231***	0.0143***	0.0329***	0.0126***
	(0.00136)	(0.00136)	(0.00137)	(0.00102)	(0.00253)	(0.00198)	(0.00249)
Experience^2	-0.000248***	-0.000248***	-0.000233***	-0.000335***	-0.000145**	-0.000460***	-0.000219***
	(2.93e-05)	(2.95e-05)	(2.94e-05)	(2.34e-05)	(5.74e-05)	(4.18e-05)	(6.02e-05)
Males	0.113***	0.0876***	0.101***	0.0787***	0.0933***	0.0486***	0.133***
	(0.0100)	(0.0102)	(0.00966)	(0.00768)	(0.0158)	(0.0146)	(0.0171)
Foreign	-0.0739***	-0.0353**	-0.0531***	-0.0403***	-0.0662***	0.00363	-0.0301
	(0.0154)	(0.0168)	(0.0165)	(0.0139)	(0.0244)	(0.0196)	(0.0495)
Medium firm	0.0789***	0.0878***	0.0762***	0.0467***	0.109***	0.0590***	0.0422**
	(0.00845)	(0.00862)	(0.00848)	(0.00733)	(0.0147)	(0.0144)	(0.0175)
Large firm	0.155***	0.161***	0.151***	0.124***	0.144***	0.111***	0.151***
	(0.0106)	(0.0112)	(0.0106)	(0.00918)	(0.0180)	(0.0125)	(0.0261)
Supervisor	0.109***	0.119***	0.106***	0.0732***	0.137***	0.0374***	0.0976***
	(0.00906)	(0.00912)	(0.00907)	(0.00739)	(0.0155)	(0.0129)	(0.0197)
Public sector	0.0409***	0.0759***	0.0465***	-0.0521***	0.137***	0.0248*	-0.0102
	(0.0116)	(0.0119)	(0.0115)	(0.00722)	(0.0217)	(0.0127)	(0.0239)
Indefinite contract	0.119***	0.126***	0.117***	0.0917***	0.105***	0.141***	0.121***
	(0.0102)	(0.0101)	(0.0102)	(0.0109)	(0.0191)	(0.0166)	(0.0176)
Full time	-0.0495***	-0.0338**	-0.0482***	0.0312***	-0.110***	0.0150	0.0141
	(0.0132)	(0.0134)	(0.0133)	(0.0105)	(0.0212)	(0.0151)	(0.0340)
Secondary sector	0.0499*	0.0492*	0.0437	-0.0193	0.131***	0.0162	-0.108**
	(0.0290)	(0.0294)	(0.0288)	(0.0192)	(0.0365)	(0.0529)	(0.0486)
Construction sector	0.0619**	0.0637**	0.0602**	0.0218	0.129***	-0.0152	-0.0580
	(0.0271)	(0.0282)	(0.0271)	(0.0240)	(0.0365)	(0.0559)	(0.0532)
Services sector	0.0270	0.0352	0.0209	-0.0632***	0.116***	-0.0186	-0.136***
	(0.0280)	(0.0282)	(0.0277)	(0.0190)	(0.0355)	(0.0517)	(0.0496)
Skilled	0.280***	0.389***	0.264***	0.212***	0.235***	0.283***	0.272***
	(0.0188)	(0.0176)	(0.0191)	(0.0165)	(0.0287)	(0.0256)	(0.0421)
White collar	0.0423**	0.0838***	0.0330**	0.0488***	0.0212	0.0971***	-0.00758
	(0.0166)	(0.0161)	(0.0167)	(0.0151)	(0.0235)	(0.0262)	(0.0387)
Blue collar	0.0787***	0.0956***	0.0766***	0.0361**	0.0756***	0.0808***	0.0714**
	0.280***	0.389***	0.264***	(0.0170)	(0.0240)	(0.0259)	(0.0348)
Constant	1.767***	1.803***	1.609***	1.840***	1.531***	1.265***	0.761***
	(0.0329)	(0.0429)	(0.0423)	(0.0431)	(0.0662)	(0.0739)	(0.0959)
R-squared	0.527	0.512	0.530	0.477	0.363	0.463	0.297
Obs.	30581	30592	30581	11,160	4,442	5,935	9,044

Source: own elaboration from PIAAC data. Estimates calculated using sample weights and applying the Jackknife procedure. Statistical t in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Next, returns to education are analyzed taking account of the degree of (mis)match with the requirements of the job. To do this, different specifications of equation (2) are estimated. To estimate the ORU equations it becomes necessary to approximate the years of education required for the job and the years of over- or under-education. Different methods have traditionally been used to proxy the educational mismatch: the objective method, the subjective method (direct and indirect), and the statistical one. With the objective method different characteristics of each occupation are examined, such as the difficulty of the tasks to be performed or the type and level of training required, and then compared with the workers characteristics. The subjective methods bases on information provided by the workers, who are explicitly asked whether they considered themselves to be overeducated, undereducated or adequately matched for their job (direct method), or they are asked about the educational level that they think is required for their job, comparing then these responses with their own educational level (indirect method). Finally, the statistical methods compare the education acquired by any individual with the average or modal value of education of workers in a similar occupation[7].

In this study, years of educational mismatch have been estimated by the indirect subjective method, comparing the level of education that workers report as necessary to get a particular job with the level of education that the worker has achieved. In particular, years of educational mismatch are calculated as the difference between the years of education corresponding to the highest educational level attained by workers (YRSQUAL in the PIAAC database) and the years of education required to get their job (YRSGET in PIAAC database). Table 3 shows the distribution of educational mismatch.

Table 3. Educational mismatch distribution (percentage)

	Pool	**Nordic**	**Mediterranean**	**Continental**	**Eastern**
Properly matched	51.6	53.3	50.0	50.5	52.8
Overeducated	29.1	28.1	28.6	24.3	32.9
Undereducated	19.3	18.6	21.4	25.2	14.3
	100	100	100	100	100

Source: own elaboration from PIAAC data.

The estimates for returns to education taking account of educational mismatch are presented in Table 4. The first column shows the results of a classic ORU equation with years of required, over- and under-education; the second column offers the results when the PIAAC scores of numeracy skills are also included. Besides, the next four

[7] A detailed discussion of the advantages and disadvantages of each method can be found in Hartog (2000), where it is pointed out that the use of one or another estimation method does not affect the results obtained as regards wage returns, so the choice of the method will depend on available information.

columns give the results of this last specification for the different blocs of countries. In any case, all regressions include the same control variables related to individual characteristics and employment status that were considered when estimating the mincerian wage equations. The results obtained from the standard ORU equation are as expected according to previous literature[8], with higher returns for years of required education (5.4%); positive returns, although lower, for the years of overeducation (2.4%) and negative returns for years of undereducation. These results show that educational mismatch significantly contributes to explain part of the wage gap among workers doing a similar job. When the scores for numeracy skills are included, it is observed that the variables referred to educational mismatch maintain their significance, although its effect on wages is slightly reduced. For the pool of countries, a wage premium of 5% and 2% is now estimated for years of required and over-education, respectively. Similarly to what happened to returns to years of schooling in the mincerian regressions, the highest returns to years of required education correspond to the Continental and Eastern blocs (with a return around 6.7%) whereas the lowest returns to both years of required and overeducation are estimated for the Mediterranean countries. In any case, these results suggest that part of the wage effect operates through the skills actually acquired by workers. In regard to numeracy skills, we observe a positive and significant effect on wages (around 0.07%) for all countries considered together, with the greatest returns to skills being again estimated for Eastern countries (around 11%).

Table 4. ORU equations with educational mismatch and skills mismatch

	Pool		**Nordic**	**Mediterranean**	**Continental**	**Eastern**
	1	2	3	4	5	6
Years required	0.0541***	0.0499***	0.0478***	0.0410***	0.0674***	0.0668***
	(0.00204)	(0.00221)	(0.00167)	(0.00301)	(0.00380)	(0.00576)
Years Over	0.0240***	0.0206***	0.0291***	0.0160***	0.0412***	0.0257***

[8] See, for example, Hartog (2000) or McGuiness (2006) for a review of this literature.

	(0.00281)	(0.00287)	(0.00252)	(0.00408)	(0.00452)	(0.00676)
Years Under	-0.0250***	-0.0220***	-0.0203***	-0.0187***	-0.0296***	-0.0242**
	(0.00402)	(0.00406)	(0.00230)	(0.00581)	(0.00391)	(0.0101)
Numeracy		0.000709***	0.000732***	0.000566***	0.000613***	0.00111***
		(0.000125)	(0.000103)	(0.000216)	(0.000157)	(0.000242)
Experience	0.0181***	0.0178***	0.0222***	0.0152***	0.0324***	0.0133***
	(0.00137)	(0.00137)	(0.000984)	(0.00251)	(0.00199)	(0.00245)
Experience^2	-0.000268***	-0.000255***	-0.000328***	-0.000179***	-0.000465***	-0.000240***
	(2.92e-05)	(2.92e-05)	(2.24e-05)	(5.66e-05)	(4.23e-05)	(5.99e-05)
Males	0.113***	0.103***	0.0810***	0.0952***	0.0556***	0.134***
	(0.00966)	(0.00929)	(0.00751)	(0.0158)	(0.0140)	(0.0166)
Foreign	-0.0458***	-0.0287*	-0.0380***	-0.0433*	0.0135	-0.0150
	(0.0154)	(0.0164)	(0.0136)	(0.0249)	(0.0195)	(0.0479)
Medium firm	0.0755***	0.0733***	0.0427***	0.107***	0.0537***	0.0396**
	(0.00839)	(0.00842)	(0.00757)	(0.0149)	(0.0145)	(0.0173)
Large firm	0.146***	0.143***	0.115***	0.138***	0.0973***	0.149***
	(0.0104)	(0.0103)	(0.00896)	(0.0174)	(0.0126)	(0.0255)
Supervisor	0.0934***	0.0914***	0.0688***	0.118***	0.0272**	0.0877***
	(0.00837)	(0.00839)	(0.00711)	(0.0146)	(0.0125)	(0.0195)
Public sector	0.0250**	0.0303***	-0.0604***	0.120***	0.0191	-0.0348
	(0.0113)	(0.0113)	(0.00726)	(0.0217)	(0.0126)	(0.0240)
Indefinite contract	0.111***	0.110***	0.0909***	0.0995***	0.129***	0.110***
	(0.0102)	(0.0102)	(0.0109)	(0.0193)	(0.0163)	(0.0175)
Full time	-0.0620***	-0.0605***	0.0197*	-0.117***	-0.000286	-0.00245
	(0.0126)	(0.0127)	(0.0103)	(0.0209)	(0.0152)	(0.0332)
Secondary sector	0.0272	0.0222	-0.0232	0.107***	-0.0149	-0.121**
	(0.0292)	(0.0291)	(0.0190)	(0.0376)	(0.0497)	(0.0478)
Construction sector	0.0367	0.0360	0.0121	0.104***	-0.0504	-0.0722
	(0.0276)	(0.0277)	(0.0242)	(0.0387)	(0.0529)	(0.0531)
Services sector	0.00410	-0.000602	-0.0614***	0.0907**	-0.0495	-0.146***
	(0.0278)	(0.0276)	(0.0193)	(0.0367)	(0.0491)	(0.0488)
Skilled	0.173***	0.162***	0.143***	0.141***	0.176***	0.141***
	(0.0196)	(0.0199)	(0.0162)	(0.0306)	(0.0256)	(0.0405)
White collar	-0.0103	-0.0168	0.0174	-0.0193	0.0303	-0.0774**
	(0.0164)	(0.0165)	(0.0145)	(0.0239)	(0.0247)	(0.0358)
Blue collar	0.0421**	0.0412**	0.00999	0.0495**	0.0376	0.0188
	(0.0166)	(0.0168)	(0.0165)	(0.0238)	(0.0247)	(0.0340)
Constant	1.711***	1.577***	1.798***	1.495***	1.221***	0.660***
	(0.0320)	(0.0415)	(0.0445)	(0.0648)	(0.0761)	(0.0950)
R-squared	0.539	0.541	0.487	0.377	0.477	0.315
Obs.	30386	30386	11,113	4,399	5,897	8,977

Source: own elaboration from PIAAC data. Estimates calculated using sample weights and applying the Jackknife procedure. Statistical t in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Since the economic effects of education and educational mismatch appear to act, at least partly, through the skills actually acquired by workers, we next analyze whether returns to years of education differ among workers with different levels of skills. By studying whether skills heterogeneity affects wages, we will analyze whether returns to years of education, or the wage premium to years of over-education, are similar or not depending on the level of skill achieved. According to the score achieved in the skills assessed, the OECD defines six levels of skills: level 0: with scores lower than 175; level 1: scores between 176 and 225; level 2: scores between 226 and 275; level 3: scores from 276 to 325; level 4: scores between 326 and 375; and level 5: with scores greater than 375. Given the relatively low number of observation found in levels 0 and 5 defined by PIAAC, in the present study the sample is segmented in four levels of achievement, taken the numeracy skill as reference, corresponding to a low level (0 and 1 in PIAAC), medium-low (2 in PIAAC), medium-high (3 in PIAAC), and high level (4 and 5 in PIAAC).

Results obtained for the mincerian regressions with this segmentation based on the numeracy skill levels are shown in Table 5. In the framework of the classical mincerian equation, without considering educational mismatch, it is observed that higher levels of acquired skills drive to higher returns to years of education, a result in line with the human capital hypothesis, which suggests that higher individual productivity (as proxied by higher skills) leads to higher wages. In particular, returns to attained education range from 2.3% for individuals with a low level of numeracy skills to 3% for those with a medium-low level, or 4.6% for those with a medium-high level, and to 5.3% for those reaching a high skill level of numeracy skills. This trend is observed for all the country blocs being analyzed: for the Mediterranean countries, where the returns to education were the lowest, the estimated returns to years of education vary between 2% for workers with a low level of skills to 4.6% for those with a high skill level; in the Nordic countries, the range of variation goes from 2.8% to 5%; whereas in the Continental and Eastern blocs (where returns to education were the greatest), a greater heterogeneity is even found, with returns to years of education going from around 2% for individuals with a low level of skills to more than 6% for those with a high level of numeracy skills.

Table 5. Mincerian equations by levels of numeracy skills

		Level of numeracy skills			
		Low	**Medium-low**	**Medium-high**	**High**
Pool	Schooling	0.0232***	0.0307***	0.0458***	0.0529***
		(0.00481)	(0.00313)	(0.00334)	(0.00521)

	R-squared	0.405	0.497	0.541	0.554
	Obs.	3809	9461	12150	5161
Nordic	Schooling	0.0279***	0.0291***	0.0391***	0.0493***
		(0.00653)	(0.00279)	(0.00244)	(0.00331)
	R-squared	0.331	0.402	0.453	0.539
	Obs.	1,054	3,002	4,627	2,477
Mediterranean	Schooling	0.0204***	0.0275***	0.0348***	0.0463***
		(0.00658)	(0.00393)	(0.00497)	(0.0111)
	R-squared	0.258***	0.341***	0.372***	0.438***
	Obs.	1,044***	1,709***	1,391***	298***
Continental	Schooling	0.0189**	0.0372***	0.0617***	0.0634***
		(0.00748)	(0.00491)	(0.00453)	(0.00699)
	R-squared	0.342	0.400	0.456	0.508
	Obs.	558	1,628	2,515	1,234
Eastern	Schooling	0.0282***	0.0357***	0.0613***	0.0626***
		(0.00830)	(0.0112)	(0.00568)	(0.0118)
	R-squared	0.221	0.224	0.265	0.334
	Obs.	1,153	3,122	3,617	1,152

Source: own elaboration from PIAAC data. Estimates calculated using sample weights and applying the Jackknife procedure. Statistical t in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6 offers the estimates for the ORU regressions when the sample is segmented according to the level of numeracy skills. Similarly to what was observed in the segmented mincerian regression, the estimates from the ORU equation show that returns to years of required education are higher for workers with a high level of numeracy skills (6.6%) than for those with a medium level (6.1% for medium-high or 4.4% for medium-low) or with a low level of skills (4%). This result is again consistent through the different blocs of countries, with an increase in returns to years of required education being observed as the level of skill raise, reaching the greatest returns to years of required education (around 8% for each additional year) for individuals with a high level of skill in Continental and Eastern countries. As regards the returns to years of educational mismatch, no clear pattern is observed for returns to years of undereducation, although heterogeneity in skills seems to translate in wages, with a significant pay penalty being observed mainly for individuals with a medium level of skills. Estimates for the wage premium found for overeducated workers tend to support the results described for returns to years of attained and required education. Workers who show a low level of numeracy skills do not receive any significant wage premium for years of over-education or, when significant, this wage premium is lower than that estimated for workers with a medium or high level of skills (whereas a wage premium of 0.9% is estimated for workers with a low level of numeracy skills, this return raise to 1.7%, and increase its statistical significance, for individuals with a medium-low level and reach around 2% for individuals with a medium-high or a high level of numeracy skills). A similar pattern is found in all blocs of countries being considered, with the highest returns for years of overeducation being found for individuals with a medium-high or a high level of skills and lower returns (and in some cases not significantly distinct from zero) for individuals with a low level of numeracy skills. This result is consistent with the idea of Chevalier (2003), who points out that the assumption of skills homogeneity within educational levels does not hold, what leads this author to differentiate between ‘genuinely’ and 'apparently' overeducated workers. In this vein, some workers could be seen as being overeducated according to their educational level but if their level of skills is low they could be thought as being only 'apparently' overeducated; in this case, our results suggest that they would not receive a wage premium for those years of over-education or, in any case, this wage premium would be lower.

These results tend hence to confirm the hypothesis of skills heterogeneity, with this individual heterogeneity affecting wages. Therefore, not only years of education or educational mismatch, but also the skills actually acquired by the individuals as a result of the amount of education, its quality, or other variables such as individual innate abilities or their family and socio-economic background, play an important role in explaining the returns associated to years of education.

Table 6. ORU equations by levels of numeracy skills

	Level of numeracy skills			
	Low	**Medium-low**	**Medium-high**	**High**

Pool	Years required	0.0395***	0.0440***	0.0609***	0.0661***
		(0.00562)	(0.00333)	(0.00356)	(0.00587)
	Years Over	0.0124*	0.0177***	0.0307***	0.0394***
		(0.00694)	(0.00475)	(0.00425)	(0.00746)
	Years Under	-0.0131	-0.0196***	-0.0269***	-0.0295***
		(0.00863)	(0.00606)	(0.00704)	(0.0102)
	R-squared	0.416	0.507	0.554	0.564
	Obs.	3760	9380	12097	5149
Nordic	Years required	0.0387***	0.0402***	0.0520***	0.0564***
		(0.00867)	(0.00334)	(0.00259)	(0.00394)
	Years Over	0.0200**	0.0249***	0.0309***	0.0404***
		(0.00991)	(0.00431)	(0.00380)	(0.00588)
	Years Under	-0.0229***	-0.0133***	-0.0170***	-0.0361***
		(0.00823)	(0.00426)	(0.00362)	(0.00619)
	R-squared	0.336	0.412	0.469	0.546
	Obs.	1,043	2,985	4,611	2,474
Mediterranean	Years required	0.0345***	0.0380***	0.0487***	0.0620***
		(0.00742)	(0.00415)	(0.00511)	(0.0114)
	Years Over	0.0115	0.0173***	0.0209***	0.0418**
		(0.00945)	(0.00590)	(0.00679)	(0.0169)
	Years Under	-0.0130	-0.0197***	-0.0227**	-0.0120
		(0.0110)	(0.00734)	(0.0106)	(0.0195)
	R-squared	0.269	0.352	0.391	0.463
	Obs.	1,027	1,688	1,386	298
Continental	Years required	0.0341***	0.0534***	0.0865***	0.0796***
		(0.00891)	(0.00563)	(0.00546)	(0.00925)
	Years Over	0.00724	0.0365***	0.0605***	0.0468***
		(0.0112)	(0.00760)	(0.00815)	(0.0108)
	Years Under	-0.00913	-0.0204***	-0.0313***	-0.0437***
		(0.00936)	(0.00694)	(0.00605)	(0.0128)
	R-squared	0.361	0.410	0.479	0.522
	Obs.	550	1,614	2,503	1,230
Eastern	Years required	0.0561***	0.0575***	0.0749***	0.0780***
		(0.0114)	(0.0133)	(0.00632)	(0.0145)
	Years Over	0.0219*	0.0152	0.0368***	0.0290**
		(0.0115)	(0.0133)	(0.00811)	(0.0134)
	Years Under	-0.00418	-0.0121	-0.0440***	-0.0644**
		(0.0194)	(0.0175)	(0.0123)	(0.0288)
	R-squared	0.250	0.248	0.277	0.349
	Obs.	1,140	3,093	3,597	1,147

Source: own elaboration from PIAAC data. Estimates calculated using sample weights and applying the Jackknife procedure. Statistical t in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4. Conclusions

The aim of this study was to analyze the economic effects of education and educational mismatch in ten European countries by taking into account not only the years of education received by workers, but also the basic skills that they actually acquired. Using the PIAAC database, returns to education were first estimated through mincerian classical equations. The results indicate that both years of education and acquired skills contribute to determine wages, being the results obtained as regard years of education robust to the introduction of scores assessing the numeracy skills. It is however noteworthy that returns to education slightly decrease when basic skills are introduced into the analysis, suggesting that part of the positive effects of education on wages manifested through skills actually acquired by individuals. The effects of basic skills are also robust to the introduction of years of schooling in the specification, showing that both aspects of education (years of schooling and skills acquired) contribute to explain, among other variables, individuals' wages.

Besides, significant mismatches between jobs' educational requirements and individuals' educational attainments are found to appear in the European countries. In particular, it is estimated that near 50% of workers show some type of educational mismatch, with almost 30% of workers in the sample appearing to be overeducated. When estimating the returns to years of required education and to years of educational mismatch, it is found that educational mismatch contributes to explain some of the observed wage differentials between workers who occupy a similar position, with positive returns to years of over-education and wage penalties in the case of undereducation.

Finally, when analyzing the heterogeneity in skills among workers it is found that returns to education and to years of educational mismatch vary depending on the level of skills actually acquired by workers. In line with the human capital theory, it appears that a higher productivity (proxied by skills levels) is associated with higher wages. Thus, the higher the level of skills achieved by an individual, the higher the returns to years of education attained by the worker or to years of education required for the job. Also, the wage premium for years of over-education tends to increase as the level of skills achieved raises. These results tend therefore to confirm that not only the years of completed education but also the skills actually acquired by the individuals affect wages, with skills heterogeneity being an important factor when analyzing the returns to education and to educational mismatch.

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