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Education, educational mismatch and occupational status: an analysis using PIAAC data

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Abstract

The aim of this paper is to estimate the effect of longer schooling on the probability of entering a high-skill job and analyse whether the size of this effect depends on the (mis)match between the education attained by workers and the education required by the jobs. We use PIAAC data to estimate a multinomial logit model that predicts the odds of working in each occupational category and then simulate how these probabilities change for workers who have completed one more year of education, broken down by whether or not this additional year matches the educational requirements of the job. Our results suggest that, as observed from wages estimated according to an ORU equation, better education is positively associated with better jobs but the increased probability of getting a high-skill job as a result of completing one more year of education is greater for required than for mismatched education. The results differ notably by gender, with women being the ones who benefit most from an increase in education, especially in the absence of educational mismatch. These trends are observed whatever the institutional context, but we also found noteworthy differences by country.

Keywords Education · Educational mismatch · Occupational status · Multinomial logit models

JEL Classification C25 · I21 · J24

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1 Introduction

The increase of individuals´ education has been one of the most outstanding stylized facts in modern economies since the beginning of the twentieth century. Nowadays, according to OECD data, most of the population aged from 15 to 19 years is, on average, enrolled in education, and the higher education rates for young men and women are expected to reach 46% and 31%, respectively, over the next few years (OECD, 2022).In addition to this notable change on the labour supply side, another equally significant shift has occurred in labour demand, prompted by technological change and its impact on employment (Vivarelli, 2014). Technological progress has had a huge impact on wages and jobs with wide-ranging consequences for the structural composition of employment by gender and skills (Olivetti & Petrongolo, 2014). Besides, the increasing use of robots at work is skill-biased, as it is associated with a decline in occupations requiring the lowest levels of education in favour of jobs requiring higher qualifications (Autor et al., 2003; Graetz & Michaels, 2018; OECD, 2019). In this context, one key question has to do with how these major labour market challenges interrelate with each other. In particular, it is interesting to analyse whether, as a result of the structural change in employment composition, a better education is a necessary condition for gaining access to the most attractive jobs (Ra et al., 2019). According to the OECD (2022, pp.147), "The deep changes that have occurred in the labour market over the past decades suggest that better-educated individuals have (and will continue to have) an advantage as the labour market becomes increasingly knowledge-based".

The positive association between better education and better jobs is a well-documented stylized fact in modern labour markets. However, there is the possibility of educational mismatch, i.e., the situation where the education attained by the worker does not match the qualifications required by the employer, debilitating this relationship. The literature has provided a vast amount of evidence on across-the-board drawbacks associated with educational mismatch, which affect not only workers, but also firms and entire countries. These obstacles lower workers' wages, detract from their job satisfaction and diminish their career prospects (Leuven & Oosterbeek, 2011; McGuiness, 2006; McGuiness et al., 2018b; Quintini, 2011). This paper extends the literature by examining a further limitation derived from educational mismatch, namely, the weaker effect of longer schooling on the probability of getting high-skill jobs if the additional education does not meet the job requirements.

The distortion that educational mismatch causes on the direct relationship between better education and better jobs has been previously suggested by García-Mainar et al. (2015). They examined the link between workers´ personal and job-related characteristics and the unequal occupational distribution by gender, focusing particularly on the role played by overeducation. Using multivariate regression analyses, they found that higher education graduates are less likely to enter a gender-dominated occupation, but they also document a positive correlation between overeducation and occupational segregation by gender.

Our study goes a step further and establishes a clear analogy with the widely documented outcome that returns to education are not homogeneous: they are higher for required years of schooling and lower for mismatched years of schooling. In this regard, we raise the following research question: just as the returns to education depend on the (mis)match between attained and required schooling, could the size of the effect of longer schooling on the probability of getting a high-skill job vary according to the degree of fit between education attained by workers and education required by jobs? Although many authors have estimated differentiated coefficients for required and mismatched education using models with continuous dependent variables (mainly wage equations), our research is, to the best of our knowledge, the first to consider this differentiation when estimating discrete choice models.

We estimate a multinomial logit model that predicts the odds of working in each occupational category based on human capital, measured according to education, competencies and experience. We then calculate how these probabilities change with a one extra year of education completed by the worker, broken down according to whether or not this additional year meets the educational requirements of the job. As the literature suggests that the causes and consequences of educational mismatch differ by gender see, for example, Addison et al. (2019); Moro-Egido (2020) and that the institutional context might strongly determine the outcomes associated with education and educational mismatch see, for example, Davia et al. (2017); McGuiness et al. (2018a), we estimate our model by gender and by country. Our results show that, as widely documented from wages estimated according to an overeducation/required education/undereducation (ORU) equation–see Leuven and Oosterbeek (2011); McGuiness (2006); McGuiness et al. (2018b); Quintini (2011) for comprehensive reviews-, better education is positively associated with better jobs and with a higher occupational status, but the increase in the probability of getting a high-skill job as a result of an extra year of education is greater for required than for mismatched education. The results differ notably by gender, with women being the ones who benefit most from longer schooling, especially in the absence of educational mismatch. These trends are observed whatever the institutional context and differ notably by country. The increase in occupational status derived from an extra year of education is highest for matched education in the Eastern and continental European and Nordic countries and lowest for mismatched education in the Mediterranean countries.

The rest of the paper is organized as follows. After a literature review in Sect. 2, Sect. 3 details the data used in the research. Section 4 describes the methodology applied in our study. The main results are reported and discussed in Sect. 5. Finally, Sect. 6 summarizes the main conclusions of our research.

2 Literature review

The literature has studied educational mismatch in depth. The reasons explaining educational mismatch vary according to the economic theory propping up the analysis[1]. In the framework of human capital theory, based on the seminal work by Mincer (1974), education defines individuals´ productivity and, therefore, wages. Given that marginal productivity is determined by the labour supply, overeducation would imply an underutilization of workers human capital and is expected to disappear over individuals´ lifelong careers. In fact, over- and undereducation may be the result of a trade-off between schooling and other forms of human capital, particularly experience and training, as suggested by Sloane et al. (1996); Kiker et al. (1997)[2]. Moreover, according to the job mobility hypothesis (Sicherman, 1991), overeducated individuals may use their surplus education as a substitute for labour market experience to accumulate the human capital needed for upward career mobility[3]. As opposed to the human capital theory, the job competition model (Thurow, 1975) focuses on the demand side, suggesting that job characteristics are the main factor determining individuals wages. Workers compete for jobs, and an individual with a higher educational level is in a better position within a particular job queue. Therefore, overeducation is a valuable endowment to compete for better jobs. The job shopping theory also assumes that overeducation may be a strategic asset: individuals may accept less-demanding jobs than the ones that they are capable of performing as a way to enter jobs commensurate with their educational level (Jovanovik, 1979; Sicherman & Galor, 1990). Finally, the assignment model (Sattinger, 1993) provides a middle ground between the opposite views of the human capital and job competition models. It argues that workers' productivity —and consequently wages— depends on both the demand and supply sides of the labour market and is determined in part by job characteristics (e.g., required education) and in part by individual characteristics (e.g., acquired education). Note that, from this last perspective, educational mismatch may become a persistent, rather than transitory, phenomenon in the labour market.

There is vast empirical evidence to support the fact that an educational level above (below) what is required to get or to do a job leads to worse labour market outcomes than those enjoyed by individuals (workmates) with the same education but employed in a job commensurate with their human capital (possessing the right level

[1] McGuinness (2006) provides a good review of the literature on overeducation as regards different theoretical frameworks.

[2] For an analysis of how the different forms of training impact overeducation, see Verhaest and Omey (2010).

[3] Dolton & Silles (2008) find no evidence of a significant link between experience and overeducation, with UK graduates that are overeducated for their first job after leaving college being more likely to be overeducated in subsequent jobs. Albert et al. (2023) document that job mobility partially corrects overeducation in the case of Spanish graduates, but, even so, educational mismatch pattern tends to persist for years after graduation. Meroni & Vera-Toscano (2017) also provide evidence of the trap effect of overeducation among recent graduates for several European countries.

of education)[4]. It has been widely demonstrated that the wage returns to attained education are higher (lower) if they (mis)match the requirements of the job, as first suggested by Duncan and Hoffman (1981). In addition, overeducation is associated with lower job satisfaction and with greater job mobility, which is not always a guarantee of a better job. Leuven and Oosterbeek (2011); McGuiness (2006); McGuiness et al. (2018b); Quintini (2011) provide comprehensive reviews of this branch of the literature. As a result of this not-always-successful mobility of over(under)educated workers, educational mismatch could turn chronic, at which point it becomes not only an individual but also a social problem (Dolton & Vignoles, 2000; Frenette, 2004; McGuinness & Wooden, 2009; Rubb, 2003).

Hence, most of the literature dealing with the topic assumes that educational mismatch is the result of a misfit between educational attainment and job requirements, which has negative consequences for individuals, firms and countries[5]. Nonetheless, only a few papers have examined how educational mismatch per se checks workers prospects of getting a more attractive job. Acosta-Ballesteros et al. (2018) document that worker overeducation for their first job is a strong determinant of poorer future career prospects in the case of Spain. They decompose the differential probability of workers matched and mismatched in their first job being overeducated for subsequent jobs. As a result, they demonstrate that educational mismatch alone plays a more important role than worker attributes in explaining a greater probability of educational mismatch occurring in future occupations. Overeducation also shapes the association between higher attained educational level and lower job segregation, as discussed by García-Mainar et al. (2015). They estimate a multinomial logit model with data for Spain and conclude that job segregation by gender is lower for university graduates. However, they also found that educational mismatch distorts the above relationship, as there is a positive correlation between overeducation and the odds of working in a gender-dominated occupation. Focusing on wages, Castagnetti et al. (2018) point out that overeducated women in Italy face a higher gender pay gap than women with the required qualifications. They also indicate that overeducation is an important driver of the gender pay gap in that country given the worse unobserved characteristics of overeducated women. The distribution of earnings within educational groups also differs for matched and mismatched workers, as emphasized by Budría and Moro Egido (2008). Differentiating between workers with overqualification, incorrect qualification and strong qualification (e.g. those capable to do a more demanding job -overqualified- but without the skills necessaries to do their

[4] Note that the requirements to get and to do a job may differ between them. Moreover, the requirements to either get or do a job may change over time. For example, the educational level required to do a job may vary between workers recently hired and those of earlier generations, and the educational level set by employers to get a job may reflect the level of schooling needed to fill vacancies to which workers are likely to be promoted. Nonetheless, as emphasized by Leuven & Oosterbeek (2011), it is the data available in each case what determine whether the research focuses on the educational level needed either to get or to do a job.

[5] Another point that has been analysed at length is how the different measures of educational mismatch condition its incidence, also highlighting the importance of considering overeducated workers as a heterogeneous group in terms of skills (see, for example, Flisi et al., 2017; McGuinness et al., 2018; Choi et al., 2020).

current job -incorrect qualified-), they document that wage inequality within education groups in Spain is remarkably higher for strongly mismatched workers.

Overeducation incidence is usually higher among women than among men in the international context (see McGuinness et al., 2018a). Gender differences in educational mismatch may arise for several reasons. Thus, the seminal paper by Frank (1978) argues that women are more exposed to overeducation as that they are less mobile due to family constraints. Differences in career prospects and expectations between men and women may also play a role (Redmon & McGuinness, 2020; Robst, 2007). Moreover, gender differences in preferences and personality (e.g., Chevalier, 2007; Gneezy et al., 2003; Jetter & Walker, 2020) and occupational segregation by gender (e.g., García-Mainar et al., 2015) have been also proved to be important in a clear analogy with the explanatory reasons of the gender wage gap. In a recent paper, Boto-García and Escalonilla (2022) analyse the gender differences in the prevalence of overeducation, focusing on the role played by individuals´ attributes (pre- and postgraduation mobility and experience, field of study or first job search method) as potential drivers of overeducation. Using microdata for Spanish graduates at the beginning of their careers, they conclude that men and women show a similar risk of overeducation, once differences in characteristics are controlled for.

Spatial variation in educational mismatch incidence can be explained, to a certain extent, by national institutions and macroeconomic structural factors.[6] With the support of several waves of the European Union Survey of Living Conditions data, Davia et al. (2017) conclude that overeducation rates tend to be higher in countries with a surplus of highly educated workers, while strong employment protection legislation and trade union density are associated with lower rates of overeducation. By contrast, Delaney et al. (2020) document, using the Labour Force Survey data for 28 European countries, that youth graduate overeducation rates are inversely related to the share of workers holding tertiary education. Also relying on the European Labour Force Survey data, McGuinness et al. (2018a) conclude that countries with a higher share of women participating in the labour force have lower levels of overeducation rates. In addition, they provide evidence on the significant role played by labour market flexibility to explain the differences in overeducation rates between countries.

The papers summarized along this section provide the benchmark for the research question raised in the present paper, namely: just as the returns to education depend on the (mis)match between attained and required schooling, could the size of the effect of longer schooling on the probability of getting a better job vary according to the degree of fit between education attained by workers and education required by jobs? To analyse this issue, we disaggregate the research question into four, each one of them giving a concrete answer to the paper main concern:

Question1: The returns to education depend on the (mis)match between attained and required schooling.

[6] Macroeconomic conditions may also play a role in both the explanation and the dynamics of overeducation for a given country (see Charalambidou & McIntosh, 2020 for the case of Cyprus).

Question 2: The magnitude of the effect of one more year of education on the probability of getting a high-skill job also depends on the (mis)match between attained and required schooling.

Question 3: The magnitude of the effect of one more year of education on the probability of getting a high-skill job depends on the (mis)match between attained and required schooling and varies by gender.

Question 4: The magnitude of the effect of one more year of education on the probability of getting a high-skill job depends on the (mis)match between attained and required schooling and (do not) varies by country.

3 Data

The results provided in this paper rely on Programme for the International Assessment of Adult Competencies (PIAAC) data for 2012. The main added value of this international database, managed by the OECD, is that it measures the human capital of the population aged from 16 to 65 years, focusing particularly on their competencies. Previous databases, like the Adult Literacy Survey (ALS) or the Adult Literacy and Life Skills Survey (ALLSS) also assessed the skills of the adult population, but PIAAC includes a greater number of participating countries and also evaluates a wider range of competencies. Thus, apart from literacy competencies, PIAAC also assesses mathematical skills and, for some countries, problem-solving skills. Note that PIAAC provides a specific test to measure the above competencies and reports the results in terms of ten plausible values that indicate the performance of each individual on a scale of 0 to 500 points. In our research, we approach competencies as the average of their respective ten plausible values, changing the scale to 0 to 1000 to facilitate interpretation. Beyond the information regarding the quantity and quality of education, the survey also provides rich, harmonized information on other socio-demographic characteristics, like age, gender, civil status, etc., as well as occupational status and other job characteristics, such as wages, working hours or activity sector.

Our sample only includes countries whose data raise no concerns with respect to their reliability and which also provide full information on each of the variables used in our study[7]. In particular, the variables used in our research provide information regarding occupation classified according to the International Standard Classifications of Occupation 2008 (ISCO-08), human capital approximated by schooling, work experience and mathematical competencies[8], as well as gender and civil status. We also use information regarding the log of hourly wage. Finally, we approximate the potential educational mismatch by comparing

[7] The countries included in the sample are Belgium, Czech Republic, Denmark, Estonia, Finland, Ireland, Italy, Japan, Korea, Netherlands, Norway, Slovak Republic, Spain, Sweden, Poland and the United Kingdom.

[8] All the estimations have been replicated using literacy skills. The results are very similar to the findings reported here for numeracy in both quantitative and qualitative terms. These results are available upon request. Problem-solving skills have not been considered as the information is only available for certain countries but not for others.

Table 1 Descriptive statistics by gender

	Men	Women	t-stat or z-stat (p-value)
Hourly wage	18.78 (24.26)	15.91 (20.18)	14.14 (0.00)
Years of schooling	13.21 (2.92)	13.62 (2.76)	–15.98 (0.00)
Competencies	566.54 (93.50)	549.03 (84.41)	21.55 (0.00)
Experience	18.63 (12.69)	17.00 (11.74)	14.68 (0.00)
Civil status: married	0.6398	0.6237	3.65 (0.00)
Adequately educated	0.5241	0.5305	–1.40 (0.16)
Observations	23,445 (48.83%)	24,567 (51.17%)	–

The columns "Men" and "Women" report means and standard deviations in brackets, except for file "Observations", where the percentage of the sample by gender is showed in brackets. The last column provides the t or z-statistics of the difference by gender as well as the p-value in brackets

Table 2 Occupational distribution by gender (%)

	Men	Women	z-stat (p-value)
Managers	8.26	4.90	14.87 (0.00)
Professionals	17.28	23.72	−17.48 (0.00)
Technicians and associate professionals	14.90	15.27	−1.14 (0.25)
High-skill occupations	*40.44*	*43.89*	*−7.70 (0.00)*
Clerical support workers	7.63	15.71	−27.49 (0.00)
Service and sales workers	11.56	25.48	−39.12 (0.00)
Skilled agricultural, forestry and fishery workers	1.14	0.43	8.84 (0.00)
Craft and related trades workers	18.40	2.33	58.17 (0.00)
Plant and machine operators and assemblers	12.82	3.00	40.09 (0.00)
Elementary occupations	8.01	9.16	−4.51 (0.00)
Low-skill occupations	*59.56*	*56.11*	*7.56 (0.00)*

Italics provide the summ of the upper files

the years of schooling completed by individuals with the years of education they believe would be necessary to get their job. In particular, PIAAC survey includes a question asking "(…) what would be the usual qualifications, if any, that someone would need to get this type of job?". Thus, we apply a subjective method which calculates the mismatched years of education as the difference between schooling attained by individuals and schooling required by firms, which is zero for adequately educated individuals.

Table 1 lists the descriptive statistics for the above-mentioned variables broken down by gender -men (women) representing 48.83% (51.17%) of the sample, and Table 2 shows the distribution of men and women by occupational categories. We have classified as high-skill occupations those jobs that, according to the ILO (2020), involve tasks requiring high skill levels (Managers; Professionals, and Technicians and associate professionals). The reminder categories have been classified as low-skill occupations (Clerical support workers; Service and sales workers; Skilled agricultural, forestry and fishery workers; Craft and related trades workers; Plant and machinery operators and assemblers, and Elementary occupations).

As it can be observed, while women who attend school on average almost half a year longer than men, are more educated than men, their level of competency is lower: 549, on average, compared to 566.5 for men. Gender-based differences regarding labour market experience are noteworthy, with women having 1.63 fewer years of experience than men. Women also earn a noticeably lower hourly wage than men. The above-mentioned differences by gender are statistically significant. Finally, about 53% (47%) of women are adequately educated (mismatched) for the job that they perform, whereas the figure for adequately matched workers is slightly lower in the case of men (52.41% of the sample); however, the difference by gender is not statistically significant. Regarding the distribution of men and women by occupational categories, there are, strikingly, only about half as many female than male managers. By contrast, women account for a notably larger proportion of professionals. As a result, almost 44% of women hold a high-skilled job, which is a higher proportion than for men at 40.44%. Of the low-skill occupations, women are mainly service and sales workers (25.48%) or clerical support workers (15.71%), and men are mainly craft workers (18.40%) and operators and assemblers (12.82%). Gender differences in the occupational distribution are statistically significant, except for the case of technicians and associate professionals.

4 Methodology

Given that this paper examines whether the strength of the relationship between a higher level of education and a greater probability of getting better jobs depends on the (mis)match between attained and required education, the methodology described below seeks to extend the ORU model to the sphere of discrete choice models.

While the traditional Mincer equations estimate a unique wage return for every year of attained schooling see Eq. 1, the ORU model offers a broader perspective by estimating differentiated coefficients for the wage returns to education depending on whether workers´ education matches the requirements of their jobs see Eq. 2:

$$ln(w_i) = \alpha + \beta S_i + \gamma X_i + u_i \tag{1}$$

$$ln(w_i) = \alpha + \beta_r S_{ri} + \beta_m S_{mi} + \gamma X_i + u_i \tag{2}$$

where $ln(w_i)$ is the log wage, S_i indicates the years of attained schooling, X_i is a vector of explanatory variables (typically experience and experience squared, as well as other worker attributes), and finally u_i is the error term. As it can be observed, the ORU equation decomposes S_i into S_{ri}, S_{mi}, indicating the years of education required by jobs and the years of mismatched education (measured as attained minus required schooling).

Focusing on the aim of our research, a multinomial logit model is estimated to evaluate the probability of a sample individual enjoying a particular labour status.

In our case, there are J occupational alternatives, and we have K explanatory variables. Therefore, the probability of individual i being located in alternative j is given by:

$$p_{ij} = \frac{exp\left(X_i'\alpha_j\right)}{\sum_{j=1}^{J} exp\left(X_i'\alpha_j\right)} \tag{3}$$

where X_i' is a vector of K explanatory variables associated with the individual i, and α_j are the coefficients for individual i linked to alternative j.

For the purposes of identification, all coefficients are expressed, as is common practice, with respect to an alternative selected as a reference category. Taking the first alternative as our reference, we have:

$$p_{ij} = \frac{exp\left(X_i'\beta_j\right)}{1 + \sum_{j=2}^{J} exp\left(X_i'\beta_j\right)} \tag{4}$$

where $\beta_j = \alpha_j - \alpha_1$.

Based on the estimated model, it is possible to calculate the average marginal effects of the changes in the explanatory variables on the probability of individual i being associated with each one of the J alternatives. In particular, we are interested in calculating the effects of longer schooling on the probability of entering a certain occupational category. To do this, we first estimate the model and predict the odds of working in each occupational category and then calculate how these probabilities change for workers who have completed one more year of education, *ceteris paribus the rest of the variables*, broken down by whether or not this additional year matches the educational requirements of the job.

When interpreting the results, remember that, by definition, the sum of probabilities is the unit. Therefore, an increase in the probability of entering a given occupational category(ies) will always be offset by a reduction in the probability(ies) of entering the remaining occupational category(ies).Related to the above, one drawback when interpreting the results of a probability distribution is that, in this case, there is no definite way of deciding whether a modification of the above-mentioned probabilities can be interpreted as positive or negative in terms of the individual's occupational status. To solve this drawback, each probability needs to be assigned a value in terms of occupational status using an objective weighting system. We used the International Socio-Economic Index (ISEI) of occupational status to assign an occupational status to each occupation. This index enjoys consensus among social sciences researchers, and thus we can sum and compare different probability distributions in terms of a global resulting occupational status (Ganzeboom, 2010). Further explanations of the procedure are given in Sect. 5.1.

Table 3 Returns to education from Mincerian and ORU equations

	Coefficient	Coefficient	Robust t-Stat
Attained education (β)	0.056		59.20
Required education (β_{r})		0.069	72.11
Mismatched education (β_{m})		0.024	20.74
Mathematical competencies	Yes	Yes	
Experience and its square	Yes	Yes	
Civil status	Yes	Yes	
Country dummies	Yes	Yes	

Table 4 Effects of education on the probability of getting a high-skill job

	Attained schooling	Required schooling	Mismatched schooling
Managers	0.72	1.07	0.34
Professionals	6.54	7.74	3.08
Technicians and associate professionals	0.61	0.86	0.12
High-skill occupations	*7.87*	*9.67*	*3.54*
Clerical support workers	−0.33	−0.45	−0.07
Service and sales workers	−2.08	−2.61	−0.62
Skilled agricultural, forestry and fishery workers	−0.42	−0.22	−0.08
Craft and related trades workers	−2.08	−2.10	−1.49
Plant and machine operators and assemblers	−1.46	−1.94	−0.76
Elementary occupations	−1.50	−2.36	−0.52
Low-skill occupations	*−7.87*	*−9.67*	*−3.54*

Italics provide the summ of the upper files

5 Results

This section reports the main findings of our research. They should be interpreted with caution, given the limitations of the data analysis carried out (see Conclusions for a further detail). Having this warning in mind, the results reported in this section establish a clear analogy with the widely documented outcome that wage returns to education are, far from being homogeneous, higher for required years of schooling and lower for mismatched years of schooling. Besides, if we compare the returns calculated using ORU equations and estimated using standard Mincerian wage equations, the usual result is[9]:

$$\beta_r < \beta < \beta_{\mathrm{m}}$$

[9] See, for example, Murillo Huertas et al. (2012); Iriondo & Pérez-Amaral (2016); Nieto & Ramos (2017).

Table 5 Effects of education on the probability of getting a high-skill job broken down by gender

	Attained schooling		Required schooling		Mismatched schooling	
	Men	Women	Men	Women	Men	Women
Managers	1.11	0.52	1.61	0.70	0.48	0.29
Professionals	5.20	7.67	6.23	8.92	2.43	3.58
Technicians and associate professionals	0.73	0.34	1.14	0.50	0.26	−0.09
High-skill occupations	*7.05*	*8.53*	*8.98*	*10.12*	*3.17*	*3.79*
Clerical support workers	−0.01	−1.16	−0.09	−1.32	0.22	−0.75
Service and sales workers	−0.83	−4.02	−1.28	−4.46	0.04	−1.81
Skilled agricultural, forestry and fishery workers	−0.44	−0.29	−0.24	−0.16	−0.05	−0.08
Craft and related trades workers	−2.78	−0.49	−2.79	−0.57	−2.03	−0.27
Plant and machine operators and assemblers	−1.81	−0.69	−2.60	−0.92	−0.88	−0.29
Elementary occupations	−1.17	−1.88	−1.99	−2.67	−0.46	−0.60
Low-skill occupations	*−7.05*	*−8.53*	*−8.98*	*−10.12*	*−3.17*	*−3.79*

Italics provide the summ of the upper files

Thus, we first test the hypothesis of heterogeneity of returns to education using our data. In this way, we can also find out whether the above inequality holds even when we control for both the quantity and the quality, measured as competencies, of schooling. The results are shown in Table 3.

Question 1: The returns to education depend on the (mis)match between attained and required schooling.

Our results strongly support the idea that returns to schooling are not homogeneous, even when we compare individuals with similar levels of competencies. For instance, if we assume that every year of attained schooling has the same return, that is, we estimate a Mincer wage equation, the resulting coefficient indicates that one additional year of education increases wages by 5.6%. However, the increase in wages derived from schooling is as high 6.9% if this education meets employer requirements, whereas it accounts for barely 2.4% for an additional year of mismatched education. In conclusion, more education increases wages, but the extent of this increase depends on the (mis)match between attained and required schooling.

Based on these findings, we formulate our next question, namely: The effect of a longer education on the probability of getting a better job also depends on the (mis) match between attained and required education. Table 4 reports the marginal effects of an increase in education on the probabilities of entering each occupational category, taken “Elementary occupations” as the reference category. They have been calculated as indicated in Sect. 4.

Question 2: The magnitude of the effect of one more year of education on the probability of getting a high-skill job also depends on the (mis)match between attained and required schooling.

Table 4 shows how longer schooling correlates with an increase in the probability of entering a high-skill occupation and hence decreases the probability of accepting a low-skill job, especially with respect to the occupational category Professionals. The size of this increase clearly depends on the degree of fit between attained and required schooling, which is optimum (minimum) for (mis)matched education. Interestingly, a perfect analogy can be established between the results reported in Table 4 and the findings obtained when comparing the returns to education derived from Mincer and ORU wage equations. Thus, the increase in the probability of entering a high-skill occupation derived from one additional year of attained education is, *ceteris paribus* the rest of the variables, 7.87%. However, if this schooling matches the educational requirements of the job, then the increase is as much as 9.67%, whereas this figure is much lower (less than half of the rate for an additional year of attained schooling) if there is educational mismatch.

It is also interesting to study whether the above-mentioned patterns are observed for both men and women, or, by contrast, there is any significant gender-related difference. Thus, the next question that we raised was whether the effect of an increase in education on the probability of getting a better job not only depends on the fit between attained and required education but also varies by gender. The results, reported in Table 5, highlight the following findings.

Question 3: The magnitude of the effect of one more year of education on the probability of getting a high-skill job depends on the (mis)match between attained and required schooling and varies by gender.

First, longer schooling correlates with a higher probability of entering a high-skill occupation and hence to a decrease in the probability of accepting a low-skill job for both men and, especially, women. Thus, for example, one more year of attained education increases the probability of performing an occupation in the group denoted as professionals by 5.2% for men and 7.67% for women, *ceteris paribus* the rest of the variables. Second, the effect of longer schooling in terms of a greater probability of getting a high-skill job strongly depends on the (mis)match between attained and required education, again for both men and women. For example, if a man extends his education by one year and this education meets the educational requirements of the job, then his probability of getting a high-skill occupation increases by 8.98%, whereas this increase is barely 3.17% if there is no such match. On the other hand, if woman extends her education by one year and her education matches the educational requirements of the job, then the increase in the probability of entering a high-skill occupation rises to an optimum 10.12%, whereas the rate is 3.79% if there is no such match between attained and required education. Note also that the effect size of one additional year of matched education for men (8.98%) is quite similar to that of one additional year of attained education for women (8.53%). Overall, these results suggest that it is women who benefit most from higher educational attainment, especially in the absence of educational mismatch.

Since the literature suggests that the institutional context could strongly determine the outcomes associated with education and educational mismatch, we also analyse whether the results reported so far are robust to different educational and institutional systems and hence whether or not they vary by country. To test this hypothesis, we grouped the countries represented in our sample into the following

Table 6 Effects of education on the probability of getting a high-skill job by gender and country

	Attained schooling		Required schooling		Mismatched schooling	
	Men	Women	Men	Women	Men	Women
High-skill occupations						
Continental Europe	7.32	9.82	9.53	11.23	3.04	4.96
Mediterranean	6.05	6.85	7.16	7.66	2.57	2.85
Nordic	7.96	9.22	9.39	9.91	3.95	4.56
Eastern Europe	7.47	9.26	9.55	11.37	2.79	3.50
British Isles	6.28	7.67	8.95	9.78	2.36	3.14
Asia	6.28	7.60	8.41	9.89	3.84	4.09
Low-skill occupations						
Continental Europe	−7.32	−9.82	−9.53	−11.23	−3.04	−4.96
Mediterranean	−6.05	−6.85	−7.16	−7.66	−2.57	−2.85
Nordic	−7.96	−9.22	−9.39	−9.91	−3.95	−4.56
Eastern Europe	−7.47	−9.26	−9.55	−11.37	−2.79	−3.50
British Isles	−6.28	−7.67	−8.95	−9.78	−2.36	−3.14
Asia	−6.28	−7.60	−8.41	−9.89	−3.84	−4.09

groups: continental Europe (Belgium, Denmark, Netherlands), the Mediterranean (Italy, Spain), the Nordic countries (Finland, Norway, Sweden), Eastern Europe (Czech Republic, Estonia, Poland, Slovak Republic), the British Isles (Ireland, United Kingdom) and Asian countries (Japan, Korea). Table 6 shows the results for high-skill and low-skill occupations as a whole (results detailed by occupational category are shown in Tables A1 and A2 of the appendix).

Question 4: The magnitude of the effect of one more year of education on the probability of getting a high-skill job depends on the (mis)match between attained and required schooling and (do not) varies by country.

Table 6 illustrates that an increase in education correlates with a higher (lower) probability of entering a high-skill occupation (low-skill job), and that this positive effect is maximum for matched schooling, intermediate for attained schooling and minimum for mismatched schooling for all of the blocks of countries considered. It also shows that the benefit of one additional year of education is unfailingly higher for women than for men, especially in the absence of educational mismatch, also in all of the blocks of countries considered. Therefore, our findings appear to be robust to the institutional context.

Nonetheless, we also observe remarkable differences by country regarding the size of the above-mentioned patterns. Thus, the increase in the probability of occupying a high-skill job derived from one extra year of education is notably high for women in continental and Eastern European countries, especially in the absence of educational mismatch: the probability of women with one more year of schooling from Eastern European countries getting a high-skill job increases by 11.37% if this

Table 7 Effects of education on the aggregate occupational status by gender and country

	Aggregate occupational status		Increase due to attained schooling (%)		Increase due to required schooling (%)		Increase due to mismatched schooling (%)	
	Men	Women	Men	Women	Men	Women	Men	Women
Continental Europe	47.44	43.63	5.21	7.05	6.82	8.12	2.14	3.22
Mediterranean	42.36	40.65	5.08	5.85	5.99	6.81	2.13	2.45
Nordic	45.84	45.42	6.08	6.83	7.18	7.46	3.00	3.37
Eastern Europe	41.62	42.22	5.51	7.41	7.05	9.05	1.94	2.67
British Isles	44.99	41.98	4.43	5.59	6.35	7.26	1.62	2.33
Asia	42.83	37.95	4.89	6.14	6.58	7.81	2.84	3.28
Full sample	43.68	41.74	5.36	6.62	6.81	7.93	2.35	2.86

schooling matches the job requirements (the respective figure for Eastern European men is 9.55%). By contrast, the positive effect of a better education on the probability of getting a better job is smallest for men living in Mediterranean countries or the British Isles and, to a lesser extent, also for Mediterranean women with educational mismatch: the probability of men from Mediterranean countries with one more year of education entering a high-skill occupation improves by only 2.57% if this education does not match the job requirements (if there is a match, then the improvement in their prospects is as much as 7.16%).

5.1 Increase in the aggregate occupational status derived from longer schooling

The results reported up to now show the effects of one additional year of education on the changing odds of working in each of the nine ISCO-08 major groups. Albeit interesting, these results could be misleading. Suppose an individual who attends one additional year of schooling, and, as a consequence, his/her probability of entering a job of the occupational categories 1 and 2 increases. An increase in the probability of entering those occupations necessarily implies a decrease in the probability of entering the reminder occupational categories; in discrete choice models an increase in the probability of obtaining one particular result is equal to a decrease in the probability of getting the other results, because, by definition, the sum of probabilities is always equal to one. Thus, to clarify whether or not the increased probability of entering occupations 1 and 2 is a desirable outcome, it is necessary to define an objective, synthetic index where probabilities can be added assigning different weights to each occupational category. In this way, the sum of the change in odds derived from longer schooling will be positive or negative, but different from zero.

To this end, we rely on the ISIE index proposed by Ganzeboom (2010). This is an index that summarizes occupational status by scaling jobs according to the average level of both the earnings and the education of the job holders. The index uses the same occupational classification as our database (ISCO-08) and was constructed based on representative pooled data from the International Social Survey Programme (ISSP) waves 2002–2007 referred to a large number of countries and workers. Using the ISIE index, we can compare the initial occupational status of each of the collectives that we consider (men and women, for example) and assess the improvement of their status when an increase in education takes place.

Table 7 reports the effects of an increase in schooling on the ISIE occupational index, considering a possible mismatch between attained and required education, broken down by gender and estimated by blocks of countries. The column “Aggregate occupational status” shows the ISIE index for each block of countries and by gender. The reminder three right columns show how this index changes when individuals increase their education in one year, broking down by whether or not this additional year matches the educational requirements of the job.[10]

As the two first rows show, with the exception of the Nordic and, to a lesser extent, the Eastern countries where figures for both genders are quite similar, men enjoy a higher global occupational status than women do, especially in the Asian countries. An increase in education consistently enhances the occupational status of workers, but the size of the effect depends on a possible (mis)match between attained and required education and varies by gender and by country. Hence, in line with our other findings, the effect of an increase in education on the improvement of occupational status is biggest (smallest) when this education (mis)matches job requirements and is more pronounced for women than for men. An increase in education has an optimum effect on the occupational status of women living in Eastern European countries: one additional year of education matching the job requirements increases their occupational status by more than 9%, which is two percentage points above the figure for to their male compatriots. At the other end of the scale, the poorest effect is for the British Isles, where an increase in education that does not match company requirements improves occupational status by only 1.62% for men and 2.33% for women.

6 Conclusions

A large number of papers have focused on analysing the multiple disadvantages associated with educational mismatch in detriment to workers, firms and countries. This paper aims to document a further limitation derived from educational mismatch, namely the weaker effect of an increase in education on the probability of

[10] As matter of example, the figure corresponding to an additional year of attained schooling for men in Continental Europe (5.21%) has been calculated as follows: The average ISIE index for this group is 47.44. The increase in this aggregate occupational status when individuals attain one more year of education is 2.47, which leads to a value of the index of 49.91. Thus, 5.21% is the ratio between the increased and the original indexes.

The increase in the aggregate occupational status (2.47) has been calculated by multiplying the average value of the ISIE index by occupation times the changed odds of entering each occupation after increasing attained education. The changed odds of entering each occupation after increasing schooling are reported in Tables A1 and A2 of the Appendix.

entering high-skill jobs when this longer schooling does not meet job requirements. To achieve this goal, we relied on PIAAC data to answer a research question aligned with the widely documented result that an additional year of schooling contributes most to labour market success if it provides the education needed to perform the job. In particular, we estimate multinomial logit regressions to examine whether the effect of an increase in education on the probability of getting a high-skill job depends on the degree of fit between the education attained by the worker and the education required by the employer. Our data analysis has some noteworthy limitations. Thus, the error term of our equations includes omitted variables that could be correlated with individuals´ schooling and that could potentially vary across genders, thus distorting the reported results. That is the case, for example, of mobility in response to educational mismatch. A possible sample selection bias has not been considered, so we implicitly assume that additional schooling does not change individuals' propensity to work. Finally, the procedure followed to measure the educational mismatch -i.e., the subjective method- has several shortcomings widely acknowledged in the literature (see, for example, Hartog, 2000); the main one is its lack of rigorous instructions, which usually leads to overstated figures of overeducation as workers tend to perceive their job as requiring higher competencies to be performed than what are actually needed.

Our results suggest that an extra year of education is positively associated with a higher probability of getting a high-skill job, but the size of this effect clearly depends on the degree of fit between attained and required education: it is highest for matched education and lowest for mismatched education. Although this outcome holds for both men and women, women are the ones who benefit most from higher educational attainment, especially in the absence of educational mismatch. These trends seem to be robust to diverse educational and institutional systems. However, we also found interesting differences by countries regarding the size of the above-mentioned effects. Hence, women from Eastern European countries benefit most from an extra year of matched education, while men from the British Isles benefit least from an additional year of mismatched education.

As pointed out in research on the topic, educational mismatch implies that workers cannot be certain about the possible returns from further investment in education, as their wages and job satisfaction depend on a coincidental match between attained and required education. The results discussed in this article are aligned with this idea, as they provide evidence that educational mismatch strongly debilitates the relationship between better education and better jobs, thus adding to the list of disadvantages for workers derived from this phenomenon. Hence, our research supports policy recommendations aimed at helping workers enter jobs commensurate with their human capital, such as measures designed to combat aspects that increase the odds of workers being over(under)educated.

Appendix

For appendix see Table 8, 9

Table 8 Detailed effects on high-skill occupations by gender and country

	Attained schooling		Required schooling		Mismatched schooling	
	Men	Women	Men	Men	Women	Men
Managers						
Continental Europe	1.60	0.61	2.52	0.83	0.67	0.51
Mediterranean	0.51	0.18	0.73	0.28	0.47	0.31
Nordic	1.10	0.70	1.34	0.88	0.60	0.41
Eastern Europe	1.96	1.15	2.08	1.31	0.65	0.49
British Isles	−0.01	−0.30	0.83	−0.11	−0.53	−0.48
Asia	1.05	0.27	1.48	0.33	0.50	0.22
Professionals						
Continental Europe	6.22	9.94	7.75	11.70	2.54	5.46
Mediterranean	4.67	5.83	4.95	6.66	2.10	2.55
Nordic	6.77	9.04	7.75	9.64	3.63	4.95
Eastern Europe	3.79	7.03	4.66	8.41	1.42	2.58
British Isles	5.43	7.58	6.92	9.17	2.22	3.80
Asia	4.17	7.01	5.83	8.81	2.55	3.51
Technicians and associate professionals						
Continental Europe	−0.50	−0.73	−0.74	−1.29	−0.18	−1.00
Mediterranean	0.87	0.83	1.48	0.72	0.00	−0.01
Nordic	0.08	−0.53	0.31	−0.62	−0.28	−0.80
Eastern Europe	1.72	1.08	2.81	1.65	0.72	0.44
British Isles	0.86	0.38	1.20	0.71	0.67	−0.19
Asia	1.07	0.31	1.10	0.75	0.78	0.36

Table 9 Detailed effects on low-skill occupations by gender and country

	Attained schooling		Required schooling		Mismatched schooling	
	Men	Women	Men	Men	Women	Men
Clerical support workers						
Continental Europe	−1.03	−2.83	−1.42	−3.57	−0.36	−2.57
Mediterranean	0.37	−0.78	0.45	−1.02	0.68	−0.57
Nordic	−0.28	−1.52	−0.38	−1.57	0.01	−1.05
Eastern Europe	0.20	−0.15	0.47	−0.06	0.36	0.01
British Isles	−0.04	−2.36	−0.24	−2.69	0.54	−1.18
Asia	0.71	0.09	0.64	−0.04	0.21	0.14
Service and sales workers						
Continental Europe	−0.90	−3.92	−1.38	−4.18	−0.05	−1.80
Mediterranean	−0.43	−3.01	−0.61	−2.52	0.52	−1.15
Nordic	−1.41	−5.07	−1.71	−5.14	−0.36	−2.49
Eastern Europe	0.18	−3.81	0.07	−4.68	1.03	−1.81

Table 9 (continued)

	Attained schooling		Required schooling		Mismatched schooling	
	Men	Women	Men	Men	Women	Men
British Isles	−1.23	−3.73	−2.24	−4.61	−0.16	−1.25
Asia	−1.08	−3.82	−1.86	−4.86	−0.65	−2.07
Skilled agricultural, forestry and fishery workers						
Continental Europe	−0.19	−0.13	−0.10	−0.07	0.04	−0.05
Mediterranean	−0.52	−0.21	−0.29	−0.12	0.00	−0.12
Nordic	−0.54	−0.31	−0.29	−0.15	−0.05	−0.08
Eastern Europe	−0.27	−0.42	−0.23	−0.28	−0.07	−0.07
British Isles	−0.50	−0.03	−0.26	−0.04	−0.09	−0.01
Asia	−0.59	−0.37	−0.25	−0.21	−0.14	−0.10
Craft and related trades workers						
Continental Europe	−2.43	−0.27	−2.65	−0.26	−1.33	0.01
Mediterranean	−2.73	−0.23	−2.35	−0.18	−2.61	0.02
Nordic	−2.79	−0.33	−2.66	−0.32	−2.21	−0.19
Eastern Europe	−3.94	−0.96	−4.10	−1.19	−2.77	−0.57
British Isles	−1.98	−0.21	−1.76	−0.24	−1.12	−0.13
Asia	−2.21	−0.74	−2.64	−1.05	−1.46	−0.51
Plant and machine operators and assemblers						
Continental Europe	−1.52	−0.33	−2.22	−0.36	−0.69	−0.14
Mediterranean	−1.36	−0.46	−1.96	−0.53	−0.89	−0.17
Nordic	−1.95	−0.53	−2.70	−0.72	−0.98	−0.28
Eastern Europe	−2.23	−1.46	−3.43	−1.93	−0.84	−0.51
British Isles	−1.34	−0.25	−2.24	−0.36	−0.86	−0.08
Asia	−2.06	−0.56	−2.36	−0.80	−1.12	−0.36
Elementary occupations						
Continental Europe	−1.26	−2.35	−1.76	−2.80	−0.65	−0.40
Mediterranean	−1.37	−2.16	−2.41	−3.30	−0.27	−0.87
Nordic	−0.99	−1.45	−1.65	−2.00	−0.36	−0.48
Eastern Europe	−1.41	−2.47	−2.34	−3.24	−0.51	−0.54
British Isles	−1.19	−1.09	−2.21	−1.84	−0.68	−0.48
Asia	−1.06	−2.19	−1.94	−2.93	−0.67	−1.20

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